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RESEARCH ARTICLE

Stochastic Energy Management Strategy for Autonomous PV–Microgrid Under Unpredictable Load Consumption

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ABSTRACT This paper introduces a novel energy management strategy incorporating stochastic elements designed for off-grid photovoltaic (PV) systems supplying multiple loads in environments marked by unpredictable power usage. In these PV microgrid applications, unpredictable power consumption can lead to discrepancies between energy supply and demand, compromising system reliability and efficiency. This issue is especially pertinent in providing reliable electricity to remote or rural areas where conventional grid infrastructure is not available or reliable. To overcome this challenge, this paper addresses the random variability in load consumption by modeling it as a Markov decision process (MDP). The MDP framework facilitates the development of an effective decision-making process, accounting for the probabilistic nature of energy consumption patterns. Furthermore, by integrating MDP-based load consumption prediction into the energy management system, real-time optimization of both PV power and battery charging and discharging within the microgrid is achieved. This integration balances energy production and consumption, enhancing overall system efficiency. Three scenarios were examined to evaluate the effectiveness of the suggested strategy in enhancing the real-time operation of off-grid PV systems: standard test conditions, time-varying climatic profiles, and real-time weather situations. The findings indicate that the proposed strategy can adapt to dynamic load profiles, ensuring efficient energy utilization while maintaining microgrid stability.

INDEX TERMS Photovoltaic system, battery storage, state of charge, energy management, stochastic control, Markov decision process.

NOMENCLATURE

P_{bat}	Battery power $[W]$.
P_{load}	Load power demand $[W]$.
P_{pv}	PV power $[W]$.
v_{pv}	Output PV module voltage $[V]$.
i_{pv}	Output PV module current $[A]$.
v	Output capacitor voltage $[V]$.
i	Inductor current $[A]$.
T	Cell temperature $[^\circ C]$.
G	Irradiance $\left[W/m^2\right]$.
θ_t	Continuous-time Markov process.
Q	Transition matrix.
C_{pv}	Input capacitor $[F]$.
C	Output capacitor $[F]$.
R_C	Output capacitor resistance $[\Omega]$.
L	Inductance $[H]$.
R_L	Inductance resistance $[\Omega]$.
R_M	Internal resistance of MOSFET $[\Omega]$.
R_D	Internal resistance of diode $[\Omega]$.

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R_{θ_t} Equivalent DC load activates at instant t [Ω].
v_{bat} Battery voltage [V].
i_{bat} Battery current [A].
C_{bat} Battery capacity [F].

Abbreviation

BES	Battery energy storage.
DC	Direct-current.
EMS	Energy management system.
MPPT	Maximum power point tracking.
MDP	Markov decision process.
PMC	Power management controller.
PV	Photovoltaic.
SoC	State of charge.

I. INTRODUCTION

Using fossil fuels has led to severe environmental issues, such as contamination and increased greenhouse gas emissions. As an attempt to mitigate the impact of these contaminants, researchers have developed efficient renewable energy sources, such as the ones based on wind, hydropower, and sunlight [1], [2], [3], [4]. One renewable energy source, in particular, has drawn much attention recently: photovoltaic (PV) energy. PV systems depend only on sunlight, which is abundant and free. Additionally, sunlight-based facilities demand relatively low maintenance and can work well for many years [5], [6], [7], [8].

PV panels and related technology are becoming more cost-competitive with traditional forms of energy production [9], [10]. On-grid and off-grid PV systems are two different methods of utilizing solar radiation to produce electricity. These two systems are crucial for a more sustainable and decentralized energy future, providing customized solutions for various energy requirements and situations. On-grid PV systems are directly linked to the utility grid. Off-grid PV systems function autonomously, utilizing battery storage to save surplus energy produced during the day for later use, especially at night or during low sunlight hours. Off-grid systems are frequently utilized in remote or rural locations with limited or intermittent grid access.

As a result, the lower cost has motivated researchers and practitioners to implement off-grid PV conversion systems. Such a system is a decentralized PV solution specially tailored for local communities, supplying energy to locals, thus reducing transmission losses and increasing energy efficiency [8], [11], [12], [13], [14]. Off-grid PV systems within microgrids provide many advantages, such as enhanced energy resilience, less dependence on fossil fuels, and improved energy accessibility for isolated regions.

Overall, off-grid PV conversion systems are a cost-effective and sustainable solution for providing power to remote or isolated communities where industrial energy services are unavailable. Some real-world applications of these systems include remote homes and cabins, telecommunication towers, remote monitoring stations, farms, rural electrification projects, and disaster relief operations. The low cost of implementation of an off-grid PV system makes it an ideal solution for these remote areas. Note that an off-grid PV system consists of a few elements: (i) a solar panel array, (ii) a battery energy storage (BES), and (iii) a circuit that controls both the power generated by the solar panels and the current supplied to the load.

Off-grid PV systems in microgrid settings function as the main energy source, commonly combined with additional energy storage solutions such as batteries. Integrating batteries in off-grid PV-microgrid systems has become increasingly necessary as they help ensure reliable and stable access to electricity. Note that a battery stores energy during sunny hours and feeds power back into the during other times. This enhances the overall efficiency and reliability of the off-grid PV system, extending its working operation and making it an attractive energy solution for remote communities.

The other part of the circuitry depends on a charge controller. It regulates the flow of electricity from the solar panels to the battery bank to prevent overcharging or damage to the batteries. An energy management system (EMS) must be considered for optimal utilization of energy generated by PV systems. EMS monitors and controls the PV systems in the microgrid. EMS maximizes the self-consumption of PV-generated power and confirms that energy storage is used cost-effectively. EMS aids in forecasting energy demand and guaranteeing sufficient energy supply to match the demand, thereby diminishing the risk of power failures. Furthermore, EMS allows real-time monitoring and control, enabling remote troubleshooting and maintenance, which is particularly important for remote or off-grid locations for maximizing the performance and economic benefits of the system.

DC-DC converters are crucial components in off-grid PV-microgrid systems, performing various important duties in addition to batteries. The converters optimize energy transfer and management in the microgrid by modifying voltage levels to suit the needs of multiple loads or storage devices. They are essential for optimizing energy transfer between the PV panels, batteries, and other microgrid components to maximize energy usage and system efficiency. DC-DC converters play a crucial role in off-grid PV-microgrid systems by facilitating efficient energy conversion, administration, and system optimization to cater to the varied energy requirements of remote or isolated communities.

A. LITERATURE REVIEW

Recent literature on energy management strategies for PV conversion systems has focused on optimizing power generation and increasing system efficiency through maximum power point tracking (MPPT) algorithms, energy storage systems, advanced control and monitoring systems, and distributed PV systems. A growing body of research on energy management control strategies for PV-microgrid systems focuses on optimizing energy generation, consumption, and storage and reducing energy waste.

The authors of [15] present an energy management strategy and control power for off-grid PV systems. This control strategy is designed to improve the system's efficiency by drawing the maximum power available from the PV source while simultaneously regulating the battery's state of charge to meet energy needs. A related study presents an energy management system designed to ensure the stable operation of a PV-battery microgrid [16]. This system utilizes model predictive control for an interlinking converter. A charging scheme oriented towards the state of charge (SOC) is devised to regulate BES, smoothing out PV output fluctuations. In [17], an innovative EMS was tailored for an isolated microgrid. The realization of this advanced EMS hinges on the adoption of new technology for energy management, employing FPGA as the central controller. This configuration greatly enhances system monitoring capabilities, enabling comprehensive oversight of the entire setup. The proposed EMS guarantees harmonious power distribution from the primary sources or backup generators to designated loads, ensuring optimal energy flow alignment. The paper [18] introduces an optimal energy management approach tailored specifically for DC microgrids. In grappling with the multifaceted techno-economic hurdles inherent in such systems, which range from maintaining power quality and stability to optimize fuel consumption and efficiency amid the integration of diverse power sources such as renewables, the authors present an EMS harnessed through the innovative Salp swarm algorithm, offering a robust framework to address the intricate dynamics of DC microgrid operations effectively.

In [19], an energy management strategy was developed to delineate the distinct operational modes of both subsystems. This strategy aims to distinguish different operational modes of subsystems within the system. The main control objectives are to regulate output power to meet overall demand and to extend the battery lifespan by maintaining its SoC, using the system dynamic model to suit various environmental conditions and load demands. In this context, the study in [20] focuses on the control boundaries and effective energy saturation management within a representative standalone DC microgrid. This entails precisely allocating variable power loads across different sources based on their respective capacities. This includes scenarios such as prioritizing regenerative braking in instances of minimum battery State of Charge and fully satisfying power load demands when batteries are at maximum SOC. An approach to regulate the output power of a hybrid energy system was proposed in [21]. This system comprises renewable energy sources with battery banks and a variable load. Through the formulation of an energy management strategy, the hybrid energy system is characterized as a switched nonlinear system with parameters of unknown values. Subsequently, an adaptive control methodology is put forward to meet the varying power demands across different scenarios, even in instances of arbitrary switching. A related study advocates for using FPGA to drive energy management within a hybrid microgrid featuring multiple sources and a backup system [22]. Functioning as an exceptionally adaptable and reprogrammable logic device, the FPGA facilitates the exploration of diverse scenarios tailored to customer requirements and prevailing weather conditions, thereby paving the way for future experimentation and optimization.

The authors of [23] propose a nonlinear predictive energy management approach tailored for PV systems with battery storage. This strategy relies on load demand predictions generated by artificial neural networks. Furthermore, it integrates an empirical model for lithium-ion battery capacity degradation into the optimization framework, enhancing the accuracy and effectiveness of the management system. The studies [24], [25] introduce an energy management strategy based on probabilistic forecast models, anchored in a state space energy system model operating under various stochastic loads. Central to these approaches is the utilization of a state space modeling framework, which integrates forecasting capabilities to effectively manage diverse random loads of varying temporal significance and facilitate the implementation of demand-side response. The author of [26] presents a pioneering EMS framework designed to address the complexities arising from multiple uncertainties inherent in renewable generation and load profiles. Initially, the authors employ deep learning techniques to generate scenarios reflecting each uncertainty. Subsequently, they introduce a novel clustered quantile scenario reduction algorithm aimed at streamlining computational processes while preserving the stochastic characteristics of the generated scenarios, offering real-time monitoring and control capabilities for appliances. A related study delves into the highly stochastic and unpredictable nature of electricity demand within standalone microgrids [27]. An accurate load model stands as a crucial input for designing an economically viable and reliable renewable-based rural electrification system for rural communities, as well as for demand management systems. This study introduces a comprehensive methodology for delineating the energy consumption load profile of a rural community, a key factor in determining the most cost-effective sizing of renewable energy sources for rural electrification endeavors. The load parameters are generated randomly, and a bottom-up approach is employed to estimate the energy usage of the rural community.

The insights from these inquiries indicate a notable oversight in current research, as they fail to account for the unpredictable load behavior. This behavior is pivotal in upholding the stability and efficiency of microgrid systems. The effectiveness and dependability of microgrid systems hinge significantly on precise estimations of load consumption, a task complicated by its inherently random characteristics.

The paper [28] presents a method for managing the energy within a microgrid connected to the main power system, accounting for fluctuations in load demand and output powers under both deterministic and probabilistic conditions. Addressing this energy management challenge, the study employs an efficient algorithm, namely the equilibrium optimizer, to solve the multi-objective function. This function encompasses objectives such as minimizing costs, enhancing voltage profiles, and improving voltage stability. A related study introduces a forecast-driven stochastic scheduling strategy tailored for the optimal operation of an isolated hydrogen microgrid [29]. Initially, power and load changes were forecasted using a bidirectional long short-term memory convolutional neural network, modeled end-to-end. Subsequently, stochastic optimization of the energy management system was achieved through deep reinforcement learning, aiming to minimize the microgrid's lifecycle cost. Monte Carlo simulations were employed to generate stochastic scenarios, enabling an analysis of uncertainties in the wind and the load, while also considering the energy capacity degradation of the storage system. The paper [30] tackles the challenge of uncertainty stemming from renewable distributed energy sources and load demand to ensure optimal scheduling within grid-connected microgrids. This study introduces a multi-time-scale stochastic optimization model designed to minimize operational costs while maximizing reliability in the face of these uncertainties. Utilizing the Monte Carlo method, stochastic scenarios are generated to simulate the microgrid's uncertainty. The stochastic optimization model is formulated considering various factors, including the energy balance in expected scenarios, the operational costs of distributed energy sources, charging and discharging characteristics, and ensuring stable operation across multiple stochastic scenarios. Further insights on this topic can be found in references [31], [32], [33], [34], and [35].

Table 1 compares the current study and existing literature, focusing on power optimization, load behavior forecasting, and data prerequisites. Analysis of the entries in Table 1 highlights a notable gap in exploring stochastic load behavior and a prevalent reliance on prior microgrid system data in previous studies. This paper endeavors to fill this void by investigating the repercussions of abrupt and unpredictable load fluctuations on off-grid DC PV-microgrid dynamics. Specifically, it aims to elucidate the implications for power optimization and energy management without the need for pre-existing data on such systems.

Stochastic modeling is an effective tool for forecasting unpredictable load consumption to improve the performance of PV microgrids. This type of modeling uses probability theory and statistical analysis to model random variables that represent load consumption behavior. Using mathematical algorithms, stochastic models can predict future load consumption patterns with a certain degree of accuracy, enabling better planning and management of power generation and storage. By accurately forecasting the unpredictable load consumption behavior, the PV microgrid can optimize its power production and usage more efficiently. This leads to a more reliable power supply.

TABLE 1. Comparison between this study and related works in the literature.

Literature	Power optimization aspect	Load forecasting	Previous data requirement
[15]	Deterministic	–	No
[16]	Deterministic	–	No
[17]	Deterministic	–	No
[18]	Deterministic	–	No
[19]	Deterministic	–	No
[20]	Deterministic	–	No
[21]	Deterministic	–	No
[22]	Deterministic	–	No
[23]	–	Neural networks	Yes
[24]	–	Probabilistic model	Yes
[25]	–	Probabilistic model	Yes
[26]	–	Stochastic model	Yes
[27]	–	Probabilistic model	Yes
[28]	Deterministic	Probabilistic model	Yes
[29]	Neural networks	Neural networks	Yes
[30]	Probabilistic	Probabilistic model	Yes
This paper	Stochastic	MDP	No

The Markov chain process is a powerful mathematical tool that can be exploited to model and predict real-time unpredictable events. In a Markov chain, the system's future state only depends on the present state and not on any previous states. This means that a Markov chain can model a constantly changing and evolving system. The Markov chain can provide insights into the likely outcomes of different scenarios by analyzing the probabilities of transitioning from one state to another [36], [37]. One of the main advantages of using a Markov chain in modeling real-time events is its ability to capture the system's dynamic nature. Real-time events are often complex and unpredictable, and traditional models may not be able to capture accurately all of the variables and factors involved. Another advantage of using a Markov chain is its simplicity and flexibility. They can also be adapted to model various systems, from simple processes to complex systems with multiple interacting variables. However, by using a Markov chain, we can account for the randomness and uncertainty inherent in real-time events, which can be used to inform decision-making and improve outcomes.

This paper's main contribution is emerging the Markov decision process (MDP) as a promising tool for real-time characterizing load consumption in off-grid PV systems. This paper highlights the importance and utility of load characterization using the Markov chain process to improve the energy management control design for off-grid PV-microgrid systems and its benefits in probabilistic unpredictable load consumption forecasting and system performance optimization.

To the best of the authors' knowledge, this paper is the first to suggest an approach for managing energy in PV conversion systems that accounts for unpredictable load consumption driven by a Markov process. This configuration embodies the key novelty of this paper. By considering uncertainties in the system and energy storage limitations, the proposed approach can improve the performance of the off-grid PV conversion system, increase its efficiency, and reduce its operating costs. This approach is beneficial for PV systems subject to unpredictable fluctuations in energy demand, as it allows the system to adapt to changing conditions and make optimal decisions in real-time.

The primary contributions of the innovative energy management strategy in this paper can be outlined as follows:

1) This paper represents a pioneering study that leverages the MDP to introduce a groundbreaking stochastic energy management strategy designed for PV microgrids operating in the face of unpredictable load consumption.
2) The MDP exhibits a stochastic real-time response, distinguishing the proposed energy management and enhancing efficiency and effectiveness. This feature facilitates stochastic load consumption predictions, aiding in managing generated power within the photovoltaic microgrid. The system adapts to various scenarios based on customer needs and weather conditions.
3) The proposed energy management excels in establishing power flow management amidst unpredictable load behavior, ensuring consumer satisfaction across all operating conditions due to the high accuracy inherent in the proposed strategy.
4) The proposed energy management strategy controls the charging and discharging of batteries, thereby contributing to an extended lifespan for the batteries.

The arrangement of this article is as follows. Section II presents the architecture of the off-grid DC PV-microgrid with multiple loads. Section III displays the proposed algorithm for stochastic energy management. In Section IV, the efficacy of the proposed approach is demonstrated through simulations under diverse conditions. The paper concludes by providing some concluding remarks in Section V.

II. OFF-GRID DC PV-MICROGRID WITH MULTIPLE LOADS

The off-grid PV DC microgrid is a self-contained power system disconnected from the utility grid [38], [39], [40]. As seen in Fig. 1, this system comprises a PV solar array, a battery bank for energy storage, a charge controller to regulate the charge/discharge of the batteries, and a DC distribution system to supply power to multiple loads.

The PV solar array comprises one or more solar panels that convert sunlight into energy. Energy is then fed to the charge controller, which regulates the energy supplied to the battery. The battery stores excess energy generated during the day to compensate for insufficient energy production by the solar panels [41], [42], [43].

The DC distribution system supplies power to multiple loads, such as lighting, appliances, and electronics in general, through a series of DC circuits. The loads are connected to the DC distribution system through individual circuit breakers or fuses [24], [44].

Next, we describe how to model the off-grid PV system shown in Fig. 1.

A. PV GENERATOR MODEL

The PV array, commonly known as the PV panel, is combined with other components to create the PV generator system, see Fig. 2. The PV generator system includes a DC-DC converter circuit linked to the PV module, a capacitor, an inductor, resistors, a diode, and a MOSFET. The operational concept involves a signal $u(t)$ governing the MOSFET, directing the current flow through the circuit.

The state of the PV generator system can be expressed as: $x(t) = [v_{pv}(t),\ i(t),\ v(t)]' \in \mathbb{R}^3$, where $v_{pv}(t)$ denotes the PV voltage, $i(t)$ denotes the inductor current, and $v(t)$ represents the voltage in the capacitor. The PV generator dynamics can be written as follows [45], [46], and [47]:

$$\dot{x}(t) = f(x(t))x(t) + g(x(t))u(t), \quad t \geq 0, \quad x_0 \in \mathbb{R}^3, \quad (1)$$

where the system matrices are

$$f(x(t)) = \begin{bmatrix} \frac{1}{C_{pv}}\frac{i_{pv}}{v_{pv}} & -\frac{1}{C_{pv}} & 0 \\ \frac{1}{L} & -\frac{R_L+R_D+\frac{R_C R_{\theta_t}}{R_C+R_{\theta_t}}}{L} & -\frac{R_{\theta_t}}{L(R_C+R_{\theta_t})} \\ 0 & \frac{R_{\theta_t}}{C(R_C+R_{\theta_t})} & -\frac{1}{C(R_C+R_{\theta_t})} \end{bmatrix},$$

$$g(x(t)) = \begin{bmatrix} 0 \\ \frac{-R_M+R_D+\frac{R_C R_{\theta_t}}{R_C+R_{\theta_t}}}{L} i(t) + \frac{R_{\theta_t}}{L(R_C+R_{\theta_t})} v(t) \\ -\frac{R_{\theta_t}}{C(R_C+R_{\theta_t})} i(t) \end{bmatrix}.$$

B. BATTERY ENERGY STORAGE

The dynamic model of a battery energy storage system can be represented by a set of differential equations that describe the rate of change of various variables, such as the battery voltage, current, and state of charge. The SoC represents the amount of energy stored in the battery as a percentage of its maximum capacity, and it follows the equation [38]:

$$\frac{dSoC}{dt} = \frac{i_{bat}}{C_{bat}}, \quad (2)$$

where i_{bat} is the current flowing through the battery, and C_{bat} is the battery capacity.

C. CONTROL SPECIFICATIONS

The control objectives for a standalone DC PV–microgrid with stochastic load consumption require a sophisticated energy management system that dynamically balances the supplied power while optimizing the system's energy efficiency. The proposed control strategy has multiple objectives. This involves maximizing the PV power generated, optimizing the battery system operation, and maintaining a balance between the PV power generation and the load consumption, especially in unpredictable and random load variations.

Another control goal is to balance the supply of solar energy and the demand from the load while guaranteeing the optimal operation of the battery storage system. To achieve

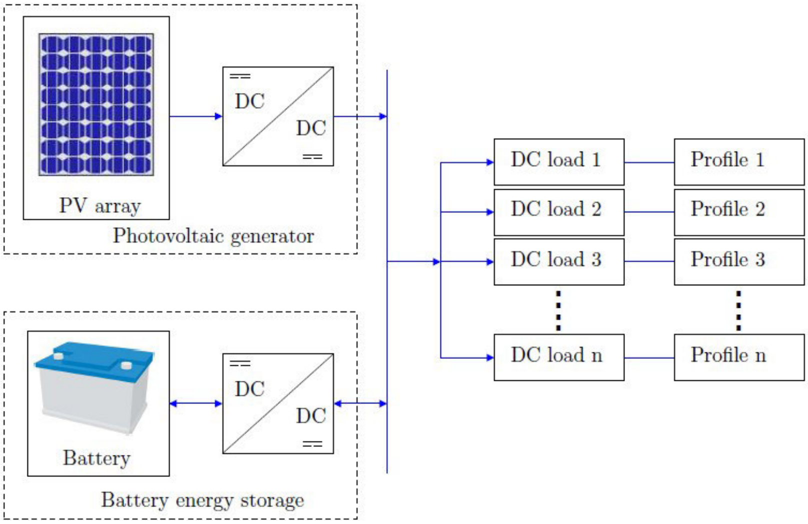

FIGURE 1. Scheme of the off-grid DC PV-microgrid system.

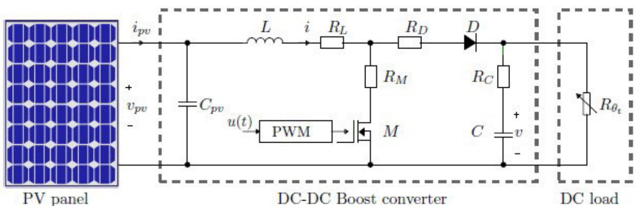

FIGURE 2. Schematics of the PV generator system.

this, the energy management system must be capable of real-time monitoring, forecasting, and decision-making based on the available information.

The next section emphasizes how the stochastic approach can be deployed to achieve this goal.

III. ENERGY MANAGEMENT BASED ON MARKOV DECISION PROCESS

This section introduces an innovative energy management for an off-grid DC PV–microgrid to supply multiple loads. The structure of the off-grid PV microgrid with a pioneering energy management strategy is illustrated in Fig. 3. This marks a significant advancement in the field, as we are the first to propose and elucidate this novel scheme for energy management.

The proposed energy management system offers a fresh perspective on optimizing energy utilization by leveraging the MDP. The proposed EMS is responsible for optimizing the system operation by monitoring and managing the power flow between the PV source and the load. Furthermore, controlling the charging and discharging of the batteries. It contains a power optimization block, which maximizes the output of the PV panels while minimizing the energy lost.

The power management controller (PMC) receives information about the load consumption from the MDP. This controller considers load consumption and predicts the future load demand. Furthermore, this controller deals with the battery storage capacity and the available energy from the PV panels, confirming the optimal use of energy storage and corresponding resources.

A. STOCHASTIC FORECASTING OF LOAD CONSUMPTION

The overall power consumption in PV microgrids that supply various loads with varying power profiles can display unpredictable behavior as a result of user behavior or the specific characteristics of the appliances being used. For example, some loads may have intermittent usage patterns or varying power demand over time. Furthermore, the distribution of power across the loads can also affect the stochastic behavior of the global load consumption. If the loads have distinct power profiles, with one load demanding higher power during the daytime and another load wanting more power at night, the overall load consumption will fluctuate throughout the day. The fluctuations in load consumption, which follow a random pattern, might significantly affect the overall stability and reliability of the microgrid. The fluctuation of energy sources poses a significant challenge in designing a microgrid that can efficiently meet the energy demands of all loads, while simultaneously reducing energy wastage and maintaining system stability. Achieving optimal performance necessitates meticulous monitoring and management.

The dynamic model of load consumption behavior is a crucial element in the development of energy management strategies for standalone PV microgrids. An efficient energy management strategy must be carefully designed. This design sought to achieve the balance between power generation and consumption in real-time and optimize the utilization of available PV power to fulfill the energy requirements of the system. By considering the dynamic model of load consumption behavior, energy managers can accurately

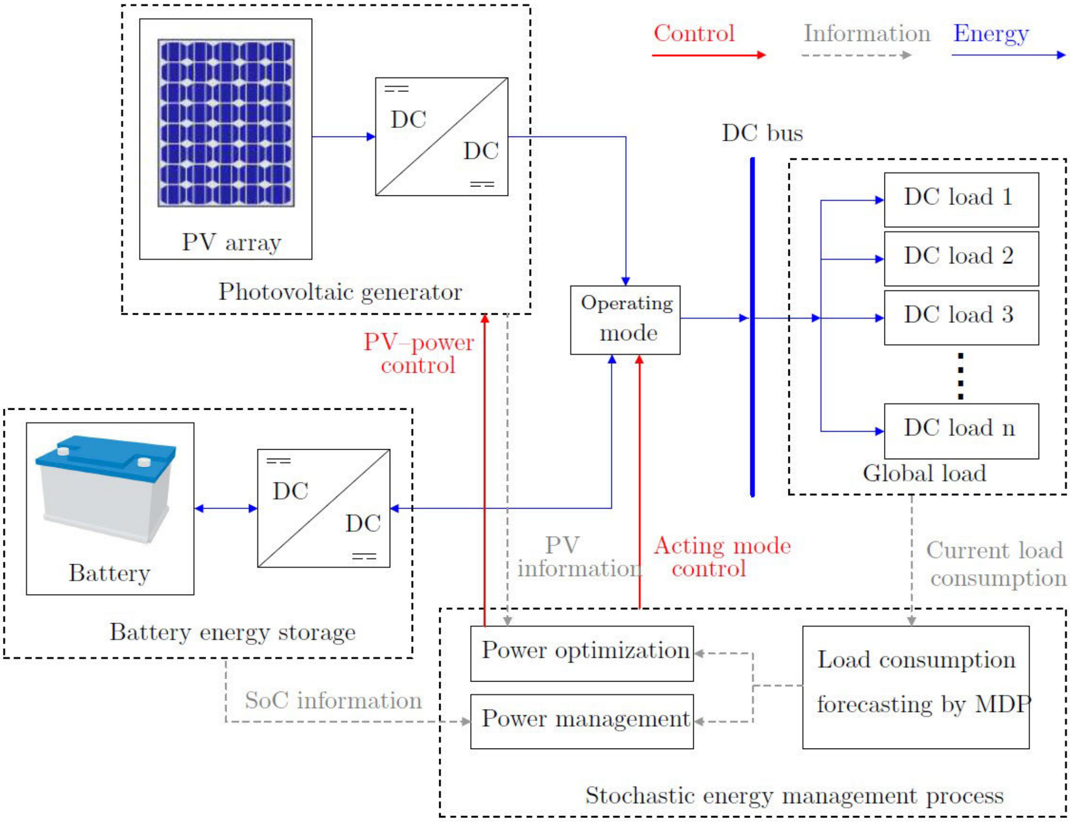

FIGURE 3. Structure of the DC PV microgrid with the energy management system.

predict the energy demand of the system at any given time. This enables them to optimize the energy usage to meet this demand. This allows for the optimal utilization of energy produced by the PV system, reducing the unnecessary loss of surplus energy. It also ensures that the system can meet energy demands without being overloaded and that the battery bank is charged and discharged in a way that prolongs its lifespan. Hence, taking into account the dynamic model of load consumption behavior guarantees that the energy management approach is tailored to adapt to fluctuations in energy demand over time, leading to enhanced energy efficiency and decreased operating expenses.

This enables more efficient exploration of the PV energy generated, minimizing the excess energy waste and ensuring that energy demands are met without overloading the system. Additionally, it ensures that the battery bank is charged and discharged in a way that extends its lifespan. Therefore, considering the dynamic model of load consumption behavior ensures that the energy management strategy is designed and adapted to the changes in energy demand over time. This concept will lead to enhanced energy efficiency and decreased running costs, therefore ensuring a dependable and sustainable energy supply for the standalone PV system serving many consumers.

By considering the dynamic model of load consumption behavior, the energy management process can accurately predict the energy demand of the system at any given time. This allows for the efficient utilization of energy to fulfill the required level of demand. In the context of estimating sudden, unpredictable changes that occur in real-time microgrid systems, a continuous–time Markov process can be employed. This process models the parameter behavior over time as it transitions between different states. It also allows for making predictions and guiding decision-making based on probabilistic estimates of the load behavior, taking into account abrupt and random variations [36], [37].

The design of control for PV systems using MDP entails the development of a mathematical model that represents the system's state space, action space, and reward function. The state space encompasses the complete range of potential states that the system can occupy, including the current load demand. The action space includes the complete range of potential actions that the system can undertake, including modifying the generated power and adjusting the battery charge level in response to the load demand. The reward function represents the system's objective, which is typically to manage the produced power by renewable energy sources.

In the sequence, we present an algorithm for the MDP aimed at estimating the unpredictable load consumption for the microgrid system illustrated in Fig. 3.

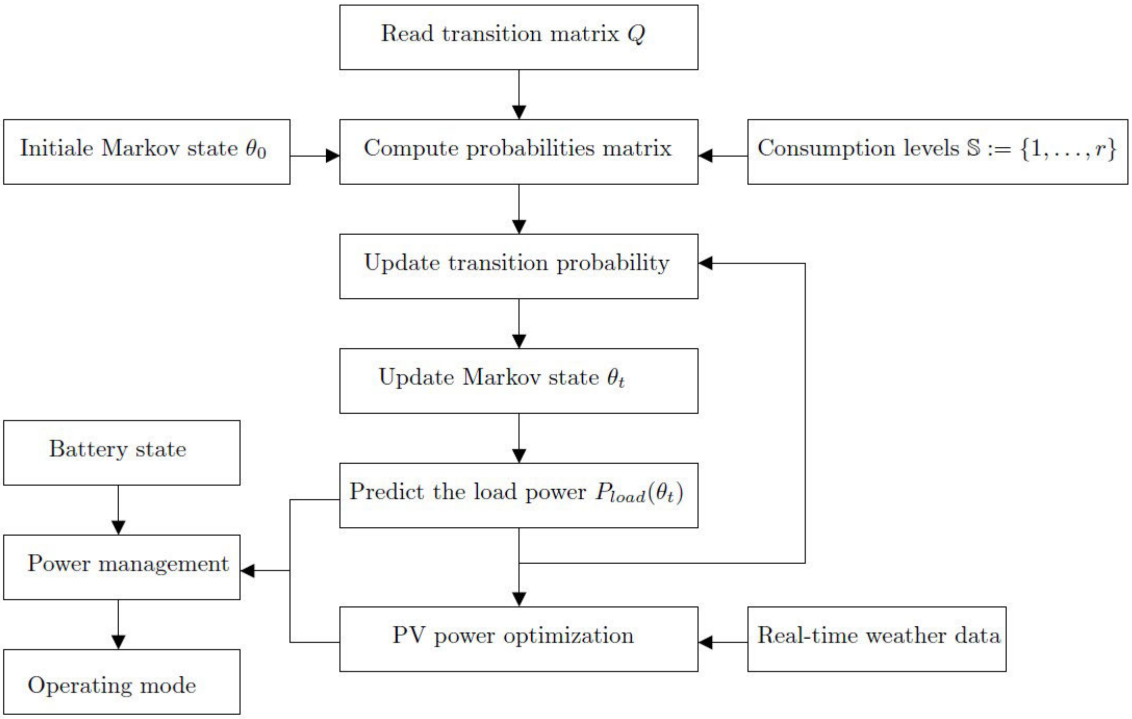

FIGURE 4. MDP-based energy management algorithm.

Step 1: Define the state space. The first step in implementing the Markov process is to define the state space. The state space might include different energy consumption levels for a PV–microgrid system with multiple loads. For instance, a load can be activated or deactivated at any moment. Therefore, each load has the potential to be either 'on' or 'off.' As a result, we find 2^n distinct modes from the Markov chain θ_t to represent each scenario. Accordingly, we have the corresponding consumption levels $P_{load}(\theta_t)$, see [48] and [47] for further details.

Step 2: Define the transition probabilities. Given a state space as $\mathbb{S} := \{1, \ldots, r\}$, where r is the total possible load consumption levels, we can consider probability transition as $\Pr[\theta_{t+\hbar} = j|\theta_t = i]$, where i and j represent the current and next load consumption levels $P_{load}(\theta_t)$, respectively.

The future power load demands are estimated with stochastic aspect by the MDP $\{\theta_t, \ t \geqslant 0\}$ described by the following transition probability:

$$\Pr[\theta_{t+\hbar} = j|\theta_t = i] = \begin{cases} \pi_{ij}\hbar + o(\hbar), & \text{if } i \neq j, \\ 1 + \pi_{ii}\hbar + o(\hbar), & \text{if } i = j, \end{cases} \tag{3}$$

where $\pi_{ij} \geq 0$, $i \neq j$; $\pi_{ii} = -\sum_{\{j:j\neq i\}} \pi_{ij}$, is the switch rate from state i at instant t to state j for all $i, \ j \in \mathbb{S}$, while $\lim\limits_{\hbar\to 0} = \frac{o(\hbar)}{\hbar} = 0$.

Step 3: Evolution of the power consumption with updates. We use the Markov chain θ_t to predict the power $P_{load}(\theta_t)$. However, we update the probability transition matrix when new data becomes available. For example, if the load consumes more energy than expected in a given period, the higher energy states' probabilities would increase. In contrast, the probabilities for the lower energy states would be decreased.

Step 4: Repeat the process The algorithm continues to predict and update the state probabilities in a continuous loop, providing real-time probabilistic estimates of the load consumption. These estimates can be utilized to make decisions regarding the charging process, such as modifying the charging power or terminating the charging process.

By using the MDP-based load forecasting algorithm's functionality, the predicted load consumption $P_{\text{load}}(\theta_t)$ integrates into the real-time operations of the off-grid PV system's MPPT control strategy as illustrated in Fig. 4. This integration empowers the PV system to continually receive updates from the prediction model, enabling dynamic adjustments to its output levels.

By leveraging MDP-based predictions, the energy management process gains the ability to discern optimal actions for PV-microgrid across various states. These actions extend beyond mere adjustments to PV output. They encompass strategic decisions such as battery charging or discharging and activating backup power reserves stored within the batteries. This holistic approach ensures that the PV system operates harmoniously with the anticipated load dynamics, optimizing energy utilization.

In the following sequence, we present the proposed strategies for optimizing PV power and managing power.

B. PV POWER OPTIMIZATION

Unpredictable load behavior plays a pivotal role in determining the functionality and dependability of DC PV microgrids. Load variations impact the system's energy balance, altering the power consumption patterns and thereby affecting the optimal operation of the MPPT controller. Incorporating this stochastic load behavior into the system dynamics is imperative for designing robust MPPT controllers capable of adapting to unpredictable load variations. By accounting for stochastic aspects, designers can develop MPPT algorithms that dynamically adjust the photovoltaic system's operating point in response to real-time changes in load conditions, optimizing energy capture and enhancing system efficiency.

Considering random load variations enables the development of more reliable and resilient off-grid photovoltaic systems that can effectively withstand and accommodate the uncertainties inherent in standalone applications, thereby ensuring consistent and stable power supply even under fluctuating load conditions. The unpredictable load changes impact the output power supplied by the PV panel according to the following equation [49]:

$$P_{pv} = P_{load}(\theta_t)\left(\frac{i_{pv}}{i_{load}}\right)^2 (1-u(t))^2. \tag{4}$$

In what follows, we introduce a stochastic control strategy based on the dynamics of the PV generator (1). The PV power is expressed by [47] and [50]:

$$\begin{aligned} P_{pv} &= v_{pv} i_{pv}, \\ &= n_p I_{ph} v_{pv} - n_p I_{rs} v_{pv}\left(\exp\left(\frac{k_{pv} v_{pv}}{n_s}\right) - 1\right). \end{aligned} \tag{5}$$

Given that $k_{pv} = \frac{q}{\eta k T}$ represents the inverse of the thermal voltage.

In designing a dynamic system to ensure the operation of the PV system around its maximum power point under abrupt load variations, one crucial approach involves utilizing the derivative of the PV power P_{pv} with respect to PV voltage v_{pv} as the output dynamical system. This derivative serves as a key indicator of how close the system is to the MPP. By continuously monitoring and analyzing this derivative, the system can promptly detect deviations from the MPP caused by abrupt load changes.

In response, the control system can swiftly adjust the operating conditions, such as the voltage and current supplied by the PV panels, to realign the system to the MPP. The PV system is designed to adapt in real-time, ensuring optimal efficiency and maximum power generation, even when faced with abrupt changes in demand. The system's flexibility to adjust to different environmental and load situations improves its resilience, guaranteeing dependable and steady power generation.

The system output is expressed as follows:

$$\begin{aligned} y(t) &= \frac{dP_{pv}}{dv_{pv}} = i_{pv} - \frac{n_p k_{pv}}{n_s} I_{rs} v_{pv} \exp\left(\frac{k_{pv} v_{pv}}{n_s}\right), \\ &= \left[\frac{i_{pv}}{v_{pv}} - \frac{n_p k_{pv}}{n_s} I_{rs} \exp(\frac{k_{pv} v_{pv}}{n_s}) \quad 0 \quad 0\right] x(t). \end{aligned} \tag{6}$$

The primary objective of this strategy is to achieve maximum power point tracking despite unpredictable changes in the load, i.e., $\lim_{t\to\infty} y(t) = 0$.

For this, we define the error signal $e(t) \in \mathbb{R}$ as

$$\dot{e}(t) = x(t) - x_d(t), \tag{7}$$

where $x_d(t)$ represents the desired optimal trajectory of the system state $x(t)$ when the PV output power reaches its maximum.

The concept here is to drive the error $e(t)$ to zero over time, i.e., $\lim_{t\to\infty} [x(t) - x_d(t)] = 0$. For this purpose, we define the control law $u(t)$ as follows:

$$u(t) = K_1(\theta_t)x(t) + K_2(\theta_t)e(t). \tag{8}$$

By using the norm H_∞, the PV system achieves the maximum power point under random load variations by minimizing the following objective function for the gain matrices $K_1(\theta_t)$, $K_2(\theta_t)$ and a given scalar δ:

$$J_\infty = \mathbb{E}\left[\int_0^\infty [e'(t)e(t) - \delta^2 x_d'(t) x_d(t)]dt\right]. \tag{9}$$

The overall structure of the PV power controller is depicted in Fig. 5. To extract the maximum available power from the PV module, the MPPT searching block dynamically generates the trajectory $x_d(t)$ for the system state $x(t)$ in real-time, based on the measured values of irradiance G and temperature T. Additionally, the predicted load consumption $P_{load}(\theta_t)$ is sent to the MPPT controller block along with $x_d(t)$ and $x(t)$, enabling it to compute the optimal duty cycle $u(t)$ for the DC-DC converter. This ensures that the PV power output closely follows the maximum power point.

C. ENERGY MANAGEMENT STRATEGY

To ensure a harmonious equilibrium between the power generated by the PV system and the power consumed, while considering the battery SoC in the DC PV-microgrid, as illustrated in Fig. 3, it's essential to incorporate an energy management algorithm capable of real-time operation while considering the battery SoC. As illustrated in Fig. 6, the proposed algorithm functions by firstly acquiring data on the optimized PV power output denoted as P_{pv}. Subsequently, it utilizes a MDP algorithm to forecast the expected load consumption, represented by $P_{load}(\theta_t)$, where θ_t indicates the current load state. By leveraging the MDP algorithm, which is adept at handling stochastic and dynamic decision-making

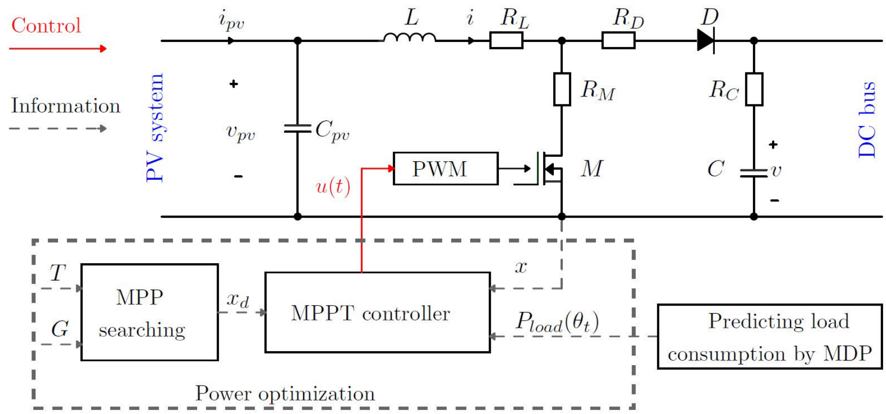

FIGURE 5. Schematics of the controlled DC-DC boost converter.

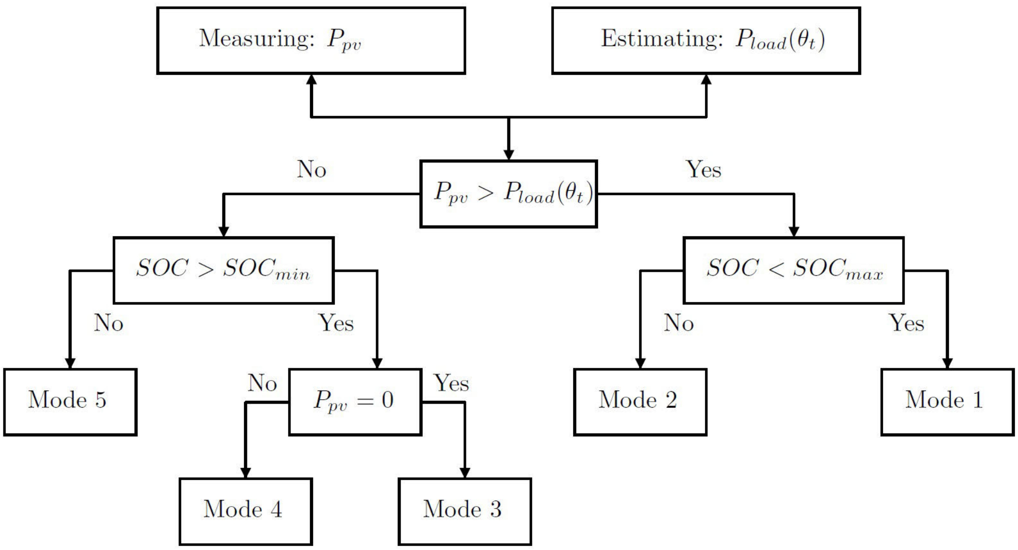

FIGURE 6. Stochastic energy management strategy.

processes. This predictive capability enables proactive adjustments in the power management strategy, ensuring that the PV system operates optimally while maintaining the battery SoC within desirable levels.

The following modes are considered.

Mode 1: The produced photovoltaic power exceeds the demand of the load ($P_{pv} > P_{load}(\theta_t)$), and the excess power will be stored in the battery.

Mode 2: The produced photovoltaic power is sufficient to supply the load, and the battery state of charge achieves its maximum capacity. It is then necessary to disconnect the battery.

Mode 3: No PV energy is produced ($P_{pv} = 0$). Thus, only the battery feeds the load.

Mode 4: The PV system does not produce enough power, i.e., $0 < P_{pv} < P_{load}(\theta_t)$. If the battery is charged, it will provide the required power.

Mode 5: No energy from the PV source and no charge in the battery. Thus, the battery will be disconnected.

Based on the real-time operating modes provided by the proposed energy management strategy, the system effectively controls power flow within the DC PV–microgrid by manipulating the three switches, namely S_1, S_2, and S_3, within the power management block, as depicted in Fig. 7.

IV. SIMULATION RESULTS AND DISCUSSIONS

This section provides simulation data aimed at showcasing the efficacy of the proposed energy management strategy, particularly in addressing stochastic elements. To emulate real-world conditions, our simulations focus on an off-grid photovoltaic system comprising components commonly found in practical applications. Specifically, the system includes a Siemens SP75 solar module, a DC-DC boost converter, and a lithium-ion battery. Detailed specifications of the system components are provided in Table 3, Appendix.

In our simulations, we considered that the PV generator supplied power to a network of three distinct loads, each

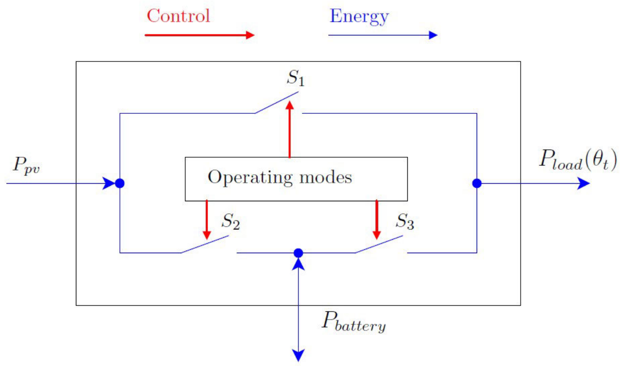

FIGURE 7. Power management block.

TABLE 2. Levels of the global load consumption.

θ_t	1	2	3	4	5	6	7	8
$P_{load}(\theta_t)$ (W)	10	180	80	120	60	100	40	250

with its power demand profile. Recognizing the dynamic nature of energy consumption over time, we identified eight distinct scenarios corresponding to various levels of global load consumption, as given in Table 2. These scenarios were determined by a Markov chain model, denoted by θ_t, which captures the probabilistic transitions between different load consumption states according to the following probability rate matrix:

$$Q = \begin{bmatrix} -16 & 1 & 3 & 5 & 2 & 3 & 2 & 2 \\ 3 & -17 & 3 & 2 & 2 & 2 & 2 & 3 \\ 2 & 5 & -18 & 2 & 1 & 2 & 4 & 2 \\ 1 & 1 & 2 & -14 & 6 & 1 & 2 & 1 \\ 7 & 5 & 3 & 6 & -33 & 4 & 3 & 5 \\ 3 & 5 & 2 & 1 & 4 & -19 & 2 & 2 \\ 5 & 5 & 2 & 4 & 2 & 10 & -31 & 3 \\ 4 & 5 & 2 & 4 & 2 & 3 & 4 & -24 \end{bmatrix}$$

A. RESULTS

The simulations were conducted for three scenarios: (i) standard test conditions, (ii) time-varying climatic profiles, and (iii) real-time weather conditions collected at Goiânia, Goiás, Brazil.

1) FIRST SCENARIO: STANDARD TEST CONDITIONS

In this scenario, we simulated the PV generator assuming a consistent, typical atmospheric condition. This involved maintaining a constant irradiance level of $\lambda = 1000W/m^2$ and fixing the PV cell temperature at $25°C$.

Using the MDP-based energy management algorithm depicted in Fig. 4, real-time estimations of global load consumption were performed based on the transition matrix Q, as illustrated in Fig. 8(a). Noteworthy, Fig. 8(b) underscores the effectiveness of the proposed MDP-based strategy in proactive decision-making. This is particularly evident in its ability to respond to unpredictable dynamic load demands by accurately predicting and adapting to various load patterns.

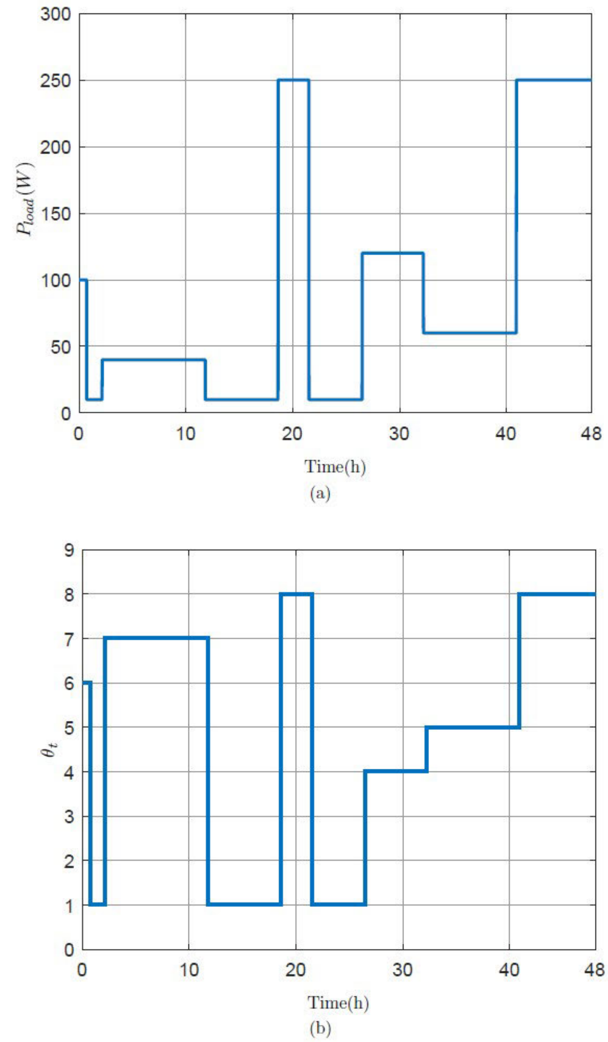

FIGURE 8. (a) Estimated load consumption, and (b) Markov chain evolution.

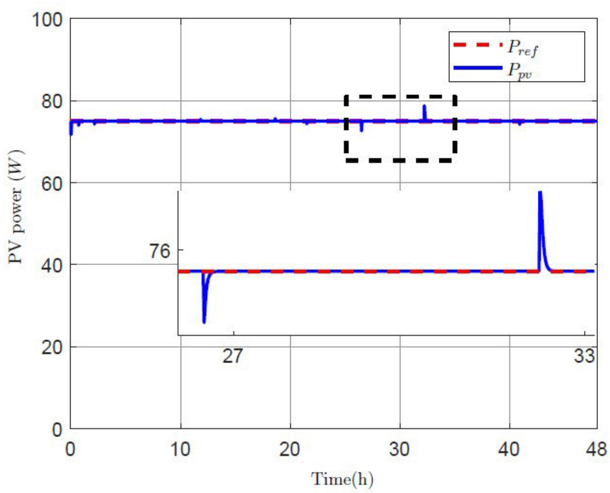

FIGURE 9. PV panel power under standard test conditions.

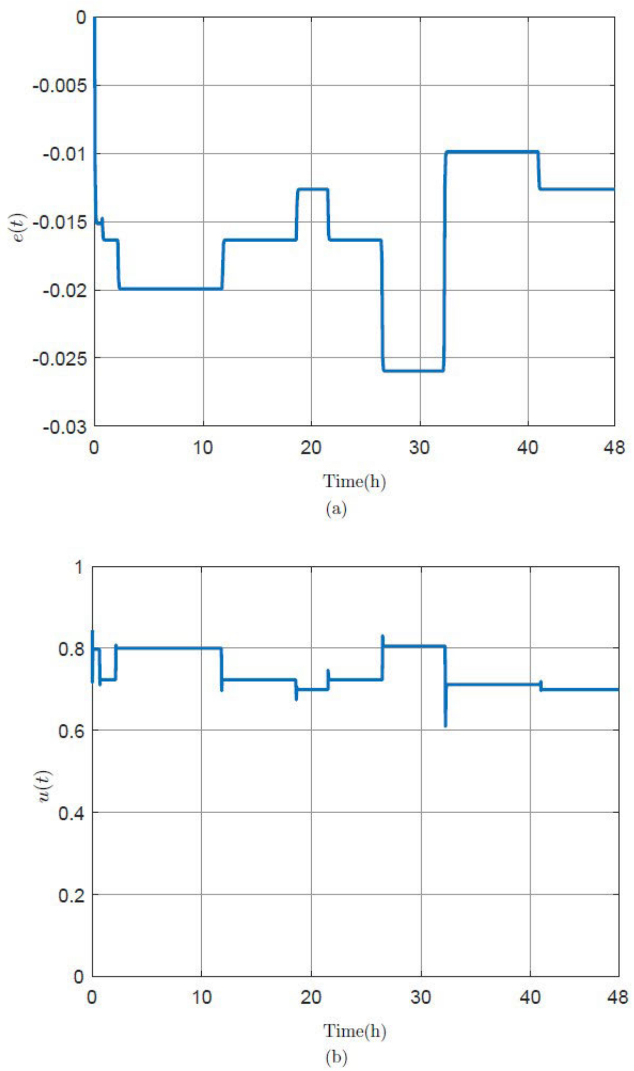

FIGURE 10. **(a) Tracking error, and (b) control law.**

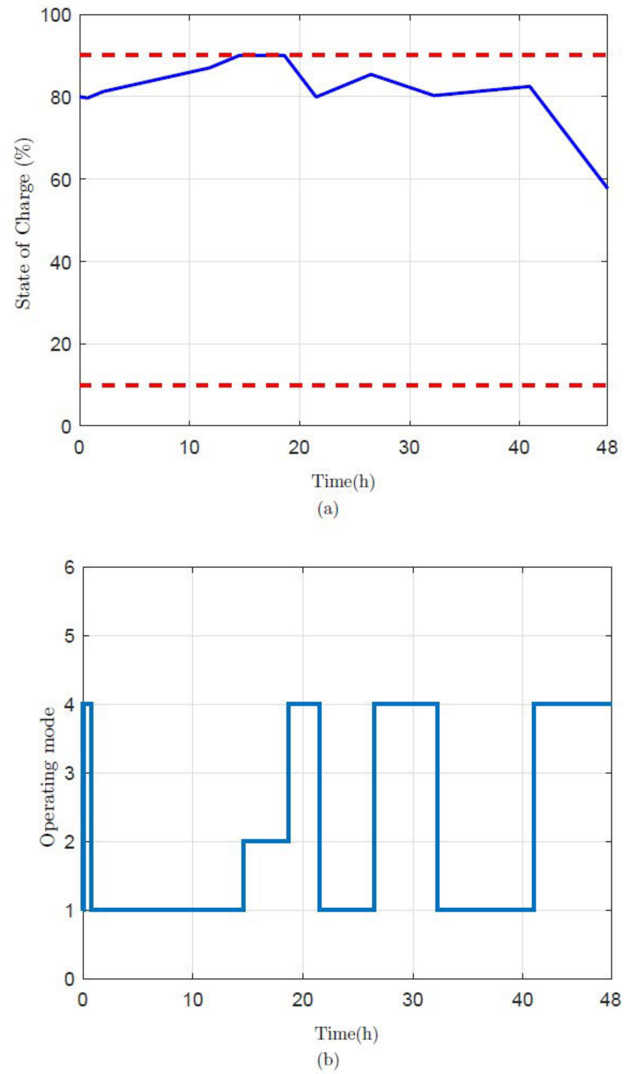

FIGURE 11. **(a) State of charge, and (b) Operating modes of the microgrid.**

Fig. 9 presents the output power response under the control scheme illustrated in Fig. 5. The illustration demonstrates the controlled system's ability to closely track the optimal power trajectory (P_{ref}), swiftly accommodating abrupt changes in load. This observation highlights the efficacy of the suggested control approach in delivering rapid responses during system initialization and sustaining stability amidst variable and unforeseen load conditions. These results validate the proposed method's capacity to facilitate a seamless transition to desired power levels while upholding the system's overall stability.

The efficiency of the proposed algorithm in maximizing PV power to attain ideal operational states is emphasized in Fig. 10(a), showcasing negligible tracking errors ranging from 0.01 to 0.026 in absolute value. These outstanding results are credited to the meticulous tuning of the control law effort $u(t)$, illustrated in Fig. 10(b). This control law dynamically adjusts to unpredictable load fluctuations, ensuring continual and accurate power optimization.

The battery's state of charge, controlled by the suggested stochastic energy management approach, is illustrated in Fig. 11(a). It's apparent that the system adeptly handles the battery's charging and discharging based on surplus or deficit power, ensuring that the SoC consistently falls within the predetermined thresholds of $SoC_{min} = 10\%$ and $SoC_{max} = 90\%$. This practice is crucial for safeguarding the battery's health, preserving both its longevity and performance. Such favorable outcomes directly stem from the implementation of the stochastic energy management strategy depicted in Fig. 6, which delineates various operational modes crucial for achieving these objectives, as further elucidated in Fig. 11(b).

2) SECOND SCENARIO: TIME-VARYING CLIMATIC PROFILES

To demonstrate the effectiveness of the proposed strategy in optimizing the power generated by the PV generator and efficiently managing energy within the microgrid amidst fluctuating climatic conditions and unpredictable load

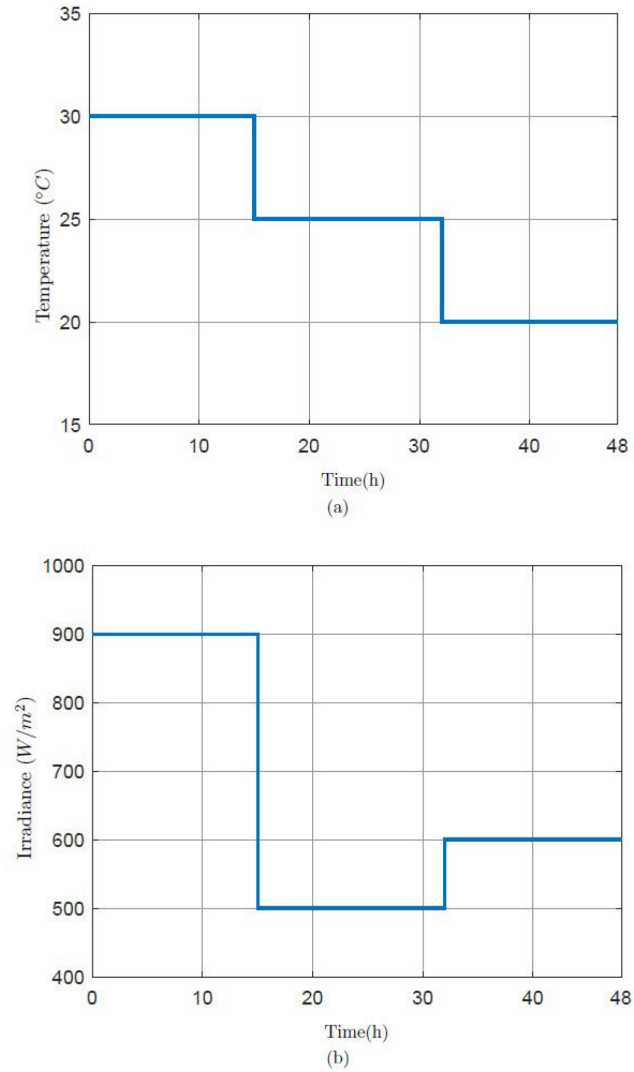

FIGURE 12. Time-varying climatic profiles: (a) temperature, and (b) irradiance.

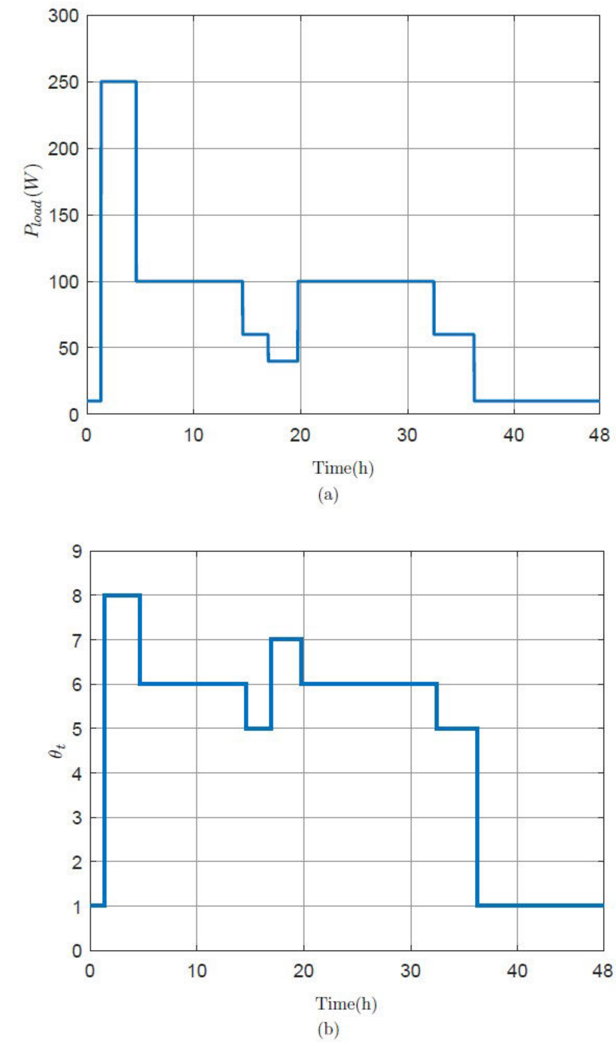

FIGURE 13. (a) Estimated load consumption, and (b) Markov chain evolution.

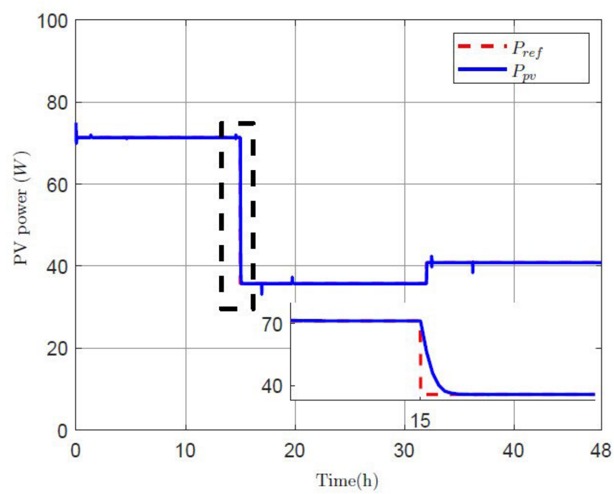

FIGURE 14. PV panel power under time-varying climatic profiles.

consumption simultaneously, the DC PV-microgrid system was simulated under time-varying irradiance and temperature profiles, as depicted in Fig. 12.

A new scenario of real-time estimations of global load consumption was conducted, as depicted in Fig. 13(a). Notably, Fig. 13(b) accentuates the efficacy of the proposed MDP-based approach in proactive decision-making of the future load consumption level.

Fig. 14 showcases the response of the output power with the applied control. It is evident from the illustration that the controlled system adeptly follows the reference power trajectory, promptly adjusting to the varying climatic conditions and sudden load changes. This observation underscores the effectiveness of the proposed control strategy in providing swift response during system startup and maintaining stability even when confronted with unpredictable loads.

The effectiveness of the proposed approach in optimizing PV power to achieve optimal operating conditions is

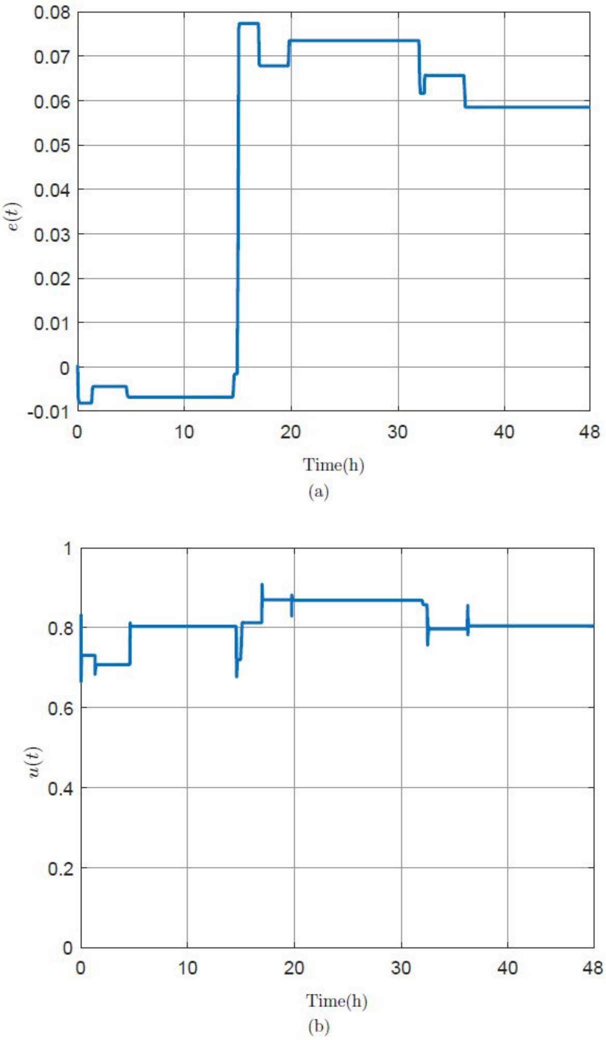

FIGURE 15. **(a) Tracking error, and (b) control law.**

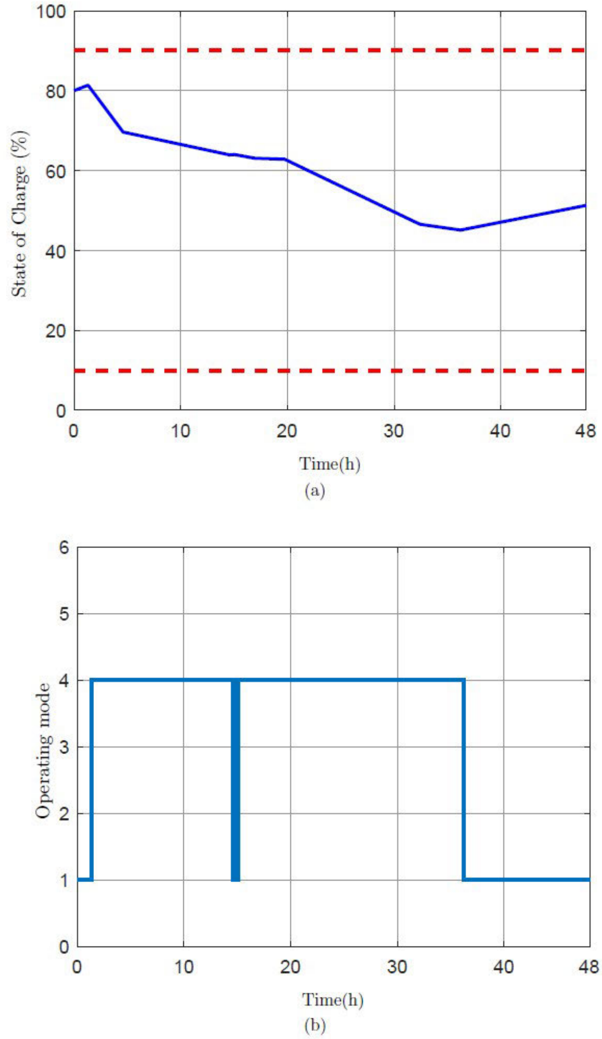

FIGURE 16. **(a) State of charge, and (b) Operating modes of the microgrid.**

underscored in Fig. 15(a), which demonstrates minimal tracking errors ranging between 0.01 and 0.08 in absolute value. These remarkable performances are attributed to the diligent adjustment of the control law effort $u(t)$ that dynamically adapts to both random load fluctuations and varying climatic profiles in tandem, as depicted in Fig. 15(b).

The battery state of charge, regulated by the proposed stochastic energy management strategy, is depicted in 16(a). It is evident that the system effectively manages the charging and discharging of the battery based on the surplus or deficit power. This practice safeguards the battery, preserving its longevity and performance. These results stem from the proposed stochastic energy management strategy depicted in Fig. 6, with the corresponding operating modes outlined in Fig. 16(b).

3) THIRD SCENARIO: REAL-TIME WEATHER CONDITIONS

In this case, the efficacy of the multi-objective stochastic control will be examined under real-time weather circumstances, which are provided in Fig. 17. These data were collected in the weather station located at Universidade Federal de Goiás (UFG)–School of Electrical, Mechanical and Computer Engineering (EMC), Goiânia, Brazil (data available freely at `sites.google.com/site/sfvemcufg/weather-station`).

In this scenario, the anticipated load profile and the jumps in the load closely mirrored the trajectories depicted in Fig. 18.

Fig. 19 depicts the optimized power produced by a PV generator under real-time weather conditions. The simulated data provides valuable insights into the dynamic performance of the solar power system. For example, Fig. 19 shows the system could adapt to varying weather patterns.

The battery state of charge controlled by the proposed stochastic energy management strategy is illustrated in Fig. 20(a). As can be seen, the system could charge and discharge the battery according to the real-time weather cycles.

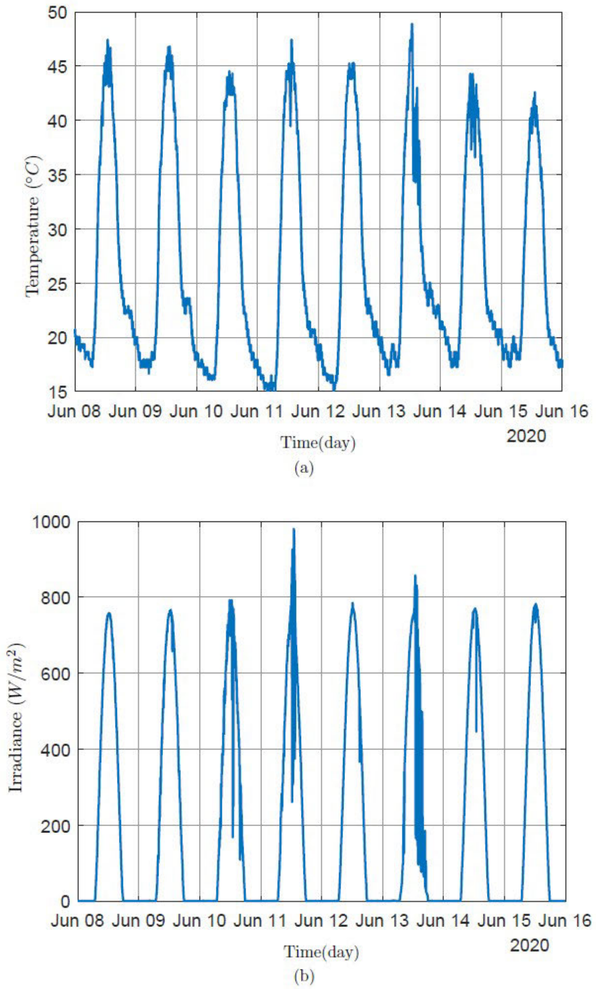

FIGURE 17. Eight-day real-time data for (a) temperature and (b) irradiance.

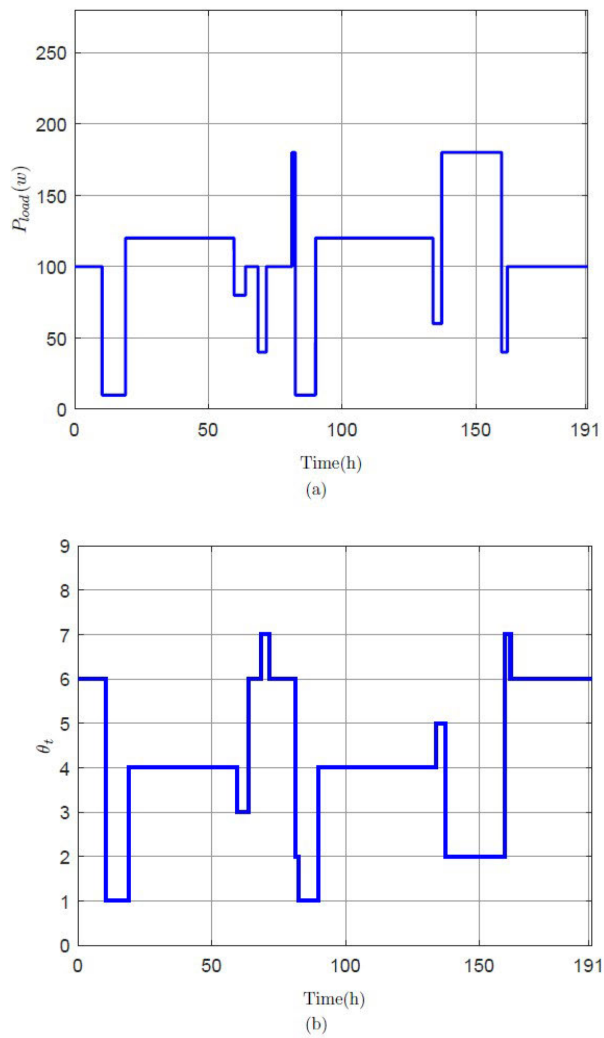

FIGURE 18. (a) Estimated load consumption, and (b) Markov chain evolution.

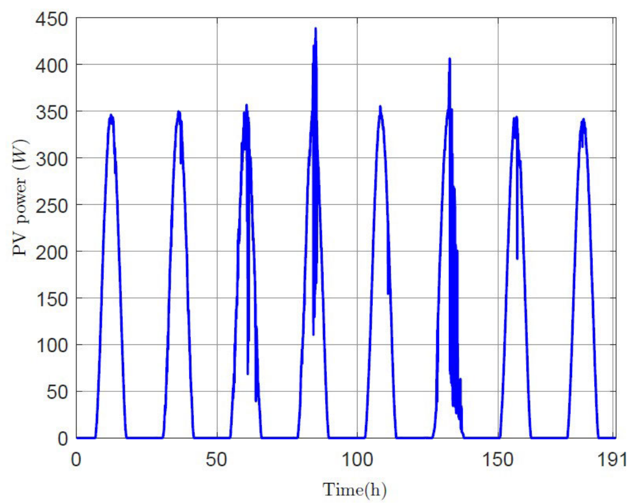

FIGURE 19. PV panel power under real-time weather conditions.

Peaks in the SOC curve signify periods of surplus solar energy, during which the battery is efficiently charged to its maximum capacity. Conversely, troughs in the curve indicate times when the system relies on stored energy, showcasing the effectiveness of the energy management strategy in maintaining a consistent power supply. The results allow us to discern the strategy's ability to balance energy generation and consumption, adapting to fluctuations in solar irradiance and random load demand, with the corresponding operating modes illustrated in Fig. 20(b). Furthermore, the smooth transitions and minimal fluctuations in the SOC curve indicate the robustness and reliability of the proposed energy management approach.

In summary, the simulation results contribute valuable insights into the effectiveness of the off-grid PV system's energy storage and utilization, showcasing the successful implementation of a stochastic energy management strategy.

B. DISCUSSION AND IMPLICATIONS

The simulation data illustrates the strategy depicted in Fig. 3. To the best of the authors' knowledge, this strategy is new for off-grid PV systems. In addition, the way in which this approach manages energy seems promising because it can

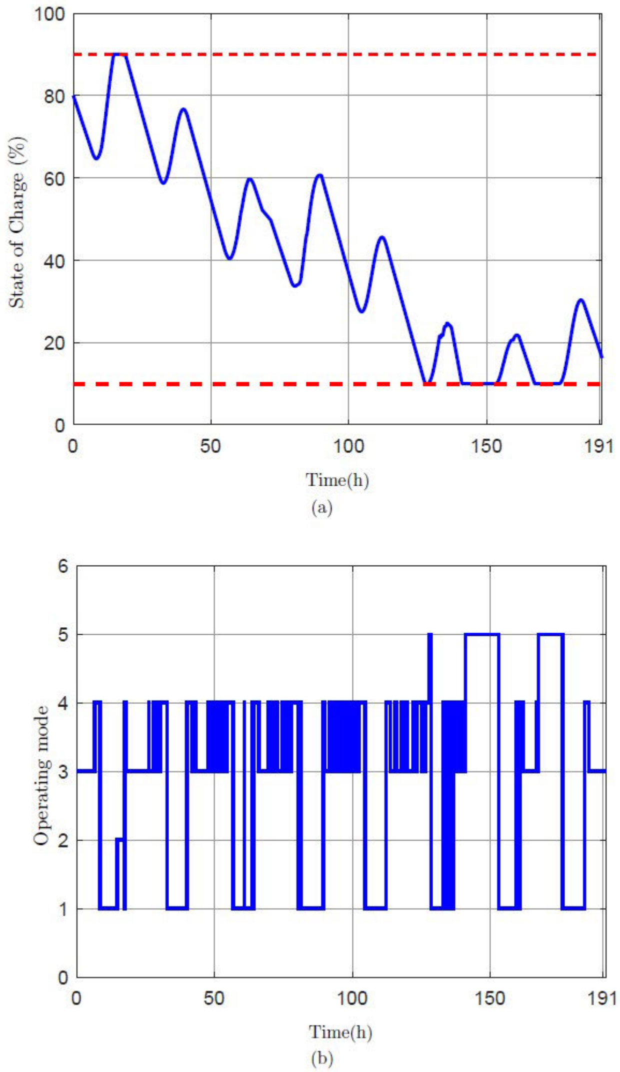

FIGURE 20. (a) State of charge, and (b) Operating modes of the microgrid.

handle stochastic-driven loads. MDP is key for stochastic forecasting of load consumption.

Unlike traditional stochastic approaches, a Markov chain solely relies on the present state to determine the future state of the system without consideration for any prior states. Our findings underscore the critical role of the Markov chain in effectively modeling dynamic systems undergoing continuous change and evolution, exhibiting superior performance and adaptability for handling stochastic forecasting of the load consumption in real-time.

In this context, the study [47] utilizes Markov chain modeling to analyze and predict load behavior within DC off-grid PV systems. The authors introduce a novel approach to stochastic MPPT control, specifically designed to accommodate the unpredictable nature of load consumption. This strategy integrates the H_∞ technique to optimize PV power generation amidst random load fluctuations. The study proposes a robust solution for optimizing energy production in off-grid PV systems by leveraging Markov chains and advanced control techniques. While the proposed strategy effectively addresses the challenges posed by random load behavior in off-grid PV systems, it fails to consider the impact of battery behavior on energy storage management. Consequently, the absence of comprehensive energy management that encompasses both load forecasting and battery dynamics significantly hinders the performance and dependability of the study.

This paper effectively addresses this drawback through the implementation of MDP-based energy management, which stands as the primary advantage of the proposed approach. This technique has the potential to greatly improve the effectiveness and reliability of off-grid PV system management strategies by considering the complicated load behavior, PV power generation, and battery storage dynamics. This approach holds the potential to significantly enhance the effectiveness and robustness of off-grid PV system management strategies. Through its consideration of these factors, the MDP-based energy management approach aims to improve scalability, and cost-effectiveness in managing off-grid PV systems.

Stochastic approaches typically excel in scalability compared to deterministic ones due to their capability to model uncertainty and variability more effectively. MDP stands out in this regard as they possess the ability to dynamically adjust energy generation and storage based on future forecasts. This inherent adaptability makes MDP well-suited for accommodating varying load demands and environmental conditions, thus enhancing scalability in off-grid PV systems. Additionally, through precise predictions of future loads, MDP can mitigate the requirement for surplus capacity, thereby lowering both capital and operational expenses.

V. CONCLUSION

This study aimed to address the challenge of managing energy in a PV microgrid characterized by unpredictable load demand. This methodology utilizes the MDP framework to optimize energy usage by taking into account intermittent solar power generation. It also incorporates batteries into the proposed model to provide continuous energy production during the operation.

The findings underscore the significance of incorporating stochastic modeling to represent the variability in energy generation and consumption accurately. This approach enhances the adaptability of microgrid systems, which is essential for assuring consistent operation in the face of changing conditions.

The simulation results indicate that the proposed methodology has promise for implementation in real-time scenarios. The strategy is innovative and effective in terms of energy efficiency, positioning it as a promising solution to enhance the resilience and efficiency of microgrid operation in the presence of unpredictable load consumption. Specifically, numerical findings reveal a power optimization efficiency was greater than 99.5%.

This study promotes the exploration and use of sophisticated decision-making frameworks within the context of renewable energy systems. As a perspective, investigating the scalability and applicability of this approach across different microgrid configurations and environmental conditions would be valuable for advancing the field, considering multiple energy sources.

APPENDIX

See Table 3.

TABLE 3. PV microgrid specification.

Parameters	Value	Unit
PV module SP75		
series-parallel cells (N_s, N_p)	$(36, 1)$	
Maximum power, P_{max}	74.8	W
Voltage at Maximum power, V_{mp}	17	V
Current at Maximum power, I_{mp}	4.4	A
Open circuit voltage, V_{oc}	21.7	V
Short circuit current, I_{sc}	4.8	A
Reverse saturation current, I_{rr}	1.5885×10^{-8}	A
Temperature coefficient, K_I	2.06	$mA/^\circ C$
Ideality factor, η	1.2	
Lithium–ion battery		
Nominal voltage, v_{bat}	52.2	V
Battery capacity, C_{bat}	100	Ah
Efficiency of Battery Charge, η_c	0.9	
Efficiency of Battery Discharge, η_d	0.9	
DC-DC Boost converter		
Input capacitor, C_{pv}	1	mF
Output capacitor, C	100	μF
Output capacitor resistance, R_C	0.162	Ω
Inductance, L	10	mH
Inductance resistance, R_L	0.48	$m\Omega$
Internal resistance of MOSFET, R_M	0.27	Ω
Internal resistance of diode, R_D	0.24	Ω

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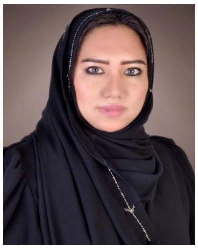

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