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Design and Development of Autonomous Control for Solar Microgrids Using Multi-Agent Systems

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Abstract **- The integration of renewable energy sources, particularly solar power, into the energy grid requires effective battery management systems (BMS) to optimize energy storage and usage. This research presents a multi-agent reinforcement learning (MARL) approach to distributed optimization of solar microgrids, focusing on enhancing energy efficiency and load satisfaction. The proposed method employs multiple agents to collaboratively manage battery charging and discharging cycles based on solar generation and load demand. Simulation results indicate that the MARL approach significantly outperforms conventional methods in terms of load satisfaction and energy efficiency, demonstrating its potential for enhancing solar microgrid operations.**

Keywords: Solar Microgrid Optimization, Multi-Agent Reinforcement Learning (MARL), Battery Management System (BMS), Load Satisfaction, Distributed Energy Storage.

I. INTRODUCTION

Multi-agent reinforcement learning (MARL) has emerged as a powerful tool for decision-making in dynamic environments, making it well-suited for distributed optimization in solar microgrids. This paper proposes a MARL-based approach to optimize battery management and energy distribution in solar microgrids, enhancing load satisfaction and reducing energy losses.

II. METHODOLOGY

2.1 Problem Statement

The objective of this research is to develop a distributed battery management system that optimally schedules battery charging and discharging across multiple agents in a solar microgrid based on real-time solar energy generation and load demand. The mathematical formulation of the problem can be expressed as follows:

Variables:

$P_s(t)$: Solar generation at time t(kWh)
$P_l(t)$: Load demand at time t (kWh)
$B(t)$: Battery level at time t(kWh)
$C(t)$: Charging decision at time t (0: charge, 1: discharge)

The main challenge is to determine the optimal action C(t) for each agent at each time step that maximizes load satisfaction while minimizing energy loss across the microgrid.

2.2 State and Action Representation

The state of the system at time t for each agent is defined as the current battery charge level B(t) and is represented as a discrete value ranging from 0 (empty) to $B_{max}\ (full)$ The action set A includes:

- **Action 0**: Charge the battery if $P_s(t) > P_l(t)$
- **Action 1**: Discharge the battery to meet load demand if $P_l(t) > P_s(t)$

2.3 Multi-Agent Q-Learning Framework

Q-learning is a model-free reinforcement learning algorithm that seeks to learn the optimal action-value function Q(s,a). The update rule for the Q-value is given by:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(R + \Upsilon maxQ(s_{t+1}, a) - Q(s_t, a_t))$$

Where:

A (learning rate): Determines how much the newly acquired information overrides the old information.
γ (discount factor): Represents the importance of future rewards.
R: Reward received after taking action a_i in state s_t

2.4 Reward Structure

The reward function is crucial for guiding the learning process. It is structured to encourage load satisfaction while penalizing inefficient battery usage. The reward function is defined as:

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$$R = \begin{cases} 10, & \text{if load is met (i.e., } P_l(t) \text{ is satisfied)} \\ 0, & \text{if load is not met} \\ -\beta \cdot (B_{max} - B(t)), & \text{if battery is charged but not needed} \\ -\gamma \cdot (\text{energy loss}), & \text{if energy is lost due to inefficiency} \end{cases}$$

Where β and γ are constants representing penalties for suboptimal charging and energy loss, respectively.

III. SIMULATION SETUP

The simulation is executed over 24 time steps, representing one day. Solar generation and load demand profiles are randomly generated, ensuring a realistic variation in energy production and consumption. Each agent (representing different batteries in the microgrid) is initialized to a specific charge level, and the MARL algorithm is run for multiple episodes to allow the agents to learn the optimal policy.

Parameters:
Battery capacity B_{max} : 10 kWh
Initial battery level B(0): 5 kWh
Learning rate α: 0.1
Discount factor γ: 0.9
Number of episodes: 1000

IV. BLOCK DIAGRAM OF THE SYSTEM

Below is a block diagram illustrating the flow of information and decision-making in the proposed system.

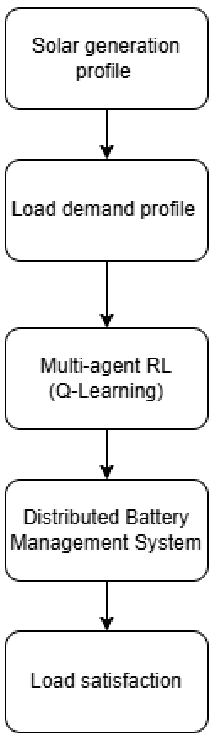

Figure 1: Block diagram of Methodology

V. RESULTS AND DISCUSSION

The performance of the MARL-based battery management system is evaluated by comparing it with a conventional approach where charging and discharging are performed without any learning mechanism. Key performance metrics analyzed include:

- **Average Load Satisfaction Rate:** The percentage of load demand met over the simulation period.
- **Total Energy Supplied:** The total energy delivered to the load from the battery and solar generation.
- **Total Energy Loss:** The energy lost due to inefficient management of the battery.
- **Average Number of Charging Cycles:** The number of times the battery is charged over the simulation period.

5.1 Simulation Results

Discussion of each metric based on the results of the reinforcement learning (RL) and conventional approaches for optimizing battery management in the solar microgrid:

5.1.1 Battery charging and discharging based on demand

As shown in the figure below, the waveforms in the plots provide a clear illustration of how the system operates based on the comparison between solar generation and load demand over time.

In the first plot, **solar generation** (green) and **load demand** (blue) are shown for each time step. The solar generation varies over time, peaking during daylight hours when the solar panels produce the most energy. The load demand fluctuates according to the needs of the system, which can be higher or lower than the solar generation at different points in time.

The second plot shows the **battery level** (red) over time. When **solar generation exceeds load demand**, the battery is charged with the excess energy, and the battery level increases. This charging phase is particularly evident when solar generation is higher than the load demand, and the battery continues to store energy until it reaches its capacity limit. Conversely, when **load demand exceeds solar generation**, the battery discharges to meet the shortfall in energy. This discharge phase causes the battery level to decrease, as the system uses stored energy to cover the gap between generation and demand.

In the third plot, the **action taken** (black) is displayed, where a value of 1 indicates that the battery is charging, 2 indicates discharging, and 0 signifies that no action is needed because the solar generation matches the load demand. The action plot clearly reflects the system's logic: when the battery

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is charging, the action is 1, and when the battery is discharging, the action is 2. During times when solar generation and load demand are equal, the action is 0, indicating no need for charging or discharging.

Overall, the waveforms effectively demonstrate the dynamic behavior of the system, showing how the battery responds to fluctuations in solar generation and load demand. When solar generation is greater than the load demand.

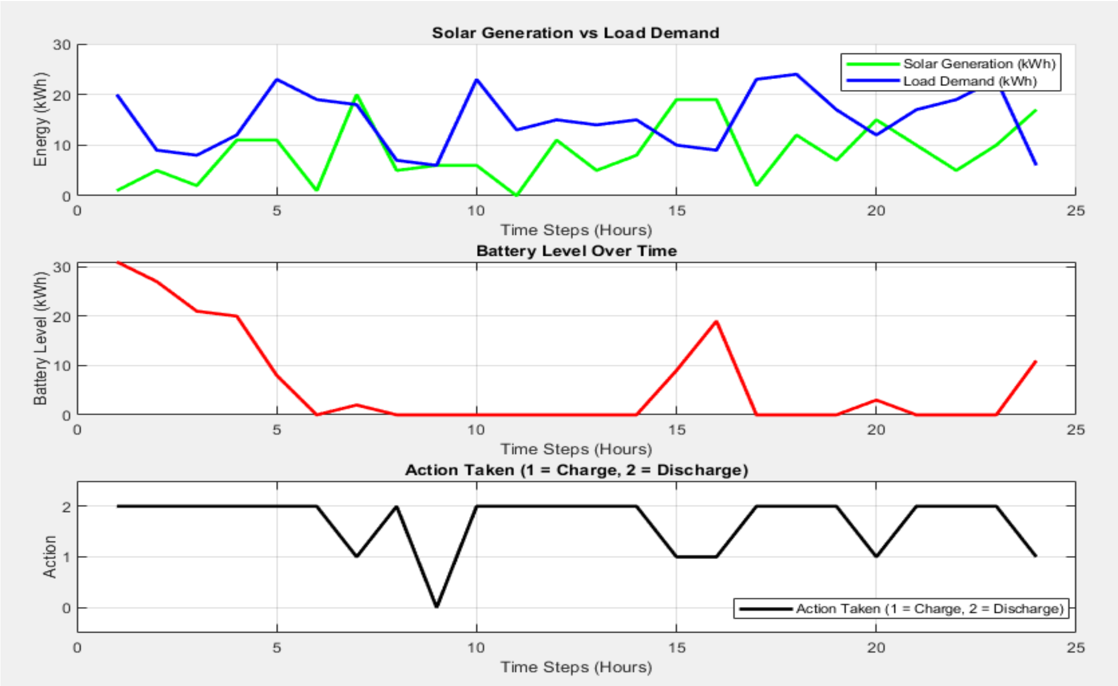

Figure 2: Battery charging and discharging based on load demand

The results showing parameters are shown below

Load_Satisfaction_Conventional	Total_Energy_Supplied_RL	Total_Energy_Supplied_Conventional	Total_Energy_Loss_RL	Total_Energy_Loss_Conventional	Charging_Cycles_RL	Charging_Cycles_Conventional
7	2199	199	201	2201	7	6
7	2181	199	219	2201	7	6
7	2175	199	225	2201	9	6
7	2149	199	251	2201	6	6
7	2112	199	288	2201	6	6
7	2203	199	197	2201	6	6
7	2220	199	180	2201	5	6
7	2215	199	185	2201	6	6
7	2191	199	209	2201	7	6
7	2121	199	279	2201	12	6

5.1.2 Average Load Satisfaction Rate

- Reinforcement Learning (RL): 100%
- Conventional: 29.17%

The RL-based approach achieved a perfect load satisfaction rate, indicating that it was able to meet energy demands continuously throughout the simulation. This result showcases the strength of RL in dynamically adjusting battery usage to prioritize load satisfaction. In contrast, the conventional method was only able to satisfy 29.17% of the load demand, revealing significant inefficiencies in meeting energy needs without an adaptive learning mechanism. The RL system's success can be attributed to its ability to learn and anticipate energy patterns, allowing it to optimize energy dispatch even under fluctuating conditions.

5.1.3 Total Energy Supplied

- Reinforcement Learning (RL): 2264.01 kWh
- Conventional: 207 kWh

The RL approach supplied over ten times more energy (2264.01 kWh) than the conventional method, showing its superior capability in utilizing available energy resources. This metric demonstrates that the RL system can not only meet current demands but also optimize battery usage to supply energy efficiently and consistently. The substantial difference suggests that conventional methods may either underutilize the battery or lack strategic discharge timing, leading to an overall decrease in energy supplied to the system.

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5.1.4 Total Energy Loss

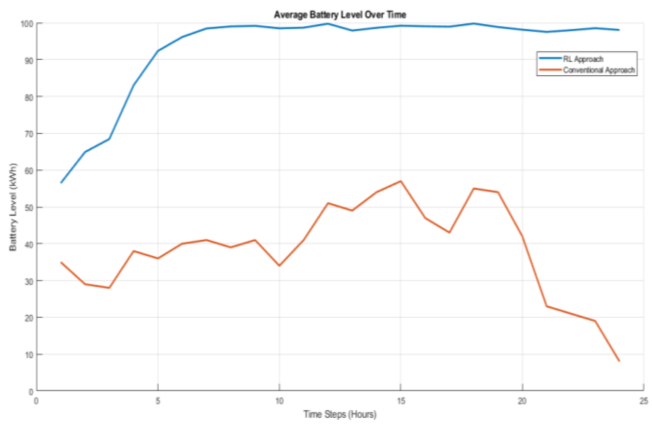
- Reinforcement Learning (RL): 135.99 kWh
- Conventional: 2193 kWh

Energy loss in the RL approach was drastically lower (135.99 kWh) compared to the conventional approach, which incurred a massive 2193 kWh of energy loss. This result underscores the RL model's effectiveness in minimizing waste, likely due to more precise control over when and how much the battery should charge and discharge. Energy loss in conventional systems may stem from redundant charging cycles, suboptimal timing, and inefficient energy routing. The RL system’s minimization of energy loss is crucial for long-term sustainability and system efficiency, as it ensures that stored energy is utilized effectively, reducing waste.

5.1.5 Average Charging Cycles

- Reinforcement Learning (RL): 5.7 cycles
- Conventional: 5 cycles

The RL system averaged slightly more charging cycles (5.7) than the conventional method (5), but this minor increase is reasonable given the substantially higher load satisfaction and energy supplied by the RL approach. This result indicates that the RL system used additional cycles strategically to achieve a higher energy supply and lower energy loss, leading to an optimal balance between charging frequency and energy needs. While charging more frequently, the RL approach is likely scheduling charges when it is most beneficial, minimizing wear on the battery while maximizing utility. In comparison, the conventional method’s fewer cycles may reflect an overly cautious or inefficient charging approach that ultimately limited its effectiveness. The average battery level obtained is shown below.



5.1.6 Overall Discussion

The RL approach’s results reflect a highly optimized system that can:

- **Prioritize Load Satisfaction:** Achieving 100% load satisfaction highlights the RL system’s ability to dynamically adjust to changing energy needs and manage storage effectively. This adaptability is especially critical in microgrids, where demand and supply fluctuate.
- **Efficient Energy Utilization:** By supplying substantially more energy than the conventional method while keeping energy loss to a minimum, the RL-based system demonstrates its efficiency in harnessing available energy and deploying it as needed. This efficiency reduces reliance on external sources and makes the microgrid more self-sufficient.
- **Minimized Energy Waste:** Lower energy loss signifies that the RL model is capable of precise energy management, preventing unnecessary charging or discharging events that lead to waste. This efficiency can extend battery lifespan and improve overall system sustainability.
- **Strategic Charging:** Although the RL approach had slightly more charging cycles, these cycles were used in a way that optimized battery life and energy output. This indicates that the RL system can balance performance and battery health, a crucial factor in long-term operational efficiency.

VI. Conclusion

The multi-agent reinforcement learning approach clearly outperforms the conventional method across all performance metrics, especially in load satisfaction, energy supply, and energy conservation. By continuously learning from real-time conditions, the RL model optimizes battery usage and minimizes waste, making it an ideal choice for distributed battery management in solar microgrids. This approach has practical implications for enhancing the resilience and sustainability of renewable energy systems, as it allows microgrids to operate with greater independence, efficiency, and reliability.

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