https://doi.org/10.1051/e3sconf/202454703017

Utilizing Artificial Neural Networks for Intelligent Battery Energy Storage Control in Microgrid Energy Management

J. Rajalakshmi[*1], *S. N. Nisha Rani*[2]

[1] rajee.gopalan@gmail.com SRM Madurai college for Engineering and Technology, Pottapalayam, Sivagangai District
[2] rani.nisha@gmail.com Fatima Michael college of Engineering and Technology, Madurai.

Abstract: This paper presents an intelligent control approach for a microgrid system comprising photovoltaic panels, grid connection, and lithium-ion battery energy storage. The energy management strategy revolves around regulating the charging and discharging of by incorporating an advanced controller into the DC/DC two directional converter. An essential aspect of this approach entails the incorporation of Artificial Neural networks (ANN) for accurate predetermination of the charge state of the battery and for controlling the two directional converter. Output from simulations conducted in the MATLAB/ Simulink environment illustrate its effectiveness, also their reliability of the proposed control method.

1 Introduction

Renewable resources have garnered significant interest for microgrid systems due to their status as primary energy sources, alongside their numerous advantages over fossil fuels [1]. The renewable energy resources of fuel cells pv cells etc., offer advantages such as minimal emissions, affordability, and dependable performance. [2]. However, a major challenge associated with these energy sources is their dependency on meteorological conditions, rendering microgrids unstable and reliant on weather fluctuations[3].]. Consequently, energy storage plays a pivotal role in adjusting electric power generation and power demand within microgrids. The primary objectives of storing surplus power in microgrids include load balancing storing excess energy during low demand periods, and supplying stored energy to meet load demands [4]. Lithium-ion (li-ion) batteries emerge as the preferred electrochemical battery type due to their superior characteristics compared to other battery types. Nonetheless, the use of lithium-ion batteries necessitates the implementation of battery management Methods to safeguard against potential hazards such as battery explosions [5]. Notably, incidents like the overheating of li-ion batterypacks in Japan Airlines 787 underscore the importanceof BMS in ensuring battery stability and effective energy management within microgrids. Li-ion batteries are typically connected to microgrids via two directional DC/DC converters, which regulate theinput voltage to match the load voltage. Theseconverters play a vital role in managing battery charging and discharging operations, akin to fly back converters utilizing an inductor instead of a BJT [6]. The primary aim of battery management system methodis to prolong the battery lifecycle by safeguarding against potential issues raising from the nonlinear behavior of renewable energy sources. Key parameterssuch as battery SOC, depth of discharge (DoD), and temperature serve as principal elements forbattery monitoring. In this study, our focus lies specifically on SoC, expressing the stored charge in the battery in terms of its total rated capacity. Due to nonlinearity of li-ion battery voltage, direct SoC measurement is not feasible.

Predetermining SoC is crucial for the control of battery and Battery management methods, leading to the development of several estimation methods in recent years. Energy counting, or ampere-hour counting, emerges as the predominant technique for estimating possible storage of the battery (SoC), entailing the incorporation of battery current. [6]. While effective when known value of SOC, this way of procedure is less suitable for other battery types. Another method presented in [7] involves calculating SoC relied on the relationship between battery state of charge and open circuit voltage, primarily applicable to lead-acid batteries. Kalman filter (KF) algorithms have also been utilized by several authors for SoC estimation due to their robustness [8]. However, one significant limitation of this method is the requirement for a suitable battery model, with proper state initialization necessary for model convergence. In our study, we employ a deep forward neural network to predetermine SoC, facilitating its utilization in battery management systems.

Effective coordination between renewable energy sources and lithium-ion batteries is to provide the necessary energy for loads and maintain the energy balance of the microgrid, a fundamental objective of microgrids [9]. Microgrids, distribution networks

---

[*] Corresponding author: rajee.gopalan@gmail.com

comprising energy resources with less voltages, storage systems, and control systems, are designed to meet for various applications [10]. These applications ranges from small houses [11] to smart towns [12], with distributed loads classified as DCor AC Bus based on their electrical resource [13, 14]. Decentralized electricity system have garnered increased to the rise the usage of generators and other loads. [15].

Regulating the DC bus represents a significant challenges in microgrid systems based on the instability ofrenewable energy and the consumed power by loads, necessitating effective storage system of energy. Lithium-ion batteries serve as the primary means of balancing microgrids, stabilizing the system in the absence of renewable energy by storing surplus energy. The microgrid through two directional DC/DC converters, batteriesmanage charging and discharging operations to balance power at the DC bus [16]. Numerous studies have focused on voltage control of DC bus through bi-directional converter control, with traditional controlmethods such as Proportional Integral Derivative controllers utilized in literature. These control strategies are optimal only for linear systems. Nonlinear methods such as sliding mode controls, as mentioned in [17], offer greater performance but necessitate accurate mathematical modeling and detailed system knowledge. Despite their effectiveness, the intermittent nature of renewable energy resources, their dependence on meteorological conditions,random load demands, and weakness in grid can complicate the plant model and performs unsatisfactoryexecution [18]. Those disadvantages have spurred experimenters to explore and to imply nonlinear control strategy to mitigate the effects of nonlinearities and parameter uncertainties in a grid-connected system. The primary use of artificial control in microgrids lies in improving dynamic performance and enhancing robustness against interruptions, ultimately ensuringfor the client loads of effective energy supply. Recent works have highlighted various intelligent microgrid system control, including the utilization of fuzzy-sliding-mode control methods [19]. As concluded in this control overview, applying AI techniques enables optimal sizing, parameter optimization and tuning method for the development, or replacement of traditional controllers.

Here, we conduct an inspection and experiment on control methods of a grid-connected microgrid comprising Photovoltaic panels, the electrical grid, and battery energy storage systems (BESS). We employ a control with intelligent structure to inspect and employ the basic controllers of bidirectional switching regulators. The main development proposed in the study include the utilization of ANN controllers NARMA-L2, which serve as reliable controllers for bidirectional DC/DC converters, the control methods based on deep forward neural network for SoC estimation, and the integration of SoC into the energy governance block. The other parts of the paper is structured as various parts: part 2 outlines the approach utilized for estimating SoC, part 3 provides an overview of the microgrid system, part 4 elaborates on the energy management algorithm employed in this study, and part 5 delineates the simulation scenario.

2 State of Charge Estimation

The State of charge (SoC) estimation utilizes artificial neural networks (ANNs) due to their adaptness in modeling complex, nonlinear systems. The ANN model for battery SoC is designed using MATLAB/Simulink, adhering to the following steps:

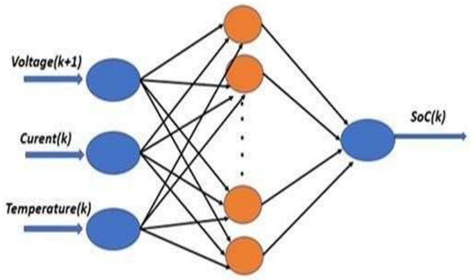
- Database selection for learning andvalidation.
- ANN optimization of its architecture.
- Validation mode implementation.

Fig. 1 depicts the proposed SoC estimation structure, which is relied on a neural feed-forward network (FFNN). This FFNN model incorporates inputs such as current, voltage and battery temperature measurements.

Fig. 1. State of Charge of Feed Forward Neural Network estimation

In this structure depicted in Fig. 2, here we can derive the relationship between the output Y (K) and the input U (K).

$Y\ (\mathrm{K}) = F(U(\mathrm{K}), U(\mathrm{K}-1)..., U(\mathrm{K}-\mathrm{n}))$ ---(1)



The function F represents the hyperbolic tangent (tanh), commonly employed as the activation function in the deep(hidden) and as a linear system function in the output layer.

All parameters are acquired subsequent to the training of neural network process employing back propagation calculation steps.

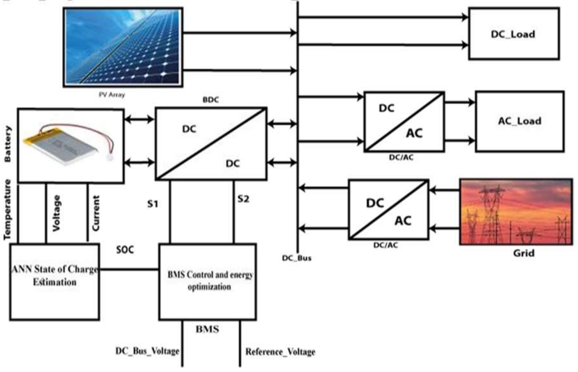


Fig 2. Proposed microgrid (distributed) system

The Microgrid (distributed) System

The depicted model in Figure 3 proposes a configuration incorporating various renewable energy sources, notably photovoltaic panels, as the essential energy source. It also includes a storage system of energy consisting of a li-ion battery, along with integration with the electrical grid. The electrical grid is utilized only in urgent cases during demand of the PV power generation to meet the system's power demand and the state of charge falls below a predefined minimum threshold (SOC_min). Every energy source is sized to ensure that together they can meet the demands of the system's loads. The cumulative power requirement for both AC and DC loads is designated as 15 kW, hence prompting the sizing of each source to deliver a combined output of 15 kW.

The lithium-ion battery utilized with the system features specifications of 48 Voltage and 315 Ampere hour. Additionally, a two directional DC/DC converter is employed to regulate the voltage up to 220 V. For the PV panels, American Solar Wholesale 280 M cells of power output of 280 W and a maximum voltage of 37 V are chosen. To meet the requiredpower output, 54 cells are utilized, with six cells connected with series to achieve a 220 V.Consequently, no boost converter is required for the PV panels and the DC bus. Furthermore, parallel connection with nine cells enhancing the current capacity.

The electrical grid is dimensioned to provide backup power as necessary and is connected to the system through an AC/DC converter to ensure compatibility with the microgrid configuration.

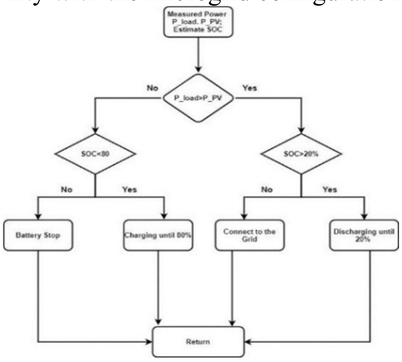


Fig 3. Battery energy storage Method

Battery energy storage Method

Lithium-ion batteries require careful management of energy because of sensitivity to charging and discharging cycles, which significantly impact their performance and safety. Overcharging and over-discharging are common causes of accidents involving li-ion battery explosions. Therefore, effective control of the state of charge (SoC) is essential for both extending storage life and ensuring safety. In this study, we employ an efficient technique for estimating the SoC of the battery, depicted in the following chart.

The strategy for energy management outlined in the flowchart is centered on the battery's state, which operates in three modes: charging, discharging, and stop modes. The selection of the battery mode is determined by the Battery Management method which utilizes information on State of Charge of battery and the DC bus voltage output. As the battery links to the microgrid bus through a two directional DC/DC converter, the significant role of the Battery Management method is to manage the two directional converter and oversee the breakers that ties the energy sources to the DC bus

Here, an Artificial Neural Network Controller (ANNC) is employed, with two methods as input /output control linearization conforms to a specific form, and Nonlinear Autoregressive-Moving Average Nonlinear Autoregressive-Moving Average model control when the plant model is predetermined in the same form. The primary aim of this method of control is to linearize the parameters changes of nonlinear model of the system. The Nonlinear Autoregressive-Moving Average - L2 controllers consist of two neural networks: the primary network, Nonlinear Autoregressive-Moving Average model, is utilized for system identification, representing nonlinear systems in discrete form, while the other network is dedicated to the design of the controller, as explained in Fig. 4.

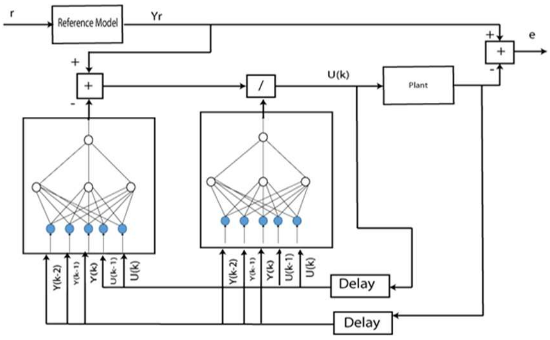


Fig 4. Model plant of NARMA-L2

Simulation

The simulation scenarios proposed here are relied on changes in irradiation levels, reflecting variations in photovoltaic power production. The scenariocomprises multiple fluctuations in irradiation levels, asdepicted in Fig. 5. The corresponding PV power production corresponding to these irradiation levels is illustrated in Fig. 6.

Fig 6 reveals that the Photovoltaic power output fluctuates, with less periods generating 15 KW while others generate high. This variability underscores the need for additional energy sources to meet the consistent 15 KW load requirement. As detailed in the "Microgrid System" section, the li-ion battery plays a critical role in stabilizing the system by managing charging and discharging operations.

Fig.7 displays the change in state of charge throughoutthis simulation, indicating how the battery's state evolves over time in response to changes in irradiationlevels and load demands.

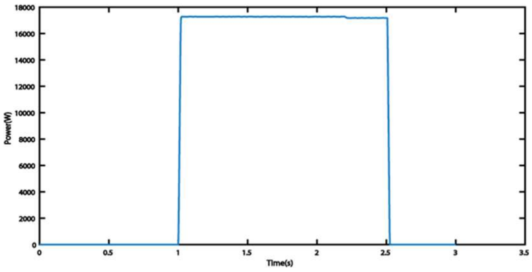


Fig. 5. Solar irradiation (W/m^2)

In start of the Execution, the photovoltaic (PV) power exceeds 15 KW, resulting in sufficient power that is reserve in the battery. However, at 0.6 seconds, there is a sudden reduction in irradiation to 200 W/m², causing a corresponding drop in PV power output.Consequently, the state of charge (SoC) begins to drop as it is utilized to meet the power demands of the microgrid. By 1 second, as depicted in Fig. 7, the SOC reaches 20%, which is the less threshold set by the Battery Management System (BMS). As a result, additional energy sources are required to maintain system stability, prioritizing the security of the battery.

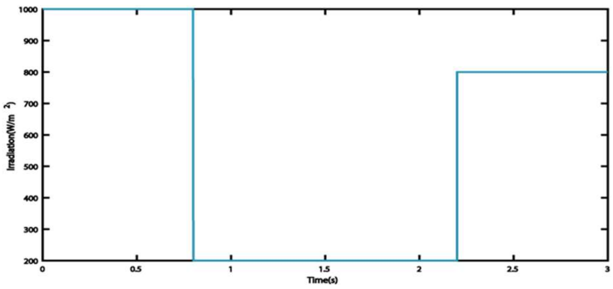


Fig. 6. Photovoltaic power

At this juncture, the grid network is integrated, as in Fig. 8. The power grid supplements the load power demand while simultaneously charging the battery, under the supervision and control of the battery storage method. The battery management system ensuresthe stabilization of the DC Bus voltage in the base weight. From this study, the voltage reference is set at 220 V, as illustrated in Fig. 9. Examining Fig 9 explains the effectiveness of the proposed method regarding conjunction speed and the discrepancy between change in voltage and the base value.

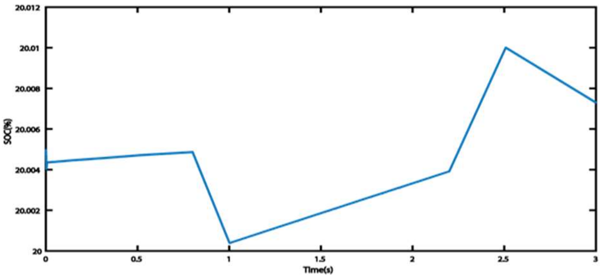


Fig 7. Battery SOC Variation

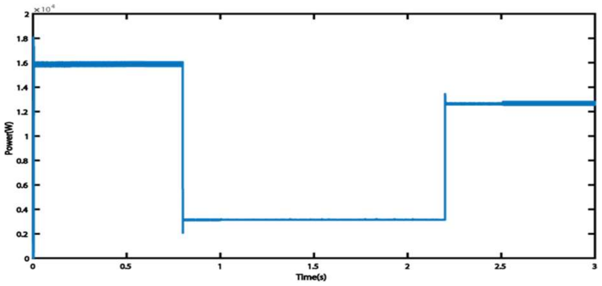


Fig 8. Grid Electrical power

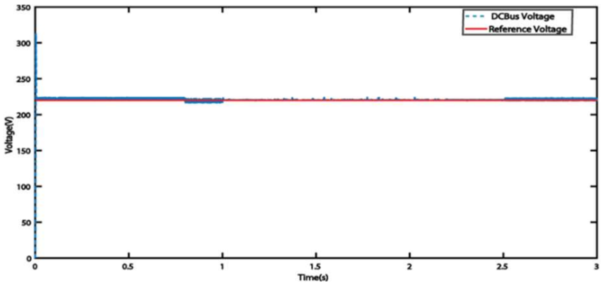


Fig 9. Differentiation of base and inferred DC BUS voltage

Conclusion

This paper presents an energy management strategy for microgrid systems, leveragingphotovoltaic as the primary electricity source, supported by battery storage and grid backup systems for stabilization. Through simulations conducted under complex scenarios, the performance of the proposed control method was found to be satisfactory for two directional DC/DC converters in microgrid applications. The simulation results underscored the advantage of the suggested technique in terms of Conjunction speed and the error between voltage variation and the base value. Additionally, future work will explore various management methods based on a self-organised system.

References

1. Vera García, Yimy E. *et al.*, "Energy management in microgrids with renewable energy sources: A literature review," *Applied Sciences*, vol. 9, no. 18, pp. 3854-3882, 2019.
2. A., Mohamed *et al.*, "Renewable Energy Potential and Available Capacity for Wind and Solar Power in Morocco towards 2030," *Journal of Engineering Science and Technology Review*, vol. 11, no. 1, pp. 189-198, 2018.
3. A.-P., Agustín *et al.*, "Weather forecasts for microgrid energy management: Review, discussion and recommendations," *Applied energy*, vol. 228, pp. 265-278, 2018.
4. F., Mohammad *et al.*, "Review of energy storage system technologies in microgrid applications: Issues and challenges," *IEEE Access*, vol. 6, pp. 35143-35164, 2018.
5. Boujoudar, Younes, Elmoussaoui, Hassan, and Lamhamdi, Tijani, "Lithium-ion batteries modeling and state of charge estimation using artificial neural network," *International Journal of Electrical & Computer Engineering (IJECE)*, vol. 9, no. 5, pp. 3415-3422, 2019.
6. Murnane, Martin and Ghazel, Adel, "A closer look at state of charge (SOC) and state of health (SOH) estimation techniques for batteries," *Analog Devices,* pp. 1-8, 2017.
7. Y. Xing *et al.*, "State of charge estimation oflithium-ion batteries using the open-circuit voltage at various ambient temperatures," *Applied Energy*, vol. 113, pp. 106-115, 2014
8. B. S. Bhangu *et al.*, "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries

for hybrid-electric vehicles," *IEEE transactions on vehicular technology*, vol. 54, no. 3, pp. 783-794, 2005

9. Kumar, G. R., Sattianadan, D., and Vijayakumar, K., "A survey on power management strategies ofhybrid energy systems in microgrid," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 2,pp. 1667-1673, 2020.
10. Mahmoud, M. S., AL-Sunni, F. M. Ur Rahman M. S., "Networked control of microgrid system of systems," *International Journal of Systems Science*, vol. 47,no. 11, pp. 2607-2619, 2016.
11. J., Bingnan and F., Yunsi, "Smart home in smart microgrid: A cost-effective energy ecosystem with intelligent hierarchical agents," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 3- 13, 2014.
12. Prinsloo Gerro, Robert Dobson, and Andrea Mammoli, "Synthesis of an intelligent rural village microgrid control strategy based on smartgrid multi-agent modelling and transactive energy management principles," *Energy*, vol. 147, pp. 263-278, 2018.
13. Zhi, Na *et al*., "An SOC-based Virtual DC Machine Control for Distributed Storage Systems in DC Microgrids," *IEEE Transactions on Energy Conversion*, vol. 35, no. 3, pp. 1411-1420, 2020.
14. Toosi, Hooman Ekhteraei *et al*., "Central power management system for hybrid PV/battery AC- bus microgrid using Typhoon HIL," *2019 IEEE 28th International Symposium on Industrial Electronics (ISIE)*, Vancouver, BC, Canada,2019, pp. 1053-1058.
15. Arabul, Fatma Keskin *et al*., "Providing Energy Management of a Fuel Cell-Battery Hybrid Electric Vehicle," *World Academy of Science, Engineering and Technology, International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering*, vol. 9, no. 8, pp. 920-924, 2015.
16. Dragičević, Tomislav *et al*., "Supervisory control of an adaptive-droop regulated DC microgrid with battery management capability," *IEEE Transactions on power Electronics*, vol. 29, no. 2,pp. 695-706, 2013.
17. Zhao, Biao, Qingguang Yu, and Weixin Sun, "Extended-phase-shift control of isolated bidirectional DC-DC converter for power distribution in microgrid," *IEEE Transactions on power electronics*, vol. 27, no. 11, pp. 4667-4680, 2011.
18. Chang, Yuan-Chih, Hao-Chin Chang, and Chien- Yu Huang, "Design and Implementation of the Battery Energy Storage System in DC Micro- Grid Systems," *Energies*, vol. 11, no. 6, 2018, Art. no. 1566.
19. Boujoudar, Younes *et al*., "Intelligent controller based energy management for stand-alone power system using artificial neural network," *International Transactions on ElectricalEnergy Systems*, vol. 30, no. 11, 2020, Art. no. e12579.