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Multi-objective algorithm for hybrid microgrid energy management based on multi-agent system

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ABSTRACT

In the dynamic landscape of renewable energies, microgrid systems emerge as a promising avenue for fostering sustainable local energy generation. However, the effective management of energy resources holds the key to unlocking their full potential. This study assumes the task of creating a multi-objective optimization algorithm for microgrid energy management. At its core, the algorithm places a premium on seamlessly integrating renewable energy sources and orchestrating efficient storage coordination. Leveraging the prowess of a multi-agent system, it allocates and utilizes energy resources. Through the combination of renewable sources, storage mechanisms, and variable loads, the algorithm promotes energy efficiency and ensures a steady power supply. This transformative solution is underscored by the algorithm's remarkable performance in practical simulations and validations across diverse microgrid scenarios, offering a prevue into the future of sustainable energy utilization.

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NOMENCLATURE

D_{DC}	: Demand for DC loads	P_{SG}	: Power supplied from grid
D_{AC}	: Demand for AC loads	P_{excess}	: Wind and PV power excess
P_{PV}	: Photovoltaic energy production	BAT_{max}	: Maximal battery capacity
P_w	: Wind energy production	CAP_{max}	: Maximal capacitor capacity
P_{DC}	: Power supplied to DC loads	BOC	: Battery state of charge
P_{AC}	: Power supplied to AC loads	SOC	: Supercapacitor state of charge
P_{SPV}	: Power supplied by PV	F_{th}	: Rapid fluctuation threshold
P_{SW}	: Power supplied wind power	LC_{min}	: Minimum charge level of the supercapacitor
P_{SB}	: Power supplied by battery	LB_{min}	: Minimum charge level of the battery
P_{SS}	: Power supplied by supercapacitor	DF_{th}	: Rapid fluctuation threshold of the demand

1. INTRODUCTION

In the realm of renewable energies, microgrid systems offer a promising avenue for local and sustainable energy generation. Effectively harnessing energy resources constitutes a major challenge within this context. The intricate interplay among renewable energy sources, storage mechanisms, and consumption patterns demands sophisticated strategies to ensure uninterrupted power supply while optimizing available resources. The literature has explored various approaches to microgrid operations within energy management paradigms [1]–[3]. However, the potential of artificial intelligence techniques has notably emerged, particularly in systems exhibiting behaviors akin to microgrids [4]. Artificial intelligence and multi-agent systems have demonstrated exceptional performance in domains such as network management, intelligent platform interfaces, and database administration. For instance, multi-agent system or MAS are utilized to meet network energy demands, adjust power based on surplus and shortage information, and choose from various options, including coordination with power grids, battery storage systems, and controllable distributed generation plants [5]. Similarly, an intelligent bidding tactic employing a continuous double auction was implemented, enabling customer engagement in demand response initiatives [6]. In research [7], a multi-agent control mechanism was introduced for buildings, where agents operate according to a newly suggested comfort metric. Similarly, another building control system was introduced [8], emphasizing the management of energy consumption. These examples highlight the relevance and effectiveness of MAS in complex energy management. Energy management through MAS for implementing a hybrid system at high altitude is discussed in research [9], based on local information, to ensure efficient and stable system operation, distributed generation sources within microgrids are regulated by an energy management system. Some studies have also addressed Enhancing microgrid dependability via distributed power control for distributed energy resources, utilizing network and MAS along with communication delay technologies to efficiently oversee distributed demand [10].

Our investigation is rooted in the assumption that each agent resides within a multi-agent system, closely linked to specific microgrid elements. A distinctive feature of our approach lies in merging the MAS framework with an optimization algorithm. This fusion enhances the integration and efficient utilization of renewable energies while optimizing storage, employing batteries and supercapacitors within a hybrid architecture. This novel synergy optimizes energy distribution, ensuring efficient and balanced power supply. The primary aim of our work is to develop a multi-objective optimization algorithm for microgrid energy management. This algorithm prioritizes renewable energy integration and efficient coordination of storage between batteries and supercapacitors.

The structure of this article entails examining fundamental aspects and requirements in section 1 that frame our energy management approach within microgrid systems. Moving forward to section 2, we outline ambitious energy management goals within microgrid systems. The microgrid architecture and the proposed multi-agent's system architecture are presented in section 3.1. In section 3.2, we develop an adaptive algorithm designed to coordinate interactions among microgrid components. Section 4 focuses on practical simulation and validation, translating theoretical expertise into empirical confirmation of the efficiency and adaptability of our algorithmic framework in various real microgrid scenarios. Throughout each of these sections, our goal is to comprehensively present our innovative energy management approach and highlight its transformative potential for sustainable energy utilization within microgrid systems.

2. ENERGY MANAGEMENT GOALS FOR A SUSTAINABLE MICROGRID: PROPOSED APPROACH

Within the scope of our approach to microgrid management using a multi-agent system, several objectives have been established to optimize energy utilization and enhance the overall system performance. Among these objectives, we focus on four primary goals that are of paramount importance for the sustainable development of the microgrid. First, our priority is to ensure the environmental sustainability of the microgrid. The seamless integration of renewable energy sources is a fundamental objective in this regard. By maximizing the proportion of renewable energy in the energy mix, our aim is to significantly reduce fossil fuel consumption and greenhouse gas emissions [11], [12]. This approach will contribute to environmental preservation and facilitate a transition towards cleaner and renewable energy. Furthermore, cost minimization is a key objective in microgrid management [13]. Through the intelligent use of batteries and supercapacitors, we seek to reduce electricity procurement costs from the main grid by storing excess energy generated from renewable sources. This optimization of resource management aims to achieve maximum economic efficiency.

Ensuring the reliability and resilience of the microgrid is also a major priority. By employing batteries and supercapacitors to ensure stable power supply, we aim to promptly detect production or demand fluctuations within the system. This approach will maintain network stability and ensure uninterrupted power supply, even during external disruptions. Lastly, energy efficiency lies at the core of our objectives. Through optimal management of energy sharing among renewable sources for mutual DC and AC load feeding, coupled with the use of machine learning algorithms to anticipate energy production and demand, we aim to maximize the utilization of available resources and minimize energy losses. This approach will enable us to optimize the overall efficiency of the microgrid and reduce energy wastage.

2.1. Cause-and-effect relationships among primary objectives

These four primary objectives are closely interconnected, with cause-and-effect relationships highlighting their interdependence. These cause-and-effect relationships underscore the interdependence of primary objectives, illustrating how targeted actions in one domain can have positive implications in others, contributing to a balanced and sustainable overall energy management in the microgrid. The diagram in Figure 1 illustrates these various relationships.

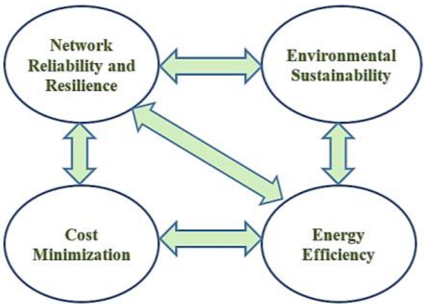

Figure 1. Cause-and-effect relationships among primary objectives

A balanced and integrated approach to energy management will synergistically achieve these goals. The use of a multi-agent system will enable a coherent and coordinated optimization of these objectives, ensuring optimal energy management for the microgrid [14], [15].

a) Environmental sustainability <=> energy efficiency:
   - Cause: By adopting measures to enhance energy efficiency, the microgrid reduces energy consumption, contributing to the preservation of natural resources and the reduction of greenhouse gas emissions.
   - Effect: Improved environmental sustainability prompts the microgrid to embrace more efficient energy practices, as heightened awareness of the importance of reducing energy consumption is reinforced.
b) Cost minimization <=> energy efficiency:
   - Cause: Through improved energy efficiency, the microgrid reduces energy consumption, leading to decreased electricity procurement and maintenance costs.
   - Effect: Cost minimization motivates the microgrid to invest in energy efficiency solutions, as substantial long-term financial savings can be realized.
c) Cost minimization <=> network reliability and resilience:
   - Cause: Cost minimization drives the microgrid to optimize resource utilization and invest in cutting-edge technologies to lower operational costs, potentially enhancing network reliability and resilience.
   - Effect: Greater network reliability and resilience mitigate costly disruptions and economic losses, thereby contributing to long-term cost minimization.
d) Energy efficiency <=> network reliability and resilience:
   - Cause: More efficient energy utilization reduces demand peaks and network strain, potentially improving network stability and resilience.
   - Effect: Enhanced network reliability and resilience maintain optimal energy performance by reducing the risk of outages and interruptions that could affect energy efficiency.
e) Network reliability and resilience <=> environmental sustainability:
   - Cause: A more reliable and resilient network can better handle fluctuations in renewable energy production, ensuring optimal utilization of these clean energy sources and reinforcing environmental sustainability.
   - Effect: Environmental sustainability drives the microgrid to invest in technologies and practices that enhance network reliability and resilience, preserving the environmental benefits of renewable energy sources.

2.2. Mechanisms for achieving primary objectives

The sub-objectives of integrating or maximizing renewable energies, collaborative energy sharing for enhanced efficiency, optimized use of storage, demand and production prediction, and control play a crucial role in achieving the four primary objectives of microgrid energy management. For these objectives, the use of specific technological tools proves essential. Firstly, the multi-agent system emerges as a significant asset for coordinating the diverse entities within the microgrid [16], such as renewable energy sources, storage systems, and consumers, allowing effective communication and decentralized decision-making. Simultaneously, renewable energy prediction through advanced models and artificial intelligence algorithms is a key element in anticipating the availability of clean energy sources, thereby facilitating their optimal integration into the microgrid [17]–[19]. Thus, the microgrid can aim for advanced, resilient, cost-effective, and environmentally friendly energy management, providing a promising energy future for local communities.

The diagram presented below in Figure 2 illustrates the objectives and means associated with energy optimization within our microgrid. This visual representation aims to highlight the interconnectedness between various energy targets. Each objective constitutes a fundamental pillar of our comprehensive approach.

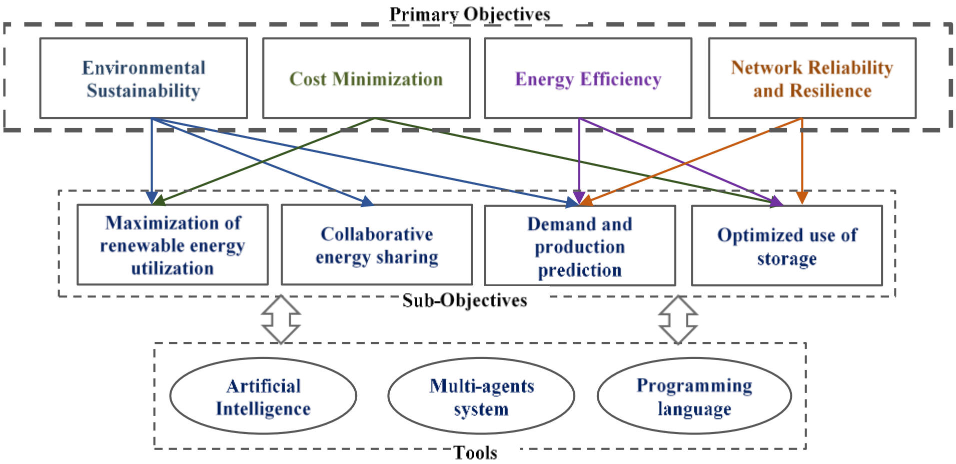

Figure 2. The objectives and means associated with energy optimization

3. THE DEVELOPED ALGORITHM FOR MICROGRID MANAGEMENT USING A MULTI-AGENT SYSTEM APPROACH

3.1. Modelling the smart grid as a multi-agent system

In this section, we delve into modeling the microgrid as a multi-agent system. This approach considers the microgrid components as individual agents, each with its own set of behaviors, roles, and interactions. By doing so, we can effectively capture the complex dynamics and interactions within the microgrid system. The agents can encompass various entities such as renewable energy sources, loads, energy storage systems, and even the central grid connection. The microgrid's operations and decision-making processes are distributed among these agents, allowing for autonomous actions and local optimization strategies. This modeling approach enables us to achieve a holistic view of the microgrid's behavior as well as taking into account the interactions between the different components and their responses to various conditions, such as changing energy availability and demand fluctuations.

3.1.1. The proposed architectural plan for microgrid

The envisaged design for the microgrid entails the integration of renewable energy sources (RE) alongside a diverse array of AC and DC loads. This configuration is supervised by an innovative modular system rooted in MAS. The chosen configuration is a hybrid architecture, combining the benefits of both DC bus and AC bus architectures by employing AC/DC and DC/AC power converters. Renewable energy source generators are connected to a DC bus, where energy is stored using energy storage devices and subsequently converted into alternating current (AC) through DC/AC power converters to supply AC loads. This architecture provides greater flexibility in energy management by leveraging the advantages of direct current energy storage and alternating current energy injection into the electrical grid [20], [21].The typical hybrid bus configuration is depicted in Figure 3 [22].

3.1.2. Proposed multi-agent system

Our energy management approach is defined by the collaborative interaction among various components within the system and the grid to accomplish predetermined goals. In our model, agents function as entities integrated across the grid infrastructure, encompassing renewable energy generation sources, energy storage units, and intelligent sensors in residential settings. Our model introduces the deployment of eight distinct agent types, each delineated alongside their interrelationships as depicted in Figure 4.

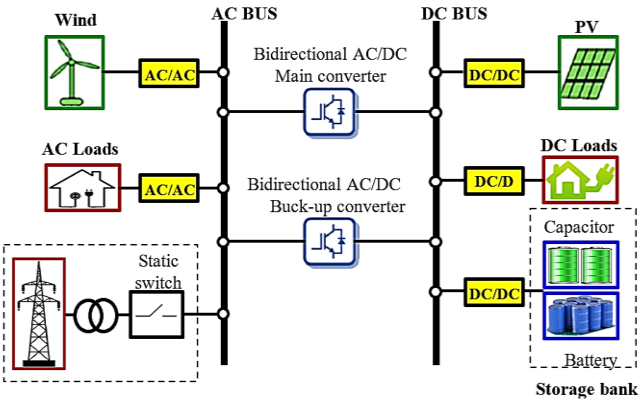

Figure 3. The typical configuration of the hybrid bus microgrid

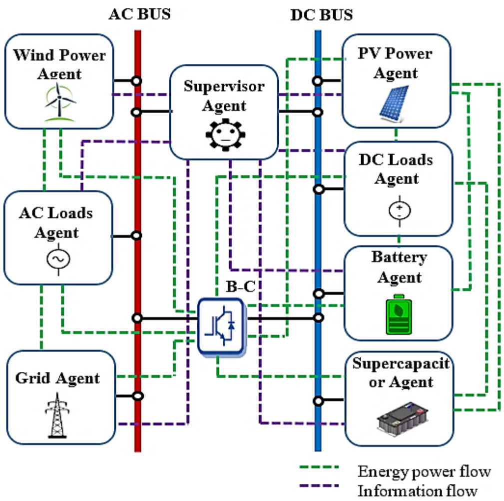

Figure 4. The proposed multi-agent's system

A key feature of our system lies in its capacity to store excess energy generated by renewable sources. Storage agents, whether batteries or supercapacitors, intervene based on the fluctuation of energy production and demand. The decision to use supercapacitors or batteries depends on the dynamics of load fluctuations and energy production fluctuations. Supercapacitors are favored for rapid and frequent changes, both for load supply and excess energy storage, while batteries are better for more stable or gradually changing conditions [23]. The algorithm assesses these conditions in real-time to make informed choices between supercapacitors and batteries, ensuring efficient load supply and energy storage in the microgrid.

Furthermore, our system ensures consistency and coordination among different energy sources and load types. For instance, surplus solar energy is utilized to power DC loads, while excess wind energy caters to AC loads. If necessary, this surplus energy can be redistributed to power other load types through bidirectional converters.

In the multi-agent system, various agents play distinct roles in managing the microgrid effectively. The supervisor agent oversees the entire system, gathering data from other agents, conducting analyses, and making global decisions to optimize renewable energy utilization while balancing supply and demand [24]. Wind and photovoltaic energy prediction agents utilize models to forecast future energy production, aiding in precise energy management planning. [25]. AC and DC demand agents monitor the energy needs of their respective loads, adjusting consumption based on predictions [26]. The battery agent manages energy storage, determining when to store or release energy. The supercapacitor agent intervenes when energy fluctuations exceed a set threshold, rapidly supplying energy as needed. Finally, the network agent handles connections to the external grid, serving as a backup when other sources are insufficient or storage systems are depleted.

Power and information flow within the microgrid operate in tandem to ensure efficient energy management and distribution [27]. The power flow initiates from renewable energy sources such as wind and solar, which supply energy to AC and DC loads according to their specific demands. Any surplus energy can be stored in batteries or supercapacitors for later use. If local energy demands exceed available supply, the grid can be utilized as a supplementary source. Simultaneously, the information flow facilitates coordination among agents. Prediction agents furnish forecasts to demand and storage agents, enabling proactive energy planning. Demand agents relay current and projected energy requirements to storage agents and the supervisor for optimization. Storage agents, informed by this data and predefined thresholds, make decisions regarding energy storage and release. Finally, the supervisor integrates information from all agents to make global decisions aimed at maximizing renewable energy utilization and meeting energy demands effectively.

The interactions between agents within the microgrid system are vital for efficient energy management and optimization. Initially, prediction agents generate forecasted data on energy production, considering factors like weather conditions and historical trends. This predictive information is shared with demand and storage agents, enabling informed decision-making based on anticipated energy availability. Storage agents, in particular, rely on these predictions along with real-time energy demands to determine optimal storage strategies. They assess forecasts and current demands continuously, deciding whether to store excess energy during peak production periods or release stored energy to meet sudden spikes in demand. As the central coordinator, the supervisor agent plays a crucial role in optimizing microgrid operations. By analyzing predictions, energy storage decisions, and real-time demand, it formulates strategies to maximize renewable energy utilization. One unique aspect of the system is its dynamic priority allocation between supercapacitors and batteries. Supercapacitors take precedence during significant energy fluctuations, offering rapid response times to address sudden energy needs efficiently. While the system prioritizes renewable energy utilization and storage solutions, there are instances where local resources may be insufficient. In such cases, the grid connection to the external power network is activated as a last resort to ensure continuous energy supply.

3.2. Algorithm development

In this section, we delve into the creation of the algorithm. Our objective is to design an intelligent and adaptive algorithm that orchestrates the interactions among agents within the microgrid. To achieve this, we formulate a set of rules, guidelines, and decision matrices that guide the behavior of each agent. These rules are carefully crafted to align with the objectives of maximizing renewable energy, efficient energy storage, and responsiveness to demand. The algorithm takes into account real-time data from prediction agents, decisions from the energy storage agent, and the overarching strategy defined by the supervisor.

The algorithm addresses three key aspects of energy management. Firstly, it focuses on optimizing the utilization of renewable energy sources and ensuring efficient distribution to DC and AC loads based on input parameters such as demands and energy production. Secondly, it efficiently manages excess energy from photovoltaic and wind sources by storing it in batteries or supercapacitors, aiming to enhance overall system performance. Lastly, the algorithm addresses remaining net demand by evaluating fluctuations in DC and AC loads. If there is a net demand for DC loads, and fluctuations exceed a threshold, the algorithm draws from stored capacitor energy to meet the demand, adjusting the capacitor's energy level accordingly. This algorithm has been implemented using the Python programming language, with a specific library dedicated to simulating multi-agent systems and microgrids called Mesa which stand for multi-agent simulation environment. This library provides a set of tools and functionalities to efficiently create, simulate, and evaluate interactions and agent behavior within the microgrid.

3.2.1. Sub-algorithm 1: Renewable energy allocation and cooperation algorithm for load supply

This sub-algorithm focuses on optimizing renewable energy utilization and cooperation in supplying loads. Given input parameters such as DC and AC demands, photovoltaic and wind energy productions, it calculates power distribution to DC and AC loads. The algorithm considers net demands and prioritizes renewable sources to ensure efficient energy allocation:

- Initialize the power variables for different sources and loads:
  P_{DC}, P_{AC}, P_{SPV}, P_{SW}, P_{SB}, P_{SS}, P_{SG} all set to 0.
  Loop through the data series:
  For i in range (length of D_{DC}):
- Calculate net demand for DC and AC loads:
  $Net\_D_{DC} = max\ (0, D_{DC}[i] - P_{PV}[i])$
  $Net\_D_{AC} = max\ (0, D_{AC}[i] - P_{w}[i])$
- Supply DC loads using photovoltaic production:
  $P_{SPV} = min\ (D_{DC}[i], P_{PV}[i])$
  $P_{DC} = P_{SPV}$
- Supply AC loads using wind production:
  $P_{SW} = min\ (D_{AC}[i], P_{w}[i])$
  $P_{AC} = P_{SW}$

- Utilize wind production if photovoltaic production is insufficient for DC loads:

```
if Net_DDC > 0:
PSW += min (Net_DDC, Pw[i] - PAC)
PDC += min (Net_DDC, Pw[i] - PAC)
Net_DDC = max (0, Net_DDC - min (Net_DDC, Pw[i] - PAC))
```

- Utilize photovoltaic production if wind production is insufficient for AC loads:

```
if Net_DAC > 0:
PSPV += min (Net_DAC, PPV[i] - PDC)
PAC+= min (Net_DAC, PPV[i] - PDC)
Net_DAC = max (0, Net_DAC - min (Net_DAC, PPV[i] - PDC))
```

3.2.2. Sub-algorithm 2: Energy excess management for battery and supercapacitor

This sub-algorithm focuses on efficiently managing energy excess from photovoltaic (PV) and wind sources by storing it in batteries or supercapacitors without exceeding their maximum capacity. The main goal is to optimize the utilization of surplus energy to enhance system performance. In the subsequent section, we will delve into a specific scenario within the algorithm, focusing on the case where the excess energy stems solely from photovoltaic production. This scenario is captured by the condition "If $P_{PV}[i] - D_{DC}[i] > 0$ and $P_w[i] - D_{AC}[i] < 0$". While we will elaborate on the particulars of this case, it is important to note that the underlying reasoning remains consistent across all three scenarios, regardless of whether the excess energy originates from wind energy, photovoltaic energy, or a combination of both:

- Calculate the surplus energy from photovoltaic (PV) and wind sources:

```
Pexcess = PPV[i] + Pw[i] - DDC[i] - DAC[i]
```

- Check if there is surplus energy to manage:

```
if Pexcess > 0:
```

- Determine the energy storage mechanism based on production and demand conditions:

```
If PPV[i]- DDC[i] >0 and Pw[i]- DAC[i] <0:
```

- Calculate the fluctuation in PV production:

```
fluctuationPV = abs (PPV[i] - PPV[i-1])
if fluctuationPV >= rapid fluctuation threshold:
```

- Store the surplus energy in supercapacitors up to their capacity

```
SOC+= min (Pexcess , CAPmax - SOC)
Pexcess -= min (Pexcess , CAPmax - SOC)
if Pexcess >0:
```

- Store the rest in battery up to their capacity

```
BOC += min (Pexcess , BATmax - BOC)
else:
```

- Store the surplus energy in battery up to their capacity

```
BOC += min (Pexcess , BATmax - BOC)
```

3.2.3. Sub-algorithm 3: Enhancing load supply efficiency through optimized storage selection and grid support

This sub algorithm is responsible for addressing the remaining net demand by either utilizing the energy stored in the battery/supercapacitor or by drawing from the grid. The process begins by calculating the fluctuations in demand for DC and AC loads compared to their previous values. If there is still a net demand for DC loads, the algorithm evaluates the demand's fluctuations. If the fluctuations exceed a threshold, the algorithm aims to first draw from the capacitor's stored energy to meet the demand. If the net demand is within the capacitor is remaining capacity (above a certain minimum threshold), the DC load is supplied directly from the capacitor's energy, and the capacitor's energy level is adjusted accordingly.

If the remaining net demand is greater than the capacitor's capacity, the algorithm ensures the load is supplied using the battery's stored energy. If the net demand still exceeds the battery's remaining capacity, the grid is tapped to fulfill the remaining demand. Similar principles apply for the case of AC loads. The same logic is followed for handling cases where the demand fluctuations exceed a predefined threshold The code effectively manages load supply using the available energy sources, considering different storage options and resorting to the grid when necessary.

In the subsequent sections of this sub algorithm, we will delve into the scenario where the net direct current (DC) demand is positive (net DC demand > 0), and the fluctuations in this demand are deemed significant. We will elaborate on how this positive net DC demand is catered to, prioritizing the utilization of energy stored in the supercapacitor, followed by the battery, before resorting to grid energy if necessary. It is important to note that the reasoning and approach presented in this section is also applied to other similar cases, such as scenarios where the net DC demand is positive but with insignificant fluctuations, as well as situations where the net alternating current (AC) demand is positive. In summary, this particular case offers an intricate insight into the methodology adopted to address diverse energy demands while adhering to storage and grid constraints:

- Verify the load requirements

```
if Net_DDC > 0 :
fluctuationDemandDC = abs(DDC [i] - DDC [i-1])
if fluctuationDemandDC > DFth :
if Net_DDC <= (SOC - LCmin):
```

- Supply the DC load with the energy stored in the capacitor

```
PSS = Net_DDC
PDC += PSS
SOC -= PSS
else:
```

- Supply the DC load with the energy stored in the capacitor up to the minimum threshold

```
PSS = SOC - LCmin
PDC += PSS
SOC -= PSS
Net_DDC -= PSS
if Net_DDC <= (BOC - LBmin):
```

- Supply the DC load with the energy stored in the battery

```
PSB = Net_DDC
PDC += PSB
BOC -= PSB
else:
PSB = BOC - LBmin
PDC += PSB
BOC -= PSB
Utilize grid energy to meet the remaining net demand
PSG = Net_DDC - PSB
PDC += PSG
```

4. SIMULATIONS AND VALIDATION

In order to comprehensively evaluate the effectiveness of our proposed approach, we conducted simulations using Python's Multi-Agent Simulation Environment. These simulations involved generating demand and production profiles through Python scripts. We systematically explored a range of scenarios to highlight the algorithm's potential impact on optimizing the management of usage priorities among renewable energy sources, storage devices, and the grid. Our analysis extended to effectively handling the storage of surplus and deficit energy, dynamically allocating resources between batteries and capacitors based on fluctuations in demand and production. Through these simulations, we aimed to demonstrate how our algorithm enhances energy distribution and storage efficiency, facilitating the optimal utilization of renewable sources while effectively addressing variations and fluctuations in energy demand and supply.

The graph in Figure 5 illustrates the energy sharing between photovoltaic (PV) and wind sources in a microgrid. The two-colored bars represent the sharing of excess energy between the two sources. It highlights the dynamics of cooperation between renewable sources. The result presented in the circular graph of Figure 6 illustrates the sharing of excess energy between DC and AC buses. When renewable sources generate more energy than required to power the associated loads, our algorithm directs the surplus solar energy towards AC loads, while the 'Wind to DC' segment represents the share of excess wind energy shared with DC loads. This leads to an optimal utilization of available resources and an overall increase in energy efficiency within the microgrid.

The graph in Figure 7 visually presents the distribution of power sources in a microgrid to meet the energy demands of both direct current (DC) and alternating current (AC) loads. Each colored bar in the graph corresponds to a specific power source and illustrates its role in providing energy to the loads. The segment labeled 'PV power generation' shows the contribution of photovoltaic panels in supplying energy specifically to DC loads. Similarly, the 'WIND power generation' segment represents the portion of energy from wind sources that is utilized to power AC loads. Furthermore, the graph includes segments such as 'Power supplied by battery,' 'Power supplied by supercapacitor,' and 'Power supplied by the grid.' These segments indicate the contribution of different energy storage and supply mechanisms. The 'Power supplied by battery' segment reflects the role of the battery in meeting energy demands, the 'Power supplied by supercapacitor' segment signifies the contribution of the supercapacitor, and the 'Power supplied by the grid' segment represents the energy sourced from the external grid.

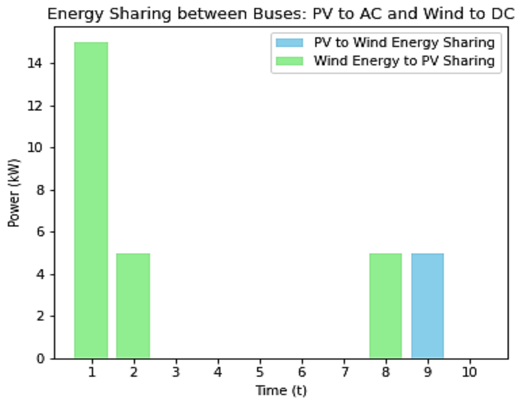

Figure 5. Energy sharing between buses: PV to AC and wind to DC

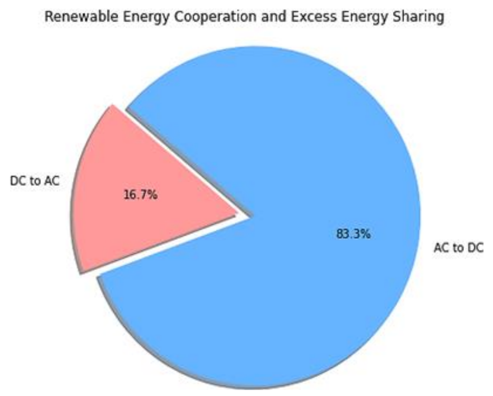

Figure 6. Excess energy sharing between buses

By analyzing the results across various simulation scenarios and carefully scrutinizing the data presented in Table 1. In the presence of fluctuations, the algorithm prioritizes the optimized utilization of energy stored in the supercapacitor after the depletion of renewable resources, with occasional utilization of the supercapacitor to ensure uninterrupted supply (scenario 4). On the contrary, in simulation scenarios 2 and 3, priority is given to the battery for powering loads, as long as the minimum storage threshold is not reached. When there is an excess of renewable energy production, our algorithm favors storage in batteries, unless notable production fluctuations occur. In the latter case, excess energy is stored in the supercapacitor, as showcased in scenario 8 (refer to Tables 2 and 3). Furthermore, when renewable resources are depleted and storage devices have reached their minimal thresholds, our algorithm invokes grid power to cater to load demands, as illustrated by scenario 10. These outcomes vividly demonstrate the flexibility and efficiency of our algorithm in managing diverse energy conditions. It adeptly adapts to demand and production variations, strategically harnessing different available storage sources to ensure reliable and optimized energy supply, while concurrently reducing dependence on the conventional grid.

Table 1. Demand fluctuations

Scenarios	Fluctuations in DC demand	Fluctuations in AC demand	Need for storage devices
S1	NaN	NaN	NO
S2	5.00%	0.00%	YES
S3	10.00%	20.00%	YES
S4	-15.00%	-30.00%	YES
S5	-5.00%	15.00%	YES
S6	25.00%	-15.00%	NO
S7	-20.00%	5.00%	NO
S8	15.00%	5.00%	NO
S9	-15.00%	5.00%	NO
S10	10.00%	20.00%	YES

Table 2. Production fluctuations

Scenarios	PV fluctuation	Wind power fluctuation	Excess production
S1	NaN	NaN	YES
S2	5.00%	-20.00%	NO
S3	10.00%	10.00%	NO
S4	-5.00%	-25.00%	NO
S5	0.00%	10.00%	NO
S6	25.00%	-10.00%	NO
S7	-5.00%	5.00%	YES
S8	-5.00%	20.00%	YES
S9	-5.00%	-15.00%	YES
S10	5.00%	-5.00%	NO

Table 3. Evolution of storage level

Scenarios	Evolution of battery storage level	Evolution of supercapacitor storage level
S1	NaN	NaN
S2	-10.00%	0.00%
S3	-15.00%	0.00%
S4	0.00%	-5.00%
S5	-5.00%	0.00%
S6	0.00%	0.00%
S7	0.00%	0.00%
S8	0.00%	20.00%
S9	0.00%	0.00%
S10	-5.00%	-5.00%

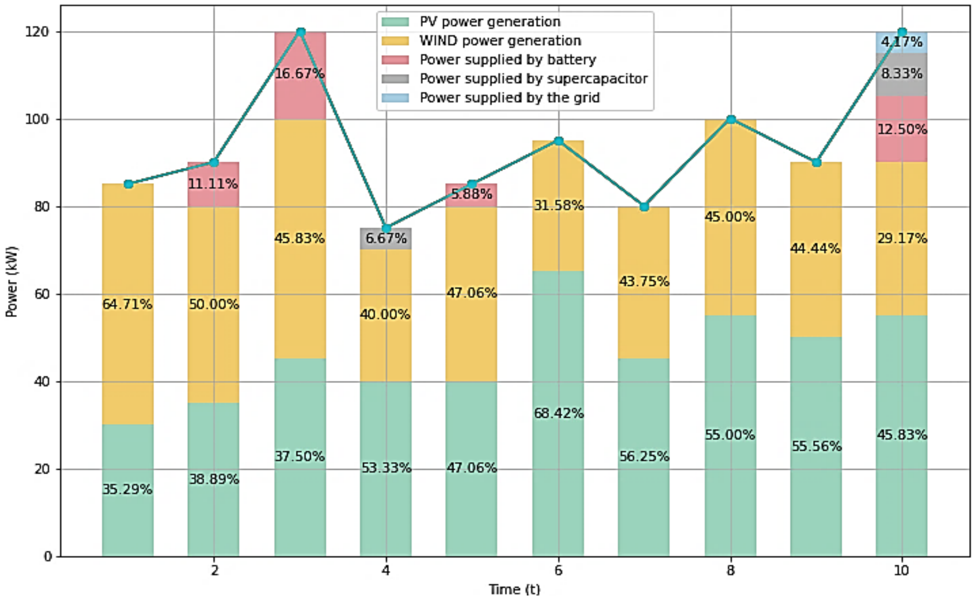

Figure 7. Power sources contributing to load supply component

5. CONCLUSION

In conclusion, our study delves into the context of renewable energies and microgrid systems, highlighting their potential for local and sustainable energy generation. However, the efficient management of energy resources presents a pivotal challenge in optimizing their utilization due to the intricate interplay between renewable energy sources, storage mechanisms, and consumption patterns. Our primary objective has been the development of a multi-objective optimization algorithm tailored for energy management within microgrids. This algorithm prioritizes the seamless integration of renewable energy sources and ensures effective storage management between batteries and supercapacitors. At the core of our approach lies the utilization of a multi-agent system, facilitating efficient coordination of energy distribution and utilization within the microgrid. By harnessing the synergy among renewable energy sources, storage units, and variable loads, the algorithm aims to enhance energy efficiency while maintaining a consistent and balanced power supply to the connected loads.

Our efforts to comprehensively evaluate the efficacy of our proposed approach involved simulations conducted within Python's multi-agent simulation environment, covering a range of scenarios. These simulations aimed to showcase the algorithm's impact on optimizing usage priorities among renewable energy sources, storage devices, and the grid. Notably, our algorithm dynamically allocates resources between batteries and capacitors based on demand and production fluctuations, effectively managing the storage of surplus and deficit energy. The outcomes of our study unveil the algorithm's versatility and efficiency in managing diverse energy conditions, adeptly adapting to variations in demand and production. By strategically leveraging various available storage sources, it ensures dependable and optimized energy supply while diminishing reliance on conventional grid sources. In summary, our work advances the understanding and application of energy management within microgrids, offering a valuable contribution to the optimization of renewable energy utilization. Through the integration of innovative algorithms and multi-agent systems, we pave the way for more resilient and sustainable energy solutions in the microgrid landscape.

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