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Second-life battery sizing and integration in the power grid for clean energy reliability enhancement

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Abstract

The integration of renewable energy sources into the power grid is vital for mitigating climate change and achieving sustainable energy goals. However, the intermittent nature of renewables presents challenges to grid reliability. Repurposing second-life batteries (SLBs) from electric vehicles and other sources offers a cost-effective and sustainable solution for grid energy storage. This study proposes an effective application of SLBs in power systems using a Discrete Wavelet Transform-Radial Basis Function Neural Network (DWT-RBFNN) for SLB management. The method is validated through simulations, demonstrating optimal reliability results using reliability indices such as the System Average Interruption Frequency Index (SAIFI) and Customer Average Interruption Frequency Index (CAIFI). Specifically, the SAIFI drops from 33 to 9 times, and CAIFI decreases from 71.5 hours to 23.5 hours after SLB control implementation. This research contributes to enhancing power reliability and clean energy production using SLBs as a viable alternative to new batteries in grid applications.

Keyword: Energy storage, second-life battery, power grid, reliability, fuzzy logic control, renewable energy

Introduction

In the pursuit of mitigating climate change and transitioning towards sustainable energy sources, the integration of renewable energy into the power grid has become increasingly prevalent. However, the intermittent nature of renewable sources such as solar and wind poses significant challenges to the reliability and stability of the grid [1]. As a result, there is a growing imperative to develop innovative solutions that enhance the reliability of clean energy while addressing grid variability. One promising solution lies in the repurposing of second-life batteries for grid applications [2].

Second-life batteries (SLB), derived from electric vehicles (EVs) and other applications, offer a cost-effective and environmentally sustainable means of energy storage [3][4][5]. By extending the lifespan of these batteries beyond their initial use, they present a valuable resource for grid operators seeking to optimize energy management and improve grid resilience [6].

Understanding the key characteristics of second-life batteries is essential for optimizing their performance and reliability in grid integration applications [7]. Research into second-life battery characteristics has shed

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light on several critical factors that influence their behavior and performance over time. The degradation pattern of second-life batteries is non-linear, with an initial rapid decrease in capacity followed by a more gradual deterioration

[8]. Furthermore, studies have highlighted the impact of operating conditions and usage patterns on second-life battery performance. Factors such as temperature fluctuations, charge/discharge rates, and depth of discharge have been identified as significant determinants of battery health and longevity [9]. Implementing appropriate control algorithms and operational protocols is therefore crucial for maximizing the reliability and efficiency of second-life battery systems in grid applications [10][11]. Distributed Energy Storage Systems (DESS) have emerged as a popular approach for integrating SLB into the power grid, particularly at the distribution level to provide localized grid support [12]. However, challenges such as optimal siting, coordination with existing infrastructure, and regulatory barriers remain significant considerations for widespread deployment [9]. Conversely, centralized storage facilities offer centralized control and dispatch capabilities, enabling grid operators to leverage SLBs for grid-wide optimization and ancillary services.

Studies have explored various aspects of second-life battery technology, integration strategies, and the implications for grid operation and renewable energy penetration. Research by Jianwei et al. [13] provides a comprehensive overview of second-life battery technologies, highlighting their potential benefits for grid applications. The authors emphasize the importance of understanding battery degradation mechanisms and developing efficient repurposing techniques to extend battery lifespan. Muhammed et al. [14] investigated the economic feasibility of integrating second-life batteries into the power grid. Through a techno-economic analysis, they assess the cost-effectiveness of different integration scenarios and identify key factors influencing the viability of second-life battery projects. Furthermore, Alessandra et al. [15] explored the environmental implications of second-life battery integration, considering factors such as battery recycling, material sourcing, and carbon emissions. Their findings underscore the importance of adopting sustainable practices throughout the battery lifecycle to minimize environmental impact. Additionally, studies by Kebede et al. [16] and Andoni et al. [17] focus on sizing methodologies for second-life batteries in grid applications. By considering factors such as grid demand, renewable energy variability, and battery degradation, these studies propose optimization algorithms to determine the optimal size and configuration of second-life battery systems. In terms of grid integration, research by Chris et al. [18] evaluates the performance of second-life batteries in providing ancillary services such as frequency regulation and peak shaving. Using simulation models, the authors demonstrate the potential of second-life batteries to improve grid stability and support renewable energy integration. Hassan et al. [19] demonstrated the effectiveness of second-life batteries in providing frequency regulation services by dynamically adjusting charge and discharge rates in response to grid frequency fluctuations.

Despite the promising potential of second-life batteries, challenges remain in terms of the effectiveness of the SLB to manage the system operation considering its less capacity and it’s integration into the grid. Therefore, this study proposed an effective application of SLB in power systems using a different approach not only for peak shaving and upgrade deferral but also to improve the power output reliability through a central substation. A Discrete Wavelet Transform-Radial Basis Function Neural Network (DWT-RBFNN) is proposed to manage the operation of the SLB while charging and discharging over a varying SOC range and in combination with an optimal sizing method that caters for the capacity handling of the particular substation. The performance of the proposed method is validated by subjecting it to mitigate a common grid fault in a substation that is modeled in MATLAB-Simulink. The proposed method demonstrates optimal reliability results using both System Average Interruption Frequency Index (SAIFI) and Customer Average Interruption Frequency Index (CAIFI) reliability indices.

2. Second-Life Battery Technology

SLBs offer a sustainable solution to energy storage by repurposing used batteries from EVs and consumer electronics for secondary applications, such as stationary energy storage in the power system. Despite having between 80 and 70 percent of their capacity and functionality remaining, these batteries would typically be discarded but are instead utilized, providing an economical and environmentally friendly means of energy storage. SLBs, predominantly lithium-ion batteries due to their high energy density and long cycle life, undergo a repurposing process involving thorough assessment, sorting, grading, and integration into energy storage systems designed for grid applications. The process of absorbing SLB after retiring from its first life application is shown in Fig 1 while the capacity degradation curve of the battery pack is shown in Fig 2.

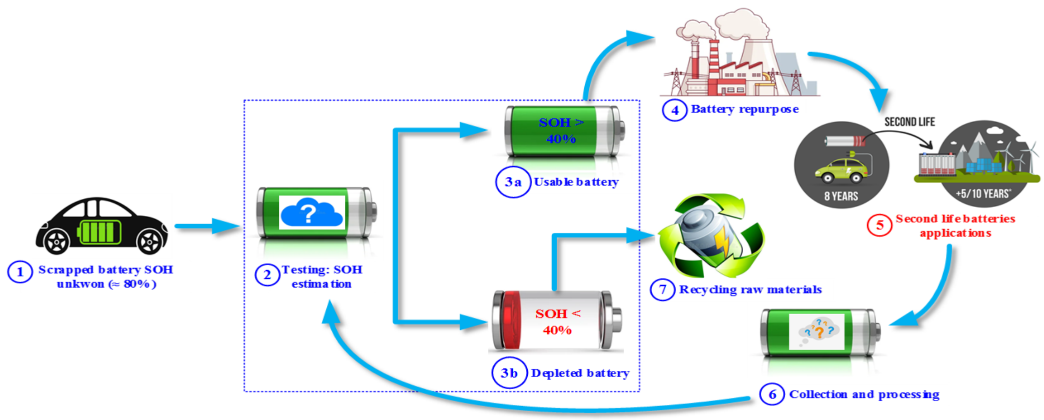


Fig. 1. Process of absorbing second-life batteries (SLB).

SLBs may experience varied degradation trends even under comparable aging settings, which further demonstrates the requirement for operational performance capability knowledge to maintain safety [20]. due to some widely unknown stressing elements that affect battery degradation, their accuracy is limited [21]. The major cause of aging is repetitive charging and discharging of the battery, which causes the electrodes and electrolytes to degrade. Therefore, a proper assessment of the battery is required using state of health (SOH) estimation. Various methods of estimating the SOH of a lithium-ion battery are shown in Fig 3.

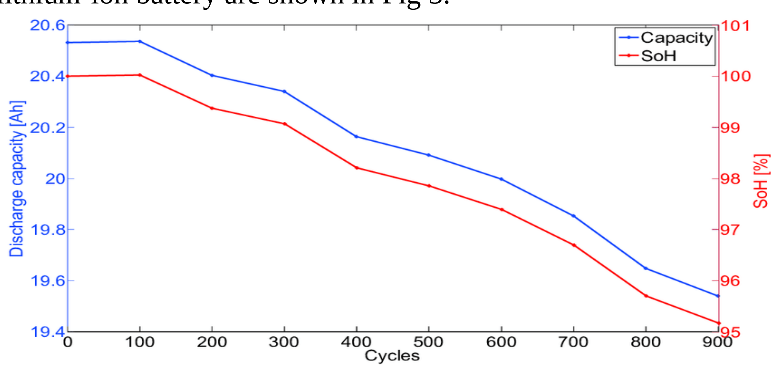


Fig. 2. Battery degradation curve with cycle.

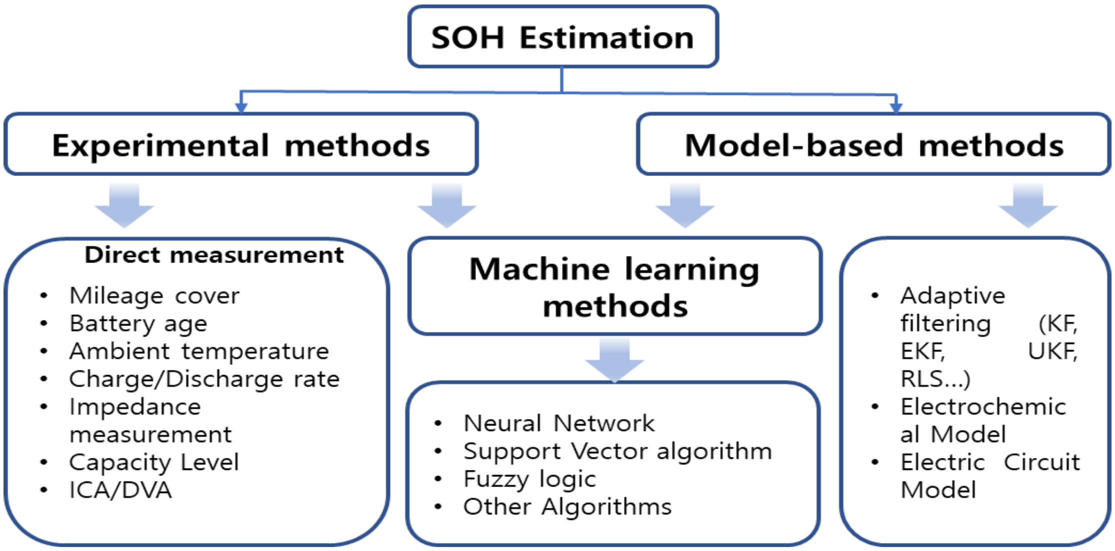


Fig. 3 Method of estimating SOH

3. Grid Optimization

The power grid network can be affected by different parts of the system and which can also be the root of network anomalies. To improve performance and reliability in the smart power system, an optimal grid operation detector is required. This work employ the Discrete wavelet transform (DWT)-radial function basis neural network (RFBNN) algorithm. DWT has been found useful in classifying all sorts of various operation in the distribution network while artificial neural network system has been proven to be one of the best algorithms used in system filtering and the backpropagation neural network (BPNN) is employed. Eq. (1) below shows the discrete wavelet transform (DWT) relation [22], where $Y(k)$ is the actual signal, $\psi(t)$ is the wavelet function, and x and y represent the scale and step magnitudes, respectively of the signal.

$$DWT(x,y) = \frac{1}{\sqrt{x}} \sum_{k} Y(k)\psi\left(\frac{t-x}{y}\right)dt \qquad (1)$$

It is crucial to understand the system's load requirements to develop a battery system that can minimize the flaws in the power grid. The actual electricity is taken into the best account because the system is filled with residential buildings. A homogeneous SLB capacity is assumed to construct the battery pack required in both series n_s and parallel n_p connections based on the system capacity. Maximum care must be used to create an ideal battery size that will meet the load demand and minimize cost. This paper employed the method used in [23] which proposed the use of Peukert's rule and evaluated load conditions to determine the best size for a Li-ion battery system taking into account its non-linear characteristics. The objective is to determine the amount of SLB in series and parallel connection required for the system which is expressed in Eq. (2) below

$$\min J = n_s \times n_p \tag{2}$$

$$n_{s,pack} = s_i \times n_s \tag{3}$$

$$n_{p,pack} = p_i \times n_p \tag{4}$$

Eqs. (3) and (4) apply to commercial products because batteries are fixed in packs for commercial purposes where $n_{s,pack}$ and $n_{p,pack}$ are the number of parallel and series connections in the battery pack, respectively, and s_i and p_i are the components of the commercial battery pack.

Constraints

The current and power of the required loads are set under constraints taking into account the Coulombic efficiency *(η_{cf})*, power conditioning system (PCS) efficiency *(η_{PCS})*, the planned battery system's series and parallel connections because the battery system constraints are reduced compared to the loads [23].

$$\delta_{chg} = \begin{cases} 1, & W_{load} > 0 \\ 0, & else \end{cases} \tag{5}$$

$$\delta_{dchg} = \begin{cases} 1, & W_{load} < 0 \\ 0, & else \end{cases} \tag{6}$$

$$W_{pack} = \delta_{chg} \times W_{load} \times \eta_{PCS} + \delta_{dch} \times W_{load} / \eta_{PCS} \tag{7}$$

$$W_{batt} = \delta_{chg} \times W_{pack} \times \eta_{cf} / (n_z \times n_p) + \delta_{dch} \times W_{pack} / (\eta_{cf} \times n_s \times n_p) \tag{8}$$

$$I_{bat} = W_{bat} / U_{bat} \tag{9}$$

Where $\delta_{chg}, \delta_{dch}, W_{load}, W_{pack}, W_{bat}, I_{bat}$, and U_{bat} are the binary terms for charge and discharge, input and output power of the load, a pack, and a single cell, as well as the cell's current and voltage, respectively. Eq. (7) is the power of the battery pack considering PCS efficiency while charging and discharging. The power and current are positive and negative respectively when the battery charge and discharges, hence, the lower bounds indicate minimum discharge values and the upper bound indicates optimum charging levels for both power and current. When employing a battery system, it is important to define a safety margin and a safe operation margin for SOC in this work is set to 20% – 90% which are shown as:

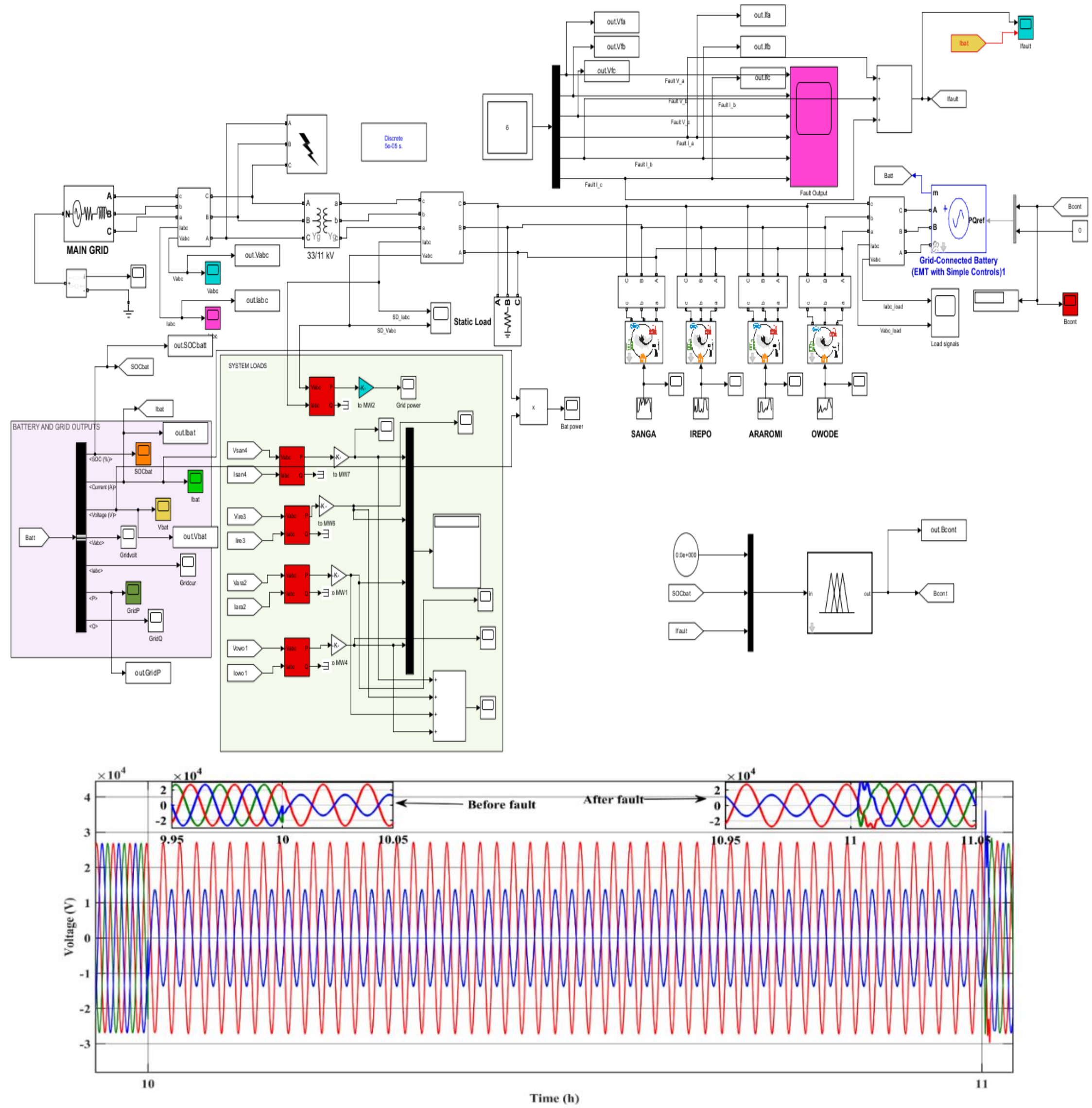
$$\underline{SOC} \le SOC \le \overline{SOC} \tag{8}$$

Where $\underline{SOC}$ and $\overline{SOC}$ are the SOC's upper and lower bounds respectively.

4. Simulation and Result

The case study used is a real Ilora Road injection Substation network structure located in Oyo city, Nigeria within the franchise of Ibadan Electricity Distribution Company (IBEDC). The system was modelled using

MATLAB/Simulink with different load profiles approximating the substation capacity of 15MVA as shown in Fig 4 (a). The current magnitude is between -20 A and 20 A while the voltage magnitude is between -2.61×104 V and – 2.61×104 V. Several major faults are then introduced into the grid system for 1 h and the simulation was done separately for each fault. The effect of the fault on the grid is shown in Fig 4 (b) while the power discharge by the SLB to maintain the functionality of the grid is shown in Fig 5.



(a)

(b)

Fig. 4. (a) Substation MATLAB model (b) System power fluctuation

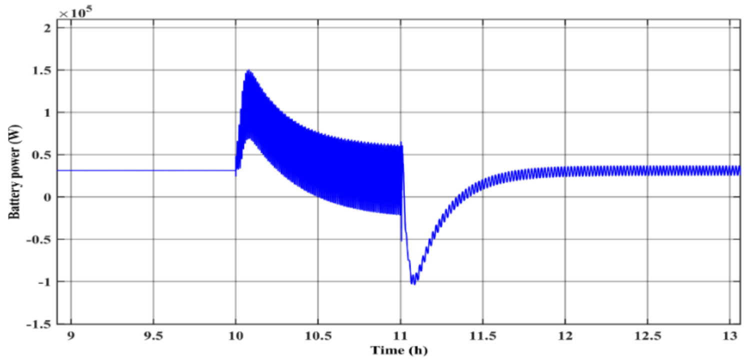


Fig. 5. Battery power discharged

Reliability Indices

The resulting output of the work is measured with two reliability indices; System Average Interruption Frequency Index (SAIFI) and Customer Average Interruption Frequency Index (CAIFI). SAIFI is the typical number of ongoing disruptions per customer over a certain area whiles CAIFI is used for measuring the consumers who are experiencing interruptions, this index displays the typical frequency of prolonged interruptions for a time duration [24]. SAIFI is calculated as illustrated in Eq. (9), where α_i is the failure rate at a point i and N_a is the customer number. The results of the before and after implementing SLB is shown is Table 1.

$$SAIFI = \frac{\text{Total number of customers affected}}{\text{Total number of customers served}} = \frac{\sum_i \alpha_i N_a}{\sum_i N_i} \tag{9}$$

CAIFI values for the system are given as shown in Eq. (10) where N_i is the number of customer interruptions.

$$CAIFI = \frac{\text{Total number of customer interruptions}}{\text{Total number of customer affected}} = \frac{\sum_i N_i}{\sum_i N_a} \tag{10}$$

Table 1. Comparison of the average number of power outages of the station per month before and after SLB control implementation

Fault Duration	Number of occurrences before SLB implementation	Number of occurrences after SLB implementation
From 5 min to 1 h	26	0
From 1 h above	9	9

The SAIFI and CAIFI of the station over one month were given to be 33 times and 71.5 hours respectively before SLB control implementation while after implementation of the SLB, it was reduced drastically to 9 times and 23.5 hours, respectively.

5. Conclusion

This study explores the application of Second-Life Batteries (SLBs) in the power grid to enhance power reliability and bolster clean energy production as a cost-effective alternative to purchasing new batteries, which can be prohibitively expensive. Proper sizing of the SLB is conducted based on charge and discharge operations in alignment with the system's capacity. A Discrete Wavelet Transform-Radial Basis Function Neural Network (DWT-RBFNN) is employed to monitor and synchronize substation activities with the SLB. The reliability of the system is assessed using reliability indices such as System Average Interruption Frequency Index (SAIFI) and Customer Average Interruption Frequency Index (CAIFI). The proposed method demonstrates effectiveness in reducing anomalies for both indices.

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