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Optimal Energy Management Strategy for Microgrids in Developing Countries: A Focus on Battery Energy Storage System

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Abstract

Microgrid failure is a significant concern in developing countries and rural areas, necessitating effective energy management strategies to enhance post-failure reliability. The battery energy storage system plays a crucial role in microgrids by managing imbalances, mitigating voltages, and improving system reliability. This paper presents a method for optimizing the energy storage system in a photovoltaic-connected microgrid. The method controls battery discharge and charge operations based on load requirements, considering fluctuations in demand over a day. Simulations using MATLAB R2022a employed state flow analysis and linear programming to minimize variable electricity prices before and after islanding events. The results demonstrate significant improvements in energy management by reducing total variable electricity costs. The proposed method enhances the performance and resilience of microgrid systems, addressing challenges associated with intermittent renewable energy and potential system failures. Effective energy storage management enables risk mitigation, improved reliability, and enhanced utilization of renewable resources, ultimately contributing to sustainable and resilient energy systems.

Keywords: Island, Microgrid, Energy System Storage, Photovoltaic System, Energy Management Strategy.

I. Introduction

Microgrids are nowadays considered to be a future trend for decentralized energy systems and receive a lot of attention (Almada et al., 2016). Integrating renewable energy systems into public grids is a good compromise in reducing electrical energy costs and improving power quality by reducing power loss and stabilizing voltage profiles (Sadeghian and Wang, 2018). Indeed, a hybrid system that is composed of a PV generator and a storage system can be used as a backup system to supply an electrical load without interruption during the loss of grid power (Pachanapan et al., 2022).

In a microgrid, it is important to maintain the energy balance for stability due to the uncertain nature of the grid (uncertain production of renewable energy systems, islanding, etc.) (Alvarez et al., 2017). The reliability of RES is a major issue in the process of balancing energy supply and demand. Energy storage systems are therefore of key importance in a microgrid because they allow an optimal use of the RES. In these microgrids, it is important to define an energy management system (EMS) that will have the role of controlling and guaranteeing the distribution and production of energy at lower costs (Sarda et al., 2022). This control system then has an essential function in increasing the reliability and efficiency of a microgrid.

If the outage phenomenon occurs during the day, the PV array and the storage system would be able to support the demand. On the other hand, only the storage system would be able to supply essential loads during the night and extreme weather conditions, due to unavailability of power from the PV array. The challenge of islanding operation is then to maintain a constant power balance between energy production and load consumption. The power mismatch will cause the system frequency and voltage to deviate from the nominal values (Pachanapan et al., 2022).

Several researchers have provided solutions for energy control in microgrids using several approaches to achieve efficient and optimal grid operation.

(Sukumar et al., 2017) proposed an EMS based on nonlinear and linear programming methods. (Iten et al., 2018) proposed an EMS based on a simulation using a fuzzy logic program and Hybrid Optimization Model for Electric Renewable (HOMER). (Khan et al., 2022) carried out a comparative analysis of EMS in terms of HRES research and technical tools used for assessment. Considering the uncertainties that can influence the HMGS, (Liu et al., 2017) proposed EMS based on other artificial intelligent methods. (Ghasemi, 2018) proposed an EMS based on stochastic and robust programming approaches.

This work emphasizes the importance of optimizing energy management strategies for microgrids, especially in developing countries, using an innovative control system to minimize costs and ensure reliable operation under variable conditions: in section 2 we present a modeling of the PV array and storage system. Then we present the methods of energy management in this system and finally give the parameters of the test system. The analysis and discussion of the different simulation cases are presented in section 3, followed by the conclusion in section 4.

II. System Model and Modeling Approach

A. System Modeling

1) Solar PV: The solar panel is a major element in the solar energy source. Photovoltaic cells in solar panels convert the penetrating radiation directly into direct current. Solar energy is a renewable source of energy that can satisfy the world's demand for energy (Liu et al., 2017). Naturally, since

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Cameroon has a high solar energy potential, it is the most suitable renewable energy system to be preferred (Kharrich et al., 2018). Mathematically, the power output of solar panels is illustrated depending on solar radiation and effects on temperature using the following Eq.1 (Sawle et al., 2021):

$$\mathbf{P_{PV} = y_{PV} \times f_{PV} \times \left(\frac{\bar{G}_T}{\bar{G}_{T,STC}}\right) \times [1 + \alpha_P(T_C - T_{C,STC})]} \quad (1)$$

T_C is the cell temperature given by the Eq. 2.

$$\mathbf{T_C = T_{amb} + (0.0256 \times G)} \quad (2)$$

Where, y_{PV} is the rated output of PV generator under standard test conditions [kW], f_{PV} is the PV derating factor [%], $\bar{G}_T$ is the Solar radiation incident on the PV generator at current time step [kW/m^2], $\bar{G}_{T,\ STC}$ is the radiation under standard test conditions [1 kW/m^2], α_P is the temperature coefficient of power [%/^{0}C], T_C is the PV cell temperature at current time step [^{0}C], $T_{C,\ STC}$ is the PV cell temperature under standard test conditions [^{0}C].

2) Energy storage system: In the system modeling, the batteries are the elements that store the energy generated by the renewable energy sources when the generated energy is more than the required load and transfer the stored energy to the system when the energy produced is not sufficient for the systems. Energy stored in these batteries and those transferred to the system is AC voltage type. Since the cost of batteries is quite high, the effect of the number of batteries on the system is very essential (Mousavi et al., 2020). The charging state of a battery is represented in Eqs. 3 and 4 below (Mohamed et al., 2019).

$$\mathbf{E_b(t+1) = E_b(t) \times (1-\sigma) - \left(\frac{E_l(t)}{\eta_{cnv}} - E_g(t)\right) \times \eta_{BD}} \quad (3)$$

$$E_b(t+1) = E_b(t) \times (1-\sigma) - \left(E_g(t) - \frac{E_l(t)}{\eta_{cnv}}\right) \times \eta_{BC} \quad (4)$$

Where $E_l(t)$ and $E_g(t)$ are the energy demand and generated power, respectively. η_{BD} and η_{BC} represent the discharge and charge efficiencies of the battery. The parameter σ is the self-discharge of the battery. η_{cnv} is the efficiency of the converter.

B. Modeling Approach:

1) Problem formulation

The process begins with the formulation of an optimization problem in which an objective function is identified. Here the objective function is to minimize the total cost of the microgrid operation given by the Eq. 5.

$$\mathbf{C_{tot} = \sum_{j=o}^{N} C_{grid}(j) \times E_{grid}(j)} \quad (5)$$

Where C_{tot} represented the total operating cost of the HRES, Cgrid (j) is cost of grid, and E_{grid} (j) is the energy stored while satisfying all operational constraints.

2) Problem constraints

The power balance and charge or discharge battery constraints are represented in Eq. 6.

$$\mathbf{\sum_{j=1}^{N} P_{PV} + P_{grid} \pm P_{BBS} - P_{load} = 0} \quad (6)$$

Where P_{PV} is the PV power output in the HRES, and the unit is kW; P_{grid} is the grid power output in the HRES, and the unit is kW; P_{BBS} is the Battery power output in the HRES, and the unit is kW; P_{load} is the load power output in the HRES, and the unit is kW.

Two conditions constrain the battery operation:

- State Of charge (SOC) boundaries to overcharge and over-discharge, SOC must be within the safe limits as described in Eq. 7 (Kumar et al., 2019).
- The capacity $E_b(t)$ of a battery bank at each time step t, lies in between minimum and maximum capacity. The DOD is the depth of discharge of the battery, which depends on the battery's technology. Then, the constraint is expressed by Eq.8 (Chauhan and Saini, 2017).

$$\mathbf{SOC_{min} \le SOC(t) \le SOC_{max}} \quad (7)$$

$$E_{bmin} \le E_b(t) \le E_{bmax} \quad (8)$$

With

$$\mathbf{E_{bmin} = (1 - DOD) \times E_{bmax}} \quad (9)$$

3) Heuristic Approach: The State Machine Logic employed in this study utilizes a finite number of states to govern the system's behavior. This logic employs state transitions and generates outputs based on the current state and input received. Each state represents a specific system situation, influenced by previous inputs, and triggers specific reactions to subsequent inputs. State transitions determine under which input conditions a state is changed from one to another. To illustrate this concept, Fig. 3 presents an example of a light switch system, demonstrating the application of the State Machine Logic.

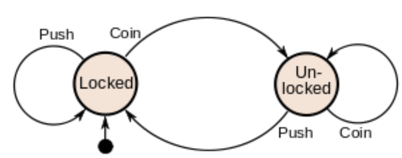

Fig. 1. *Example of machine state logic: light switch*

4) Linear Programming (LP) method: Linear programming is a viable optimization technique that can be employed to solve problems where the decision variables, objective function, and constraints are expressed as linear functions. The recommended solar PV/battery-based integrated microgrid's cost-effective operation depends on accurate linear function assignment, modeling, and training, as well as on successful real-time operation. Equation 10, which analyses the linear program (LP) optimization function (linprog), describes its standard form (Kusakana et al., 2013)

$$\min f_x^T = \begin{cases} Ax \leq b \\ A_{eq}x = b_{eq} \\ l_b \leq x \leq u_b \end{cases} \quad (10)$$

Where f, x, b, b_{eq}, l_b, and u_b are vectors, and A and A_{eq} are matrices.

The standard form of a linear programming problem is characterized by certain features, which include:

- The optimization problem is formulated with a minimization objective function.
- All constraints in the problem are of the equality form.
- All decision variables possess non-negative values.

The aforementioned standard form may be subject to modification in accordance with the specifications of the optimization problem's objective function and variable constraints.

C. Test System:

The provided system, as illustrated in Figure 2, represents an electrical network with a voltage of 20KV and a frequency of 50Hz. The network is connected to a three-phase transformer with two windings, where the secondary winding has a rating of 5KV and is configured in a star configuration. Additionally, a three-phase circuit breaker is present, which can be switched between two positions (open/closed) to create an island within the system. This circuit breaker is connected to a variable load, supplying power to the system.

The load in the system comprises a variable load of 320KW from households and a fixed load of 350KW, resulting in a total electrical load of 670KW. The photovoltaic (PV) system consists of 72 cells connected in series, forming a solar panel with a power output of 535KW. Real-time control of the PV system's power output is achieved using a maximum power point tracker (MPPT) through a DC-DC converter. The maximum power point (MPP) of the PV system depends on two random variables: solar radiation and ambient temperature.

The storage system considered the core component of the system, has a nominal power of 400KW and a capacity of 3,000KWh. During grid connection, the PV system operates at its maximum power point to contribute as much PV power to the system as possible. In this mode, the power generated by the PV system can exceed the demand. The battery in the storage system is maintained at a half-charged state (50%) during grid mode. Furthermore, the storage system can be charged either by the PV generator or by absorbing energy from the grid.

To disconnect from the public grid, the three-phase circuit breaker is operated. In this mode, a power loss occurs between 6:00 and 7:00 am, corresponding to one hour in the islanding condition. During this operation, the PV system must manage the changes in reactive and active power consumed by the load to maintain the power balance within the system.

In island mode, the battery can only be charged if the power generated by the PV array exceeds the load demand.

III. Simulations, Results, and Analysis

The modeling and simulations were performed in MATLAB R2022a software for 86000 seconds corresponding to one day. In this system, we used two different conditions (cloudy and clear weather). The performance of the islanding operation is studied in two scenarios:

- 10^4 seconds islanding (between 10000 to 20000 seconds) in clear weather;
- 10^4 seconds islanding (between10000 to 20000 seconds) in cloudy weather.

By performing these different simulations, we find the total cost of electricity.

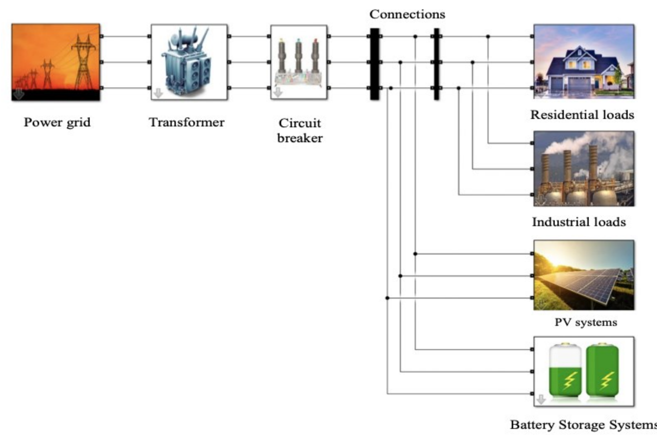

Fig. 2. The proposed microgrid test system

Figure 3 provides an overview of the system's state during a sunny day using the heuristic approach. The first curve illustrates the microgrid's frequency, reflecting the fluctuations based on the power settings within the system. The second curve represents the power levels of the photovoltaic generator, load, battery, and grid. The third curve indicates the battery's charge level, while the final curve depicts the price of electric power. Prior to islanding, the load remains below 500kW. Consequently, the battery's charge level remains at 50%, corresponding to its initial state of charge. During this period, as the photovoltaic generator is not yet producing power, the load demand is met by the battery. The battery's charge level gradually decreases from 50% to 32%. Between 20,000 and 40,000 seconds, both the consumption and PV power increase, while the battery power decreases, resulting in its drainage. The battery starts recharging when the PV power surpasses the load power. From 60,000s to 86,000s, the demand exceeds the PV output. During this interval, the load is supported by the grid, and the battery becomes fully discharged. Afterward, the load is entirely met by the grid, leading to maximum operating costs. In this particular scenario of abundant sunlight, the overall operating cost amounts to $655.23.

Fig. 3. Clearly waveforms using the heuristic method

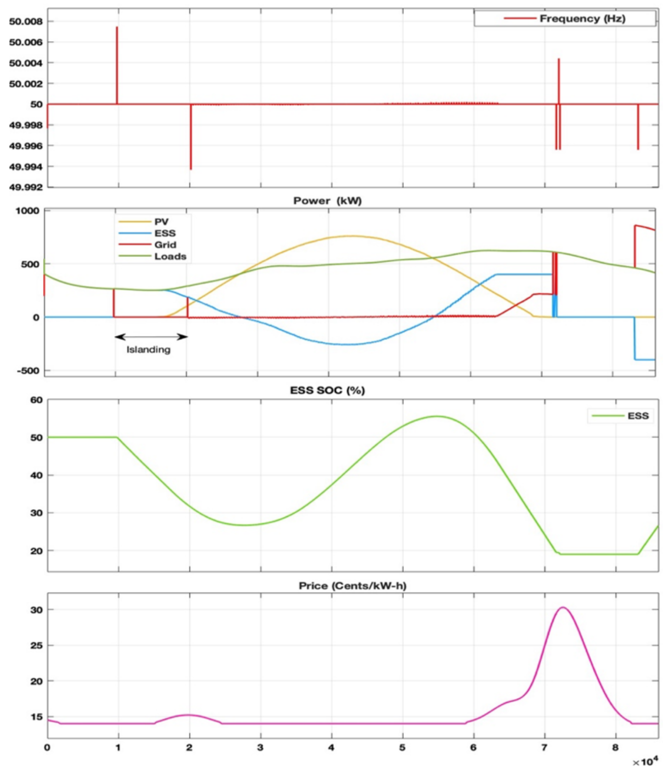

Figure 4 displays the experimental curves observed during a cloudy day using the heuristic approach. Similar to previous cases, the battery charge level before islanding remains at 50% due to higher production than demand. This period results in minimal operating costs for the network. During the islanding period, the battery experiences discharge, leading to a slight increase in prices. Between 20,000 and 70,000 seconds, the power output exhibits fluctuations due to the intermittent nature of photovoltaic production. This uncertain profile impacts the entire power grid, and during this period, the battery becomes fully discharged. Within the interval of 70,000 to 86,000 seconds, the load is supplied by the grid, resulting in the highest operating cost at that time. For the entire cloudy day, the total cost of operation amounts to $998.3.

Figure 5 depicts the curves obtained from clear weather simulations using the optimization approach. Prior to islanding, the load power remains lower than the grid power. Consequently, during this period, the battery undergoes charging, reaching up to 80% of its capacity. As the islanding period ensues, the battery is discharged, accompanied by a slight increase in energy costs. The battery discharge continues until the power generated by the photovoltaic system surpasses the load demand. Between 50,000s and 65,000s, the battery becomes fully charged. Throughout the night, the demand is met by both the battery and the grid. Within this time interval, the price of energy reaches its maximum level. For a clear day, the total operating cost using the optimization approach amounts to $625.31.

Figure 6 showcases the simulation curves obtained during a cloudy day using the optimization approach. Before islanding, the load demand remains lower than the grid power. At this stage, both the photovoltaic (PV) generator and the storage system do not supply any power. Consequently, the battery charges up to 70%, indicating the onset of islanding. During the islanding period, neither the grid nor the PV system supplies power to the load. Instead, the load is solely supported by the battery, resulting in its discharge. After 20,000 seconds, the grid power begins to decrease as the PV generator starts producing power. As a result, the operating cost remains as low as possible. Within the interval of 30,000 to 70,000 seconds, the load experiences a slight increase, reaching around 500kW. Concurrently, the PV power increases, while the battery supplies energy, gradually reaching its nominal capacity. Due to the negligible cost of renewable generation, the overall cost remains low during this period.

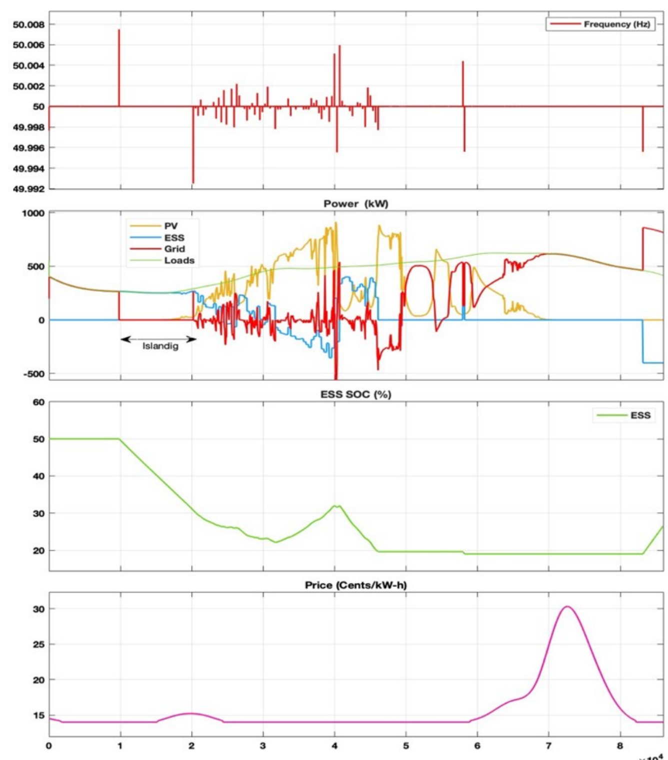

Fig. 4. Cloudy waveforms using the heuristic method

Between 40,000 and 65,000 seconds, the load is estimated to be consistently at 500kW. As the battery voltage reaches its nominal value, the charging mode is activated. Consequently, the state of charge (SOC) achieves an estimated performance index of approximately 80%. Once again, the cost remains relatively low. Within the interval of 65,000 to 86,000 seconds, the load exceeds 500kW. However, the energy requirement is still met by the battery, even as the power output of the solar panels continue to decrease. At a certain point, the battery discharges gradually, and the contribution of solar energy becomes negligible. Subsequently, the grid power takes over. The power required for charging is provided by the grid, leading to an increase in costs, reaching their maximum level. The total cost of a cloudy day, utilizing the optimization approach, amounts to $913.2.

Figures 7 and 8 show the differences between the prices and the different network powers during a clear and cloudy day respectively. The first curves in these figures give the grid cost and the second curves give the grid usage. In the beginning, the energy utilization rate is relatively low. Therefore, during this time interval, the operating cost is low. Afterward the PV power changes according to the weather conditions; during these uncertain production periods the load is fed from the grid. At the end of the day, the demand is high and the network costs are high as well.

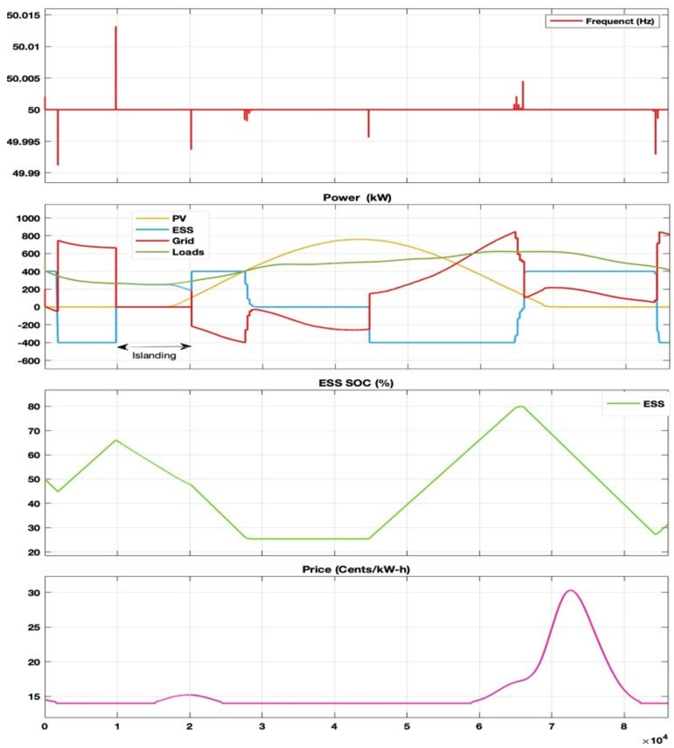

Fig. 5. Clearly waveforms using an optimization method

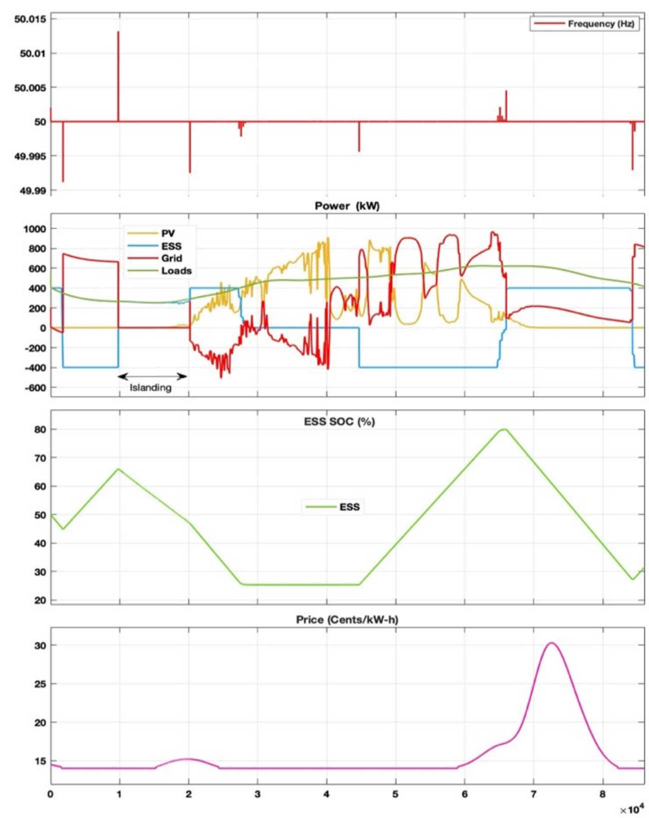

Fig. 6. Cloudy waveforms using an optimization method

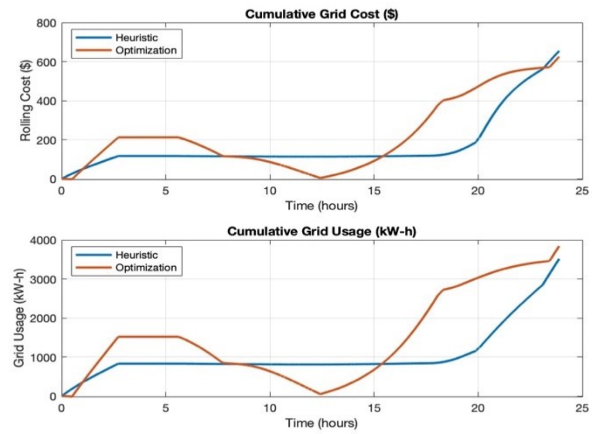

Fig. 7. Daily difference between grid cost and grid usage during the clear day using a heuristic method

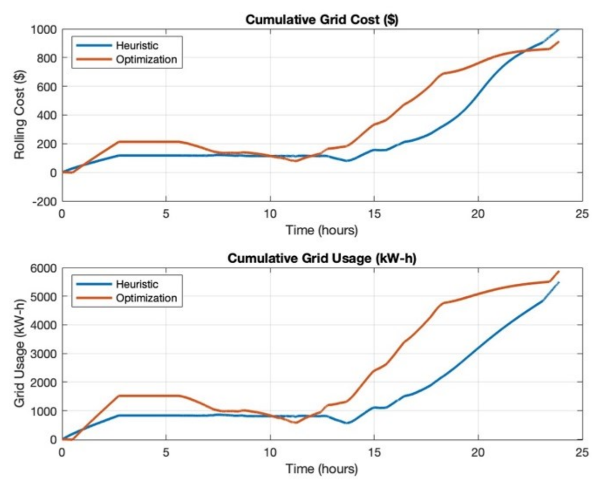

Fig. 8. Daily difference between grid cost and grid usage optimization method

IV. CONCLUSION

This paper presents an innovative energy control system for microgrids, focusing on a photovoltaic (PV) generator, storage system, grid, and load. The system minimizes grid operating costs under variable generation conditions and 10,000-second interruptions. The research focuses on providing a continuous power supply for a 24-hour period, considering cost optimization and reliable operation challenges. The heuristic method was found to be higher in clear weather conditions and 8.5232% in cloudy weather scenarios for load satisfaction. This highlights the importance of optimizing energy management strategies for microgrids, especially in developing countries.

The proposed approach enables efficient and reliable microgrid operation by leveraging battery energy storage systems and integrating renewable energy sources like the PV generator. This research contributes to the field of microgrid optimization and highlights the potential benefits of different methods for energy management in varying weather conditions. Further research can explore additional optimization methods and expand their application to other microgrid configurations, leading to more efficient and resilient energy systems in developing countries.

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