Optimization of Power Flow in Hybrid Microgrids Using AI-Based Algorithms

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ABSTRACT

Increased renewable energy applications in microgrids imply that there is currently less predictability in power generation, implying that there is a necessity of sophisticated methods to streamline the operations of the microgrid so that it operates effectively and steadily. In this work, a hybrid Artificial Intelligence (AI) framework is proposed to enhance the way power is transferred in AC and DC microgrids with energy storage systems (ESS), distributed energy resources (DERs) and integrated with the normal utility grid. The proposed solution comprised of DDPG Deep Reinforcement Learning and Genetic Algorithms address both real-time and global optimization issues. The DRL agent determines the optimal strategies to exploit RES, ESS and the grid and the GA enhances the initial parameters and critical elements of the model of the agent to achieve optimal performance. The framework is studied under different conditions and load and generation patterns in two simulation environments, one in MATLAB/Simulink and the other in Python during 24 hours. Compared to the outcomes, this DRL-GA approach is a far better solution than the Mixed Integer Linear Programming (MILP) and Particle Swarm Optimization (PSO), leading to an operation cost reduction, enhancing voltage stability as well as increasing renewables utilization. The findings provide a flexible and smart control strategy that will be efficient in microgrid energy management.

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1. INTRODUCTION

It has seen significant change in power systems with increased use of solar photovoltaic (PV) and wind turbines within the industry. The concern about the environment, the necessity to find the sustainable energy sources and the new technology is driving the change in central fossil fuel plants to the multitude of small renewable generators. Here, decentralized and flexible power distribution systems, known as microgrids, have emerged as viable options, allowing operation with both main grids and off-grid, with hybrid microgrids being increasingly popular due to support both AC and DC power distribution networks and integrate many different types of distributed energy resources (DERs) including solar PV, wind, generators on diesel and energy storage (ESS) systems composed of batteries and supercapacitors. Nevertheless, since the resources are not determined and predictable, they introduce new problems in the management of movement of power in the microgrid.

It is challenging under these conditions to manage the situations where the voltage and frequency may vary, store energy without risk, balance load and save money. Further, popular optimization methods, including MILP, Newton-Raphson and rule-based heuristics, struggle with such uncertainties. These methods are still challenging to adapt to sudden variations in the amount of power being produced and consumed.AI has now enabled managing these issues to be more flexible. DRL is a model-free method of learning to control the environment that is accomplished on-going. The control systems of microgrids can be enhanced with the usage of GA in a hybrid AI system that provides a large search space of optimal parameters.

Accordingly, this is a research paper seeking AI hybrid models to combine features of DRL with GA to realize the real-time power flow control of hybrid AC/DC microgrids which is shown in Figure 1. The objectives include cost reduction, better utilization of renewable energy and maintaining an unchanged system with varying load and energy generation patterns.

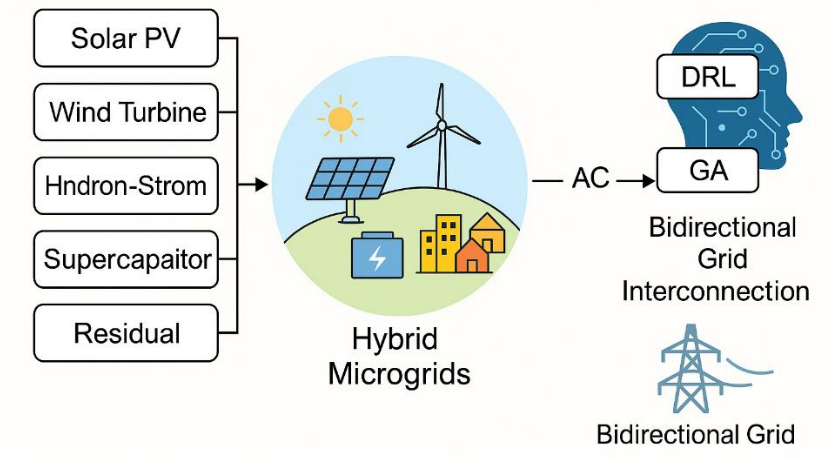

Figure 1. Overview of the proposed DRL-GA framework for hybrid microgrid optimization

2. REVIEW OF LITERATURE

Over the last few years, there has been increased interest by people to optimize power flow in hybrid microgrids due to the increased amount of renewable energy, energy storage and improved controls. The research works that we are going to discuss in this chapter have been conducted in three broad fields: traditional optimization, AI-related methods (including machine learning and reinforcement learning) and hybrid AI.

A majority of early research in microgrid optimization relied on linear programming, nonlinear programming and mixed-integer linear programming. Guerrero et al. (2011) proposed hierarchical control strategies of microgrids by relying on conventional dispatch schemes to ensure voltage and frequency control. Moreover, MPC-based energy scheduling proposed by Vázquez et al. (2010) was recommended to apply to microgrids tied to the grid.

Even though such techniques are appropriate in deterministic systems, they struggle with stochastic variations of RES and would need a substantial computer effort in large-scale optimization.

This is the reason why many individuals resort to the use of PSO, GA and ACO algorithms among other metaheuristic techniques since power flow optimization is both non-convex and non-linear. Ahead of time scheduling of a hybrid microgrid proved to be more effective with PSO, according to Liu and Wang (2023). Nevertheless, such methods have a limitation because they have predetermined rules of control and are not able to adapt to dynamics and uncertainty. Rule-based controllers are the most often selected in microgrid energy management since they are very easy to manipulate and durable. However, they cannot be recommended to be applied in the environment with high levels of uncertainty and frequently changing data.

New technologies in the management and optimization of microgrids utilize data to control them better, thanks to AI. A more successful short-term outcome was reported by Sharma et al. (2021) who relied on supervised learning to predict energy demand and RES power. However, supervised learning requires a huge set of labeled data, and it is not particularly suited to taking action sequentially.

Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used as pattern recognition in load profile and RES generation. Their prediction performance has now been improved, though they are rarely used directly in control and optimization problems.

Researchers think that DRL will be significant in the operation of microgrids since it can figure out the most excellent course of action through trial and error in the actual environment. In 2022, the authors used a DQN to enhance the cost effectiveness of the energy scheduling in grid-connected microgrids that are operated with random fluctuations. In 2021, the authors applied DDPG to regulate SOC of ESS and showed better adaptability.

Despite their other benefits, the deep reinforcement learning methods are normally slow and require the selection of appropriate hyperparameters. Moreover, untrained systems can result in controls which are unnecessary or even dangerous to complex AC/DC systems.

Research on how to address the shortcomings of single AI models by structuring AI with hybrids has been conducted recently. Tang et al. (2023) enhanced the convergence capabilities and increased the policy stability of the systems of the microgrid using PSO-tuned DDPG. However, a vast majority of the researchers have merely worked on DC microgrids or have not made comparisons with the older systems in detail.

Some microgrid optimization papers utilized either DRL or GA alone, and hardly any studies have developed a framework that combines the best of both DRL and GA in terms of hybrid AC/DC microgrids. Very minimal efforts have been exerted in the area of balancing real time power flow and cost minimization, system stability and maximization of renewable energy use in the field.

3. PROBLEM DEFINITION AND METHODOLOGY

3.1 System Description

The given study proceeds by designing a flexible and smart network, integrating the sources of energy and loads within the network. It has the following characteristics:

They are referred to as solar photovoltaic (PV) panels and wind turbines and since there is no assurance of when they will come, their trends are characterized by intermittency.

The system consists of lithium-ion batteries to store power over a long period and introduces supercapacitors to react quickly. An assortment of residential and industrial activities with varying demand changes.

By linking the grid it becomes feasible to have homes and businesses draw energy form the grid when it is economical to do so and later feed the grid with any surplus energy. This system has both connected and not connected operating modes and reflects the real hybrid AC/DC microgrids.

3.2 Objective Function

The primary objective of the optimization problem is to minimize the total operational cost of the microgrid over a defined time horizon T, considering energy purchase, generation, and possible revenue from energy export:

$$C_{total} = \sum_{t=1}^{T}\left[C_g(t)P_g(t) + C_s(t)P_s(t) - R_{sell}(t)P_{export}(t)\right] \tag{1}$$

Where:

- $Cg(t)$: Cost of energy imported from the grid at time t
- $Pg(t)$: Power drawn from the grid at time t
- $Cs(t)$: Operating cost of local sources (e.g., diesel generator)
- $Ps(t)$: Power generated by dispatchable sources
- $Rsell(t)$: Revenue per unit for energy exported to the grid
- $Pexport(t)$: Power exported to the grid at time t

3.3 Operational Constraints

The optimization is subject to the following technical and operational constraints:

Power Balance Constraint:

$$\sum P_{source}(t) = \sum P_{load}(t) \tag{2}$$

This ensures that the total power supplied meets the total demand at all times.

Battery State of Charge (SOC) Limits:

$$SOC_{min} \leq SOC(t)SOC_{max} \tag{3}$$

This maintains battery health and ensures sufficient storage availability.

Grid Exchange Limits:

$$P_{\substack{min \\ import}} \leq P_g(t) \leq P_{\substack{max \\ import}} \; and \; 0 \leq P_{export}(t) \leq P_{\substack{max \\ export}} \tag{4}$$

Voltage and Frequency Regulation:

$$V_{min} \leq V(t) \leq V_{max} \;\; ; \;\; f_{min} \leq f(t) \leq f_{max} \tag{5}$$

These constraints ensure power quality and system stability.

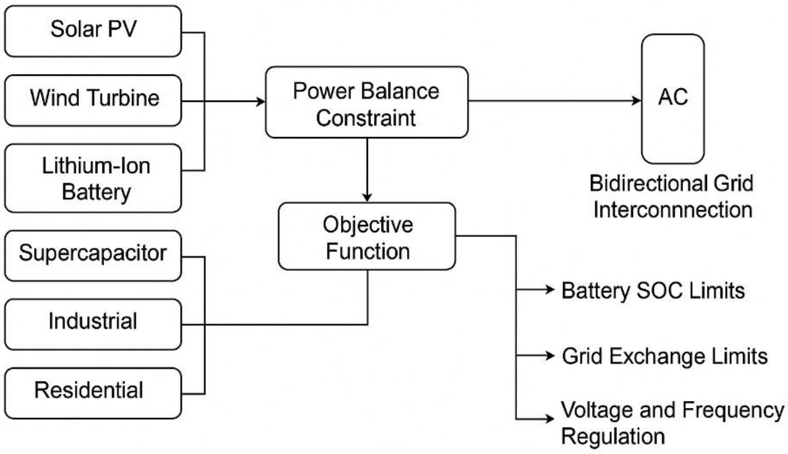

Figure 2. Block diagram of hybrid microgrid system and optimization parameters

The block diagram of hybrid microgrid system and optimization parameters is represented in Figure 2.

4. AI-BASED FRAMEWORK DESIGN

In the proposed research, a framework integrating Deep Reinforcement Learning (DRL) and Genetic Algorithms (GA) is being proposed to address the challenging, stochastic and real-time nature of the problems that hybrid microgrids have to deal with. DRL enables the robot to select appropriate action in an uncertain environment and GA enhances the performance and the learning speed of the DRL agent by modifying the neural network parameters.

4.1 Deep Reinforcement Learning (DRL) Agent Design

The DDPG is applied among many other methods primarily because it works well in continuous action spaces required to operate energy dispatch, battery storage and grid interactions in hybrid systems.

Control Objectives of DRL Agent:

- Optimal dispatch of Distributed Energy Resources (DERs)
- Battery charge/discharge scheduling
- Bidirectional grid power flow control

State Space (St):

The input state vector at time t includes:

- $D(t)$: Load demand forecast
- R_{avail} Renewable generation availability (solar/wind)
- $SOC(t)$: State of charge of the battery
- $P_{grid}(t)$: Electricity price or tariff at time t

$$S_t = \left[D(t), R_{avail}(t), SOC(t), P_{grid}(t)\right] \qquad (6)$$

Action Space (A_t):

The action vector determines how power is allocated among:

- Renewable sources
- Storage devices (charge/discharge levels)

- Grid import/export

$$A_t = \left[P_{solar}, P_{wind}, P_{\substack{charge \\ battery}}, P_{\substack{discharge \\ battery}} P_{\substack{import \\ grid}}, P_{\substack{export \\ grid}}\right] \quad (7)$$

Reward Function (r_t):

To guide the learning process, a scalar reward is computed based on system objectives:

$$r_t = -C_{total}(t) - \lambda_1 \left|V(t) - V_{ref}\right| - \lambda_2 \bigtriangleup SOC(t) \quad (8)$$

Where:

$Ctotal(t)$ isTotal operational cost at time t, $V(t) is$ System voltage, $Vref$ is Nominal reference voltage, $\Delta SOC(t)$ is Change in battery SOC (to penalize unnecessary cycling)

$\lambda 1, \lambda 2$ is Weighting factors for penalty terms.

4.2 Genetic Algorithm (GA) Optimization

In this case, a method is proposed, where the Genetic Algorithm (GA) is used to find the optimal behaviour and speed of convergence of the Deep Reinforcement Learning (DRL) agent. Since DRL is enhanced by learning with the environment, its achievement is highly reliant on the initial values of the significant neural network and hyperparameters. DRL-GA framework overcomes the challenges of tuning the DDPG agent through the assistance of a globally optimal point and adaptive updating via Genetic Algorithm. First, global search using GA, it is possible to choose improved initial weights of the actor and critic in DDPG, as random initialization may speed up the process or provide unsatisfactory results. On top of this, GA is expected to regulate important hyperparameters itself, based on the performance it receives, so a user needs to perform less manual testing. GA optimizes the valuable operation limits that include the maximum charge on battery, the maximum power to be handed over by the wind turbine, and the limitation of the amount of power that the turbine can deliver to the grid. Consequently, the DRL policy is more effective and falls within the bounds of the system components in a hybrid microgrid. GA flowchart is given in Figure 3.

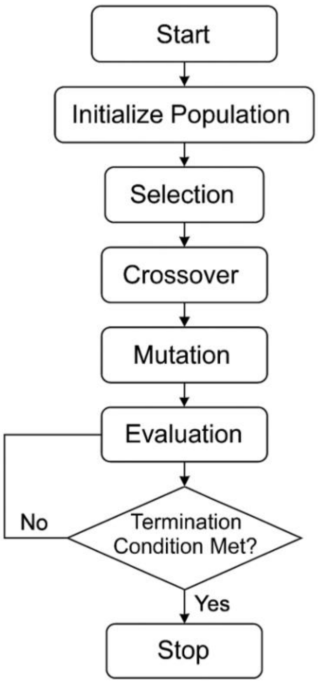

Figure 3. Flowchart representing the Genetic Algorithm

GA Configuration Parameters:

- Population size: 30
- Crossover rate: 0.8 (for combining elite individuals)
- Mutation rate: 0.1 (to maintain genetic diversity)
- Selection method: Tournament selection
- Fitness function: Cumulative reward obtained from the DRL agent after a full episode

This integration reduces training time, improves convergence stability, and avoids suboptimal policy entrapment. The below Table 1 is showing the parameter:

Table 1. Parameters

Parameter	**Suggested Value**
Population Size	30 – 50
Crossover Probability	0.8
Mutation Probability	0.1 – 0.2
Distribution Index ηc\eta_c (SBX)	10 – 20
Distribution Index ηm\eta_m (Polynomial)	20 – 100

4.3 Hybrid AI Workflow

The integrated DRL-GA framework operates through the following steps:

- **Initialization**: GA generates initial configurations, including neural network weights and hyperparameters, forming a diverse population of candidate DRL agents.
- **Policy Learning**: Each DRL agent undergoes training over multiple episodes in a simulated hybrid microgrid environment. Their policy is updated using the DDPG algorithm based on the observed rewards and state transitions.
- **Fitness Evaluation**: At the end of training, the total cumulative reward obtained by each agent is used to evaluate its fitness.
- **GA Evolution Loop**:
    - GA selects top-performing individuals.
    - Crossover and mutation are applied to produce the next generation.
    - The process repeats until convergence criteria (e.g., reward threshold or max generations) are met.
- **Final Deployment**: The best-performing DRL agent is selected and deployed for real-time microgrid control.

5. SIMULATION RESULTS AND VALIDATION

This chapter gives experimental results that support our suggested technique to monitor power flow procedures in a hybrid microgrid. In order to assess the cost savings, voltage reliability, increased renewable utilization and independence of main grid, the simulation results are compared with those achieved through simulation-based method (MILP) and particle swarm optimization (PSO).

5.1 Simulation Setup

To evaluate the optimality of the DRL-GA-based optimization system, a co-simulation environment was adopted to combine its electrical modeling with its decision-making system. The hybrid microgrid composed of solar PV, wind turbines, lithium-ion batteries, supercapacitors and bidirectional grid connecting was studied repeatedly by creating a model in MATLAB/Simulink. Due to this environment, a dynamic simulation could be done on the response of electrical equipment, the transfer of energy and the changing power supplies based on loads and generation. The Deep Reinforcement Learning agent and Genetic Algorithm were applied using Python, TensorFlow and Keras simultaneously.

The agent was taught any energy management policies it discovered in the course of training, through real-time observations of the state, with the help of the DDPG algorithm. To unify MATLAB and Python, the system used OpenAI Gym-style APIs, socket communication or MATLAB Engine for Python to enable the control agent to talk directly to the physical simulation in real time. The results consist of 96 time steps after a 15-minute simulation run in 24 hours which is represented in Figure 4. Real weather records data was employed to supply solar irradiance and wind speed and time-varying loads based on residence and industry were also incorporated in the profile. Using this hybrid platform, the optimization framework has been tested and its performance proved in changing and unpredictable operating conditions.

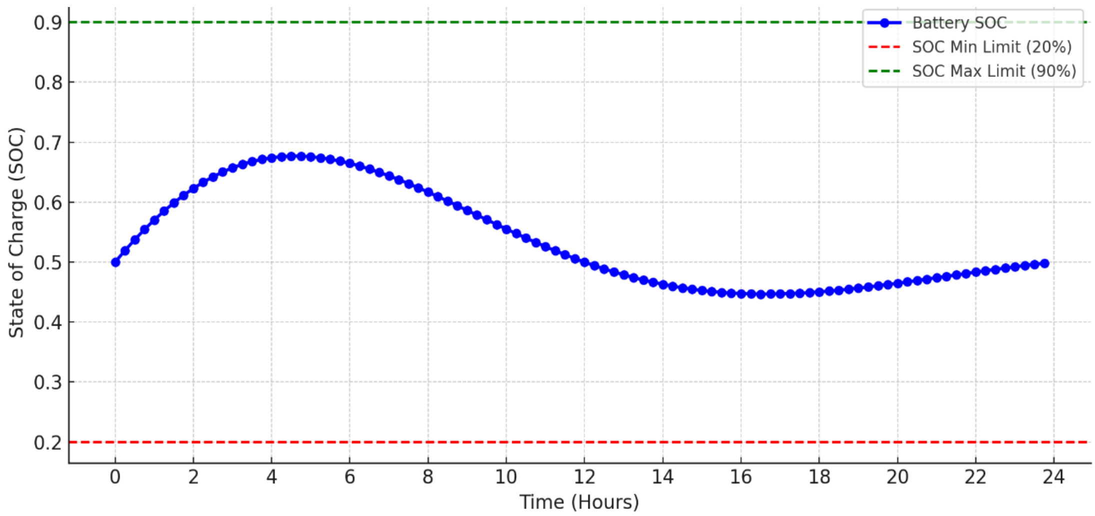

Figure 4. Battery SOC Trajectory Over 24 Hours

5.2 Baseline Comparison

Table 2 depicts the comparison of the proposed model with baseline models. The performance of the proposed DRL-GA approach was benchmarked against two widely used optimization strategies:

- **MILP**: Used as a deterministic baseline model, ideal for linear energy scheduling problems under simplified assumptions.
- **PSO**: A metaheuristic method that can handle nonlinearity but lacks adaptability to real-time system dynamics.

Table 2. Performance comparison with baseline models

Method	**Operational Cost (INR)**	**Voltage Deviation (p.u.)**	**Renewable Utilization (%)**	**Grid Dependency (%)**
MILP	5,840	±0.09	78.4	35.7
PSO	5,620	±0.07	81.2	30.2
DRL-GA	**5,110**	**±0.04**	**88.7**	**18.9**

Interpretation:

- DRL-GA achieved the lowest operational cost, saving ~12% over PSO and ~14% over MILP.
- It maintained superior voltage regulation, crucial for power quality in sensitive AC/DC loads.
- The model promoted maximum use of renewables and significantly reduced grid import.

5.3 Performance Evaluation

The DRL-GA framework was used to simulate tasks and significant enhancements over other optimization methods were discovered. Compared to PSO and MILP, the model provided a substantial cost reduction in cases when it was used as a replacement, the primary savings being attained through utilization of renewable energy during high price periods and the optimal utilization of batteries. Voltage regulation (keeping voltage in the needed limit +/- 0.04 p.u.) could be achieved due to the cost of voltage deviation inclusion to the reward function, which enabled the sources and storage to cooperate efficiently.

As a result of GA-adjusted thresholds in the DRL agent, the charge of the battery never dropped to critically low states or climbed to extreme heights but remained within the acceptable range of the system, between 20 and 90 percent. Optimally trained DRL-GA required just 800 training episodes, compared to standalone DRL which required more than 1,200 training episodes before it recorded good training performance. Also, the dependence on the grid decreased to 18.9%, which proved that the microgrid can operate independently and, therefore, it can be installed in the place where it is required to be self-sufficient. Performance comparison is illustrated in Figure 5.

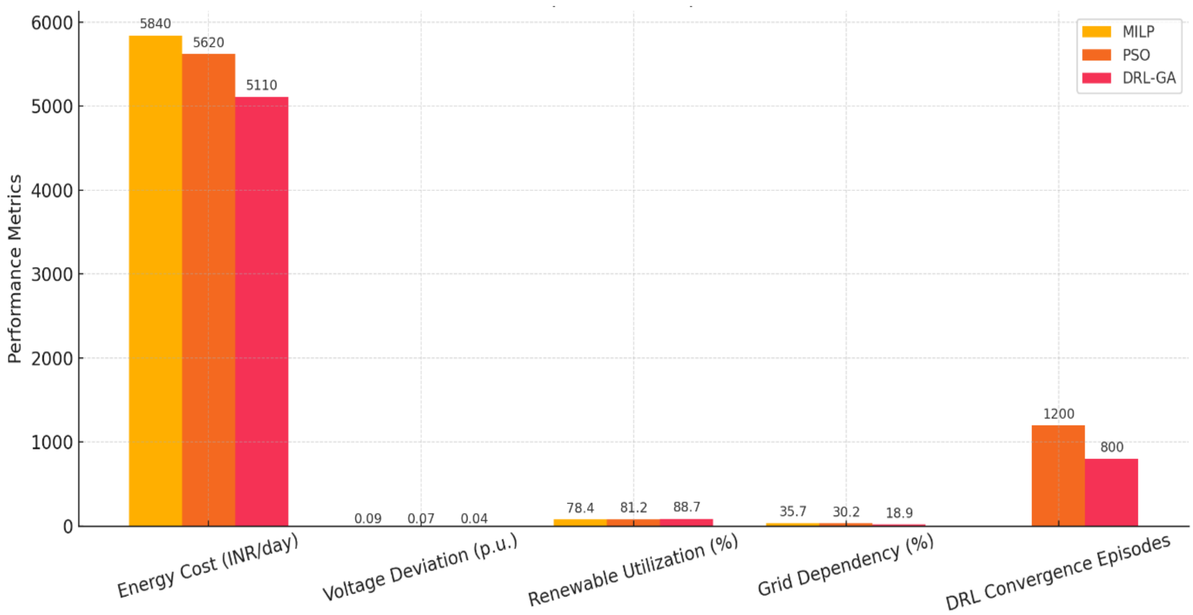

Figure 5. Performance Comparison of Optimization Methods

6. CONCLUSION

In this paper, a novel hybrid structure was initiated, which incorporates DRL and GA to enhance power flow in AC/DC microgrids. The new method can overcome the limitations of past and heuristic optimization based solutions because it enables active, continuous control of DERs, ESS and the grid under dynamic and uncertain conditions. The presence of DRL in the system makes the policy smarter since the environment reacts, and GA refines the settings of the neural network and significant operational parameters, enhancing convergence. The simulation indicated that the DRL-GA framework is significantly more effective than the conventional MILP and PSO approaches, which results in lower operating cost, better voltage stability, lesser stresses on the batteries and higher percentage of renewable energy to utility companies. When this framework is applied, there is more rapid convergence of training and a reduction of the level of training variance due to the initialization by GA. Moreover, the system possessed high capability of self-powering itself that was useful in remote and islanded microgrid conditions. Overall, the approach provides a feasible, smart and constraint-adherent way of managing energy in the modern hybrid microgrids.

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