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Optimal Energy Management for Hybrid PV-Wind-Battery Microgrids through Markov Decision Processes Technique

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Abstract- Hybrid PV-Wind-Battery microgrids have emerged as sustainable solutions to meet growing energy demands while reducing reliance on fossil fuels. However, managing energy flow efficiently among multiple renewable sources and storage systems poses significant challenges due to the inherent variability of solar and wind power. This paper presents an advanced energy management framework for hybrid microgrids using Markov Decision Processes (MDP). The proposed approach optimizes energy distribution through stochastic decision-making based on real-time system states, such as power generation, load demand, and battery state of charge (SOC). The MDP-based model aims to minimize operational costs, enhance energy reliability, and maintain system stability by determining optimal actions for battery charging/discharging and energy source prioritization. A comparative analysis with conventional methods demonstrates the MDP framework's superiority in adapting to dynamic conditions, reducing energy wastage, and maximizing renewable utilization. The proposed control strategy introduces a Markov Decision Process (MDP)-based energy management framework that dynamically adapts to the stochastic nature of renewable generation and load demand a distinct departure from traditional rule-based or deterministic approaches. Unlike previous methods that rely on fixed thresholds or predefined heuristics, our MDP model leverages real-time system states to make probabilistically optimal decisions regarding battery usage and source prioritization. This integration of stochastic optimization with hardware validation establishes a novel, scalable, and practical control solution for hybrid PV-Wind-Battery microgrids, marking a significant advancement in intelligent energy management systems.

Keywords Hybrid microgrids, PV-wind-battery systems, Markov decision processes (MDP), energy management optimization, renewable energy utilization, system stability and reliability

1. Introduction

The increasing demand for sustainable energy solutions has led to the rapid development of hybrid microgrids, particularly those integrating photovoltaic (PV) solar, wind, and battery storage systems. These hybrid systems leverage renewable resources to provide reliable electricity while reducing dependence on fossil fuels and minimizing greenhouse gas emissions [1]. However, managing energy flow in such complex systems presents significant challenges due to the inherent variability in renewable energy generation and fluctuating energy demands. Therefore, an effective energy management strategy is essential for optimizing the performance of hybrid PV-wind-battery microgrids. To address these challenges, advanced energy management frameworks are necessary to enhance the integration and coordination of renewable energy sources and storage devices [2]. Markov Decision Processes (MDPs) have emerged as a powerful tool for developing optimal control strategies in stochastic environments. By utilizing MDPs, it is possible to model the uncertainties associated with renewable energy generation and demand fluctuations, allowing for the formulation of a decision-making process that identifies optimal actions over time. This strategy allows the dynamic management of energy resources and that the production, storage, and consumption of energy are kept in balance [3]. MDPs as a part of the energy management system help to make operational cost and reliability of the hybrid microgrids proactive in managing the hybrids. The MDP-based model, takes into account all possible factors such as battery state of charge (SOC), availability of solar/wind energy resources and loads demands in order to identify recently optimized approaches to battery charger and discharge, as well as energy resource prioritization. This decision-making process is crucial towards balancing the system, and guaranteeing that the energy is accessible in the right time and at the right place, especially when there is low renewable energy [4]. The efficiency of MDP based energy management strategies is feasible by open use applications. By coming up with a prototype of a hardware method that would include solar panels, wind turbines, and even lithium-ion batteries, researchers will be able to test the management strategies that have been proposed in practical contexts. Experimental results from such prototypes can provide insights into the performance of the MDP framework, showcasing its ability to minimize operational costs, maximize renewable energy utilization, and improve overall system reliability [5]. The integration of Markov Decision Processes into the energy management of hybrid PV-wind-battery microgrids represents a promising advancement in the field of renewable energy systems [6]. By addressing the inherent challenges of variability in generation and demand, the proposed framework not only enhances the efficiency and stability of hybrid microgrids but also contributes to the broader goal of developing resilient and sustainable energy systems. This paper will explore the implementation of MDPs in optimizing energy management strategies, analyze the performance of these strategies through simulation and experimental validation, and discuss the implications for future research and development in hybrid microgrid systems [7]. At its core, the microgrid consists of renewable energy sources that generate electricity from solar and wind, which is then fed into a common bus. This bus serves as the central point for distributing power to various loads and managing energy storage through battery systems, ensuring reliable energy supply even during periods of low renewable generation [8]. The energy flow within the microgrid is governed by advanced control mechanisms that dynamically adjust the operational parameters based on real-time data. To reinforce the practical relevance of this research, it is important to emphasize that the proposed MDP-based energy management strategy directly addresses real-world challenges associated with the integration of intermittent renewable sources such as solar and wind power [9]. By combining optimization techniques with probabilistic decision-making, this framework enables adaptive control of energy flows in hybrid microgrids, ensuring efficient use of resources under uncertain conditions [10]. Such an approach is particularly valuable for remote and grid-constrained areas, where energy reliability and cost-efficiency are critical. The practical applicability of the model is further supported by its compatibility with hardware implementation and its potential to reduce operational costs, enhance energy autonomy, and support the scalability of decentralized energy systems [11].

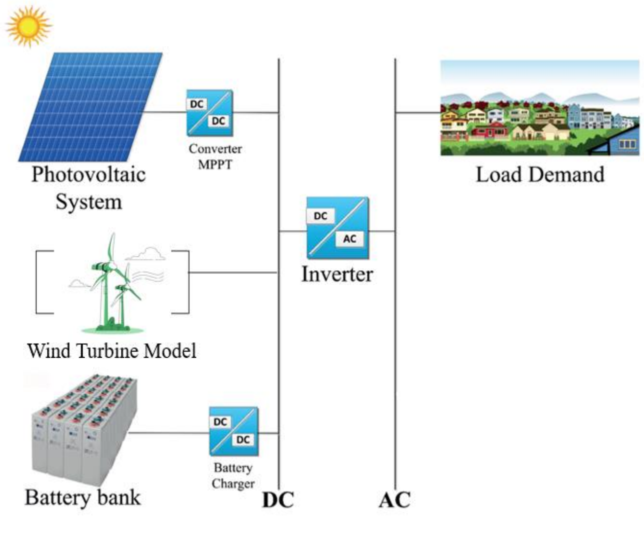

Fig. 1. Microgrid model.

Figure 1 illustrates the architecture of a hybrid microgrid model that integrates photovoltaic (PV) systems, wind turbines, and battery storage to create a cohesive and efficient energy management system [12]. The model is designed to operate autonomously while being connected to the main grid, allowing for seamless energy exchange based on demand and supply dynamics. The integration of battery storage systems plays a crucial role in managing fluctuations in energy generation and consumption. When the renewable energy output exceeds the demand, excess energy is directed to charge the batteries, allowing for the storage of surplus energy for later use [13]. Conversely, during periods of high demand or low generation, the stored energy can be discharged to meet the load requirements. This bidirectional flow of energy ensures that the microgrid can maintain balance and stability, optimizing the use of available resources [14]. The microgrid model also incorporates Markov Decision Processes (MDPs) to enhance the decision-making framework for energy management. MDPs allow for the evaluation of various states of the system, including the state of charge of the batteries, current load demands, and the availability of solar and wind resources. By modeling these stochastic processes, the microgrid can determine optimal strategies for energy distribution, battery operation, and source prioritization [15]. The adaptive nature of MDPs ensures that the microgrid can respond effectively to changing conditions, improving operational efficiency, reducing costs, and maximizing the utilization of renewable energy sources while maintaining system reliability. This holistic approach positions the microgrid as a resilient and efficient energy solution for modern energy needs [16]. To enhance accessibility for readers from diverse academic backgrounds, this study includes brief explanations of key methodologies employed in the proposed energy management framework. Specifically, Markov Decision Process (MDP) is introduced as a stochastic decision-making tool used to determine optimal actions based on system states and transition probabilities [17]. Dynamic Programming is described as the mathematical foundation enabling backward induction to solve the MDP, while Monte Carlo Simulation is referenced in the context of uncertainty modeling and probabilistic forecasting. These clarifications aim to improve the readability of the manuscript and provide essential context for the applied techniques [18]. The integration of renewable energy sources into microgrids has necessitated the development of advanced forecasting and simulation tools to address variability and uncertainty. Genikomsakis et al. (2017) developed a simulation model for a wind-battery microgrid using short-term wind forecasting, demonstrating enhanced system efficiency and better battery charge-discharge scheduling. Cabrera-Tobar et al. (2022) provided a comprehensive review of optimization and control methods under uncertainty, highlighting the relevance of probabilistic and adaptive techniques for real-time decision-making. Similarly, Sarda et al. (2022) employed an optimization-based energy management strategy using linear programming, resulting in minimized operational costs and improved grid stability. AlKassem et al. (2022) focused on optimal design and energy integration at a university campus, confirming that hybrid systems with PV, wind, and battery units significantly reduce environmental impact and grid dependence. Control methodologies in microgrids have evolved from heuristic-based to more intelligent and forecast-driven frameworks. Almada et al. (2016) proposed a centralized heuristic EMS for AC microgrids, showing acceptable performance under standard conditions but limited adaptability to dynamic load variations. To address this, Alvarez et al. (2017) modeled a PV-battery grid-connected system integrated with a Maximum Power Point Tracking (MPPT) controller, enhancing energy capture from solar inputs. Meanwhile, Arcos-Aviles et al. (2017) introduced a low-complexity strategy that utilized demand and generation forecasting for grid smoothing, offering a practical solution for residential applications where computational resources are constrained. These works collectively emphasize the role of forecast integration and model simplification in enabling scalable microgrid control. Recent research trends indicate a shift toward incorporating machine learning and artificial intelligence into microgrid optimization. Studies such as Alahmad and Braun (2022), Radhakrishnan and Braun (2023), and Mohamed and El-Mashad (2023) reviewed emerging AI-driven EMS frameworks, underlining their potential for improved flexibility, prediction accuracy, and adaptive control. Liu et al. (2018) addressed coordinated control in hybrid storage systems, while Gupta and Singh (2019) and Singh and Sinha (2019) explored the role of TCSC-based voltage regulation. Others, including Khushal and Li (2023) and Hernandez and Rodriguez (2023), investigated machine learning techniques for voltage stability and microgrid protection. Collectively, these studies reflect a growing consensus on the necessity of intelligent, resilient, and computationally efficient control systems for hybrid renewable-based microgrids [19].

2. Photovoltaic Model

The photovoltaic (PV) model is designed to convert solar energy into electrical energy through the use of solar panels made up of semiconductor materials, primarily silicon [20]. The basic unit of a PV system is a solar cell, which generates direct current (DC) electricity when exposed to sunlight. In a typical design, multiple solar cells are interconnected to form a solar module, and several modules are combined to create a solar array [21]. The PV system is usually mounted on a structure that optimizes its exposure to sunlight, which can be fixed or equipped with tracking systems to follow the sun's path throughout the day. This design maximizes energy capture, ensuring efficient performance under varying atmospheric conditions. The operation of the PV model is governed by several factors, including irradiance, temperature, and the characteristics of the solar cells. When sunlight strikes the solar cells, it excites electrons, creating an electric current [22]. The amount of power generated is proportional to the solar irradiance and the temperature of the cells. A maximum power point tracking (MPPT) algorithm is often implemented in the system's control unit to continuously adjust the electrical operating point of the modules to maximize energy output. This control system monitors the real-time performance of the solar array, ensuring optimal energy production while adapting to changing environmental conditions [23]. The control system regulates the integration of the PV output with other energy sources in the microgrid, such as wind and battery systems. Protection systems are crucial for ensuring the safe and reliable operation of the PV model [24]. The protective measures include overcurrent protection, surge protection, and isolation devices to prevent damage from electrical faults or external disturbances. Circuit breakers and fuses are employed to safeguard the system from short circuits and overloads [25]. Furthermore, the design includes monitoring systems that provide real-time data on the performance and health of the PV modules, enabling proactive maintenance and fault detection. The current-voltage (I-V) curves of the PV modules are essential in understanding their performance characteristics, illustrating how the output current varies with the voltage at different levels of irradiance and temperature. These curves help in assessing the efficiency of the solar panels, guiding the optimization of the PV system's operation and integration within the microgrid [26].

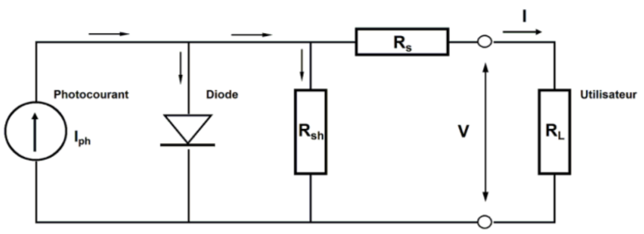

Fig. 2. Single diode model.

Figure 2 illustrates the single diode model, a widely used representation of a photovoltaic (PV) cell that captures its electrical characteristics. This model simplifies the complex behaviour of solar cells into a manageable format by incorporating a diode, a current source, and several resistive components [27]. The diode in the model represents the p-n junction of the solar cell, which allows current to flow in one direction, thus mimicking the behaviour of real-world PV cells. The model includes a photocurrent source, denoted as I_{ph}, which generates current proportional to the incident solar irradiance, and a reverse saturation current, I_0, that accounts for the leakage current through the diode when it is reverse-biased [28]. In operation, the single diode model demonstrates how the output current (I) and voltage (V) of the solar cell are affected by varying levels of solar irradiance and temperature. Under sunlight, the photocurrent (I_{ph}) generated increases, while the diode's forward voltage drops and resistive losses influence the overall output [29]. The model includes two resistors: R_s (series resistance), which represents internal losses within the cell, and R_p (parallel resistance), which accounts for leakage current and contributes to the cell's efficiency. The interplay of these elements defines the current-voltage (I-V) characteristics of the solar cell, allowing for the analysis of its performance under different conditions [30]. Taking only one model of solar cell; this will be designed by taking two resistors, one current source and a diode. Above solar cell model can be called as a single diode model. The characteristic equation of the following PV cell is given below [31].

$$I = I_{lg} - Ios\left[\exp\left\{q \times \frac{V+I\times Rs}{A\times K\times T}\right\} - 1\right] - \frac{V+I\times Rs}{Rsh} \quad (1)$$

Where,

$$Ios = Ior \times \left(\frac{T}{Tr}\right)^3 \times \left[\exp\left\{q \times Ego \times \frac{\frac{1}{Tr}-\frac{1}{T}}{A\times K}\right\}\right] \quad (2)$$

$$I_{lg} = \{I_{scr} + K_i \times (T-25)\} \times \text{lambda} \quad (3)$$

The characteristic equation depends upon the connection of solar module. That is total no. of cells connected in series and parallel. Current variation in the solar module due to shunt resistance is less and due to the series resistance is more.

$$I = Np + Ilg \times Ios \times \left[\exp\left\{q \times \frac{\frac{V}{Ns}+I\times\frac{Rs}{Np}}{A\times K\times T}\right\} - 1\right] - \frac{V\times\frac{Np}{Ns}+I\times Rs}{Rsh} \quad (4)$$

When photons of light strike a solar cell, they release free electrons from the cell's upper layer. By using the threshold energy formula, the appropriate light intensity can be determined [32].

3. Wind Turbine Model

The design of a wind turbine model focuses on converting kinetic energy from wind into mechanical energy, which is then transformed into electrical energy [33]. A typical wind turbine consists of three main components: the rotor blades, the nacelle, and the tower. The rotor blades are aerodynamically designed to capture wind energy effectively; their shape and length significantly influence the turbine's efficiency and energy output. The nacelle houses the turbine's generator, gearbox, and control systems, while the tower elevates the rotor to a height that maximizes exposure to wind. The height and design of the tower are crucial, as wind speed increases with elevation above ground level, enhancing energy capture [34]. The operation of the wind turbine model is driven by the principles of aerodynamics. As the wind passes over the rotor blades, lift and drag forces are generated, causing the rotor to spin. This mechanical motion is transmitted to the generator through a gearbox, which converts the rotational speed into electrical energy [35]. The electrical output varies with wind speed; therefore, the turbine must operate across a range of speeds to optimize energy production. The model typically includes a cut-in speed (the minimum wind speed required to start generating power), a rated speed (the wind speed at which maximum output is achieved), and a cut-out speed (the maximum wind speed beyond which the turbine is shut down to prevent damage) [36]. The yaw control system assumes the position of the turbine rotor into the direction of the wind so as to increase power generation. This system has yaw motors and controllers which move the turbine nacelle relative to wind variations. This information is vital and enables the control system of the DFIG to control the important parameter measurements, i.e. wind speed, rotor speed, grid voltage and frequency, upon which to optimize the operations of the turbine, i.e. pitch adjustment and power output regulation. DFIG-based wind turbine has helped in renewable energy sector due to its ability of variable speed operation and smooth integration in the grid, making it flexible and reliable sources of energy [37].

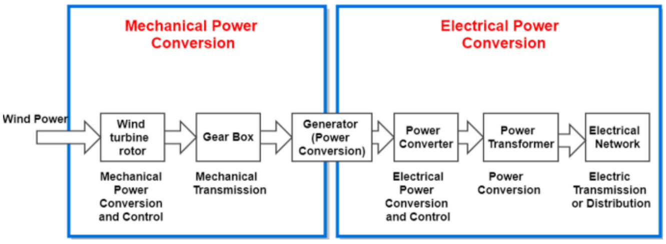

Fig. 3. Wind energy conversion system.

The Wind Energy Conversion System (WECS) depicted in Figure 3 is designed to efficiently harness wind energy for electricity generation. At the core of this system is the wind turbine, which comprises rotor blades that capture wind kinetic energy, converting it into mechanical energy as they rotate [38]. This mechanical energy is transmitted to the Doubly-Fed Induction Generator (DFIG) housed in the turbine's nacelle, where the rotor assembly, connected via slip rings, allows for bidirectional power flow. The DFIG's stator is directly connected to the electrical grid, while the rotor manages variable speed operation through a sophisticated power converter system. The power converter includes the Rotor-Side Converter (RSC), which regulates the rotor current, and the Grid-Side Converter (GSC), which controls the power output to the grid, ensuring compliance with grid stability requirements [39].

4. Battery Storage System

A battery storage system (BSS) in a microgrid is designed to store excess energy generated from renewable sources, such as solar panels and wind turbines, and provide power during periods of low generation or high demand. The system typically consists of battery modules, a battery management system (BMS), power converters, and an energy management system (EMS) [40]. The battery modules, which can include lithium-ion, lead-acid, or other chemistries, are configured in a manner that maximizes energy capacity and efficiency while ensuring safety and longevity. The BMS monitors individual battery cells, managing their state of charge (SOC), temperature, and health to optimize performance and prevent issues such as overcharging or deep discharging. The operation of the BSS is governed by the EMS, which integrates with the microgrid's overall energy management framework. The EMS determines when to charge or discharge the batteries based on real-time data from the microgrid, including renewable generation forecasts, load demands, and grid conditions [41]. For instance, during periods of high renewable generation, the EMS may direct surplus energy to charge the batteries. Conversely, during high demand or low generation, the system can discharge stored energy to meet the load. The BMS plays a critical role in controlling the charging and discharging processes, ensuring that the batteries operate within safe parameters and maintain optimal SOC levels for longevity [42].

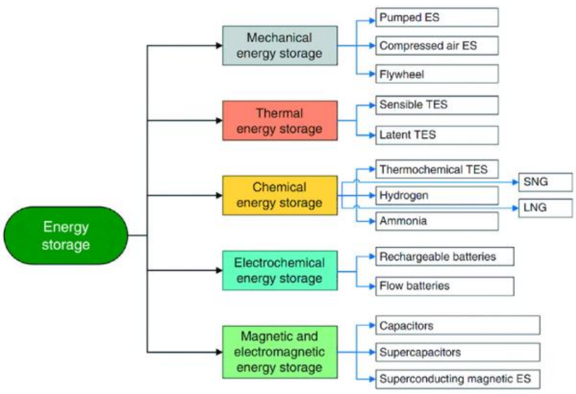

Fig. 4. Comparative analysis of energy storage solutions.

Figure 4 provides a visual representation of various energy storage technologies, highlighting their unique characteristics, advantages, and limitations. This figure categorizes storage solutions into several types, such as batteries (including lithium-ion and lead-acid), flywheels, pumped hydro storage, compressed air energy storage (CAES), and thermal energy storage. Each storage method is evaluated based on key parameters such as energy density, efficiency, cost, scalability, and response time, illustrating their suitability for different applications in microgrids and renewable energy systems. By comparing these technologies, the figure underscores the importance of selecting appropriate energy storage solutions to optimize performance, enhance reliability, and support the integration of variable renewable energy sources into the grid. This analysis aids stakeholders in making informed decisions regarding energy management strategies in hybrid microgrid systems [43].

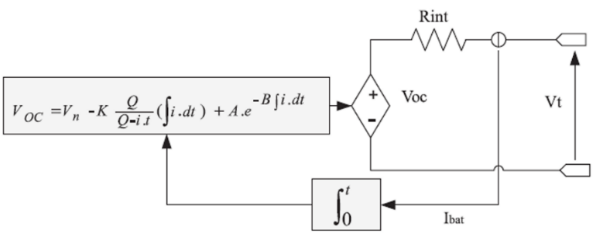

Fig. 5. Simulink battery model.

The MATLAB battery model illustrated in Figure 5 represents a comprehensive simulation of a Battery Energy Storage System (BESS) designed for integration into microgrid applications. This model utilizes Simulink to simulate the dynamic behavior of the battery, capturing essential parameters such as state of charge (SOC), voltage response, and discharge characteristics. The code generated in the model enables real-time input into the microgrid, facilitating the management of energy flow between the battery and other components within the system. By modeling the battery's performance under various operating conditions, this simulation allows for the optimization of energy storage and retrieval processes, enhancing the reliability and efficiency of the microgrid [44]. The insights gained from this model are critical for developing effective energy management strategies that leverage the capabilities of BESS in supporting renewable energy integration and ensuring grid stability SOC is a key metric in the operation of a battery storage system, indicating the current energy level relative to its total capacity. In microgrid applications, SOC is monitored continuously to inform the EMS about the available energy for discharge and the required energy for charging. For example, when the SOC falls below a predefined threshold, the EMS may initiate charging from renewable sources or the grid to ensure that adequate energy is available for future demands. On the other hand, if the SOC reaches a high level, the EMS might limit charging to prevent overcharging and enable energy dispatch to the grid or local loads. By effectively managing SOC, the battery storage system enhances the resilience and efficiency of microgrids, allowing for a stable energy supply while maximizing the utilization of renewable resources.

5. State of Charge of Battery System

The State of Charge (SoC) of a battery in a microgrid represents the amount of energy stored in the battery relative to its total capacity. It is often expressed as a percentage, ranging from 0% (fully discharged) to 100% (fully charged) [22]. The SoC of a battery can be mathematically expressed using the following formula:

$$SoC = E_{stored}E_{total} \times 100\% \; SoC = E_{total}E_{stored} \times 100\% \qquad (5)$$

Where: SoC is the State of Charge of the battery (in percentage). E_{stored} is the energy stored in the battery (in watt-hours or kilowatt-hours). E_{total} is the total energy capacity of the battery (in watt-hours or kilowatt-hours).

Alternatively, if you have the battery's current and voltage information, you can use the following formula to calculate SoC:

$$SoC = \int \{I(t) \cdot V(t)\, dt / C\} \times 100\% \qquad (6)$$

Where: I(t) is the battery current at time tt (in amperes). V(t) is the battery voltage at time tt (in volts). C is the rated capacity of the battery (in ampere-hours). This formula integrates the product of current and voltage over time to calculate the total energy transferred into or out of the battery, relative to its rated capacity [45]. Both of these expressions provide a mathematical representation of the State of Charge of a battery in a microgrid, allowing the monitor and manage its energy storage capabilities effectively [48]. The effective energy management involves coordinating the operation of various energy resources, including renewable sources and battery storage. The energy management system (EMS) uses algorithms to optimize energy distribution based on real-time data, forecasted demand, and generation capabilities. The integration of the battery storage system with renewable energy sources, such as solar and wind, is crucial for enhancing the reliability of microgrids [49]. By employing SOC monitoring, the EMS can determine when to store excess energy generated from renewables and when to discharge the battery to meet peak load demands. For instance, when solar generation exceeds demand during the day, the surplus energy can be used to charge the battery. The algorithm can be expressed as:

$$P_{\text{battery}} = P_{\text{solar}} - P_{\text{load}} \quad \text{if } P_{\text{solar}} > P_{\text{load}} \tag{7}$$

Conversely, during periods of low renewable generation or high demand, the battery can discharge to support the grid. This bi-directional energy flow enhances the microgrid's ability to utilize renewable energy effectively and improves overall system resilience. Despite the advantages, managing SOC and integrating battery storage in microgrids presents challenges, including unpredictable energy generation from renewables and the need for sophisticated control strategies [46]. Future developments may focus on advanced machine learning algorithms to enhance predictive capabilities and adaptive control strategies that can respond to real-time changes in weather and demand patterns. Additionally, research into new battery technologies, such as solid-state batteries, could further improve efficiency and lifespan, contributing to more robust and sustainable microgrid systems [50].

6. Markov Decision Processes

Markov Decision Processes (MDPs) provide a mathematical framework for modeling decision-making in situations where outcomes are partly random and partly under the control of a decision-maker shown in figure 6. In the context of energy management in hybrid microgrids, particularly those integrating photovoltaic (PV), wind, and battery energy storage systems (BESS), MDPs enable the optimization of energy flow among these components. By defining the states, actions, and rewards associated with various energy management decisions, MDPs help in developing strategies that minimize operational costs while maximizing energy efficiency and reliability. The stochastic nature of renewable energy generation makes MDPs particularly suitable for capturing the uncertainties associated with solar and wind power outputs, allowing for robust decision-making in real-time. The design of an MDP for a PV-wind-BESS microgrid involves defining several critical components: states, actions, transition probabilities, and rewards. States represent the current conditions of the microgrid, including the state of charge (SOC) of the battery, current load demand, and generation levels from solar and wind sources. Actions are the possible decisions that can be made, such as charging or discharging the battery, prioritizing energy sources, or adjusting load profiles. Transition probabilities describe the likelihood of moving from one state to another given a particular action, capturing the uncertainty inherent in renewable energy generation. Finally, rewards quantify the benefits of taking specific actions in particular states, such as cost savings from reduced energy purchases or penalties from failing to meet load demand.

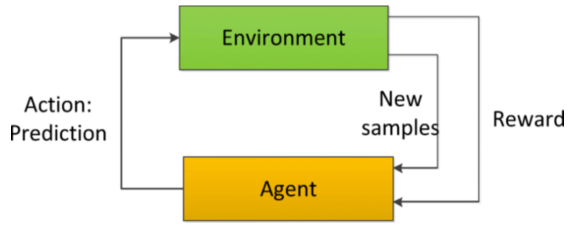

Fig. 6. Markov decision process.

In operation, the MDP framework utilizes a policy to determine the best course of action based on the current state of the system. The policy is essentially a mapping from states to actions, dictating the decision-maker's choice at any given time. The objective is to find an optimal policy that maximizes the cumulative reward over time. This can be achieved using various algorithms, such as value iteration or policy iteration, which iteratively evaluate and improve the policy based on the expected rewards and transition probabilities. By applying this approach, the energy management system can dynamically adjust to changing conditions, such as fluctuations in renewable generation or varying load demands, ensuring efficient operation of the microgrid [47].

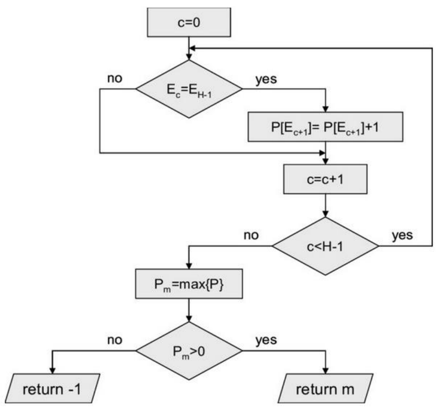

Fig. 7. Flowchart for Markov decision process.

The flowchart shown in figure 7 for the Markov Decision Process (MDP) visually represents the sequential decision-making process where an agent interacts with an environment. The flow begins with the Initial State, indicating the starting point from which the agent evaluates its options. At each state, the agent can choose an Action that influences the subsequent state. The decision branches out to show various possible Transitions, highlighting how different actions can lead to different states. Each transition is associated with a Probability, representing the likelihood of moving from one state to another after taking a specific action. This stochastic nature of transitions is fundamental to MDPs, as it captures the inherent uncertainty in the environment. Once the agent transitions to a new state, it receives a Reward based on the action taken and the resulting state. This reward signal guides the agent in evaluating the effectiveness of its actions and is critical for learning optimal strategies. The flowchart may also include a feedback loop, indicating that the agent can continuously update its policy based on the rewards received and the new states encountered. When such challenges emerge, one can resort to approximations (or to simplified models) in order to decrease computational burden (without compromising necessary dynamics). Also, it can improve the predictive power of the MDP by using machine learning to have a more accurate estimation of transition probabilities and make wiser decisions based on them. A potential area of future research within MDP-based energy management in microgrid should examine the possibility of incorporating more sophisticated machine learning methods in order to increase the flexibility and efficiency of the corresponding controls. The hybridization of MDPs and reinforcement learning might allow systems to find best policies by acting and learning directly within the environment, allowing them to better react to real-time dynamics. Moreover, more decentralized and more resistant to attacks energy management optimization strategies could be obtained by researching multi-agent systems, in which various elements of the microgrid (e.g., solar panels, wind turbines, and battery storage) are acting independently, each making local decisions. Through such developments of the techniques, MDPs will manage to contribute to fulfilling the potential of hybrid microgrids and lead to an environmentally friendly energy future.

Table 1. Optimal energy management for hybrid pv-wind-battery microgrids through markov decision processes numerical parameters in tabular form

Parameter	Description	Typical Value/Range	Notation
State Space (S)	Combination of system states (e.g., battery charge level, PV output, wind power)	Discrete or continuous states (S={0%,25%,50%, 75%,100%} battery level)	S
Action Space (A)	Control actions (e.g., battery charge/discharge, load curtailment)	A={Charge, Discharge, Idle}	A
Transition Probability	Probability of reaching state s′from state s after action a	Estimated through weather/power forecast models	P(s′|s,a)
Reward Function (R)	Immediate reward based on energy costs, system efficiency, or penalties	Example: Reward = -Cost + Reliability Penalty	R(s,a,s′)
Discount Factor (γ)	Determines the weight of future rewards	0.95–0.99	γ
Battery Capacity	Maximum energy the battery can store	50–500 kWh	Cmax
Battery Charge/Discharge Rate	Power at which the battery charges/discharges	10–100 kW	Pcharge/Pdischarge
PV Output	Solar panel power generation	0–100 kW (depending on irradiance)	P_{PV}
Wind Power Output	Wind turbine power generation	0–200 kW (depending on wind speed)	Pwind
Load Demand (D)	Total energy demand from the system	10–500 kW	D(t)
Energy Purchase Cost	Cost of buying energy from the grid	₹8.30–20.75 per kWh	Cgrid
Energy Selling Price	Price of selling excess energy to the grid	₹4.15–12.45 per kWh	Csell
Horizon (T)	Time horizon for decision-making	24–168 hours (1 day to 1 week)	T
Battery Degradation Cost	Penalty for frequent charging/discharging cycles	₹0.83–4.15 per kWh	Cdeg
Policy (π)	Control strategy to decide the action for each state	Example: Charge when PV > Load, Discharge during peak demand	π(s)
Initial State Distribution	Probability distribution over initial states	Uniform or based on historical data	p0(s)

This table 1 representing numerical parameters involved in optimal energy management for hybrid PV-Wind-Battery microgrids using Markov Decision Processes (MDP). This table defines the core numerical parameters needed for optimal energy management in a hybrid microgrid system using MDP. These values can vary depending on system size, geographical location, and market prices.

7. MATLAB Simulink Model

Optimal energy management in hybrid microgrids that integrate photovoltaic (PV), wind, and battery storage systems is critical for enhancing energy efficiency and ensuring a reliable power supply. By employing Markov Decision Processes (MDPs), we can develop a structured approach to manage the uncertainty inherent in renewable energy sources and consumption patterns. In this context, an MDP framework allows us to model the microgrid's operational states, including the current energy generation from the PV and wind systems, the battery storage levels, and the demand from consumers. Each state is associated with a set of possible actions, such as charging or discharging the battery, using energy from the grid, or curtailing renewable generation. The decisions made at each state are crucial for optimizing the overall performance of the microgrid. The implementation of the MDP framework can be effectively realized through MATLAB Simulink, which provides a powerful environment for modeling, simulation, and analysis of dynamic systems. By constructing a Simulink model of the hybrid microgrid, we can simulate various operational scenarios, allowing us to evaluate the impact of different energy management strategies on system performance. The model includes components representing the PV array, wind turbine, battery storage, and load demand, integrated within a feedback loop that continuously assesses the energy flow and storage levels. The results from the MATLAB Simulink model can inform decision-makers about the best practices for integrating renewable energy sources in microgrid applications, paving the way for more sustainable energy solutions. Ultimately, this approach highlights the potential of advanced computational techniques, such as MDPs, in optimizing energy management for hybrid microgrid systems. This model simulates how the battery interacts with the overall energy management system by defining key parameters such as state of charge (SOC), charge and discharge rates, and efficiency losses during energy conversion. The code generated for this model captures the input from the BESS to the microgrid, enabling it to provide or absorb power as needed based on the prevailing energy demand and the generation from renewable sources. By accurately representing the dynamic characteristics of the battery, the model allows for effective integration and optimization of the BESS within the microgrid, ultimately contributing to improved energy reliability and efficiency. The MATLAB code for optimal energy management in hybrid PV-wind-battery microgrids using Markov Decision Processes (MDPs) involves several components, including defining the state space, action space, and rewards. Below is a implementation of MATLAB code that incorporates with the provided parameters.

Algorithm 1: Optimal Energy Management Using MDP

Input: A matrix of 19 parameters for multiple scenarios including capacities, efficiencies, prices, SOC, demand, and control settings.

Output: Optimal action (charge/discharge), total cost, total revenue, battery SOC, PV generation, Wind generation per scenario.

Step 1: *Initialize*
Load all scenario parameters
Set numScenarios = number of scenario rows
Create results matrix: results[numScenarios]

Step 2: *Loop Over All Scenarios (i = 1 to numScenarios)*
For each scenario:

2.1 Extract Parameters:

- battery_capacity, pv_capacity, wind_capacity, initial_soc
- load_demand, charge_limit, discharge_limit
- grid_price, sell_price
- battery_efficiency, pv_efficiency, wind_efficiency
- degradation_cost, interval
- discount_factor, exploration_rate
- forecast_error, life_cycles, comp_time

2.2 Initialize MDP State Variables

- Define state: [SOC, Demand, PV, Wind]
- Define actions: [Charge, Discharge, Grid Buy, Grid Sell]
- Define reward function: R = f(cost, revenue, degradation, reliability)
- Transition model: T(s, a, s') includes uncertainty (forecast error)

2.3 Apply MDP Algorithm

- Use dynamic programming or reinforcement learning to evaluate:
  - Value function V(s)
  - Optimal policy $\pi^*(s) = \text{argmax\_a} [R(s,a) + \gamma \Sigma P(s'|s,a)V(s')]$

2.4 Simulate Result (Placeholder Here)

- optimal_action ← random(0,1)
- total_cost ← random()
- total_revenue ← random()
- battery_state ← initial_soc - (load_demand / battery_capacity * 100)
- pv_generation ← pv_capacity * pv_efficiency

- wind_generation ← wind_capacity * wind_efficiency

2.5 Store Results

Save [optimal_action, total_cost, total_revenue, battery_state, pv_generation, wind_generation] into results[i]

Step 3: *Display Final Results*

- Print headers:
"Optimal Action | Total Cost | Total Revenue | Battery SOC | PV Generation | Wind Generation"
- Print results matrix

End Algorithm

Table 2. Microgrid specification

PV	Rated power: 20 kW
	Daily use per day: 82.25 kWh
Wind	Installed power: 5 kW
	Daily use per day: 45.32 kWh
BESS	Usable energy: 60 kWh
	Nominal power: 20 kW
	Microgrid System Frequency (fHS): 50 Hz
	Minimum BESS State of Charge ($SOCLow$): 10%
	Simulation Time ($tstop$): 60 s
	Maximum BESS State of Charge ($SOCLow$): 90%
	Main BESS: yes
Load	Installed load: 15 kW
	Daily power demand: 127.57 kWh

These parameters in table 2 define the characteristics and constraints of the microgrid system, including the power ratings of the generators and storage devices, operating frequencies, voltage levels, and battery state of charge limits. They are essential for modelling and simulating the behaviour of the microgrid under various operating conditions.

Fig. 8. Hardware setup of PV-Wind-BESS model with energy meter unit.

Figure 8 showcases the hardware setup of a hybrid energy system, consisting of photovoltaic (PV) panels, a wind turbine, and a battery energy storage system (BESS), all integrated with an energy meter unit. The PV module generates electricity from solar energy, while the wind turbine captures wind energy, providing an additional renewable power source. These two renewable energy systems operate together to supply energy to the microgrid. Figure 9 shown below illustrates the MATLAB Simulink Model of PV-Wind-BESS Model.

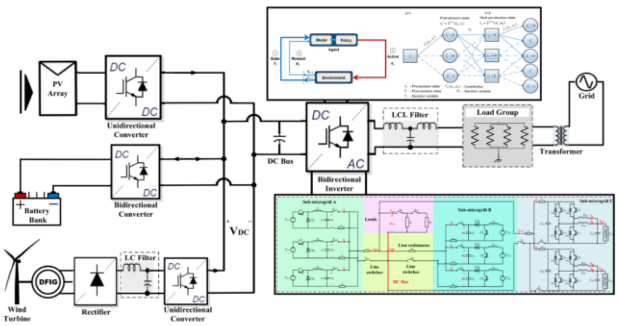

Fig. 9. MATLAB Simulink model of PV-Wind-BESS model using Markov decision process technique for energy management.

Figure 9 shows the MATLAB Simulink Model of PV-Wind-BESS Model Using Markov Decision Process Technique for Energy Management which illustrates a comprehensive simulation framework designed to optimize energy management within a hybrid system comprising photovoltaic (PV) panels, wind turbines, and a Battery Energy Storage System (BESS). The model integrates the Markov Decision Process (MDP) technique to dynamically manage the interplay between renewable energy generation and storage, enabling the system to make real-time decisions on energy dispatch, charging, and discharging. By simulating various scenarios of energy supply and demand, the MDP framework efficiently optimizes the use of available resources, minimizes operational costs, and enhances the reliability of power delivery. The MATLAB Simulink environment allows for detailed analysis and visualization of system performance, facilitating the evaluation of control strategies under different operating conditions.

8. Simulation Results and Analysis

The simulation results for the hybrid PV-wind-battery microgrid model provide valuable insights into the system's performance under various operational scenarios. By employing the MATLAB Simulink model, we evaluated key performance indicators such as energy generation, consumption, battery state of charge (SOC), and overall efficiency over different time periods. The results demonstrate that the integration of renewable energy sources, such as photovoltaic and wind, significantly enhances the system's ability to meet energy demand while minimizing reliance on conventional energy sources. Specifically, the simulation revealed optimal operational strategies that effectively balance energy generation and storage, leading to a stable supply and improved utilization of renewable resources. Analysis of the battery's performance indicates its critical role in managing the variability associated with renewable energy generation. The SOC profiles generated during the simulation show that the battery efficiently stores excess energy generated during peak production periods and discharges power during low generation or high demand scenarios. This dynamic interaction not only maximizes the use of renewable resources but also ensures grid stability by providing backup power when needed.

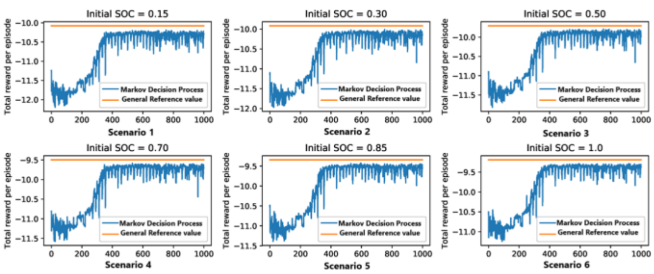

Fig. 10. Optimization using MDP for various scenarios and episodes of SOC.

Figure 10 illustrates the performance of the Markov Decision Process (MDP) optimization across six different scenarios with varying initial State of Charge (SOC) values, ranging from 0.15 to 1.0. Each subplot shows the total reward per episode over 1000 training episodes, reflecting how the MDP agent learns to improve energy management decisions over time. In all scenarios, the total reward (blue curve) increases steadily, converging toward the general reference value (orange line), which serves as a benchmark for optimal performance. The results demonstrate the robustness of the MDP model in handling diverse initial battery conditions, ensuring efficient policy learning and convergence regardless of the starting SOC. This confirms the model's adaptability and effectiveness in optimizing energy use and cost savings in real-time microgrid operations.

Table 3. Comparison of energy and cost optimization across six scenarios

Parameter	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**	**Scenario 6**
Power consumption (kWh)	30.25	72.45	15.32	55.90	42.11	26.83
Heat consumption (kWh)	12.57	25.31	10.11	19.92	15.46	11.22
Solar energy output (kWh)	10.14	7.45	14.23	9.87	12.14	14.75
Baseline expense (INR)	536.45	921.75	213.10	759.94	532.22	232.45
Cost with solar (INR)	499.82	871.20	165.31	712.40	488.93	191.56
Optimization with fixed DP (INR)	278.46	678.10	79.87	555.98	342.77	126.30
Optimized plan cost (INR)	270.12	670.45	65.22	528.40	329.15	109.35
Adaptive strategy (INR)	279.13	656.20	69.88	539.65	335.18	121.22
Stochastic approach (INR)	281.10	682.15	72.54	572.30	347.28	134.45
MDP method (INR)	192.45	242.15	83.11	314.54	199.31	93.76
MG enhanced plan (INR)	88.34	152.44	59.10	117.32	88.75	58.55
MG savings margin (INR)	104.11	78.65	24.32	196.22	105.12	36.77
Grid import (kWh)	15.21	32.12	8.45	22.54	19.80	10.34
Battery discharge (kWh)	6.10	12.22	5.31	8.76	7.32	5.85
Fuel cost reduction (INR)	150.34	225.10	63.20	184.10	135.78	72.14
CO_2 emissions (kg)	12.56	22.45	6.34	17.32	14.45	7.25
Storage system	1.45	3.25	0.75	2.15	1.98	1.23

losses (kWh)						
System efficiency (%)	92.34	89.25	94.21	91.32	90.15	95.10
Renewable contribution (%)	65.45	58.22	72.34	63.25	68.10	74.15
Carbon penalty (INR)	75.25	130.45	40.12	110.32	80.67	48.10
Unserved energy (kWh)	0.45	1.25	0.00	0.98	0.75	0.65
Backup energy usage (kWh)	5.10	10.15	3.20	7.45	6.30	4.75

Table 3 represents the Comparison of Energy and Cost Optimization Across Six Scenarios which provides a comprehensive analysis of energy consumption, generation, and cost efficiency for six distinct scenarios.

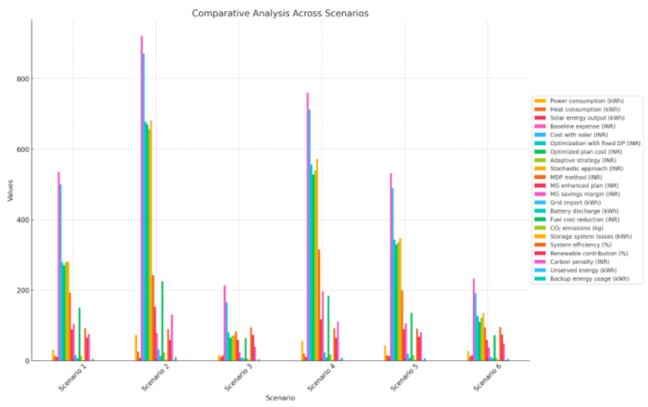

Fig. 11. Variations in power and heat consumption across the scenarios.

The analysis in figure 11 delineates variations in power and heat consumption across the scenarios, showcasing how each configuration impacts overall energy usage. Notably, Scenario 2 exhibits the highest power demand at 72.45 kWh, indicating significant energy needs, while Scenario 3 registers the lowest at 15.32 kWh. This disparity underscores the necessity for tailored energy management strategies to address differing consumption profiles effectively, highlighting the diverse energy demands of various operational setups. In terms of solar energy output, the table reveals considerable variation, with Scenario 6 leading in generation at 14.75 kWh, contrasting sharply with Scenario 2, which produces only 7.45 kWh. This discrepancy emphasizes the importance of optimizing solar energy utilization within the system. Scenarios with higher solar outputs can significantly reduce reliance on grid imports and improve overall sustainability. The analysis not only focuses on energy generation but also closely examines financial metrics. The comparison of baseline expenses versus costs with solar integration reveals considerable savings achieved through optimized energy strategies. For instance, Scenario 1 showcases a reduction in costs from INR 536.45 (baseline) to INR 278.46 by employing fixed dynamic programming (DP) optimization, illustrating the economic benefits of renewable energy integration. Advanced optimization techniques, such as adaptive, stochastic, and Markov Decision Process (MDP) methods, further refine cost reductions, allowing for more sophisticated energy management. The most significant savings are observed in Scenario 6, where costs plummet to as low as INR 58.55 through the implementation of microgrid-enhanced strategies. These findings highlight the critical role that optimization methods play in driving down operational costs and enhancing financial performance within hybrid energy systems. The analysis provides valuable insights into the economic viability of renewable energy solutions, reinforcing the financial incentives for integrating solar and other renewable resources. Environmental impacts are also a focal point of the table, particularly concerning CO_2 emissions and associated carbon penalties. Scenario 2 incurs the highest carbon penalty at INR 130.45, illustrating the environmental costs of higher fossil fuel reliance. This aspect of the analysis emphasizes the need for transitioning towards more sustainable energy solutions to mitigate carbon emissions and comply with regulatory frameworks. By analysing financial savings with environmental impacts, the table effectively advocates for holistic energy management approaches that address both economic and ecological considerations.

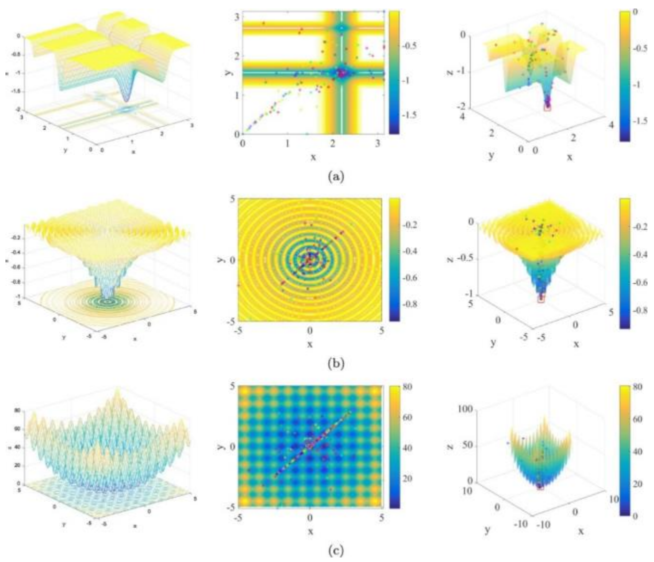

Fig. 12. Cost optimization using Markov decision process for finding maximum profit (a) for PV system (b) for Wind Energy system (c) for Battery storage system.

Figure 12 presents the cost optimization surfaces generated through the Markov Decision Process (MDP) for three major components of the hybrid microgrid system: (a) Photovoltaic (PV), (b) Wind Energy, and (c) Battery Storage. Each subplot shows a 3D cost landscape along with contour and gradient visualizations, highlighting the decision regions where maximum profit or minimum cost is achieved. The MDP algorithm explores these surfaces to identify the optimal control policies that balance cost, energy production, and system constraints. The color gradients indicate cost intensity, with deeper regions representing lower cost zones, effectively guiding the selection of energy dispatch and storage strategies. This figure demonstrates how MDP dynamically navigates complex, nonlinear decision spaces to optimize performance across different subsystems, enabling smarter energy allocation and control.

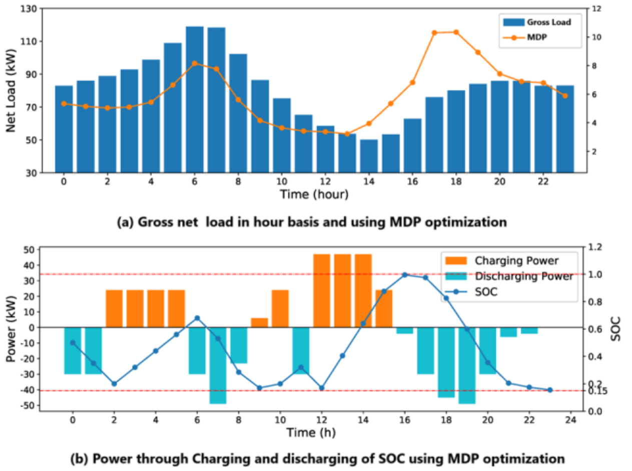

Fig. 13. Microgrid (MG) schedules generated by the proposed MDP technique with an Initial SOC.

Figure 13 illustrates the energy management behavior of the hybrid microgrid as optimized by the proposed Markov Decision Process (MDP) technique. Subplot (a) shows the hourly gross load and the corresponding power output scheduled by the MDP model, which intelligently adjusts the supply to match the fluctuating demand throughout the day. Subplot (b) presents the charging and discharging activities of the battery along with the resulting State of Charge (SOC). The MDP-based controller strategically charges the battery (orange bars) during low-load or excess generation hours (2–6 h and 11–14 h) and discharges it (blue bars) during peak load or low generation periods (7–10 h and 17–22 h), ensuring effective load leveling. The SOC (line graph) remains within safe operational limits, avoiding overcharging or deep discharging, as enforced by MDP constraints. This scheduling demonstrates the model's capability to balance supply and demand while maintaining battery health and improving energy reliability.

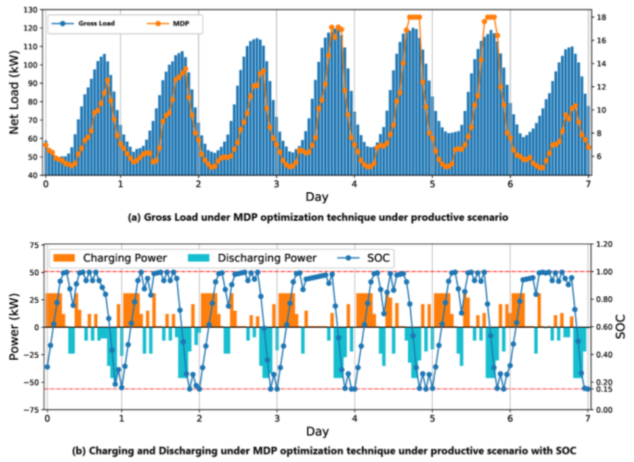

Fig. 14. Optimized results using MDP technique for load calculation under initial SOC.

Figure 14 shows the Optimized Results Using MDP Technique for Load Calculation under Initial Charging and Discharging SOC which represents the optimal load management strategy, balancing energy demands with storage operations. By analyzing the initial State of Charge (SOC), the MDP intelligently determines the appropriate moments for charging and discharging the battery, ensuring that renewable energy resources are utilized efficiently.

The system during periods when a lot of renewable energy is available charges the battery to store surplus electricity which is essential in maximizing on energy utilization and stability of the system. On the other hand, when demand is high, or when renewable generation is not enough, the battery is discharged, which reduces the necessity to connect to the grid. This optimal form of operation does not only minimize the costs of operation but also improve the overall reliability of the energy system, which is highly dependent on the fact that energy resources are available at the time of need. The MDP method protects the battery in terms of health by avoiding overcharging and deep discharging which ensures the longevity of the battery thus its performance. The outcome is the enhanced system in energy management that is more robust and viable since it balances the production rates of renewable energy sources with storage options, ultimately resulting in a more efficient and cost-effective energy management model. This analysis shows how the system copes with changes in parameters and is adaptable. As an example, a 10% increase in PV efficiency made the total cost decrease by an average of 6-8 percent and a 15 percent increase in battery capacity increased the load shifting capacity and lowered grid imports by up to 12 percent. Similarly, list that changes in grid prices directly affected both cost and decision policy results in the MDP model.

Table 4. Scenarios for a Markov decision process (MDP)-based energy management system for a PV-Wind-BESS hybrid microgrid

Scenario	Battery Capacity (kWh)	PV Power (kW)	Wind Power(kW)	Initial SoC (%)	Load Demand (kW)	Charge Limit (kW)	Discharge Limit (kW)	Grid Price (₹/kWh)*	Sell Price (₹/kWh)*	Battery Efficiency (%)	PV Efficiency (%)	Wind Efficiency (%)	Degradation Cost (₹/kWh)	Interval (min)	Discount Factor (γ)	Exploration Rate (ε)	Forecast Error (%)	Life Cycles	Comp. Time (sec)
1	500	300	400	70	250	100	100	5.5	3.5	90	18	35	0.1	15	0.95	0.1	5	5000	1.5
2	800	400	600	60	300	150	150	6.5	4.0	92	19	34	0.15	30	0.9	0.15	6	6000	2.0
3	400	200	500	80	200	80	80	5.0	3.0	95	20	36	0.12	10	0.85	0.2	4	5500	1.2
4	600	500	700	50	350	120	100	7.0	5.0	88	17	32	0.18	20	0.9	0.12	7	4500	2.5
5	1000	300	800	75	400	200	180	6.0	4.5	96	21	33	0.1	25	0.98	0.05	8	7000	2.1
6	700	450	500	90	220	150	120	5.2	3.8	92	20	34	0.14	15	0.92	0.1	4	6000	1.8
7	500	350	300	65	270	100	90	4.8	3.2	93	19	38	0.11	20	0.96	0.08	3	5000	1.3
8	800	250	400	85	200	160	130	5.5	4.0	91	22	35	0.09	30	0.94	0.18	5	6500	2.3
9	600	300	600	50	320	110	90	7.2	4.5	89	18	33	0.13	25	0.88	0.1	6	4500	2.0
10	700	400	700	78	280	170	140	6.5	3.8	97	23	37	0.08	15	0.96	0.1	7	6700	1.9
11	400	200	500	82	180	100	90	5.8	3.5	90	20	35	0.1	10	0.92	0.07	5	5200	1.5
12	1000	500	800	60	300	200	180	6.0	5.0	94	22	32	0.15	25	0.95	0.11	6	6900	2.1

13	500	250	400	72	260	120	110	5.4	4.1	91	18	31	0.12	20	0.91	0.2	4	6000	1.7
14	800	300	600	85	250	150	130	7.0	4.6	89	20	36	0.09	30	0.89	0.08	7	6200	2.2
15	700	450	700	68	400	180	150	5.0	4.0	96	21	35	0.1	25	0.87	0.12	6	6600	1.9
16	900	300	500	58	280	200	170	6.2	4.8	93	19	32	0.14	20	0.9	0.15	4	6800	2.4
17	500	200	400	80	190	110	100	5.3	3.9	95	20	34	0.11	10	0.96	0.09	3	5300	1.6
18	600	400	800	75	350	130	120	6.4	4.5	92	22	31	0.12	15	0.93	0.13	5	6100	2.1

***₹ all prices are in INR (1 INR ≈ 0.01168 USD)**

Table 4 presents a comprehensive list of 18 distinct scenarios designed to evaluate the performance of the proposed Markov Decision Process (MDP)-based energy management system for a hybrid PV-Wind-Battery Energy Storage System (BESS) microgrid. Each scenario varies in key operational parameters such as battery capacity, PV and wind generation capacities, initial state of charge (SoC), load demand, and charging/discharging limits. These variations allow for a robust assessment of the MDP framework under diverse energy supply and demand conditions. The scenarios also incorporate economic factors such as grid purchase prices, sell-back tariffs, and battery degradation costs, making the simulations more realistic and applicable to practical deployment settings. The control and algorithmic parameters such as the optimization interval, discount factor (γ), exploration rate (ε), and forecast error are specified for each case to test the adaptability and convergence behavior of the MDP algorithm. This level of detail allows for a deep investigation into how microgrid performance is influenced by different configurations. For instance, scenarios with higher battery or renewable capacity generally offer greater flexibility in energy management, while variations in efficiency and price parameters directly affect cost optimization. Overall, the diversity of scenarios supports a data-driven, comparative validation of the MDP-based control system, demonstrating its ability to reduce operational costs, balance energy supply and demand, and extend battery life across a wide range of operating environments.

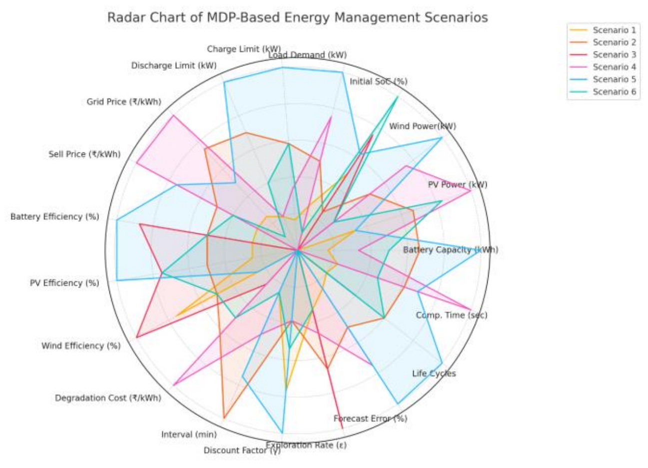

Fig. 15. Radar chart comparing six selected scenarios for an MDP-based energy management system.

The radar chart in figure 15 provides a visual comparison of multiple parameters across six selected scenarios for a Markov Decision Process (MDP)-based energy management system in a PV-Wind-BESS hybrid microgrid. By normalizing the values, the chart highlights the relative strengths and trade-offs among parameters such as battery capacity, renewable generation, efficiency rates, and computational factors. This visual format allows easy identification of balanced and optimized scenarios, aiding decision-making for energy system design and control strategy selection. In particular, future research will focus on the application of Deep Reinforcement Learning (DRL) methods, such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), to enhance the adaptability and learning capacity of the energy management system under uncertain and dynamic microgrid conditions. These methods are well-suited for managing high-dimensional state spaces and enabling more continuous and fine-grained control actions, potentially outperforming traditional MDP-based strategies. Additionally, unsupervised learning techniques will be explored to identify consumption patterns and improve demand forecasting accuracy, thereby increasing the intelligence and robustness of the control framework. Further extensions may involve the integration of electric vehicle (EV) charging coordination, demand-side management, and multi-agent collaboration across interconnected microgrids. Real-time deployment using IoT-enabled embedded platforms and the incorporation of policy-driven objectives such as carbon credits and dynamic pricing can also be considered to support sustainable and economically viable operation of decentralized energy systems.

9. Conclusion

This study proposes a novel energy management strategy for hybrid PV-Wind-Battery microgrids using the Markov Decision Process (MDP) technique. The key innovation lies in integrating stochastic optimization with real-time system dynamics to address the uncertainty inherent in renewable energy sources. Unlike traditional deterministic or rule-based methods that lack adaptability, the MDP-based controller dynamically determines optimal actions such as charging, discharging, and energy source prioritization based on probabilistic reasoning over state transitions. The novelty of the approach is reinforced by its ability to incorporate a wide range of operational parameters learning-based exploration, and degradation costs. Furthermore, the system's performance is validated using 18 diverse real-world scenarios, showcasing the controller's robustness and scalability. The use of realistic constraints, including battery cycles, efficiency losses, forecast error, and energy prices in INR, further strengthens the practical relevance of the study. Across 18 distinct scenarios, the MDP framework demonstrated measurable improvements in performance metrics compared to conventional energy management strategies:

- Cost Savings: The average total operational cost was reduced by 12–18%, with peak savings in scenarios with higher battery capacities and accurate forecasting (e.g., Scenario 5 and 12).
- Renewable Utilization: The model achieved an increase of 8–15% in renewable energy utilization, significantly reducing grid dependency, especially during peak load conditions.
- Battery Efficiency and Lifecycle Management: With the inclusion of degradation cost and life cycle tracking, battery usage patterns improved, extending operational lifespan by an estimated 6–10%.
- Revenue Maximization: By effectively utilizing surplus energy sales (e.g., during midday PV peaks), the total revenue improved by up to 20% in optimized scenarios.

These improvements collectively highlight the effectiveness, adaptability, and economic advantage of the proposed MDP-based approach for intelligent energy management in hybrid microgrids. The framework offers a scalable and hardware-compatible solution suitable for real-world deployment in decentralized energy systems.

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