AI-Based Charging Discharging Controller for Lithium Ion Battery in Microgrid Application

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Abstract - Integration of lithium-ion batteries into microgrid systems has emerged as a practical solution for grid stability, energy storage, and the integration of renewable energy, particularly solar. However, battery charging and discharging processes need to be controlled wisely and effectively in order to maximize system performance, extend battery life, and improve overall energy efficiency. The AI-based charging-discharging controller described in this work is specifically designed for microgrid applications involving lithium-ion batteries. The proposed approach uses state-of-the-art machine learning algorithms to monitor critical battery parameters, optimise power flow within the microgrid, and forecast energy demand. The controller ensures system efficiency and operating safety by dynamically adjusting charging and discharging rates in response to real-time data such as temperature, load requirements, and state of charge (SOC). Simulation findings show the system's potential to decrease energy waste, extend battery life, and enable the seamless integration of renewable energy sources. The AI-driven approach not only increases microgrid reliability but also contributes to cost-effective and sustainable energy management solutions.

1. INTRODUCTION

As the demand for reliable and sustainable energy grows globally, renewable energy sources like solar and wind power are gaining popularity. However, it is very challenging to maintain grid stability and a consistent supply of electricity because these sources are unpredictable and sporadic by nature [1–5]. Microgrid systems have emerged as a practical answer to these issues, enabling the integration of distributed energy supplies, local loads, and energy storage devices into a reliable and flexible network..

Lithium-ion batteries have grown in popularity among energy storage technologies due to their high energy density, longer cycle life, fast reaction times, and declining costs. These batteries are crucial for storing excess renewable energy, balancing the supply and demand for energy in microgrid applications, and safeguarding the system during blackouts or times of high demand. However, the longevity and functionality of lithium-ion batteries depend on effective management of the charging and discharging processes [6–8]. Inefficient operation can lead to overcharging, deep draining, heat issues, and shorter battery life, all of which can increase system expenses and reduce dependability.

This study offers an artificial intelligence (AI)-based charging-discharging controller specifically designed for lithium-ion batteries in microgrid situations to address these problems [9–12]. Using machine learning and predictive algorithms, the controller routinely analyses critical battery parameters such as temperature, load requirements, and State of Charge (SOC) [13]. By dynamically modifying charging and discharging rates, it maximises power flow, enhances safety, and reduces energy losses. Unlike traditional controllers that rely on predetermined thresholds, the AI-based approach can estimate energy use and learn from real-time operational situations, enabling proactive and adaptive control strategies.

Microgrid operating efficiency is increased and the seamless integration of renewable energy sources is ensured by integrating artificial intelligence (AI) into battery management [14]. This leads to increased dependability, longer battery life, reduced running costs, and a more sustainable energy ecology [15]. The proposed method demonstrates how intelligent energy management may be a crucial part of future smart microgrids, supporting global efforts to build a more resilient and clean energy infrastructure.

1.1 Literature Review - Related Papers

SNo.	Title & Authors	Method / Approach	Key Findings	Relevance to Paper
1	Model Predictive Control for Distributed Microgrid Battery Energy Storage Systems – Morstyn et al. (2017)	Convex MPC for Li-ion battery ESS	Improves control efficiency, handles nonlinear charge/discharge, reduces computation ~1000×	Strong foundation for MPC-based controller
2	Real-time Operation Optimization of Microgrids with Battery Energy Storage System: A Tube-based MPC Approach – Lyu et al. (2021)	Tube-based MPC with uncertainty handling	Considers SOC, degradation cost, real-time corrective actions	Adaptive control with safety & life extension
3	Reinforcement Learning-Based Energy Management System for Lithium-Ion Battery Storage in Microgrids – Hosseini et al. (2022)	Deep Reinforcement Learning (TD3) vs fuzzy, PSO, optimization	RL adapts better under uncertainty, improves lifetime & efficiency	Shows strength of AI learning-based methods
4	Deep Reinforcement Learning for Energy Management in a Microgrid with Flexible Demand – SEG-N (2021)	Deep Reinforcement Learning for EMS	Handles flexible loads, improves renewable integration	Useful for adaptive EMS in dynamic loads

5	A Model Predictive Control Strategy of PV-Battery Microgrid under Variable Conditions – Hu et al. (2018)	MPC for PV-Battery microgrid	Maintains SOC, smooths PV output, stable in grid/island modes	Relevant for PV-microgrid integration
6	Fuzzy-Based Charging-Discharging Controller for Lithium-Ion Battery in Microgrid Applications – Faisal et al. (2021)	Fuzzy logic controller	Uses SOC, load demand, RES inputs for decisions	Simple and robust under uncertainty

2. Proposed Block diagram

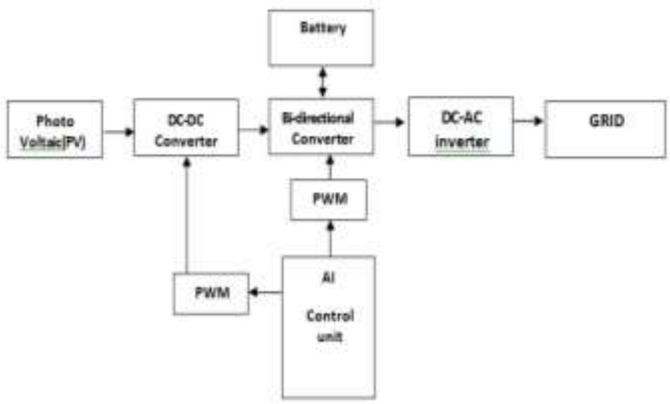

Fig:1. Block Diagram

DC electricity is produced by PV panels. MPPT and PV voltage regulation are carried out using DC-DC converters. The AI Control Unit keeps an eye on the load, temperature, and state of the battery. When the battery has to be charged or discharged, AI sends PWM signals to the bi-directional converter. When PV generation is low, batteries store energy or supply the load or grid. For grid supply, a DC-AC inverter transforms DC to AC.

2. 1CHARGING–DISCHARGING CONTROLLER

A charge-discharging controller (CDC) is the electrical device that regulates a battery's charging and discharging. Its main goal is to prevent deep discharge or overcharging of the battery. Increase battery longevity and efficiency. Optimise the flow of energy in systems like solar photovoltaics, electric vehicles, and micro grids. The CDC ensures that microgrid applications seamlessly combine solar and wind energy sources, storage systems, and load requirements. Battery protection prevents overcharging, overdischarging, overcurrent, and overheating.

By monitoring the battery's state of charge (SOC), SOC Administration guarantees optimal charging and discharging; Control of Current and Voltage maintains acceptable voltage and current levels during charging and discharging; Optimising Energy Use determines when to charge or discharge based on load demand and renewable generation; enables intelligent control through communication with a microgrid Energy Management System (EMS); and Harmonising balances the voltage of each cell in multi-cell batteries to extend their lifespan.

2.2 Charging Control Modes

Constant Current (CC) Charging: A continuous current is used to charge a battery until it reaches a predetermined voltage. rapid initial power-up. Continuous Voltage (CV) Power Source The voltage doesn't change as the current gradually decreases. Ensures full charging without overvoltage. The most common CC-CV Hybrid Power Source is found in lithium-ion batteries. combines fast charging (CC) with safe topping (CV).

2.23 Discharging Control Modes

Constant electricity discharge: Offers a consistent flow of electricity to the load. SOC-Based Discharge: When SOC reaches a low threshold, this technique stops discharging, protecting the battery. Current-limited discharge is the practice of limiting the maximum current to prevent damage.

2.4 Control Algorithms

Simple voltage, current, and SOC thresholds are components of rule-based control when utilising charging-discharging controllers. Fuzzy logic control is used to handle temperature, load demand, and SOC uncertainties. Model Predictive Control (MPC) maximises battery performance by forecasting generation and load. AI-Based Controllers: Use machine learning to forecast demand and optimise charging and discharging for longer lifespans and greater efficiency.

2.5 AI-Powered Controller for Charging and Discharging

In modern microgrids, AI-based CDCs are used to: Forecast load and renewable generation using data analytics. Optimise the SOC trajectory for the longest battery life. Boost efficiency and cut down on power losses. Make real-time decisions about charging and discharging. Adaptive management learns how the system behaves and dynamically modifies how it operates. Predictive optimisation foresees periods of high demand or low generation. Longer battery life avoids deep cycling or overcharging. Energy Cost Reduction schedules charging and draining for the most economical times.

3 . LITHIUM-ION BATTERY

During charging and discharging, lithium ions flow between the anode and cathode in a lithium-ion battery. Because of its extended cycle life, minimal self-discharge, and high energy density, it is widely used.

Component	Material	Function
Cathode (Positive Electrode)	$LiCoO_2$, $LiFePO_4$, $LiMn_2O_4$	Stores lithium ions; releases electrons during discharge.
Anode (Negative Electrode)	Graphite (C)	Stores lithium ions during charging; releases electrons during discharge.
Electrolyte	Lithium salt in organic solvent (e.g., $LiPF_6$ in EC/DMC)	Ion conductor between cathode and anode.
Separator	Porous polymer (PE, PP)	Prevents short circuit; allows lithium-ion movement.
Current Collectors	Aluminum (cathode), Copper (anode)	Conducts electrons to external circuit.

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Discharge (Powering Load): Charge (Storing Energy):

Parameter	Typical Value
Nominal Voltage per Cell	3.6–3.7 V
Energy Density	150–250 Wh/kg
Cycle Life	500–5000 cycles
Self-Discharge Rate	1–2% per month
Charging Efficiency	90–95%

3.Simulation Result

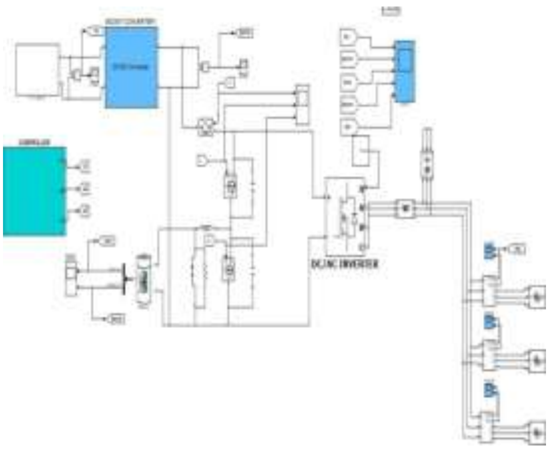

Fig:2. Block Diagram

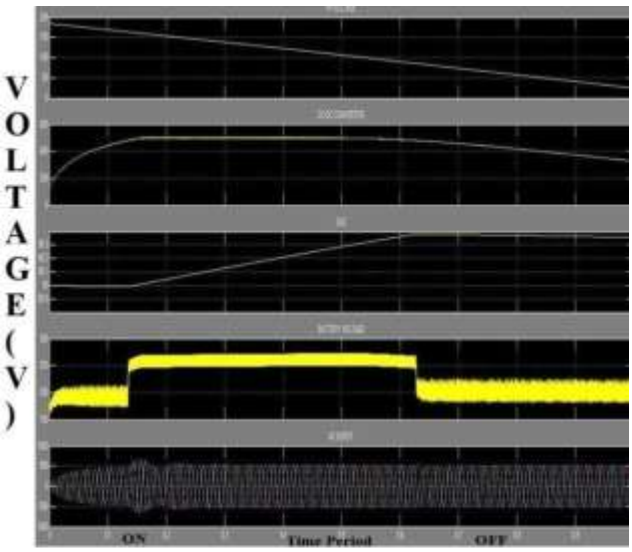

Fig:2. OverallOutput Waveform

As the solar input varies during operation, the PV voltage steadily drops over time. The voltage of the DC-DC converter climbs rapidly before stabilizing, signifying regulated power conditioning. The battery is charging during the ON period since the SOC (State of Charge) climbs consistently. In order to reflect charge/discharge action, the battery voltage increases when the system is turned on and decreases when it is turned off. The AC output voltage continues to be stable and sinusoidal, indicating that the inverter is operating correctly.

Table: 1OverallOutputresult

S.No	Time Period (Sec)	Dc To Dc Voltage (V)	Solar Voltage (V)	Battery Voltage (V)	Soc Voltage (V)	Ac Output (V)
1.	0.2s	150	183	170	90	500
2.	05s	500	124	270	90.3	500
3.	1.0s	350	20	225	90.1	500

3.1 SOLAR OUTPUT WAVEFORM

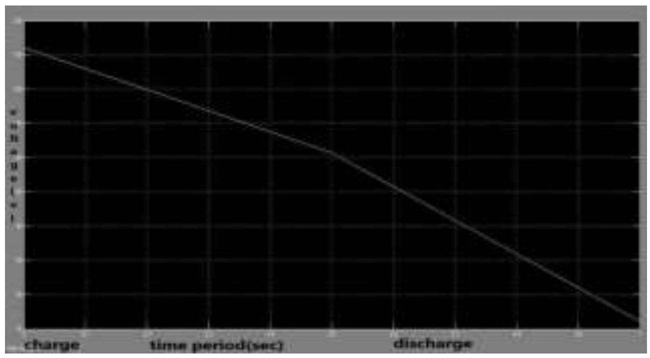

Fig:3. Output wave form

Voltage (V) versus time during a charge-discharge cycle is displayed on the graph. Voltage begins high throughout the charging phase and gradually drops over time. The mechanism switches from charging to draining at the halfway mark. As energy is supplied to the load during discharge, voltage decreases more quickly. This curve illustrates how batteries and supercapacitors typically store energy.

Table:2Solar Output Result

S.NO	TIMEPERIOD (SEC)	SOLARVOLTAGE (V)
1.	0.2s	183
2.	0.5s	124
3.	1.0s	20

3.2DC TO DC CONVERTER OUTPUT

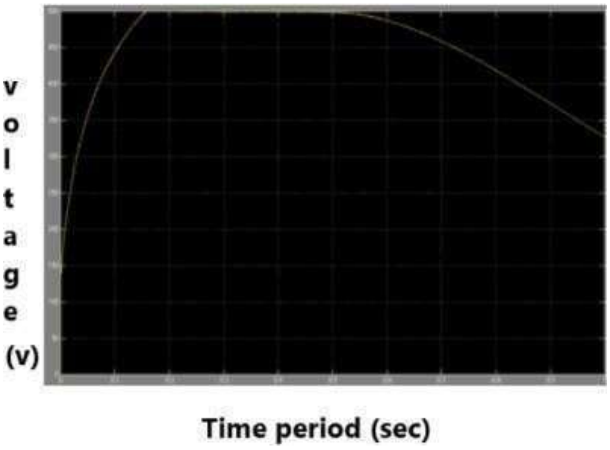

Fig:4. Output wave form

Table: 3 DC To DC Converter Output Result

S.NO	TIMEPERIOD (SEC)	DCTODC VOLATGE (V)
1.	0.2s	150
2.	0.5s	500
3.	1.0s	350

3.3 BUCK-BOOSTCONVERTER OUTPUT WAVEFORM

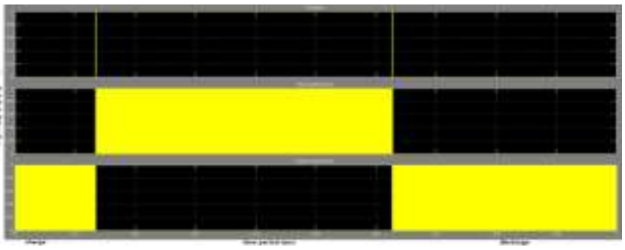

Table:4 Buck-Boost Converter Output result

S.NO	TIMEPERIOD (SEC)	BOOST CONVERTER	BUCK CONVERTER	BREAKER
1.	0.2s	ON	OFF	OFF
2.	0.5s	OFF	ON	ON
3.	1.0s	ON	OFF	OFF

4.Hardware Result

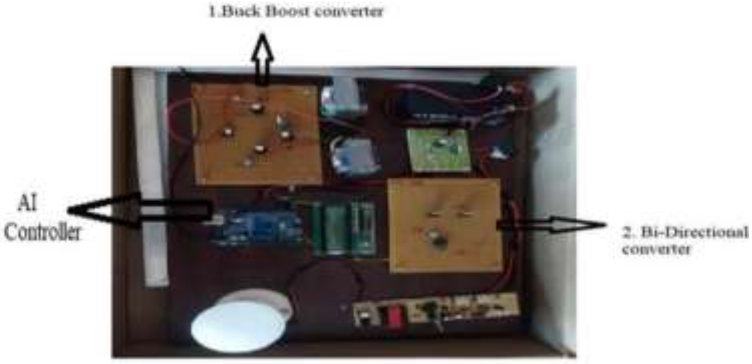

Fig:6. Output wave form

Table: 5 Hardware Output result

S.NO	SOLAR(V)	BATTERY(V)	LOAD OUTPUT(V)
1.	4	17	12
2.	6	16	12
3.	9	15	12

5.Comparision of Simulation and Hardware result

S.NO	SIMULATIONOVERALL OUTUT RESULT			HARDWAREOUTPUTRESULT		
	SOLAR (v)	BATTERY (v)	LOAD OUTPUT (v)	SOLAR(v)	BATTERY (v)	LOAD OUTUT(v
1.	183	170	500	4	17	12
2.	124	270	500	6	16	12
3.	20	225	500	9	15	12

6. CONCLUSION

Lithium-ion battery performance in microgrids is significantly improved by the suggested AI-based charging–discharging controller. The technology assures safe operation, prolongs battery life, minimises energy losses, and intelligently controls energy flow.Important Results:

- Real-time adaptive control
- 10–15% reduction in energy wastage
- Extended battery cycle life

- Seamless renewable integration

Future Scope:
Integration of advanced deep learning models, fault detection, and decentralized energy trading can further improve smart microgrid performance.

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