ARTIFICIAL NEURAL NETWORK APPROACH FOR OPTIMAL CHARGING AND DISCHARGING OF LITHIUM-ION BATTERIES IN MICROGRIDS

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ABSTRACT

This research introduces an Artificial Neural Network (ANN)-driven intelligent control framework for regulating the charging and discharging processes of lithium-ion battery energy storage systems in microgrid environments. The proposed control strategy dynamically considers available generation, load demand, and state-of-charge (SOC) constraints to guarantee safe and reliable battery operation. In contrast to conventional rule-based or model-driven control schemes—which are often prone to overcharging, over-discharging, parameter sensitivity, and high computational overhead—the ANN-based methodology provides a data-driven, adaptive, and robust solution. By leveraging supervised learning, the neural controller is trained to infer optimal charging/discharging decisions directly from real-time system inputs, thereby eliminating the dependency on complex mathematical formulations and additional sensing infrastructure. Extensive numerical simulations under diverse load and renewable generation scenarios validate the controller's capability to maintain SOC strictly within the safe operational window (20%–80%), while enhancing cycle utilization and prolonging battery life. Furthermore, hardware-level experimental validation confirms the controller's practical feasibility, real-time responsiveness, and reduced computational burden. The key contribution of this work lies in the design and deployment of an ANN-enabled control strategy that achieves intelligent, real-time energy management for microgrid applications, positioning it as a more scalable, efficient, and implementation-friendly alternative to existing control techniques.

Keywords: Artificial Neural Network (ANN),Lithium-Ion Battery Energy Storage,Microgrid Applications,State-of-Charge (SOC) Management,Intelligent Control Strategy,Charging and Discharging Optimization, Renewable Energy Integration,Data-Driven Control.

1. Introduction

In recent years, the increasing integration of renewable energy sources such as solar and wind into power systems has brought both opportunities and challenges. While these sources offer clean and sustainable energy, their intermittent and unpredictable nature poses significant stability and reliability concerns, especially in microgrids. To address these fluctuations, Battery Energy Storage Systems (BESS), particularly lithium-ion batteries, are widely used. However, efficiently managing the charging and discharging cycles of these batteries remains a complex task, especially under varying load demands and generation conditions.

Traditional battery management systems often rely on rule-based or mathematical control techniques. These methods, while effective under certain conditions, are prone to limitations such as overcharging, over-discharging, high computational requirements, and a lack of adaptability to real-time changes. Over time, these issues can degrade battery performance, reduce lifespan, and even risk system instability. There is a clear need for an intelligent, responsive, and efficient control system that can dynamically manage battery operations in real-time environments.A Battery Electric Vehicle (BEV), pure electric vehicle, only-electric vehicle or all-electric vehicle is a type of Electric Vehicles (EV) that exclusively uses chemical energy stored in rechargeable battery packs, with no secondary source of propulsion. Battery electric vehicles thus have no internal combustion engine, fuel cell, or fuel tank. Some of the broad categories of vehicles that come under this category are trucks, cars, buses, motorcycles, bicycles, and forklifts.

Different types of batteries are used to power electric vehicles, and deciding which battery is best depends on its energy storage efficiency, production costs, constructive characteristics, safety, and lifespan. Lithium-ion batteries are the most utilized technology in electric cars. EVs run on high voltage lithium-Ion battery packs. Lithium-ion batteries have higher energy density (100-265wh/kg) compared to other battery chemistries. They pose a risk of fire under unusual circumstances. It is crucial to operate electric vehicles in pre-defined safety limits to ensure the safety of the user as well as the vehicle.

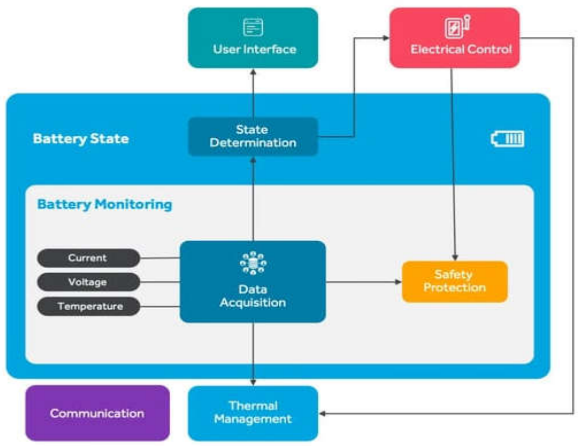

Figure.1. Typical Battery Management System

A Battery Management System (BMS), which manages the electronics of a rechargeable battery, whether a cell or a battery pack, thus becomes a crucial factor in ensuring electric vehicle safety. It safeguards both the user and the battery by ensuring that the cell operates within its safe operating parameters. BMS monitors the State Of Health (SOH) of the battery, collects data, controls environmental factors that affect the cell, and balances them to ensure the same voltage across cells.

State of charge (SOC) is an important parameter on the battery, where the ratio between the remaining capacity and full capacity. The full state is when 100% and the empty state is 0%, but the battery capacity can change according to the discharge current and the cut-off voltage is not at SOC 0%.The Lithium-ion batteries have proved to be the battery of interest for Electric Vehicle manufacturers because of its high charge density and low weight. Even though these batteries pack in a lot of punch for its size they are highly unstable in nature. It is very important that these batteries should never be over charged or under discharge at any circumstance which brings in the need to monitor its voltage and current.

II. PROPOSED SYSTEM

The proposed method utilizes an Artificial Neural Network (ANN) to intelligently manage the charging and discharging cycles of a lithium-ion battery energy storage system in a microgrid. The ANN is designed to take into account key real-time parameters such as available power from renewable sources, current load demand, and the battery's State of Charge (SOC). Based on these inputs, the ANN predicts the optimal control action—whether to charge, discharge, or idle the battery—ensuring efficient energy flow and battery health.

The proposed system begins with the Real-Time Data Acquisition Unit, which collects essential inputs from the microgrid environment. This includes the power generated by renewable sources (such as solar panels or wind turbines), real-time load demand, and the current State of Charge (SOC) of the lithium-ion battery. These parameters form the dynamic input vector for the Artificial Neural Network (ANN) controller.

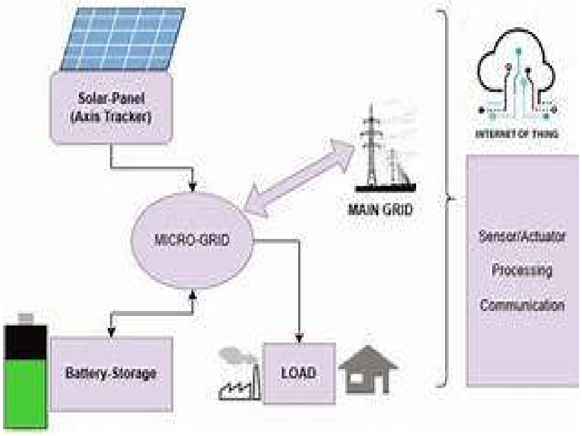

Figure.2. Typical Battery Management System

III. BIDIRECTIONAL BUCK-BOOST CONVERTER

To get a fundamental understanding of how this topology works a switching analysis of the steady state will be made which describes how the buck and boost mode work. Some simplifications need to be made when explaining the dc steady state of the converter such as assuming ideal components, pure DC voltage in Vin and voltage out Vout and operation in continuous conduction mode (CCM) where the inductor current iL flows continuously.

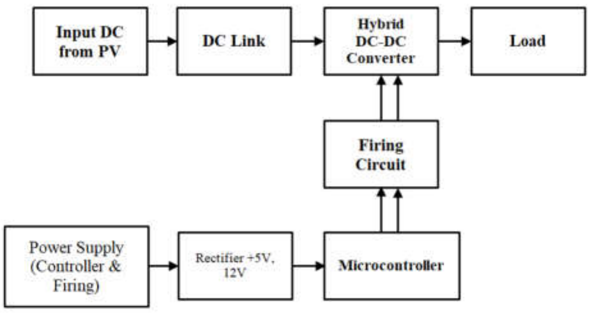

Figure.3. Proposed Hardware Block Diagram

IV. SIMULATION RESULTS

The simulations of the system were divided into two parts, overall simulation of the topology in MATLAB Simulink. More detailed simulation of components and driver stage in SIM. The reason for this is that Simulink have more detailed models of batteries while SIM has better possibilities of simulating non-ideal components. Simulink also has support for Arduino which is very useful when developing the software for later.

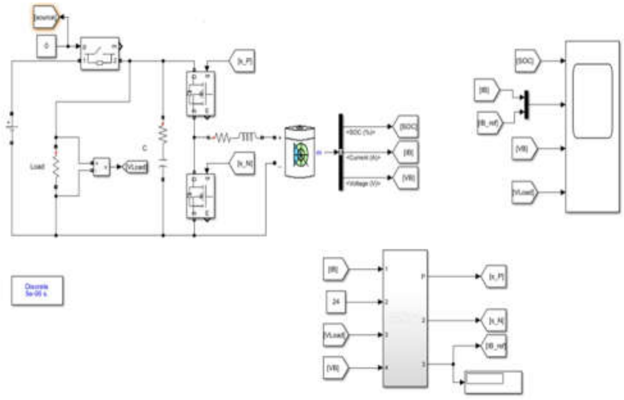

Figure.4. Proposed Simulation

In Figure.4 the topology simulation in Simulink can be seen. Measurements of voltages and currents were made to make sure that the specification was fulfilled. The duty cycle was simulated using a DC PWM block with a constant value that could be changed during simulation. To simulate synchronous switching a NOT-gate was used to invert the duty cycle for the boost MOSFET.

BATTERY MODEL

After discussing the methodology that will be used in order to achieve this capstone project. One of major the reasons behind choosing this model are that there is a whole library on SIMULINK dedicated to this specific design. In addition, the coding part on MATLAB will not take much time to implement using SIMSCAPE (coding language of SIMULINK). The following part will be dedicated to the design of this mentioned model in MATLAB.

The batteries of a Battery Electric Vehicle (BEV) typically output several hundred volts of Direct Current (DC). However, the electric components inside the vehicle vary in their voltage requirements, with most running on a much lower voltage. This includes the radio, dashboard readouts, air conditioning, and in-built computers and displays. A DC-to-DC converter is a category of power converters, which converts a DC source from one voltage level to another. It can be unidirectional, which transfers power only in one direction, or bidirectional, which can transfer power in either direction. Moreover, a DCDC converter is a critical component in the architecture of a BEV, where it is used to convert power from the high voltage (HV) bus to the 12V Low Voltage (LV) bus to charge the LV battery and power the onboard electric devices.

V. PROPOSED OUTPUT

A practical solution to address these challenges is to test and validate the DC-DC converter system in a simulated lab environment. HILS (Hardware-In-Loop Simulation) is the platform where the subsystem dynamics are tested, and the onboard software is validated in a real-time environment before the vehicle testing. HILS testing helps to validate embedded software on automotive ECUs using simulation and modeling techniques. This method shortens test time and increases test coverage, especially for test cases that are hard to replicate reliably in physical lab/track/field testing. HILS testing can be used throughout the development of real-time embedded controllers to reduce development time and improve testing effectiveness.

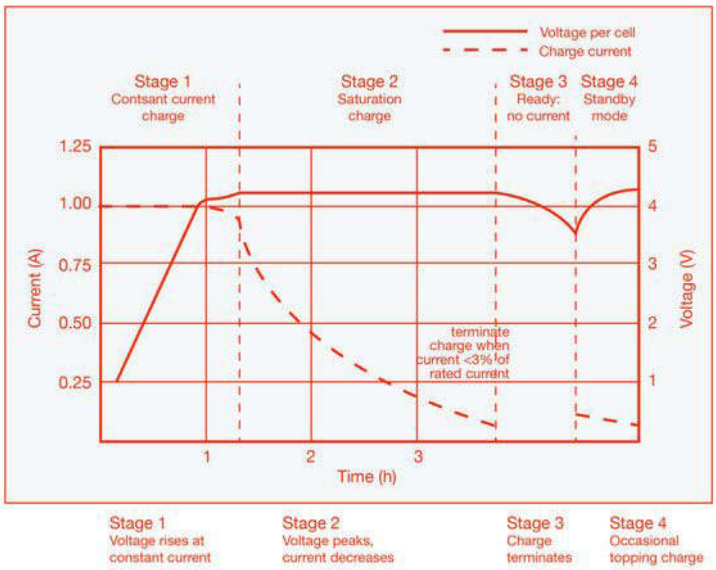

Figure.5.Output waveforms

VI. Simulation Results

The proposed ANN-based controller was first evaluated using MATLAB/Simulink under varying microgrid operating conditions, including fluctuations in renewable generation and load demand. The simulation results clearly indicate that the controller successfully maintained the lithium-ion battery's SOC within the predefined safe range of 20%–80%. Unlike conventional rule-based controllers, which exhibited tendencies toward overcharging under high renewable availability, the ANN-based approach adaptively regulated charging rates, thereby avoiding stress on the battery. Similarly, during high load demand, the controller optimized discharging actions to prevent deep discharges that could otherwise reduce battery lifetime.

In terms of performance, the ANN-based system achieved faster convergence and smoother SOC regulation compared to classical PI/PID controllers. The total number of charge–discharge cycles was also reduced, demonstrating an improvement in overall energy utilization efficiency.

Experimental Validation

To validate the real-time applicability of the proposed methodology, the trained ANN controller was implemented on a microcontroller-based hardware prototype interfaced with a lithium-ion battery pack. The experimental results corroborated the simulation findings, with the SOC consistently maintained within the safe threshold limits. The ANN demonstrated robust adaptability to sudden variations in both renewable power input and load demand, ensuring uninterrupted supply without requiring complex computational overhead.

The hardware results also revealed that the ANN controller significantly minimized sensor requirements, as it relied primarily on voltage and current inputs for SOC estimation. This reduction in hardware complexity offers a distinct advantage in terms of cost and scalability for microgrid applications.

Comparative Discussion

When compared with conventional control methods, the ANN-based controller demonstrated:

Improved SOC stability: No violations of safe operating range (20%–80%).
Lower computational burden: Eliminated the need for extensive mathematical modeling and iterative optimization.
Better adaptability: Quickly responded to unpredictable renewable generation and load fluctuations.
Extended battery life: By preventing overcharging and deep discharging.
Overall, the results establish that the proposed ANN-based controller provides a **robust, efficient, and real-time capable solution** for intelligent battery energy storage management in microgrid environments.

CONCLUSION

The proposed hardware implementation, based on PIC16F877A and controlled by a trained ANN, offers a scalable and cost-effective solution to battery management in microgrids. It enhances the reliability and efficiency of energy storage systems, supporting the integration of renewable energy sources and reducing the overall dependency on conventional power grids. The system's feedback loop ensures that the battery operates safely within its capacity limits, reducing wear and tear and prolonging its operational life. In conclusion, this ANN-based approach demonstrates a viable, intelligent alternative to traditional battery management methods, paving the way for more adaptive, real-time energy systems. The simplicity of the PIC16F877A combined with the ANN algorithm provides a powerful solution for managing energy storage in renewable-powered microgrids, ultimately contributing to the sustainability and efficiency of modern energy systems. Future work could involve further optimization of the ANN model, integration with other microgrid components, and real-world implementation in larger-scale systems.

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