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Implementation of a Fuzzy Logic Controller for Long-Term Energy Management in a Hybrid AC/DC Microgrid

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ABSTRACT

This paper presents the design and evaluation of a fuzzy logic controller (FLC) for long-term energy management in a hybrid AC/DC microgrid. The study is based on the Smart Energy Office Building (SEOB) system, which integrates photovoltaic (PV) generation, a lithium-ion battery, and a hydrogen-based energy storage system consisting of an electrolyzer, hydrogen tank, and fuel cell. Conventional rule-based state machine control (SMC) methods are limited by their rigidity and inability to adapt to dynamic operating conditions. To address this limitation, a Mamdani-type fuzzy inference system is developed using key system variables, including battery state of charge, power imbalance, and hydrogen storage level. The proposed FLC is implemented in a MATLAB/Simulink environment and evaluated through long-term simulations, including a full-year scenario, a summer week, and a winter week, using real measured data. The results demonstrate that the FLC achieves smoother control behavior, reduces switching frequency, and improves coordination between energy storage components compared with SMC. Specifically, it reduces battery cycling, extends continuous operation of the fuel cell, and enhances overall system stability. While slightly increasing grid interaction, the FLC enables a more balanced and efficient energy distribution within the microgrid. The findings confirm that fuzzy logic control provides a robust, computationally efficient, and interpretable solution for long-term energy management in hybrid microgrids, offering significant potential for improving system performance and component lifetime.

1. Introduction

Modern buildings also offer significant potential for flexible energy management, as their large and time-varying electricity demand enables the coordinated use of photovoltaic (PV) generation, battery storage, and hydrogen-based systems. Integrating distributed renewable generation and hybrid energy storage systems into such buildings can reduce dependence on the mains grid, lower operating costs, and contribute to CO2-neutral operation. Rosales-Asensio *et al.,* [1] demonstrated that combining PV and an electrochemical storage in office building microgrids not only reduces life-

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cycle energy costs but also enhances the system's ability to maintain critical loads during rare grid disturbances. Their findings highlight the growing importance of local microgrids as a means to increase both energy efficiency and supply security.

At the Institute of Electrical Energy Systems and High-Voltage Technology (IEH) at Karlsruhe Institute of Technology (KIT), the Smart Energy Office Building (SEOB) project pursues exactly this idea. It transforms an existing institute building into a testbed for a hybrid AC/DC microgrid integrating PV generation, a lithium-iron-phosphate (LiFePO4) battery, an electrolyzer, a hydrogen storage tank, and a fuel cell. Earlier simulation work by Wöhr *et al.,* [2] verified that such a hybrid energy storage system (HESS) can substantially increase self-consumption and reduce grid dependency over an entire year when controlled by a state machine-based power management strategy. However, the rule-based control is rigid and cannot adequately handle dynamic transitions or continuously changing operating conditions.

In contrast, intelligent and data-driven methods have shown great potential to enhance flexibility in building energy management. Among them, fuzzy logic control (FLC) stands out as an intuitive and robust approach that can effectively manage the uncertainty and nonlinearity inherent in real building environments. As showed by Kontogiannis *et al.,* [3], fuzzy logic provides a transparent and computationally efficient framework for decision-making, allowing control strategies to be expressed through interpretable linguistic rules rather than relying on detailed system models or advanced optimization techniques. This makes FLC particularly suitable for hybrid energy systems, where numerous interacting components and fluctuating renewable sources introduce considerable variability.

At the same time, advanced control methods such as model predictive control (MPC) have proven to enhance performance in predictive scheduling tasks. For example, Langner *et al.,* [4] experimentally compared FLC and MPC for thermal demand-response operation, focusing primarily on heating dynamics in identical buildings at KIT's Living Lab Energy Campus. Their study showed that while MPC achieves the highest cost savings under highly dynamic pricing, FLC provides comparable results with significantly lower computational effort. This trade-off is especially relevant for the SEOB microgrid, where long-term simulations, hourly sampling, and multi-energy interactions require a control strategy that is not only effective but also computationally efficient and easily interpretable. Motivated by these advantages, this thesis focuses on developing and evaluating a fuzzy logic-based control strategy for the SEOB microgrid to achieve stable, efficient, and interpretable long-term energy management.

1.1 Energy Management Strategies in Microgrids

Energy management systems (EMS) are responsible for coordinating power flows among distributed energy resources and storage units within a microgrid. Conventional EMS implementations are often based on rule-based control strategies due to their simplicity and straightforward implementation. In such systems, predefined rules determine the operating states of energy storage devices according to system variables such as power imbalance or battery state-of-charge (SOC). These approaches are widely used in practical microgrid applications because they require limited computational resources and can operate reliably in real-time control environments [5,6].

However, rule-based methods rely on fixed thresholds and predefined operating conditions, which may reduce their adaptability under highly variable renewable generation conditions. As renewable penetration increases, the variability of photovoltaic and wind generation introduces greater uncertainty in system operation, making static control strategies less effective [7].

To improve control performance, optimization-based energy management approaches have been widely studied. Techniques such as linear programming, mixed-integer linear programming, and dynamic programming have been applied to determine optimal scheduling of distributed energy resources in microgrids [8,9]. These methods typically aim to minimize operational costs or maximize renewable energy utilization while satisfying system constraints. Despite their effectiveness, optimization-based approaches often require accurate system models and high computational effort, which can limit their application in real-time control environments [10].

MPC has also been proposed as an advanced control strategy for microgrid energy management. MPC uses predictive models to anticipate future system states and optimize control decisions within a defined prediction horizon [11]. Although MPC can effectively handle system constraints and uncertainties, its practical implementation often requires high computational capability and accurate forecasting models [12].

1.2 Hybrid Energy Storage Systems in Microgrids

Energy storage systems play a critical role in balancing power fluctuations caused by intermittent renewable generation. Among various storage technologies, battery energy storage systems are widely adopted due to their fast response time and high efficiency. Lithium-ion batteries, in particular, have become the dominant technology for short-term energy storage in many microgrid applications [13].

For long-term energy storage, hydrogen-based energy storage systems have gained increasing attention. In these systems, surplus renewable electricity can be converted into hydrogen via electrolysis, stored in hydrogen tanks, and later converted back into electricity using fuel cells when required [14]. This power-to-hydrogen-to-power cycle allows energy to be stored over long periods and can support large-scale energy balancing.

Consequently, hybrid energy storage systems combining batteries and hydrogen storage have been widely investigated in recent studies [15,16]. In such systems, batteries typically provide short-term power balancing, while hydrogen storage systems serve as long-term energy buffers. However, coordinating these storage technologies introduces significant control challenges due to their different dynamic characteristics and operational constraints [17].

1.3 Fuzzy Logic Control for Microgrid Energy Management

To address the nonlinear and uncertain characteristics of renewable energy systems, intelligent control methods have increasingly been applied in microgrid energy management. Among these methods, fuzzy logic control has received considerable attention because it can handle complex system behavior without requiring precise mathematical models [18].

Fuzzy logic controllers operate using linguistic variables, membership functions, and rule-based inference mechanisms to determine control actions. This approach enables the controller to incorporate expert knowledge and manage multiple input variables simultaneously [19].

Several studies have demonstrated the effectiveness of fuzzy logic control in renewable energy systems. For instance, fuzzy controllers have been applied to regulate battery charging and discharging in photovoltaic microgrids, improving system stability and energy utilization efficiency [20]. Other studies have applied fuzzy logic strategies to coordinate multiple energy storage devices in hybrid renewable energy systems [21,22]. Compared with conventional rule-based approaches, fuzzy logic-based energy management strategies can provide smoother control responses and better adaptability under varying operating conditions [23].

Although numerous energy management strategies have been proposed for microgrids, several challenges remain. Many existing studies focus primarily on short-term operational control rather than long-term energy management. In addition, the coordination of battery storage and hydrogen-based energy storage remains a complex control problem because these technologies exhibit different dynamic characteristics and time scales.

Furthermore, hybrid AC/DC microgrids introduce additional operational complexity because power flows must be coordinated between AC and DC subsystems. Therefore, developing an effective energy management strategy capable of coordinating photovoltaic generation, battery storage, and hydrogen-based storage within such hybrid architectures remains an important research challenge.

To address these challenges, this study proposes a fuzzy logic-based energy management strategy for a hybrid AC/DC microgrid integrating photovoltaic generation, lithium-ion battery storage, hydrogen storage, electrolyzers, and fuel cells.

The main goal of this paper is to design, implement, and evaluate a fuzzy-logic control for long-term energy management of the SEOB hybrid AC/DC microgrid. The controller aims to coordinate the interaction between the PV system, the LiFePO4 battery, the electrolyzer, and the fuel cell to maintain energy balance and minimize reliance on the AC mains grid. To achieve this, a compact FLC structure is designed with defined input and output variables that reflect the system's operational states. The controller is implemented within the existing SEOB Simulink model. To evaluate system stability, energy balance, and component utilization, long-term simulations are performed for three representative operating periods: a year-round scenario, a summer week, and a winter week. Finally, the fuzzy logic control structure is compared with the state machine control previously developed to evaluate its advantages and limitations in hybrid microgrid operation.

2. Methodology

This section presents the architecture of the studied hybrid microgrid system and the design of the proposed fuzzy logic-based energy management strategy. The methodology includes the system architecture of the SEOB microgrid, the overall control structure, and the detailed design of the fuzzy inference system used to coordinate multiple energy storage components.

2.1 System Architecture of the SEOB Microgrid

The proposed energy management strategy is implemented within the simulation framework of the SEOB microgrid model. The SEOB system represents a hybrid AC/DC microgrid that integrates renewable energy sources, multiple energy storage technologies, and controllable loads within a unified energy management framework.

The microgrid consists of two interconnected subsystems: an AC subsystem and a DC subsystem. The AC subsystem is connected to the utility grid and supplies conventional AC loads, while the DC subsystem integrates renewable generation units and energy storage components. Power exchange between the AC and DC subsystems is realized through bidirectional power converters.

The DC subsystem includes several key components:

- PV generation system

- lithium-ion battery energy storage system
- electrolyzer unit
- hydrogen storage tank
- fuel cell system

The photovoltaic system provides renewable electricity to the DC bus. The battery storage system is primarily used for short-term energy balancing due to its fast response capability. The hydrogen-based storage system, consisting of an electrolyzer, hydrogen tank, and fuel cell, provides long-term energy storage by converting electrical energy into hydrogen and reconverting it into electricity when required.

When excess renewable energy is available, the electrolyzer converts electrical energy into hydrogen, which is stored in the hydrogen tank. During periods of energy deficit, the stored hydrogen can be converted back into electricity using the fuel cell. This hybrid energy storage configuration allows the microgrid to balance both short-term and long-term energy fluctuations. The overall system architecture enables coordinated operation of renewable generation and hybrid energy storage components while maintaining power balance within the microgrid in Figure 1.

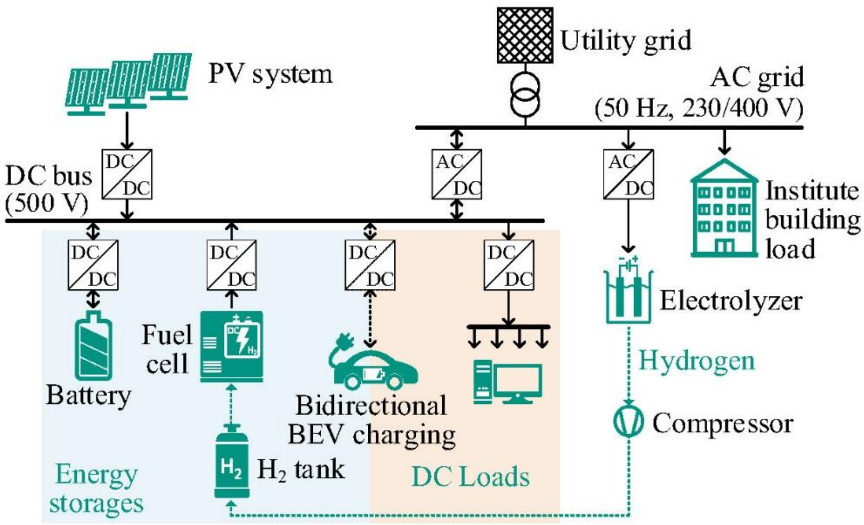


Fig. 1. Structure of the SEOB Microgrid System

2.2 Energy Management Control Structure

To coordinate the operation of the different energy storage components, an energy management controller is implemented within the SEOB microgrid model. The controller determines the operating states of the battery system, electrolyzer, and fuel cell based on the current system conditions.

The control strategy considers three key system variables:

- battery SOC
- power balance condition of the microgrid
- hydrogen storage level

The power balance condition represents the difference between renewable generation and load demand. Positive power imbalance indicates surplus renewable energy, while negative imbalance indicates a deficit in generation.

Based on these system variables, the controller determines the appropriate control actions for:

- battery charging or discharging
- activation of the electrolyzer for hydrogen production
- operation of the fuel cell for electricity generation

Compared with conventional rule-based strategies, the proposed control approach employs a fuzzy logic inference system to handle nonlinear system dynamics and uncertainties in renewable generation. The fuzzy controller receives system measurements as inputs and generates control signals for the corresponding energy storage components in Figure 2.

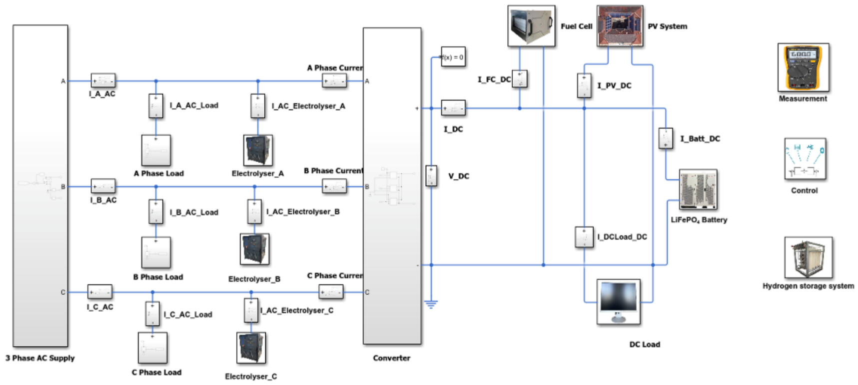


Fig. 2. Overall Control Structure of the Energy Management System

2.3 Fuzzy Inference system (FIS)

The energy management strategy is implemented using a FLC. Fuzzy logic control is particularly suitable for microgrid energy management because it can effectively handle nonlinear system behavior and uncertainties without requiring precise mathematical models.

The FIS serves as the core decision-making layer of the fuzzy logic controller. It translates the simulated system states into the appropriate control actions for the battery, fuel cell and electrolyzer. The FIS used in this thesis is based on the Mamdani-type fuzzy model, which performs nonlinear decision mapping between inputs and outputs through predefined linguistic rules. Figure 3 shows the overall structure of the FIS implemented in Simulink.

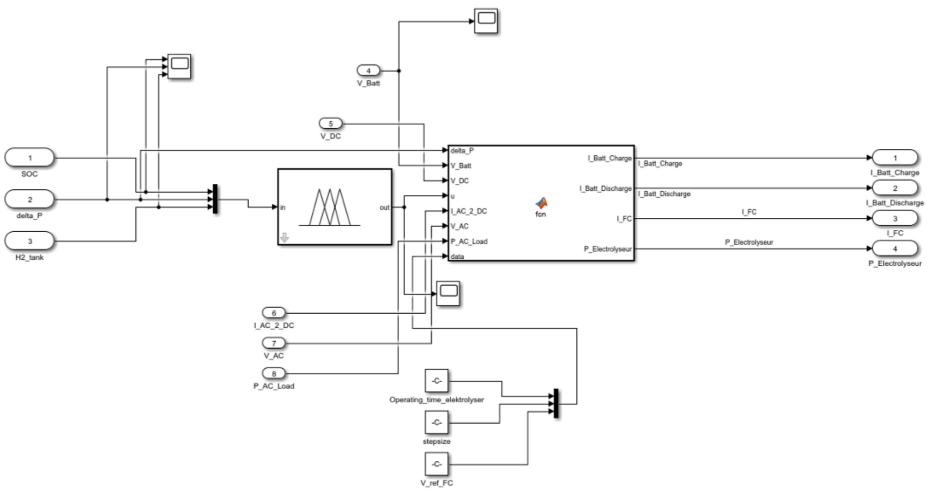


Fig. 3. Overall structure of the FIS implemented in Simulink

2.3.1 Fuzzy inference process

The fuzzy inference process converts precise input data into control outputs through three main steps: fuzzification, fuzzy inference and defuzzification. Figure 4 shows the fuzzy inference system for the SEOB energy management controller.

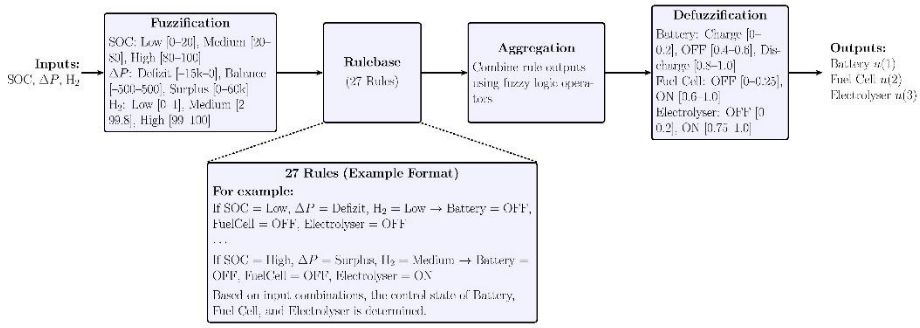


Fig. 4. Diagram of the fuzzy inference system

The fuzzification step converts each crisp input value into its corresponding degree of membership in a fuzzy set. In this thesis, triangular membership functions are used for all input variables. For a triangular MF, the membership degree increases linearly towards the centre of the fuzzy set and decreases linearly outside of it.

The inference mechanism combines the rule base and the current system states to generate fuzzy output sets. The FIS applies the Mamdani inference model, which simulates human reasoning processes in uncertain environments.

The logical operations are defined as follows: AND operator: minimum (min); OR operator: maximum (max).

Since fuzzy outputs cannot be applied directly to physical systems, they must be converted into precise values through a reverse process known as defuzzification. Common defuzzification methods include the centroid, maximum membership, and weighted average approaches [24].

2.3.2 Definition of input and output variables

All input signals are measured within the SEOB model and the output signals are transferred to the MATLAB Function block for execution. The controller uses three input variables:

1. Battery SOC
2. Power imbalance of the microgrid (Δ P)
3. Hydrogen storage level (H_2 level)

Based on these inputs, the controller generates three output control signals:

1. Battery control signal
2. Fuel cell control signal
3. Electrolyzer control signal

2.3.3 Membership functions design

Membership functions are used to describe the linguistic variables associated with the input and output parameters of the fuzzy controller.

The battery SOC input is divided into three linguistic variables representing different operating conditions of the battery system:

- Low
- Medium
- High

Similarly, the power imbalance variable (Δ P) represents the difference between generation and load demand. It is also divided into three linguistic regions with Negative, Zero, Positive, which representing energy deficit, balanced condition, and energy surplus.

The hydrogen storage level is defined according to the current amount of stored hydrogen in the tank and indicates whether the hydrogen storage capacity is low, medium, or high.

The output variables control the operating states of the battery, fuel cell, and electrolyzer. For the battery system, the controller determines whether the battery should charge, discharge, or remain idle. The fuel cell and electrolyzer outputs determine whether these devices should be activated under the current operating conditions.

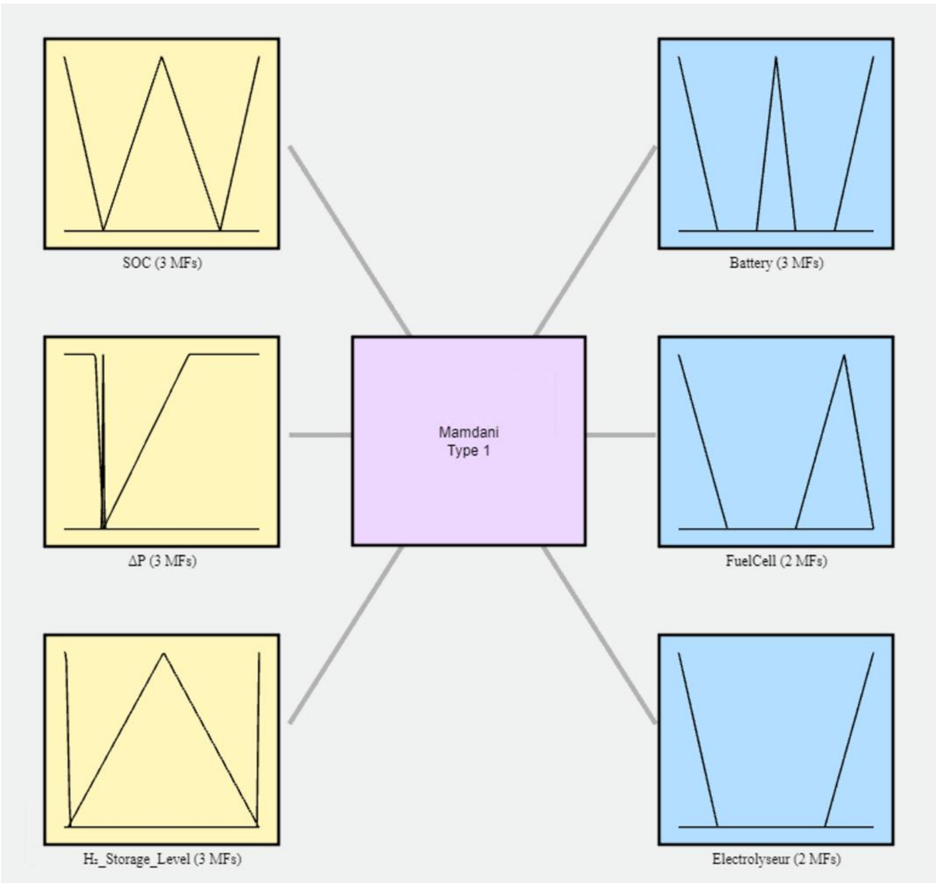


Fig. 5. Membership Functions of the Input Variables

The membership functions are designed to reflect the operational characteristics of the microgrid and the storage components. The shapes and ranges of the membership functions were selected based on the operational characteristics of the microgrid components and empirical observations from previous system operation in Figure 5.

2.3.4 Rule base design

The control decisions of the fuzzy logic controller are defined through a set of fuzzy inference rules. These rules describe the relationship between system states and control actions using linguistic expressions.

Each rule consists of a combination of input conditions and corresponding output actions. For example, a typical fuzzy rule can be expressed as:

IF SOC is Low AND Δ P is Negative AND H_2 level is Low

THEN Fuel Cell is ON AND Battery is Discharge

The complete rule base is constructed by considering different combinations of system states. In this study, the fuzzy controller uses a total of 27 rules derived from expert knowledge of microgrid operation in Table 1.

Table 1
Fuzzy Rule Base for Energy Management

No.	Δ P	SOC	H_2 Level	Battery Contral	Fuel Cell Control	Electrolyzer Control
1	Deficit	Low	Low	Off	Off	Off
2	Deficit	Low	Medium	Off	On	Off
3	Deficit	Low	High	Off	On	Off
4	Deficit	Medium	Low	Discharge	Off	Off
5	Deficit	Medium	Medium	Discharge	Off	Off
6	Deficit	Medium	High	Discharge	Off	Off
7	Deficit	High	Low	Discharge	Off	Off
8	Deficit	High	Medium	Discharge	Off	Off
9	Deficit	High	High	Discharge	Off	Off
10	Balance	Low	Low	Off	Off	Off
11	Balance	Low	Medium	Off	Off	Off
12	Balance	Low	High	Off	Off	Off
13	Balance	Medium	Low	Off	Off	Off
14	Balance	Medium	Medium	Off	Off	Off
15	Balance	Medium	High	Off	Off	Off
16	Balance	High	Low	Off	Off	Off
17	Balance	High	Medium	Off	Off	Off
18	Balance	High	High	Off	Off	Off
19	Surplus	Low	Low	Charge	Off	Off
20	Surplus	Low	Medium	Charge	Off	Off
21	Surplus	Low	High	Charge	Off	Off
22	Surplus	Medium	Low	Charge	Off	Off
23	Surplus	Medium	Medium	Charge	Off	Off
24	Surplus	Medium	High	Charge	Off	Off
25	Surplus	High	Low	Off	Off	On
26	Surplus	High	Medium	Off	Off	On
27	Surplus	High	High	Off	Off	Off

These rules ensure that the energy storage components operate cooperatively to maintain system stability and optimize energy utilization.

2.3.5 Implementation of control output (matlab function)

The final stage of the fuzzy control process converts the fuzzy outputs u(1), u(2) and u(3) into physical control signals within the SEOB model in Figure 6. This process is implemented through a MATLAB Function block that executes the control logic for the battery, fuel cell and electrolyzer.

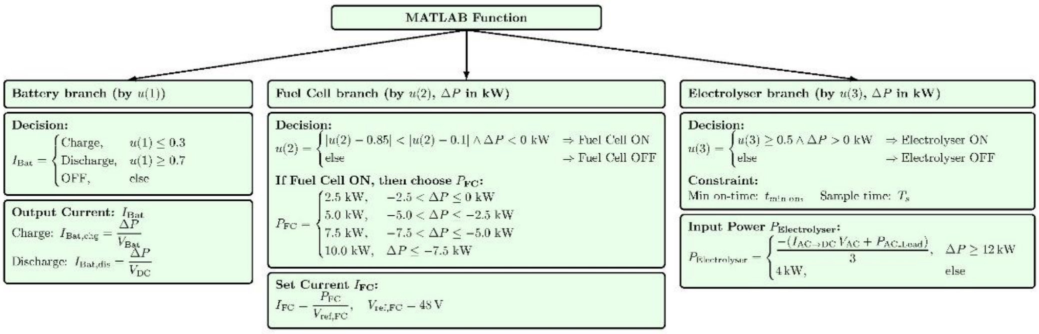


Fig. 6. Diagram of Matlab Function

3 Results

This section presents the simulation-based evaluation of the proposed FLC for long-term energy management in the SEOB hybrid AC/DC microgrid. Following the structure of the original thesis, the results are reported for three representative cases: a full-year simulation, a summer-week simulation, and a winter-week simulation. In all cases, the FLC is compared with the previously implemented state machine control (SMC) under identical input data and initial conditions, so that observed differences can be attributed to the control strategy itself rather than to external conditions.

3.1 Simulation Setup

All simulations were carried out in MATLAB/Simulink using the SEOB hybrid AC/DC microgrid model. The simulation step size was set to 60 s. The input data were based on real measured profiles in Figure 7: the PV generation data were taken from the ETI institute rooftop system for 2023, and the AC-side load data were taken from annual building load measurements of the IEH institute. The DC-side load was represented by a synthetic but realistic profile reflecting typical DC consumers such as servers or personal computers. Three representative cases were selected for analysis: a year-round simulation, a summer week with high PV generation, and a winter week with low renewable generation and stronger deficit conditions. The monitored indicators include energy balance, battery SOC, hydrogen storage level, component operating time, switching frequency, and grid exchange.

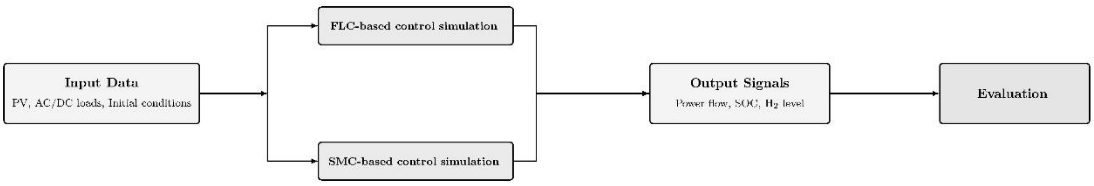


Fig. 7. Overview of the simulation framework and workflow

For the year-round case, the simulation covers the period from 1 May 2023 to 30 April 2024 in Table 2. The initial battery SOC was set to 70%, and the initial hydrogen tank level was set to 15%.

The main component parameters were retained from the original SEOB model, including a 60 kW PV system, a 150 kWh LiFePO4 battery, a 10 kW PEM fuel cell, an electrolyzer operating in the 4–48 kW range, and a 20,000 L hydrogen tank.

Table 2
Main component parameters and initial conditions

Component	Symbol	Value	Description
PV system	$P_{PV,max}$	**60,000 W**	**PV power**
Battery	E_{Batt}	**150,000 Wh**	**LiFePO4 battery capacity**
Battery initial SOC	SOC_0	**70 %**	**Initial state of charge**
Fuel cell	$P_{FC,max}$	**10,000 W**	**4*2.5 kW/stack**
Electrolyzer	P_{EL}	**4,000–48,000 W**	**Operating power range**
Hydrogen tank	Vol_{tank}	**20,000 L**	**High-pressure hydrogen storage tank**
Hydrogen initial level	H_2	**15 %**	**Initial fill level**
DC bus voltage	V_{DC}	**500 V**	**DC bus voltage**
AC grid voltage	V_{AC}	**230 V**	**AC voltage (single-phase)**

The summer-week simulation covers the period from 4 July 2023 (05:30) to 10 July 2023 (21:45), representing one of the highest-PV weeks in the year. The initial conditions were SOC = 70% and H2 level = 60%.

The winter-week simulation covers the period from 1 December 2023 (08:45) to 7 December 2023 (16:45), representing a typical low-generation and high-demand week. The initial conditions were again SOC = 70% and H2 level = 60%.

3.2 Full-Year Simulation
3.2.1 Time-Series overview

The full-year results reveal a clear seasonal pattern under both control strategies in Figure 8 and Figure 9. PV generation is high during summer and significantly reduced in winter, whereas the DC load remains nearly constant throughout the year. The AC-side exchange and electrolyzer operation follow the availability of surplus renewable power. Under both controllers, the battery SOC varies roughly within the intended operating range, while the hydrogen tank fills during high-generation months and is depleted during winter periods.

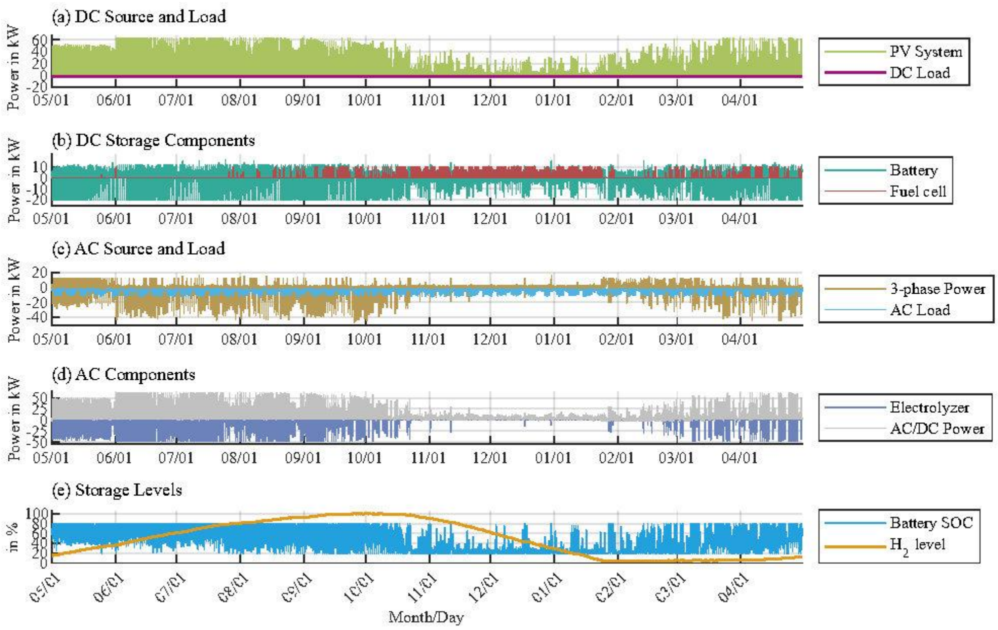


Fig. 8. Year-round result plot (State Machine Control)

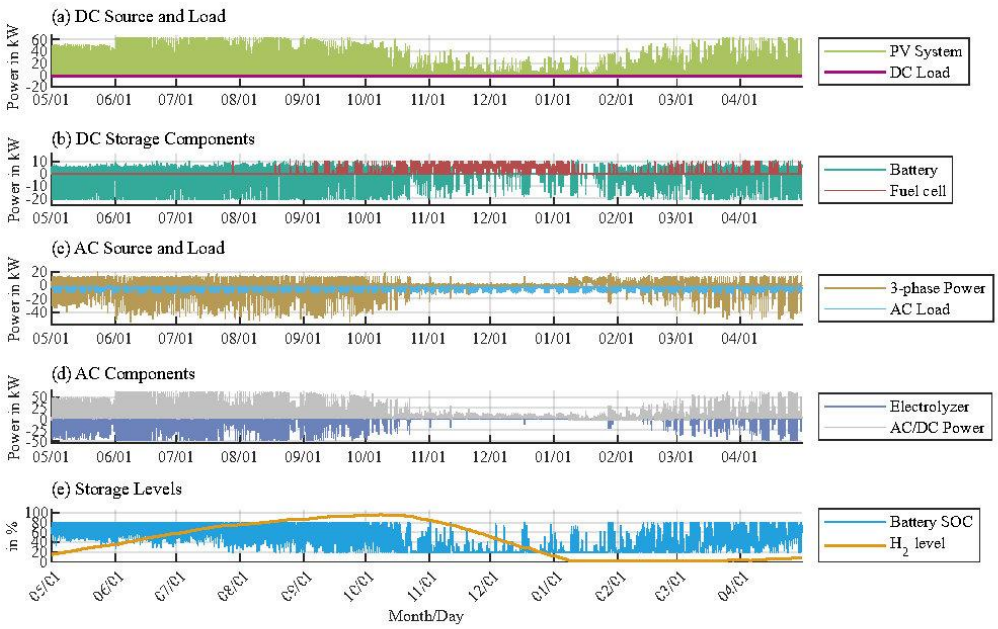
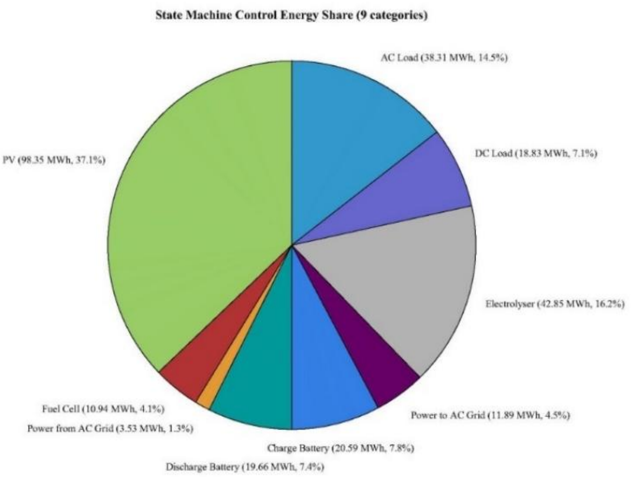


Fig. 9. Year-round result plot (Fuzzy Logic Control)

Although both controllers maintain the long-term energy balance of the microgrid, the annual plots indicate that the FLC produces smoother control trajectories. In particular, the battery and fuel cell curves show fewer short-term fluctuations than under SMC, which already suggests reduced switching activity and less aggressive cycling. This observation is confirmed quantitatively below.

3.2.2 System-Level energy balance

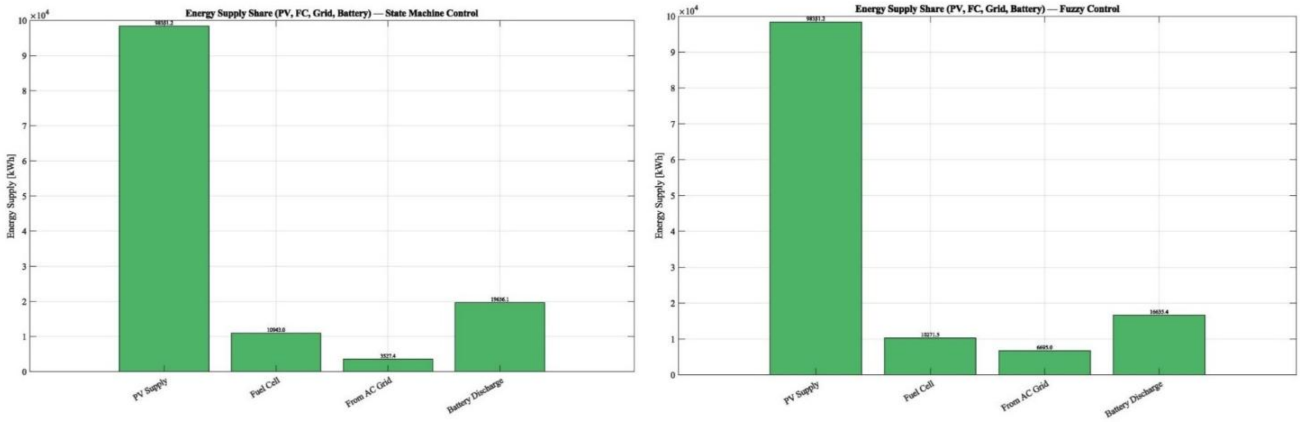
The annual energy shares highlight an important difference between both control strategies in Figure 10. In both cases, PV contributes 98.35 MWh and remains the dominant primary energy source. However, the use of surplus energy differs significantly. Under SMC, 42.85 MWh are consumed by the electrolyzer, while only 11.89 MWh are exported to the AC grid. Under FLC, electrolyzer consumption decreases to 22.76 MWh, whereas grid export increases sharply to 33.66 MWh. At the same time, both battery charging and discharging energies decrease from 20.59/19.66 MWh to 17.47/16.64 MWh.



(a) (b)

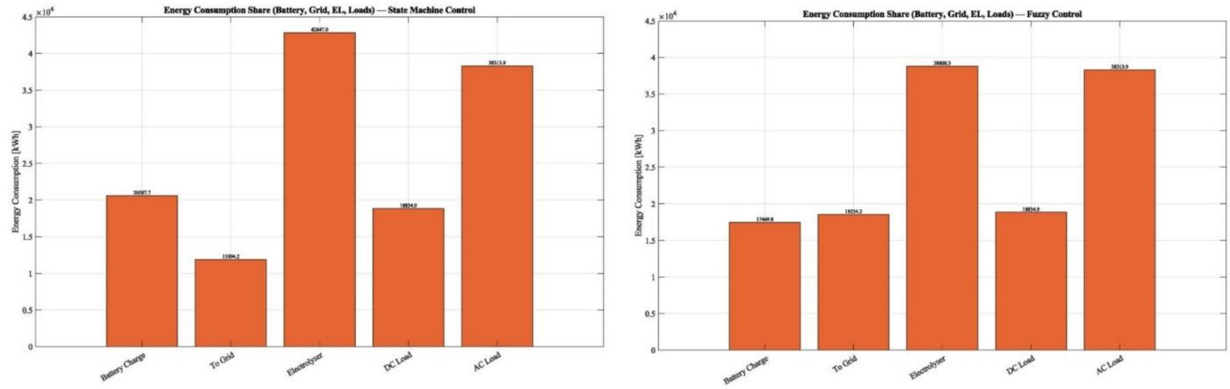
Fig. 10. Energy share distribution (a) State machine control energy share (9 categories) (b) Fuzzy control energy share (9 categories)

This shift indicates that the FLC relies less on repeated battery cycling and directs a larger fraction of surplus energy toward grid export rather than hydrogen production. The bar-chart view of annual supply and consumption confirms this redistribution in Figure 11 and Figure 12. Under FLC, annual grid import rises from 3.53 MWh to 5.42 MWh, and grid export increases markedly. On the consumption side, AC and DC loads remain identical by construction, but the electrolyzer consumes less energy under FLC.



(a) (b)

Fig. 11. Energy supply share (a) Energy supply share (PV, FC, Grid, Battery)-State Machine Control (b) Energy supply share (PV, FC, Grid, Battery)-Fuzzy Control



(a) (b)

Fig. 12. Energy consumption share (a) Energy Consumption Share (Battery, Grid, EI, Loads)-State Machine Control (b) Energy Consumption Share (Battery, Grid, EI, Loads)-Fuzzy Control

Overall, both controllers achieve an annual energy balance of about 132 MWh, but the FLC changes how energy is buffered and redistributed: less battery throughput, less electrolyzer consumption, and more active use of grid exchange.

3.2.3 Component operation analysis

The annual component statistics further clarify the operational differences. For the fuel cell, the number of activations drops from 517 under SMC to 209 under FLC, while the total operating time even increases slightly from 1474.3 h to 1523.9 h. This means that the FLC keeps the fuel cell on for longer continuous periods rather than switching it on and off frequently. For the battery, the reduction is even more pronounced: charging starts decrease from 1879 to 934 and discharging starts from 1438 to 713. Battery charged and discharged energies both fall by about 15%.

For the electrolyzer, the situation is more nuanced. Under FLC, the number of starts slightly increases from 249 to 273 and operating time rises from 1479.8 h to 1615.0 h in Table 3, but total consumed energy decreases from 42.85 MWh to 38.80 MWh in the table-based comparison. This indicates smoother, lower-power operation and fewer inefficient high-power bursts. At the system level, the hydrogen tank never reaches the absolute maximum under FLC (95.8% versus 100% under SMC), which is consistent with the lower electrolyzer energy and higher grid export.

Table 3
Overview of component operation statistics in the year-round scenario

Metric	Description	State Machine Control	Fuzzy Control	Difference
PV	Total supplied energy	98 351.21 kWh	98 351.21 kWh	/
Fuel Cell	Number of activations	517 times	209 times	↓ 60%
	Total operating time	1474.3 h	1523.9 h	↑3%
	Total supplied energy	10 943.0 kWh	10 271.5 kWh	↓ 6%
Electrolyzer	Number of activations	249 times	273 times	↑10%
	Total operating time	1479.8 h	1615.0 h	↑9%
	Total consumed energy	42 846.96 kWh	38 800.28 kWh	↓ 9.4%
H_2 level	Maximal level	100 %	95.8 %	↓ 4.2%
Battery charge	Number of activations	1879 times	934 times	↓ 50%
	Total operating time	3313.9 h	1446.2 h	↓ 56%
	Total charged energy	20 587.69 kWh	17 469.75 kWh	↓ 15%
Battery discharge	Number of activations	1438 times	713 times	↓ 50%

	Total operating time	**4123.4 h**	**3505.7 h**	**↓ 15%**
	Total discharged energy	**19 656.08 kWh**	**16 635.43 kWh**	**↓ 15%**
	Battery loss rate	**4.525 %**	**4.776 %**	**↑6%**
DC load	**Total consumed energy**	**18 834.93 kWh**	**18 834.93 kWh**	**/**
AC load	**Total consumed energy**	**38 313.90 kWh**	**38 313.90 kWh**	**/**
Grid exchange	**Energy exported to grid**	**11 894.25 kWh**	**18 534.28 kWh**	**↑56%**
	Energy imported from grid	**3527.43 kWh**	**6694.96 kWh**	**↑90%**

In summary, the annual results show that the FLC produces a more continuous operating pattern with fewer switching events and lower battery throughput, at the cost of higher interaction with the external grid.

3.3 Summer-Week Simulation

3.3.1 Power flow and control behavior

The summer-week case represents a surplus-dominated operating condition with strong daily PV peaks. Under both controllers, the system successfully absorbs the surplus through a combination of battery charging, electrolyzer operation, and export to the AC grid in Figure 13 and Figure 14. However, the short-term dynamics differ clearly. Under SMC, the electrolyzer follows a distinct threshold-driven on/off behavior, while the SOC spans a relatively wider range. Under FLC, the transitions between charging, discharging, and hydrogen production are smoother, and the hydrogen level remains comparatively stable during the week.

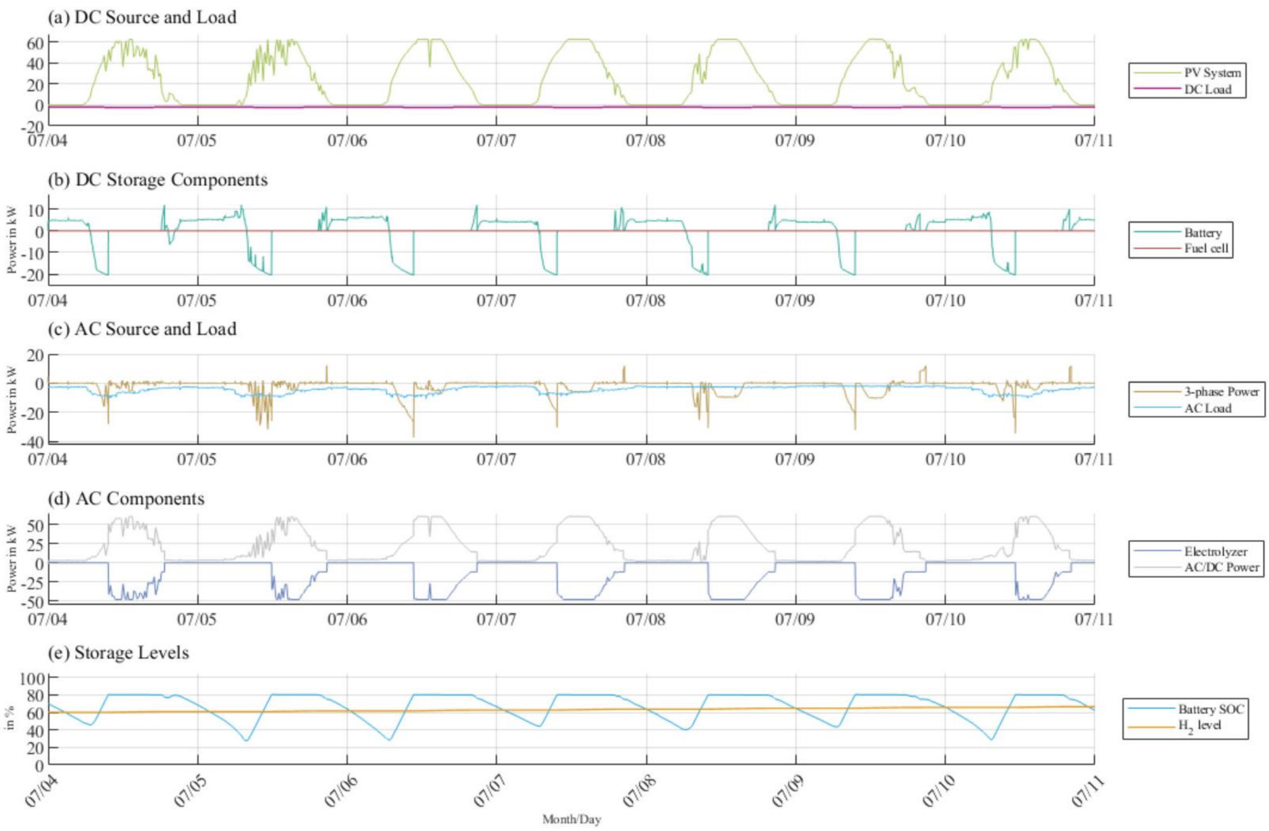


Fig. 13. Summer weeks result plot (State Machine Control)

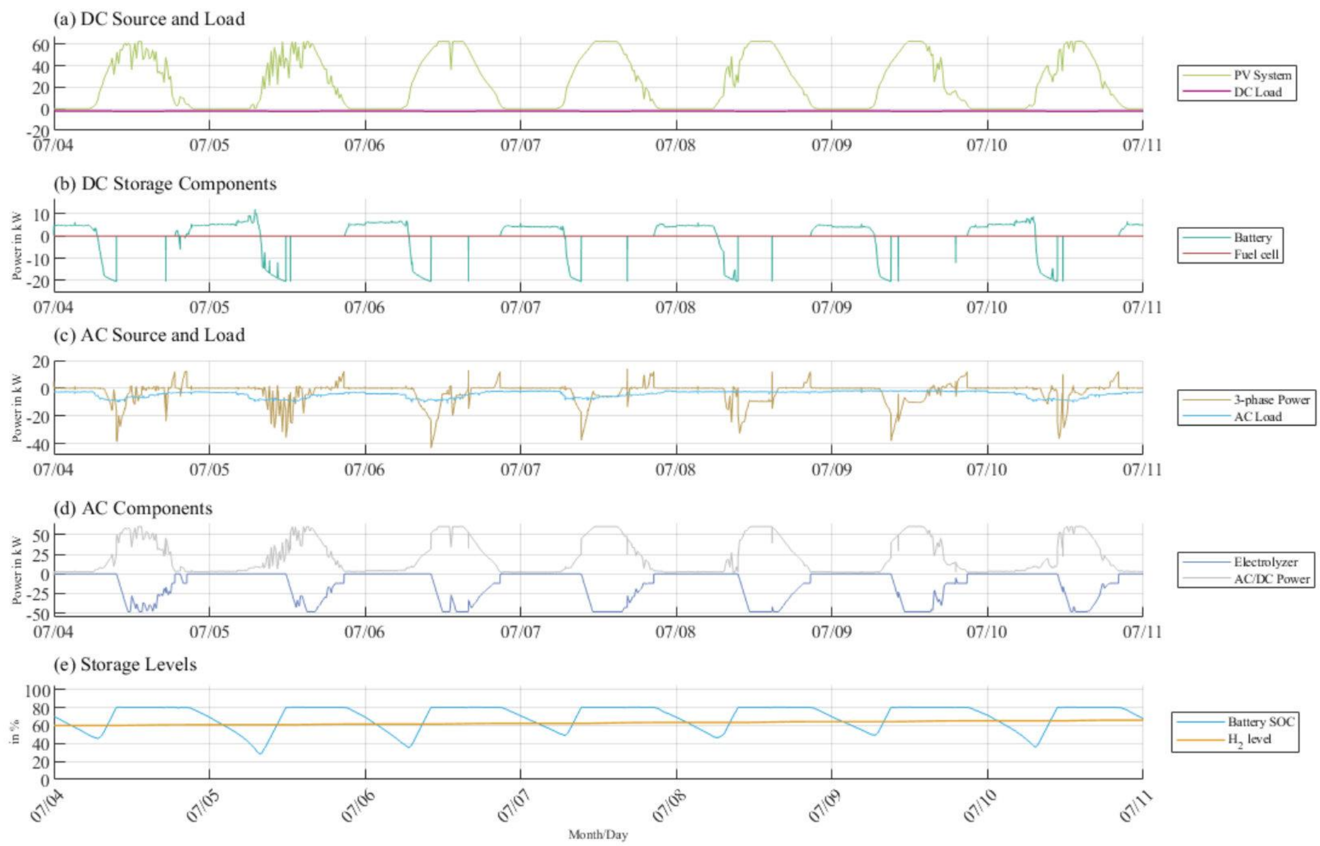
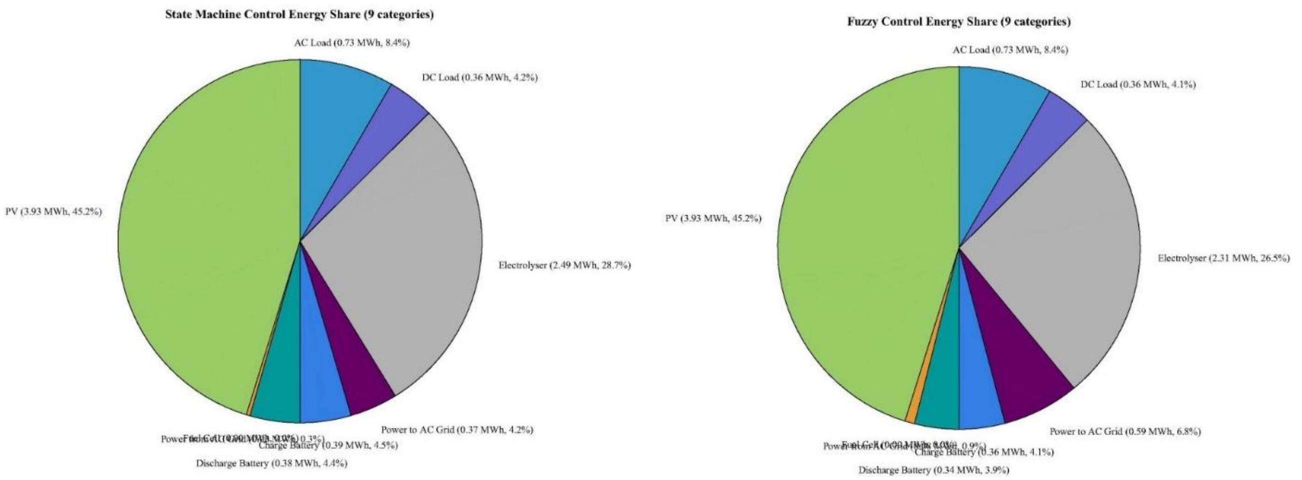


Fig. 14. Summer week result plot (Fuzzy Logic Control)

The energy-share comparison supports this interpretation in Figure 15. In the summer week, PV supplies 3.93 MWh in both cases. Under SMC, the electrolyzer accounts for 2.49 MWh and grid export for 0.37 MWh. Under FLC, electrolyzer consumption decreases to 2.31 MWh, while grid export increases to 0.59 MWh. Battery charge/discharge energies are also slightly reduced.



(a) (b)

Fig. 15. Energy share distribution in summer week (a) State machine control energy share (9 categories) b Fuzzy control energy share (9 categories)

3.3.2 Component runtime comparison

The detailed summer-week statistics confirm that the FLC reduces battery stress in Table 4. Battery charging energy decreases from 393.89 kWh to 356.33 kWh, and battery discharging energy from 384.79 kWh to 341.81 kWh. The electrolyzer runs slightly longer under FLC (73.2 h versus 70.0 h) but consumes less energy overall, again indicating smoother operation at more moderate power levels. Grid export increases substantially from 368.31 kWh to 594.75 kWh.

Table 4
Overview of component operation statistics in the summer week scenario

Dimension	Description	State Machine Control	Fuzzy Control
Simulation time range	**Period**	**2023-07-04 (05:30) → 2023-07-10 (21:45)**	**2023-07-04 (05:30) → 2023-07-10 (21:45)**
PV	**Energy supply**	**3926.56 kWh**	**3926.56 kWh**
Electrolyzer	**Starts**	**7**	**8**
	Operating hours	**70.0 h**	**73.2 h**
	Consumed energy	**2489.76 kWh**	**2305.33 kWh**
Battery charge	**Starts**	**10**	**19**
	Operating hours	**25.2 h**	**22.1 h**
	Consumed energy	**393.89 kWh**	**356.33 kWh**
Battery discharge	**Starts**	**19**	**10**
	Operating hours	**81.2 h**	**72.6 h**
	Supplied energy	**384.79 kWh**	**341.81 kWh**
To AC grid (export)	**Supplied energy**	**368.31 kWh**	**594.75 kWh**
From AC grid (import)	**Consumed energy**	**28.33 kWh**	**75.77 kWh**

Thus, under high-generation conditions, the FLC does not simply maximize hydrogen production. Instead, it distributes surplus energy more flexibly across the battery, electrolyzer, and grid, thereby reducing deep cycling and abrupt threshold-triggered behavior.

3.4 Winter-Week Simulation
3.4.1 Control behavior under power deficit

The winter-week case is the most demanding scenario because PV generation is very low and the system must rely mainly on stored energy and limited grid support from Figure 16 to Figure 18. Under SMC, both the battery and the fuel cell show frequent step-like activations and deactivations, leading to abrupt SOC changes and repeated mode switching. Under FLC, the fuel cell is operated for much longer continuous periods, while the battery is used more selectively for short support intervals. The SOC therefore evolves more smoothly, and the hydrogen tank is depleted in a more gradual and controlled manner.

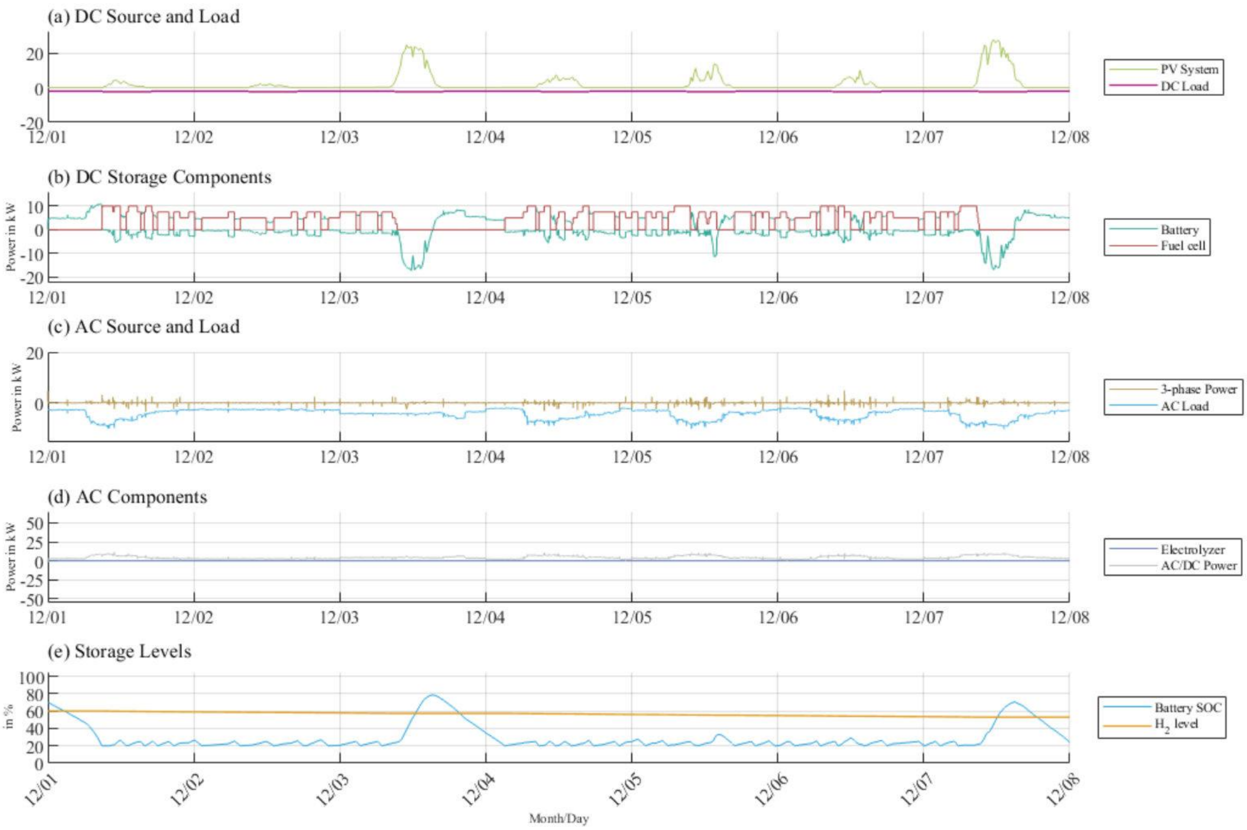


Fig. 16. Winter week Result plot (State Machine Control)

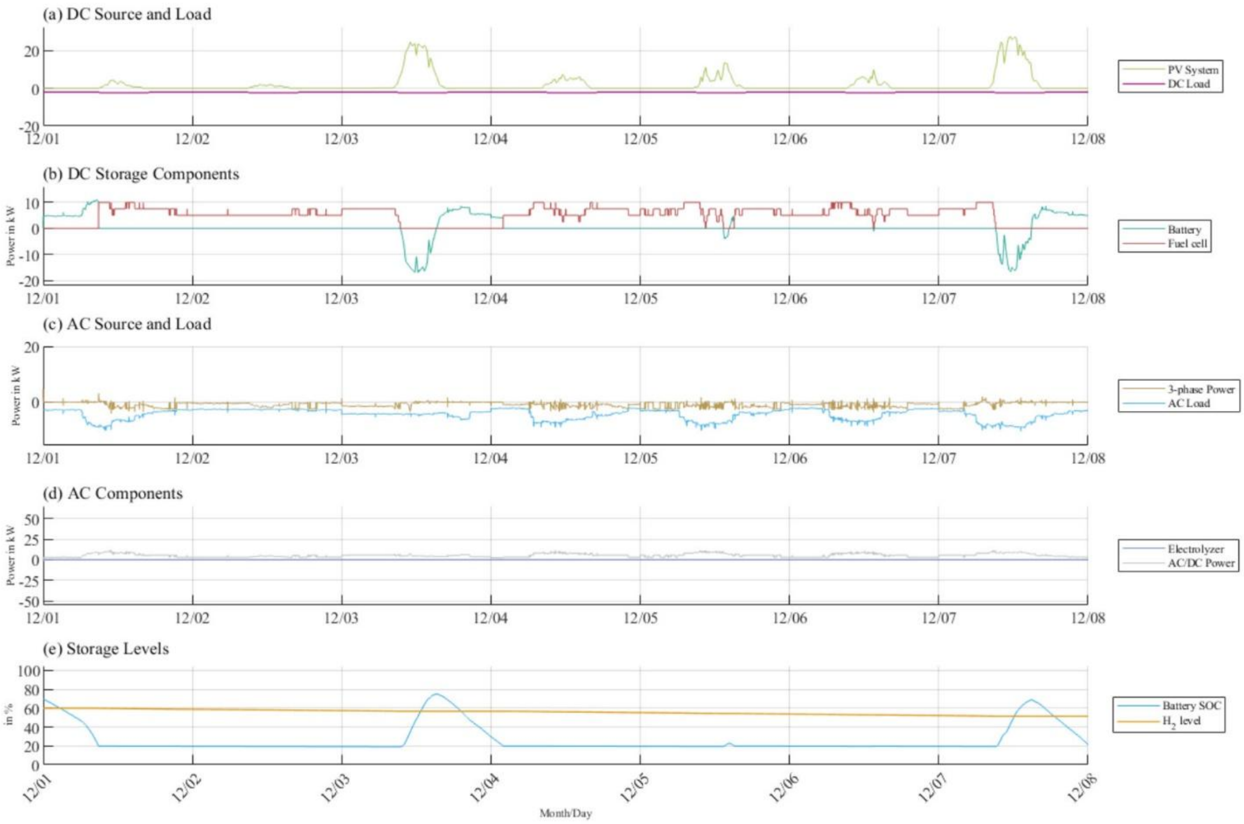
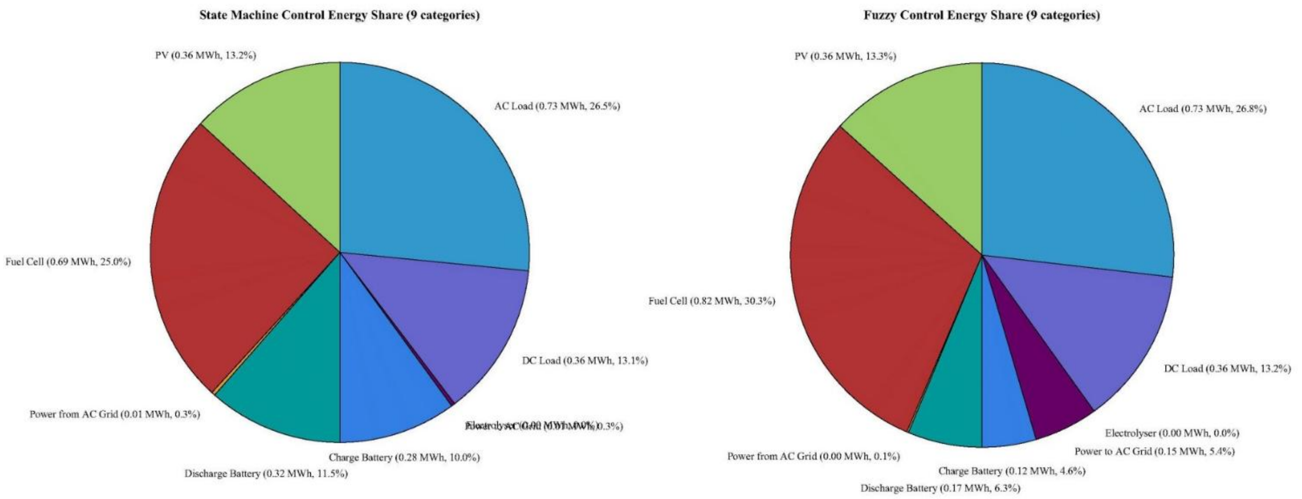


Fig. 17. Winter week Result plot (Fuzzy Logic Control)

The energy-share comparison is particularly revealing. Under SMC, the fuel cell supplies 688.5 kWh and the battery contributes 315.85 kWh by discharge. Under FLC, fuel cell supply rises to 824.0 kWh, while battery discharge drops to 170.80 kWh. Grid import also decreases from 8.55 kWh to 4.04 kWh. These values show that the FLC shifts the burden of deficit coverage from frequent battery cycling toward steadier fuel-cell-supported operation.



(a) (b)

Fig. 17. Energy share distribution in winter week (a) State machine control energy share (9 categories) (b) Fuzzy control energy share (9 categories)

3.4.2 Component runtime comparison

The runtime table makes the contrast even clearer in Table 5. Fuel cell starts fall from 32 under SMC to only 8 under FLC, while fuel cell operating time increases from 97.3 h to 125.7 h. At the same time, battery charging starts drop from 83 to 5 and battery discharging starts from 38 to 4. Battery charged energy is reduced from 275.94 kWh to 123.80 kWh, and discharged energy from 315.85 kWh to 170.80 kWh. Grid export increases under FLC because the fuel cell, operating at discrete power levels occasionally produces more than the instantaneous load, with the excess sent to the grid.

Table 5
Overview of component operation statistics in the winter week scenario

Dimension	Description	State Machine Control	Fuzzy Control
Simulation time range	**Period**	**2023-12-01 (08:45) → 2023-12-07 (16:45)**	**2023-12-01 (08:45) → 2023-12-07 (16:45)**
PV	**Energy supply**	**361.52 kWh**	**361.52 kWh**
Fuel Cell	**Starts**	**32**	**8**
	Operating hours	**97.3 h**	**125.7 h**
	Consumed energy	**688.5 kWh**	**824.0 kWh**
Battery charge	**Starts**	**83**	**5**
	Operating hours	**106.1 h**	**12.4 h**
	Consumed energy	**275.94 kWh**	**123.80 kWh**
Battery discharge	**Starts**	**38**	**4**
	Operating hours	**58.5 h**	**29.4 h**
	Supplied energy	**315.85 kWh**	**170.80 kWh**

To AC grid (export)	**Supplied energy**	**8.46 kWh**	**146.53 kWh**
From AC grid (import)	**Consumed energy**	**8.55 kWh**	**4.04 kWh**

These results show that under low-generation conditions the FLC achieves a much more stable and efficient operation by favoring longer fuel cell runtime and sharply reducing battery cycling.

3.5 Overall Discussion

Across all three scenarios, the FLC preserves the same basic energy management priorities as the original SEOB concept—battery for short-term balancing, hydrogen pathway for long-term balancing, and grid exchange as residual support—but it executes these priorities in a much smoother way. The main effect is not a change in annual feasibility, since both SMC and FLC maintain the microgrid energy balance, but a change in operational quality: fewer switching events, lower battery throughput, longer continuous operating periods of the fuel cell, and more flexible use of the grid. This becomes particularly evident in the winter week, where the FLC reduces fuel cell activations by 75% and battery charging activations by almost one order of magnitude.

From the perspective of long-term operation, these results support the conclusion that the FLC is better suited to hybrid storage coordination than the threshold-based SMC. It does not eliminate grid interaction; on the contrary, it increases grid exchange in some periods. However, this is precisely part of its stabilizing behavior, since the controller avoids forcing all short-term fluctuations into internal storage devices. Instead, it uses the grid, battery, and hydrogen pathway in a more balanced and less abrupt manner.

4. Conclusion

4.1 Summary

The SEOB hybrid microgrid is the real implementation of a research and demonstration system that integrates both AC and DC grids. It includes photovoltaic generation, lithium iron phosphate batteries, fuel cell systems, an electrolyzer with high-pressure hydrogen storage tanks, and both AC/DC and DC/DC converters. Its design objective is to ensure stable DC-bus operation, improve renewable energy utilization, and reduce dependence on the public grid.

This thesis presented the design and implementation of an FLC for the SEOB hybrid AC/DC microgrid. The goal was to improve the overall energy management performance compared to the conventional SMC by introducing a smoother and more adaptive control approach. All controller development and validation were carried out in the MATLAB/Simulink environment and tested using the SEOB model, which is based on real PV generation and load data.

The FLC was built using a Mamdani-type fuzzy inference system with three input variables—power imbalance (ΔP), battery SOC, and hydrogen storage level (H2 level). These inputs coordinated the main control actions: battery charge or discharge, fuel cell operation, and electrolyzer activation. With clearly defined membership functions and rule bases, the controller achieved gradual adjustments rather than abrupt switching. This enabled smoother power flow, more stable operation of components, and improved coordination between distributed generation, storage systems, and the AC grid.

The FLC and SMC were evaluated under identical conditions using several metrics, such as energy balance, component runtime, switching frequency, and grid interaction. Across all investigated scenarios year-round operation, a summer week with high PV availability, and a winter week with low solar input the FLC consistently showed more stable and efficient behavior. It reduced switching events by up to 75%, extended the continuous operating periods of the fuel cell and battery, and lowered unnecessary charge–discharge cycles. It also kept the DC-bus voltage stable and handled changes in generation or demand more smoothly. The improved interaction with the AC grid and better use of available hydrogen contributed to a more balanced overall energy flow.

In summary, the fuzzy logic controller achieved smoother operation, higher energy efficiency, and longer component lifetime compared with the rule-based SMC method. These results confirm that fuzzy control provides a reliable and robust solution for long-term energy management in hybrid AC/DC microgrids. The successful implementation in the SEOB system highlights its potential for further applications in intelligent microgrid control and renewable energy integration.

5.2 Outlook

The FLC developed in this study has demonstrated clear advantages in simulations; however, several aspects can be improved. Future research could explore four main areas: optimizing the fuzzy inference system, integrating predictive and learning-based control methods, and validating the controller in real time.

First, in conventional fuzzy logic design, the shape and range of membership functions (MFs) are typically defined manually. These functions are often evenly distributed or adjusted according to expert knowledge. This approach is simple, yet subjective, and may not accurately reflect the actual system's behavior. Future studies could focus on automatically optimizing MFs using data-driven or algorithm-based methods, such as genetic algorithms, particle swarm optimization, or gradient search. This would reduce dependence on human experience, make the controller more robust, and enable it to adapt more effectively to changing conditions in the SEOB system.

Second, integrating MPC could further enhance the current framework. Within the SEOB model, MPC can predict short-term variations in PV generation, building load and battery SOC, and then optimize control actions over a defined time horizon. By incorporating forecasted data, such as solar irradiance, building load, and hydrogen tank level, an MPC layer could act as a supervisory optimizer above the fuzzy controller. This hybrid FLC–MPC structure would combine the smooth, adaptive logic of fuzzy control with the predictive optimization of MPC, enabling faster, more efficient system responses.

Third, Reinforcement Learning (RL) also represents a promising research direction. Unlike fuzzy or predictive control, RL can learn optimal strategies directly through interaction with the system environment. Combining RL with fuzzy logic, for example, by using fuzzy rules as interpretable policy structures, would allow the controller to continuously learn from data and improve its decision-making abilities over time. A Fuzzy–RL framework could make the controller more flexible and reduce the need for manual tuning.

Finally, future work should include real-time and hardware-based validation. This would involve deploying the fuzzy controller on an industrial PC or PLC and connecting it to the physical SEOB. Testing the control algorithm under real operating conditions, including communication delays, sensor noise, and load fluctuations, would demonstrate its performance outside an idealized simulation. These experiments are essential for identifying practical issues, such as computation delay or data synchronization, and ensuring reliable performance in real applications.

In summary, future research should focus on making the fuzzy controller more autonomous, predictive, and ready for real-world deployment. Through optimizing its structure, combining it with MPC and RL, and validating it in real systems, fuzzy logic control can evolve into a practical and powerful tool for managing modern hybrid micrografts.

Author Contributions

Junze Li: Conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, project administration. **Yan Chen**: Supervision. **Junpeng Lyu**: Supervision

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Data Availability Statement

The data are not publicly available due to privacy restrictions but are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Rosales-Asensio, E., de Simón-Martín, M., Borge-Diez, D., Blanes-Peiró, J. J., & Colmenar-Santos, A. (2019). Microgrids with energy storage systems as a means to increase power resilience: An application to office buildings. *Energy*, *172*, 1005-1015. https://doi.org/10.1016/j.energy.2019.02.043

[2] Wöhr, E., Eser, D., Suriyah, M., & Leibfried, T. (2024, November). Long-Term Power Management of a Building-Integrated DC Microgrid with Hybrid Energy Storage System in Grid-Connected Mode. In *2024 9th IEEE Workshop on the Electronic Grid (eGRID)* (pp. 1-6). IEEE. https://doi.org/10.1109/egrid62045.2024.10842891

[3] Kontogiannis, D., Bargiotas, D., & Daskalopulu, A. (2021). Fuzzy control system for smart energy management in residential buildings based on environmental data. *Energies*, *14*(3), 752. https://doi.org/10.3390/en14030752

[4] Langner, F., Kovačević, J., Spatafora, L., Dietze, S., Waczowicz, S., Çakmak, H. K., ... & Hagenmeyer, V. (2025). Experimental evaluation of model predictive control and fuzzy logic control for demand response in buildings. *Applied Energy*, *401*, 126666. https://doi.org/10.1016/j.apenergy.2025.126666

[5] Ullah, Z., Wang, S., Lai, J., Azam, M., Badshah, F., Wu, G., & Elkadeem, M. R. (2023). Implementation of various control methods for the efficient energy management in hybrid microgrid system. *Ain Shams Engineering Journal*, *14*(5), 101961. https://doi.org/10.1016/j.asej.2022.101961

[6] Colson, C. M., Nehrir, M. H., & Pourmousavi, S. A. (2010, July). Towards real-time microgrid power management using computational intelligence methods. In *IEEE PES general meeting* (pp. 1-8). IEEE. https://doi.org/10.1109/pes.2010.5588053

[7] Wang, J., Pratt, A., & Baggu, M. (2018, February). Design of a state machine for smooth microgrid transition operation. In 2018 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT) (pp. 1-5). IEEE. https://doi.org/10.1109/isgt.2018.8403397

[8] Yang, Y., Zhang, S., & Xiao, Y. (2015). An MILP (mixed integer linear programming) model for optimal design of district-scale distributed energy resource systems. *Energy*, *90*, 1901-1915. https://doi.org/10.1016/j.energy.2015.07.013

[9] Prodan, I., & Zio, E. (2014). A model predictive control framework for reliable microgrid energy management. *International Journal of Electrical Power & Energy Systems*, *61*, 399-409. https://doi.org/10.1016/j.ijepes.2014.03.017

[10] Roslan, M. F., Hannan, M. A., Ker, P. J., Mannan, M., Muttaqi, K. M., & Mahlia, T. I. (2022). Microgrid control methods toward achieving sustainable energy management: A bibliometric analysis for future directions. *Journal of Cleaner Production*, *348*, 131340. https://doi.org/10.1016/j.jclepro.2022.131340

[11] Garcia-Torres, F., Bordons, C., & Ridao, M. A. (2018). Optimal economic schedule for a network of microgrids with hybrid energy storage system using distributed model predictive control. *IEEE transactions on industrial electronics*, *66*(3), 1919-1929. https://doi.org/10.1109/tie.2018.2826476

[12] Schwenzer, M., Ay, M., Bergs, T., & Abel, D. (2021). Review on model predictive control: An engineering perspective. *The international journal of advanced manufacturing technology*, *117*(5), 1327-1349. https://doi.org/10.1007/s00170-021-07682-3

[13] Cagnano, A. E. D. T., De Tuglie, E., & Mancarella, P. J. A. E. (2020). Microgrids: Overview and guidelines for practical implementations and operation. *Applied Energy*, *258*, 114039. https://doi.org/10.1016/j.apenergy.2019.114039

[14] Unamuno, E., & Barrena, J. A. (2015). Hybrid ac/dc microgrids — Part I: Review and classification of topologies. *Renewable and Sustainable Energy Reviews*, *52*, 1251-1259. https://doi.org/10.1016/j.rser.2015.07.194

[15] Dawoud, S. M., Lin, X., & Okba, M. I. (2018). Hybrid renewable microgrid optimization techniques: A review. *Renewable and Sustainable Energy Reviews*, *82*, 2039-2052. https://doi.org/10.1016/j.rser.2017.08.007

[16] Indragandhi, V., Logesh, R., Subramaniyaswamy, V., & Vijayakumar, V. (2018). Multi-objective optimization and energy management in renewable based AC/DC microgrid. *Computers & Electrical Engineering*, *70*, 179-198. https://doi.org/10.1016/j.compeleceng.2018.01.023

[17] Azeem, O., Ali, M., Abbas, G., Uzair, M., Qahmash, A., Algarni, A., & Hussain, M. R. (2021). A comprehensive review on integration challenges, optimization techniques and control strategies of hybrid AC/DC Microgrid. *Applied Sciences*, *11*(14), 6242. https://doi.org/10.3390/app11146242

[18] Alghassab, M. A. (2024). Fuzzy-based smart energy management system for residential buildings in Saudi Arabia: A comparative study. *Energy Reports*, *11*, 1212-1224. https://doi.org/10.1016/j.egyr.2023.12.039

[19] Vivas, F. J., Segura, F., & Andújar, J. M. (2022). Fuzzy logic-based energy management system for grid-connected residential DC microgrids with multi-stack fuel cell systems: A multi-objective approach. *Sustainable Energy, Grids and Networks*, *32*, 100909. https://doi.org/10.1016/j.segan.2022.100909

[20] Driankov, D., Hellendoorn, H., & Reinfrank, M. (2013). *An introduction to fuzzy control*. Springer Science & Business Media. https://doi.org/10.1007/978-3-662-11131-4

[21] Althubaiti, M., Bernard, M., & Musilek, P. (2017, April). Fuzzy logic controller for hybrid renewable energy system with multiple types of storage. In *2017 IEEE 30th Canadian conference on electrical and computer Engineering (CCECE)* (pp. 1-6). IEEE. https://doi.org/10.1109/ccece.2017.7946738

[22] Chowdhury, N. A., Yang, F., & Bai, F. (2023). Energy Management of AC Residential Microgrids Using Advanced Fuzzy Inference Method. In *2023 IEEE International Conference on Energy Technologies for Future Grids (ETFG)*. IEEE. https://doi.org/10.1109/etfg55873.2023.10408298

[23] Cavus, M., Dissanayake, D., & Bell, M. (2025). Deep-fuzzy logic control for optimal energy management: A predictive and adaptive framework for grid-connected microgrids. *Energies*, *18*(4), 995. https://doi.org/10.3390/en18040995

[24] Luukka, P., & Stoklasa, J. (2024). Possibilistic mean based defuzzification for fuzzy expert systems and fuzzy control—LSD for general fuzzy sets. *Journal of Computational and Applied Mathematics*, *441*, 115663. https://doi.org/10.1016/j.cam.2023.115663