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Vivek Shrivastava
Jagdish Chand Bansal
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Power Engineering and Intelligent Systems

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B. K. Panigrahi
Editors

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Preface

This book contains outstanding research papers as the proceedings of the International Conference on Power Engineering and Intelligent Systems (PEIS 2024). PEIS 2024 has been organized by National Institute of Technology, Uttarakhand, India, and technically sponsored by Soft Computing Research Society, India. The conference is conceived as a platform for disseminating and exchanging ideas, concepts, and results of researchers from academia and industry to develop a comprehensive understanding of the challenges of the advancements of intelligence in computational viewpoints. This book will help in strengthening congenial networking between academia and industry. We have tried our best to enrich the quality of the PEIS 2024 through the stringent and careful peer-review process. This book presents novel contributions to Power Engineering and Intelligent Systems and serves as reference material for advanced research. PEIS 2024 received many technical contributed articles from distinguished participants from home and abroad. After a very stringent peer-reviewing process, only 82 high-quality papers were finally accepted for presentation and the final proceedings.

This book presents second volume of 40 research papers related to power engineering and intelligent systems and serves as reference material for advanced research.

Srinagar, Uttarakhand, India — Vivek Shrivastava
New Delhi, India — Jagdish Chand Bansal
New Delhi, India — B. K. Panigrahi

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Study of the Optimal Sizing of Battery Energy Storage Systems for Microgrid Applications

Nirdesh Singh and D. K. Jain

Abstract Battery energy storage (BES) is an essential element that enables microgrids (MGs) to function in a dependable, resilient, and economically viable manner. The sizing of the BES, which can result in the MG having superior performance, flexibility, efficacy, and efficiency compared to conventional power systems, is one of the most significant challenges in MG. Implementing a battery energy storage system (BESS) that is suitably sized and implemented not only aids in meeting peak demand but also enhances the benefits of renewable energy sources integration, refines power quality control, and reduces the expenses associated with expanding or reconfiguring distribution networks. This article provides an overview of the primary methodologies utilized in electrical networks to ascertain the most suitable dimensions, placement, and operation of Energy Storage Systems (ESSs) and Distributed Generators (DGs). Furthermore, this study also investigates the benefits of the ESS and a range of technologies.

Keywords Energy storage · Sizing · Renewable energy source

1 Introduction

In recent years, rising population and demand have led to a massive rise in the number of green energy generators added to the power grid [1]. Microgrids (MG) are small power grids made possible by increased distributed generation (DG) resources. These resources are mostly placed at the distribution level. The United States Department of Energy (DOE) provides a comprehensive elucidation of MG in Ref. [2]. A microgrid consists of inputs and distributed energy sources (DERs) connected by a set of electrical boundaries that are precisely defined. It can connect and disconnect from the grid as a single controllable entity, enabling it to function in grid-connected or island configurations [3]. By their very nature, most DG supplies are intermittent. Conversely, consumers use different amounts of energy at other times of the day.

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One of the most critical challenges for MG is to keep the balance between generation and load. Various methods have been used to deal with this problem, such as energy storage systems (ESS), load shifting, load shedding, and connecting to the utility grid. The installation of ESS and the DG resources have received more attention [4]. ESS is capable of enhancing power network performance and balancing loads. Some valuable features are improving power quality, lowering dependability, reducing peak shaving, and making renewable energy sources less unpredictable [5]. Several ESS technologies have been used in MG, but batteries have gotten the most attention [6].

Not forgetting the best way to run and handle storage systems in a distribution network is imperative, mainly whenever DG integration is involved. Inadvertent and unregulated ESS operation could result in substantial losses for the ESS and DG operators. It's hard to know ahead of time what each generation plant's operational state will be because power from renewable energy sources is random and hard to predict. This is especially true if the plant hasn't yet figured out the best way to work with the ESS and the grid. It also does not always consider the state of charge (SOC) or the number of charging and discharging processes for ESS, specifically Battery Energy Storage System (BESS). An ESS of the right size must be connected to a microgrid. A huge ESS costs a lot to build, and an ESS that is too small might not provide any practical or economic benefits. An increase in ESS capacity does not invariably result in the most cost-effective operational expenditure for the MG system. The influence of BES size on the planning cost of microgrid expansion is illustrated in Fig. 1. A larger BES increases the initial investment cost linearly while the operation cost decreases nonlinearly. The point at which the sum of these two costs is minimum is frequently regarded as the optimal point.

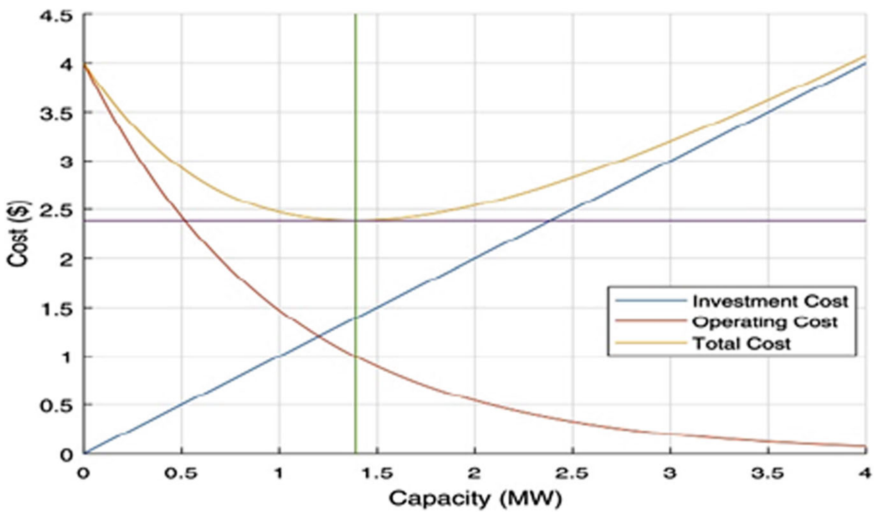


Fig. 1 Variation in ESS magnitude w.r.t investment and operating cost [7]

Frequent charge and recharge cycles and inaccurate upper and lower limits of SOC can seriously shorten the life of BESS [8]. Various types of Energy Storage Systems (ESS) have been developed, with some being commercially available with various technical characteristics that make them different. Some of the storage systems are Flywheel Energy Storage (FES), Super Capacitors, and other energy storage technologies such as fuel cells, Superconducting Magnetic Energy Storage (SMES), compressed air energy storage, Battery Energy Storage (BES), and pumped hydro energy storage. A summary of specific technical attributes of various energy storage systems is presented in Table 1.

This study provides a comprehensive analysis of the most effective way to size and allocate Energy Storage Systems (ESS) in the power system and examines various control schemes for operating ESS. Integrating Distributed Generation (DG) and Energy Storage Systems (ESS) has been suggested to improve the stability and dependability of the Generation of renewable energy sources. Figure 2 illustrates the standard setup of a grid that incorporates both DG and ESS.

The rest of the paper is designed as follows.

A literature review is done in Sect. 2. The application (Role) of ESS on the generation and end-user sides, along with the general algorithm for placement and sizing of an ESS, is discussed in Sects. 3 and 4, respectively. The system's performance is analyzed in Sect. 5, and Sect. 6 concludes the paper with future directions.

Table 1 Technical attributes of the various energy storage systems [7]

Type of energy storage	Storage duration	Efficiency (%)	Cost ($/kWh)	Lifetime (years)	Power rating (MW)
Superconducting magnetic energy storage (SMES)	Minutes-hours	95–98	1000–10,000	20+	0.1–10
Flywheel energy storage	Sec-minutes	85–95	1000–5000	~ 15	0.0–0.25
Supercapacitor	Sec-hours	84–97	300–2000	10–30	0–0.3
Lead-acid battery	Min-days	63–90	200–400	5–15	0–20
Li-ion battery	Min-days	75–97	600–2500	5–15	0–0.1
Compressed air energy storage	Hours-months	50–89	2–50	20–60	5–300
Hydrogen energy storage (fuel cell)	Hours-months	20–66	–	5–15	0–50
Pumped hydro energy storage	Hours-months	65–87	5–100	40–60	100–5000

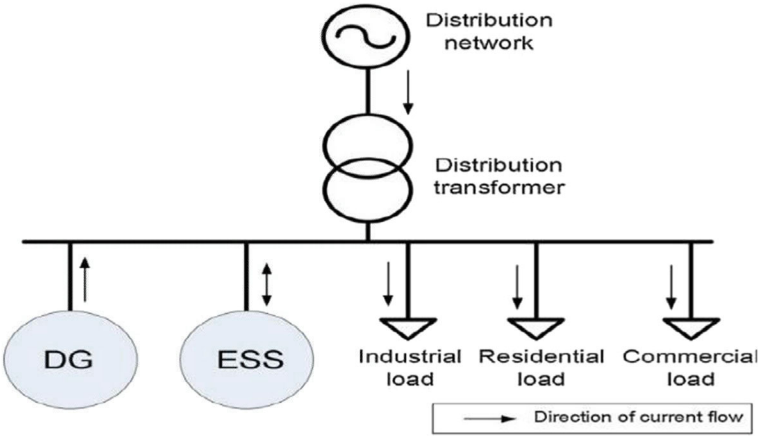


Fig. 2 Configuration of a typical distribution generation with DG and ESS

2 Literature Review

Determining the ideal size for battery storage in microgrid (MG) applications is complex. Several writers have examined the problem of determining the perfect size for energy storage systems, employing different levels of specificity and a range of optimization methods. A novel technique is presented in to achieve appropriate Battery Energy Storage (BES) size in Microgrids (MG) to reduce operational expenses [9]. Introduces an optimization issue in which the sizing of Battery Energy Storage (BES) is determined using particle swarm optimization [10]. This approach incorporates demand response to enhance the stability of microgrid (MG) frequency regulation. The investigation of load uncertainty to improve the reliability of an MG is detailed in reference, where the goal is to minimize the overall cost through the use of BES [11]. The optimal capacity of the ESS to enhance the power quality of the MG is determined in [12]. To make the system more resilient to extreme events, the optimal method for determining the capacity and location of photovoltaic (PV) and BES production is examined in [13]. The best BES size for three grid-connected and isolated MG situations based on operation cost is looked at in [14]. However, neither the optimal period for BES replacement nor capacity degradation is considered suggests a new way to figure out where and how big an ESS should be to support the grid best [15]. The study in proposed the best way to size a PV-wind-battery system on an island [16]. The study considered the uncertainty of the PV and wind power outputs and the load demand. An optimal sizing method for a stand-alone residential microgrid was introduced in to lower the cost of operation, the amount of greenhouse gases released, and the amount of energy needed for critical dumps [17]. In reference, an iterative simulation-based optimization algorithm for determining the optimal PV array and battery capacities for an isolated PV system was proposed

[18]. To accomplish this, a comprehensive dynamic model was employed to simulate the performance of the lead-acid battery. However, most earlier studies failed to investigate the decline in battery life [16–18]. Because battery storage systems (BSS) are more expensive to buy and don't last as long as other parts of a microgrid, more and more research is being done to find the best way to make them work and how big they should be; this is being done by using different methods to estimate how long batteries will last. A linear model was used to predict the lead-acid battery lifetime degradation by only looking at the discharged power effect [19]. This was part of a proposal for the best size of a residential microgrid. A two-step method was suggested for counting the number of battery operation cycles to find out the battery size, the depth of discharge (DOD) value, and its lifetime [20]. Using previous wind data, a stochastic cost–benefit analysis model was created [21]. Benders' decomposition was proposed as a method in Nick [22] for determining the acceptable size and location of the ESS. The Benders Decomposition method was inherently limited in generating optimization problems, involving dual variables to reduce the solution space. In Qiu [23], a two-stage planning approach was proposed to achieve optimal allocation and operation of microgrids to reduce costs associated with the grid, distributed generation, battery energy storage, and controllable loads. For the ESS sizing problem, Bucciarelli [24] proposed a two-step approach: in the first step, storage capacity is optimized by minimizing installation and daily operation costs; in the second step, the optimal control of the ESS is determined in consideration of the capacity of the ESS; and so on. In Babacan [25], a bi-level optimization strategy based on GA was implemented to reduce voltage fluctuations via BESS. The location and sizing of BESS were investigated in Salee and Wirasanti [26] to reduce total network losses and provide voltage support. To strike a balance between the cost of BESS and its ability to calm the wind, Zhang [27] introduced a method for sizing BESS. An overview of the literature review is also described in tabular form in Table 2.

3 Application (Role) of ESS on the Generation Side

First, the ESS can facilitate the time shifting of energy output. Secondly, it can be utilized as seasonal energy storage, which entails time shifting over an extended period. The ESS can aid in ramp rate control, which is a method of regulating the power output of the generation, particularly for sources with fluctuating output, such as photovoltaic and wind power. Additionally, the ESS is crucial for voltage control support [7]. The Energy Storage System (ESS) can contribute to the maintenance of grid voltage stability by providing reactive power to the network. In addition, the Energy Storage System (ESS) may stabilize the voltage of the network by providing power during disruptions that may occur on the utility side. It can also charge or discharge in response to abrupt changes in load to reduce voltage drops and increases. Furthermore, ESS aids in reducing reverse power flow that may result

Table 2 Summary of literature review

References	Streamlined component	Method	Objective function	ESS application
[9]	Sizing	Particle swarm optimization (PSO) incorporating dynamic demand response (DR)		System stability improvement
[11]	Sizing	MILP	Cost minimization	Enhancing stability
[13]	Allocation + sizing	Principle of capacity utilization for non-black-start (NB-S) generating units and electricity demand	Investment and operation cost and capacity accessibility	Enhance resiliency
[14]	Size	Nonlinear optimization method	Optimal operation cost	Economical
[15]	Siting and sizing and energy capacity	The constraints of the MV and HV grids are expressed in a linearized form	Reserve provision	Gird support
[8]	Sizing	Modeling and simulation	Considering suppressed demand effects	Improving reliability
[17]	Sizing	Particle swarm optimization	Minimize cost, reduce greenhouse emissions, curtail dump energy	Improving stability
[18]	Sizing	Bi-objective techno-economic optimization	Minimum cost and maximum availability level	
[19]	Sizing and analysis	Mixed integer linear programming	Intrinsic stochastic behavior of renewable energy and uncertainty of load	Increased adoption of smart grid technology
[20]	Sizing and selection of battery	Mixed integer linear programming	Battery's optimal size, depth of discharge, and lifetime cycling	Cost reduction
[21]	Size	Cost–benefit analysis	Reduce generator running and ESS investment costs	Solve intermittency
[22]	Size and location	Extract convex OPF conditionally using the Benders decomposition method	Reduce ESS and daily operating costs	Voltage support, grid congestion mitigations

(continued)

Table 2 (continued)

References	Streamlined component	Method	Objective function	ESS application
[23]	Size and location	Self-computed two-stage algorithm	Reduce expenditures on the grid, BESS, DG, and controllable demand	Network support, smooth output generation
[24]	Size	Two-stage stochastic algorithm	Minimize the total installed storage capacity	Voltage support
[25]	Size and location	Method for bi-level optimization based on GA	Minimize voltage fluctuations	Voltage support
[26]	Size and location	GA	Minimize the deviations of voltage and the loss of power	Voltage support, power loss reduction
[27]	Size	Modulation by variable interval reference improved PSO	Achieve maximum annual revenue by minimizing the discrepancy between reference and actual output	Voltage support

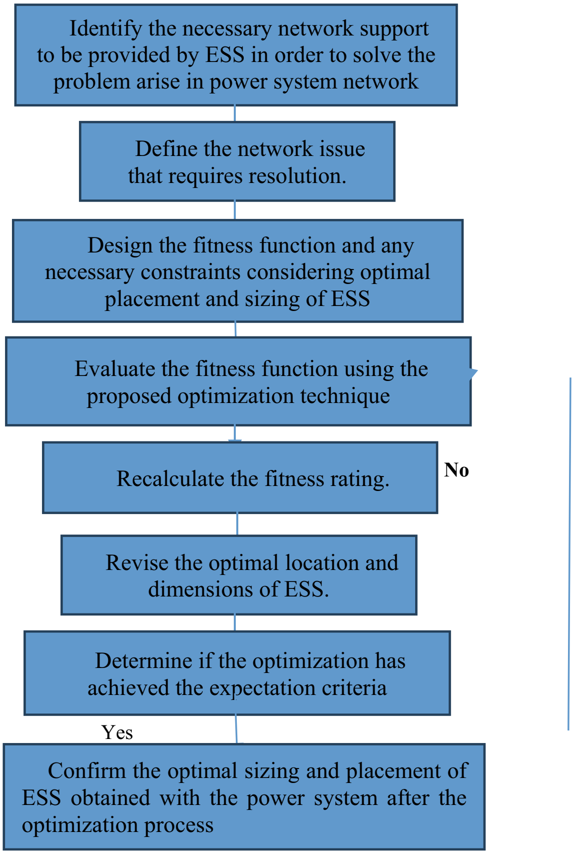
from the integration of distributed generation, the substitution of spinning reserve, the implementation of peak shaving, and, lastly, the provision of black start support during grid outages [7, 28].

4 Applications (Role) of ESS for the End User

At the end-user level, the primary function of ESS is to meet energy and power demands [7]. The end users rely heavily on the ESS to improve power dependability. The ESS can substitute fuel-guzzling end-user generators (which serve as a reserve for the power supply system). Aside from brief power outages, the backup ESS provides electricity. The ESS also plays a crucial role in enhancing the ride-through capability of household appliances and industrial loads by serving as an uninterrupted power supply (UPS). Several techniques for the location and sizing of energy storage systems (ESS) have been proposed in the literature.

Figure 3 depicts the general algorithm for placement and sizing ESS.

Fig. 3 General algorithm for placement and sizing of an ESS



5 Results and Discussion

To illustrate the outcome of battery bank size, the capacity of various battery quantities was measured. By examining Fig. 4, it is evident that the battery lifetime rises when the number of batteries is greater. However, beyond a certain battery number, this growth has a detrimental impact. The theory behind this is that raising the number of batteries under the same operating circumstances will result in a reduction of the current discharged from each cell, hence accelerating the depreciation of the battery capacity [29].

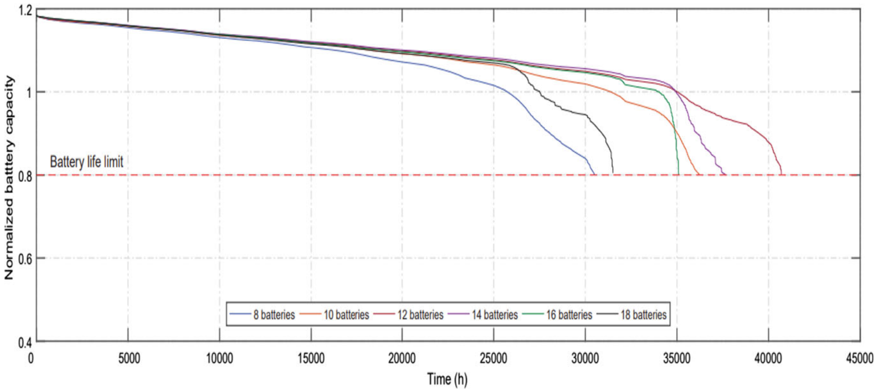


Fig. 4 Impact of battery bank size on battery capacity (6-optimal)

6 Conclusion and Future Directions

MGs equipped with Energy Storage Systems (ESS) can enhance the system's reliability, increase economic viability, and reduce greenhouse gas (GHG) emissions as sustainable development solutions. This paper offers a comprehensive analysis of energy storage systems, encompassing aspects such as sizing, technology, advantages, allocation, and control mechanisms. The primary emphasis is on optimizing the efficiency of energy storage systems (ESS) by determining the optimal size, placement, and management. The literature review uncovered that the incorporation and functioning of Energy Storage Systems (ESSs) and Distributed Generators (DGs) in electrical networks is a nascent study area, as evidenced by the limited number of publications in the specialized literature.

From a futuristic standpoint, a more intricate examination of Battery Energy Storage Systems (BESS) becomes imperative to assess their dynamic impact comprehensively. This entails a meticulous analysis of battery degradation, DC-to-DC converters, voltage source inverters, and the dynamic behaviors exhibited by filters and transformers.

To guarantee the optimal planning and operation of BESS, conducting a thorough techno-economic analysis is essential. This analysis should encompass a detailed consideration of capital costs, operational expenses, maintenance requirements, and other pivotal factors influencing the aging process of BESS.

References

1. Gungor VC (2011) Smart grid technologies: communication technologies and standards. IEEE Trans Ind Inf 7(4):529–539
2. Ton DT (2012) The US department of energy's microgrid initiative. Electr J 25(8):84–94

3. DOE microgrid workshop report. https://www.energy.gov/oe/articles/2012-doe-microgrid-workshop-summary-report-september-2012. Accessed 30 July 2012
4. Loh PC (2013) Autonomous control of interlinking converter with energy storage in hybrid AC-DC microgrid. IEEE Trans Ind Appl 49(3):1374–1382
5. Lasseter RH, Paigi P (2004) Microgrid: a conceptual solution. In: IEEE 35th annual power electronics specialists conference. IEEE, Aachen, Germany, pp 4285–4290
6. Gouvei C (2013) Coordinating storage and demand response for microgrid emergency operation. IEEE Trans Smart Grid 4(4):1898–1908
7. David WG (2015) Energy storage for sustainable microgrid, 1st edn. Academic Press, Amsterdam, Netherlands
8. Jiang Q (2013) A battery energy storage system dual-layer control strategy for mitigating wind farm fluctuations. IEEE Trans Power Syst 28(3):3263–3273
9. Chen S (2011) Sizing of energy storage for microgrids. IEEE Trans Smart Grid 3(1):142–151
10. Kerdphol T (2016) Optimum battery energy storage system using PSO considering dynamic demand response for microgrids. Int J Electr Power Energy Syst 83:58–66
11. Abdulgalil MA (2019) Enhancing the reliability of a microgrid through optimal size of battery ESS. IET Gener Transm Distrib 13(9):1499–1508
12. Fu Q (2012) Microgrid generation capacity design with renewables and energy storage addressing power quality and surety. IEEE Trans Smart Grid 3(4):2019–2027
13. Zhang B (2017) Optimal allocation of PV generation and battery storage for enhanced resilience. IEEE Trans Smart Grid 10(1):535–545
14. Salman UT (2020) Optimal sizing of battery energy storage for grid-connected and isolated wind-penetrated microgrid. IEEE Access 8:91129–91138
15. Massucco S (2020) Siting and sizing of energy storage systems: towards a unified approach for transmission and distribution system operators for reserve provision and grid support. Electr Power Syst Res 190(45)
16. Maleki A (2016) Optimal sizing of a grid independent hybrid renewable energy system incorporating resource uncertainty, and load uncertainty. Int J Electr Power Energy Syst 83:514–524
17. Akram U (2018) An improved optimal sizing methodology for future autonomous residential smart power systems. IEEE Access 6:5986–6000
18. Ibrahim IA (2017) Optimal sizing of a standalone photovoltaic system for remote housing electrification using numerical algorithms and improved system models. Energy 126:392–403
19. Atia R (2016) Sizing and analysis of renewable energy and battery systems in residential microgrids. IEEE Trans Smart Grid 7(3):1204–1213
20. Masaud TM (2019) Correlating optimal size, cycle life estimation, and technology selection of batteries: a two-stage approach for microgrid applications. IEEE Trans Sustain Energy 11(3):1257–1267
21. Xia S (2018) Optimal sizing of energy storage system and its cost-benefit analysis for power grid planning with intermittent wind generation. Renew Energy 122:472–486
22. Nick M (2018) Optimal planning of distributed energy storage systems in active distribution networks embedding grid reconfiguration. IEEE Trans Power Syst 33:1577–1590
23. Qiu J (2018) Optimal allocation of BESS and MT in a microgrid. IET Gener Transm Distrib 12:1988–1997
24. Bucciarelli M (2018) Optimal sizing of energy storage systems under uncertain demand and generation. Appl Energy 225:611–621
25. Babacan O (2017) Siting and sizing of distributed energy storage to mitigate voltage impact by solar PV in distribution systems. Sol Energy 146:199–208
26. Salee S, Wirasanti P (2018) Optimal siting and sizing of battery energy storage systems for grid-supporting in electrical distribution network. In: International ECTI northern section conference on electrical, electronics, computer and telecommunications engineering (ECTI-NCON). IEEE, Chiang Rai, pp 100–105
27. Zhang F (2017) Battery ESS planning for wind smoothing via variable-interval reference modulation and self-adaptive SOC control strategy. IEEE Trans Sustain Energy 8:695–707

28. Ai WL (2019) Review on the optimal placement, sizing and control of an energy storage system in the distribution network. J Energy Storage 21:489–504
29. Alramlawi M, Souidi Y, Li P (2019) Optimal design of PV-battery microgrid incorporating lead-acid battery aging model. In: IEEE international conference on environment and electrical engineering and 2019 IEEE industrial and commercial power systems Europe (EEEIC/I&CPS Europe)

Integrated State of Charge and State of Health Method for Operating Range Prediction in Electric Vehicles

S. Parthasarathi, M. A. Ganesh, S. Manoj, and E. Harikrishna

Abstract Research on the battery of electrical vehicles is exponentially increasing. Real-time operating range prediction is a significant research problem. According to the literature, the operating range is predicted by only the State of Charge (SOC) value of the battery. Such methods result in a prediction error of 0.5% within 449 km, leading to uncertainty for the driver. By integrating SOC and SOH by operating range formula, the proposed MATLAB model includes the degradation rate of the battery with the charge level. For instance, the operating range is always predicted as 449 km with only SOC value. Whereas, the predicted operating range decreases to 447 km with the integrated SOC and SOH method. Thus, this method enhances accuracy and reliability. Lithium-ion battery characteristics, including nominal voltage and SOC, are considered in the model. Simulation results demonstrate a gradual decrease in operating range over time, exhibiting a slope of $0.000333333x + 363.3333$.

Keywords State of Charge (SOC) · State of Health (SOH) · Range estimation

1 Introduction

The global shift toward electric vehicles (EVs) is driven by their contribution to energy security and pollution reduction. In the modern world increasing the demand for electrical energy. An electric vehicle battery is a rechargeable power source for Battery Electric Vehicles (BEVs) or Hybrid Electric Vehicles (HEVs), with lithium-ion batteries being the most commonly used type [1]. Lithium-ion batteries have the

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advantages of high energy low self-discharge, long life and density. The parameters of the battery include capacity, State of Charge (SOC), State of Health (SOH), nominal voltage, internal resistance, cycle life, and *C*-rate [2].

1.1 SOC Estimation

SOC represents the current available energy in a battery, expressed as a percentage. It's like your fuel gauge—a full SOC means a 'full tank,' ready to go [3]. SOC directly impacts the immediate driving range. SOC estimation methods can be broadly categorized into indirect and direct methods.

Direct Methods. Various direct methods like terminal voltage, open circuit voltage, impedance spectroscopy, impedance measurement, and are employed for SOC determination [4]. The open circuit voltage method involves measuring the voltage of the battery when it is at rest which is established through calibration. The terminal voltage method measures the voltage across the terminals of the battery to estimate SOC. In the impedance measurement method, the impedance of the battery is used. Frequency response of the impedance is used in the impedance spectroscopy method, to measure the SOC. RC equivalent circuits are developed for estimating the SOC [5], which produced a 2.2% error rate. Thevenin equivalent circuits produced a 1% error rate. Thus, Thevenin is a more robust option for accurate SOC estimation. But these methods are not reliable when deployed in real-time.

Indirect Methods. Indirect measurement methods include neural networks, Fuzzy neural network, and support vector machine (SVM). In the neural network method, the neural networks are trained using historical data to establish a relationship between various battery parameters and SOC. SVM method is used to classify battery states and estimate SOC. Fuzzy neural network method combines fuzzy logic and neural networks, handles uncertainties and imprecise information in battery behavior to estimate SOC accurately. LSTM-based neural networks utilizes a Long Short-Term Memory (LSTM) neural network for SOC estimation [6]. OCV submodels are developed to estimate the SOC in electric vehicle batteries [7, 8]. Other than neural networks, Kalman filter, Extended Kalman filter and Central-difference Kalman filter (CDKF) is used for the Estimation of SOC [9]. Dynamic voltage responses during constant current discharging combined with optimization techniques like particle swarm optimization (PSO) to determine precise SOC [10]. A fractional-order model (FOM) is established to describe battery behavior, and the fractional-order multi-innovation unscented Kalman filter (FOMIUKF) is employed for precise SOC estimation.

1.2 SOH Estimation

SOH is a measure of degradation of a battery over time. Over time, batteries their capacity to hold a charge decreases, and naturally degrades [3]. SOH, though less directly involved in current systems, has a strong influence. SOH is the ratio of the maximum battery charge to its rated capacity. A battery includes many characteristics, such as battery capacity, conductivity, and internal resistance [11, 12]. SOH methods can be classified as direct and indirect methods.

Direct Methods. Various direct methods like capacity measurement, internal resistance measurement are used for SOH determination. Capacity measurement determines the maximum charge a battery can hold, with decreased capacity indicating degradation. Internal resistance measurement tracks the increase in resistance within a battery, as higher resistance is a sign of aging. Equivalent Circuit Models track how internal parameters change over time, providing clues about degradation. Other techniques, like Electrochemical Impedance Spectroscopy (EIS), provide deeper analysis of degradation.

Indirect Methods. Indirect methods involve machine-learning methods and model-based [13]. More complex SOH estimation methods often involve battery modeling or data analysis. Data-driven approaches like Differential Voltage Analysis (DVA) and Incremental Capacity Analysis (ICA) examine voltage curves during charging, looking for shifts that correlate with SOH. Kalman Filters and their extensions can model battery behavior while updating parameters related to aging employs a Light Gradient Boosting Machine (LGBM) model for accurate SOH estimation [14–16]. Testing demonstrates the method's high accuracy, with a low average absolute error of 0.89 Ah. The Transferable Learning model is used to reduce the error [17].

1.3 Integrated SOC and SOH Estimation

Hybrid methods frequently combine techniques, such as using a Kalman filter to improve the accuracy of coulomb counting estimations [18]. A new method has been developed to estimate the (SOC) and (SOH) of lithium-ion batteries, taking into account temperature and aging effects [19]. This method uses a combination of three algorithms: Unscented Kalman Filter (UKF), Forgetting Factor Recursive Least Squares (FFRLS), and Total Least Squares (TLS). FFRLS method is used to update the battery model parameters in real time as the battery ages. TLS is used to improve the initial battery health prediction. UKF is used to calculate the charge level, which then helps to refine the health estimation. The method was tested with capacity decay up to 10%, and temperature changes up to 35 °C achieving very low error rates. This research could help in better managing batteries in electric vehicles and microgrid systems. To monitor SOC and SOH of lithium-ion batteries simultaneously, a joint estimation algorithm is designed [20].

Table 1 Battery specifications

Battery capacity	40.5 kWh
Range	465 km
Battery capacity	126 Ah

The battery of the Tata Nexon is considered for the simulation. The Tata Nexon Electrical Car battery specifications are given in Table 1.

Initially, the battery's operating range is a maximum of 465 km. However, aging leads to a decreased range. Determining the battery aging range using the SOC estimation algorithm measurement method has encountered errors. Use of SOC-SOH for accurate performance [21]. The objective is to reduce the operating range prediction slope. Thus, the paper's contribution is to develop a SOC-SOH model in MATLAB and estimate the operating range.

The remainder of this paper is organized as follows. Section 2 discusses the proposed Simulink model. The experimental results and discussion are presented in Sect. 3. Section 4 sums up the discussion with the conclusion.

2 Proposed Simulink Model

The proposed MATLAB Simulink model as shown in Fig. 1, estimates the State of Charge (SOC), and State of Health (SOH), which in turn calculates the working range of the 126 Ah battery pack.

The main Simulink model consists of five sub-models (i) Battery model, (ii) Thermal model, (iii) SOC model, (iv) SOH model, and (v) Range Prediction model. For simulation, the following assumptions are made to model the system. (i) One ohm is considered the load of the vehicle. (ii) The maximum range of the vehicle is 465 km. (iii) The effect of vehicle dynamics on the range prediction is zero. The model and parameters of the sub-models are explained below.

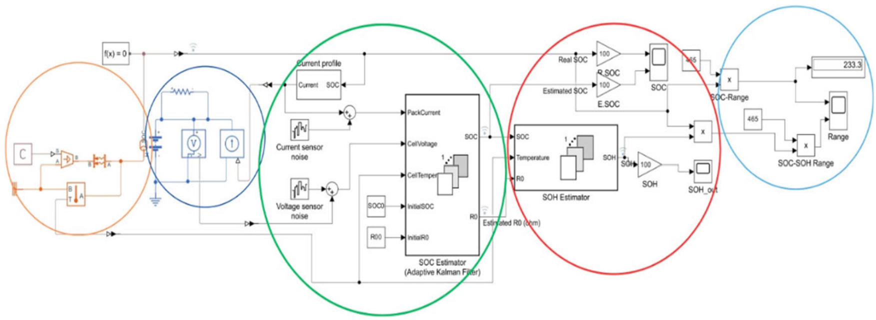

Fig. 1 Simulink model for range estimation