23rd International Conference on Renewable Energies and Power Quality (ICREPQ'25)
Tenerife (Spain), 25th to 27th June 20245
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.23, September 2025

Battery Management System for Energy Communities Using a Cost-Sensitive Rule-Based algorithm

Marcos Trujillo-Trujillo[1], Juan A. Méndez-Pérez[1], Santiago Torres-Álvarez[1], Alberto Hamilton-Castro[1]
Jose M. Gonzalez-Cava[1], Iván Castilla-Rodríguez[1], Benjamín González-Díaz[2]
[1] Departamento de Ingeniería Informática y de Sistemas, Universidad de La Laguna (ULL). Camino San Francisco de Paula, 19. 38200 La Laguna (Tenerife), Spain.
[2] Departamento de Ingeniería Industrial, Universidad de La Laguna (ULL). Camino San Francisco de Paula, 19. 38200 La Laguna (Tenerife), Spain.

Abstract. Energy Communities (ECs) drive decentralized energy production and consumption, fostering active citizen participation. Within this framework, battery systems play a crucial role in efficiency and optimization, requiring an effective Battery Management System (BMS) to optimize energy control. This paper presents a rule-based approach for effective battery energy management within an energy community. The proposed system integrates a set of predefined rules that determine battery operation by considering factors such as hourly energy prices, photovoltaic power generation, and user consumption patterns. This approach enables more efficient energy utilization, reduces dependence on the electrical grid, facilitates cost reduction, and ensures stability of the local energy network.

Keywords. Energy Community, Battery Management System, Rule-based System.

Nomenclature

P_G	power supplied by the grid (kW)
P_{PV}	photovoltaic power generation (kW) by a single community member
$P_{PV,tot}$	total photovoltaic power generation (kW) of the community.
P_B	battery power (kW)
P_L	power load (kW)
β	sharing coefficient (%)
SoC	State of Charge (%)
C	energy cost (€/kWh)
C_{low}	low cost of energy (€/kWh)
I_b	battery charging or discharging current (A)
$I_{surplus}$	surplus current (A) generated by the photovoltaic system that exceeds the local demand
Q	battery capacity (Ah)
ΔT	time interval between two measurements (h)
V_b	battery voltage (V)
η_{chg}	charge efficiency (%)
η_{dis}	discharge efficiency (%)
$I_{b,max}$	maximum current supported by the battery (A)
$I_{b,min}$	minimum current supported by the battery (A)

1. Introduction

Efficient energy management is a key factor in the transition towards a more sustainable energy generation and consumption model. Energy Communities (ECs) are emerging as an innovative and essential model for driving this transition in Europe [1]. Comprising citizens, businesses, and local entities, aim to promote the sustainable and decentralized production, distribution, and consumption of energy. These communities align with goals to minimize energy consumption and encourage flexible energy use by active consumers, thereby reducing the high energy loads on the power grid [2]. A defining characteristic of energy communities is their ability to foster active citizen participation in energy management, contributing to the democratization of energy.

Managing an Energy Community (EC) requires making decisions at multiple levels, including defining the renewable energy sharing quota among community members, dynamically managing demand, and overseeing the operation of the Battery Energy Storage (BES) system. A suitable control architecture to deal with these problems comprises a global manager ("scheduler"), which would optimize the sharing coefficients among the EC members, and design strategies to properly balance the demand curve; and a set of local managers ("controllers"), which would apply the global commands by interacting with the internal grid devices and the local BES [3].

The local Battery Management Systems (BMSs) can provide several grid services to the system, such as preventing voltage drops, providing frequency control or reducing grid congestion [4],[5], and can therefore help to reduce overall grid costs. By reducing the maximum grid usage [6], the user can save on capacity payments.

Despite the benefits of integrating BES into energy communities, several challenges persist in energy management. One of the main issues is the unpredictability of renewable energy sources, such as photovoltaic (PV) generation, which depends on weather conditions and often leads to supply-demand imbalances. Additionally, energy pricing variability complicates decision-making regarding when to store or consume energy. Another critical challenge is the lack of adaptive and efficient control strategies, as traditional energy management systems often rely on predefined schedules or static rules that do not account for real-time conditions [7],[8]. These limitations can lead to inefficient battery operation, increased costs, and suboptimal grid interaction.

To address these challenges, this paper proposes a rule-based system for energy management aimed at optimizing battery operation within an energy community. The proposed system, developed in MATLAB, is modular and scalable, allowing for flexible adaptation to different community configurations and member profiles. By leveraging data on energy consumption, photovoltaic (PV) generation, and hourly electricity prices, the system dynamically determines the optimal charging or discharging behavior of the battery. The rule set has been designed to operate with minimal computational complexity while ensuring responsiveness to changing energy conditions. This approach enables more efficient use of available resources, reduces dependency on the external grid, and contributes to minimizing overall energy costs. In doing so, it also enhances the reliability and stability of the local energy network, especially in contexts with high renewable energy penetration.

The interaction between the various actors within an energy community necessitates the implementation of a sophisticated Energy Management System (EMS) capable of supporting informed decision-making. At the heart of such a system lies a deep understanding and analysis of the key components that constitute the community—namely, the generation, consumption, and storage systems. Accurate characterization and modelling of these elements are essential for optimizing energy flows and ensuring efficient operation.

This article is structured as follows: Section 2 presents an overview of the applied methodology, detailing the developed energy community model and the implemented control algorithm. Section 3 discusses the results, analyzing the performance of the rule-based system. Finally, Section 4 concludes the paper and outlines potential directions for future work.

2. Methodology

The foundation of the proposed approach is a modular and scalable simulation model developed in MATLAB. The proposed system adopts a multi-level control strategy [3],[9] to manage energy flows within the energy community. At the tactical level, a global scheduler oversees the overall coordination among members, while at the operational level, individual local controllers manage the behavior of each community member in real time. This study concentrates specifically on the Battery Management System (BMS), focusing on the operational-level control of a single prosumer. The BMS operates based on a set of predefined rules that consider local generation, consumption, and storage conditions to determine the optimal charging or discharging actions.

The following figure illustrates the architecture of the multi-level control system, highlighting the interaction between the local and global controllers.

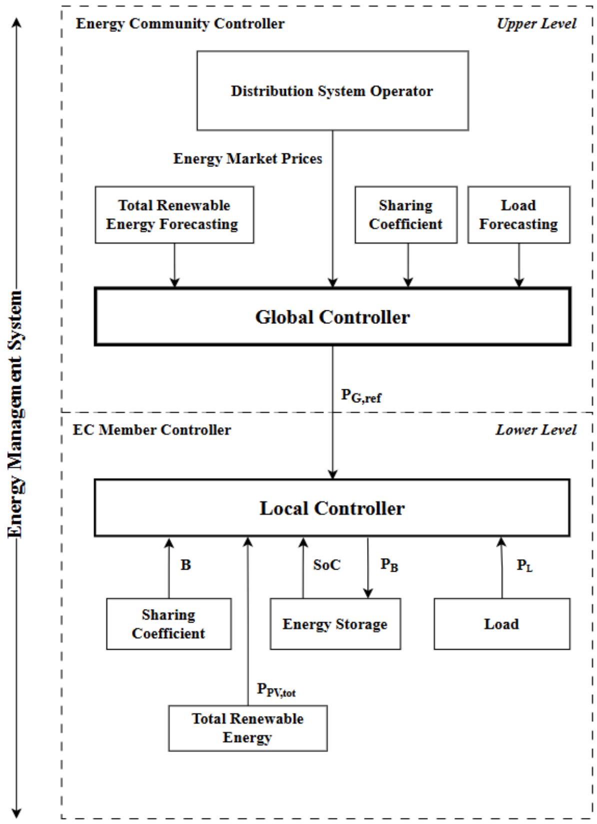

Fig. 1. Architecture of the multi-level control system.

2.1. Energy Community Model

The model includes a detailed representation of an Energy Community (EC), aimed at simulating the distribution and management of energy within the community. A modular, object-oriented approach was adopted in MATLAB, featuring five key interconnected classes: Site, Battery, PV, Load, and Controller. Each of these classes plays a specific role in the overall energy management system, creating a comprehensive framework for simulating community energy dynamics.

The Site class represents an individual community member, which can be either a prosumer (simultaneously generating and consuming energy), a consumer, or a generator. This flexibility allows for modelling various configurations of energy producers and users within the community. The Site class receives data about its battery and, in cases where applicable, consumption or generation profiles, enabling it to operate in different modes.

The Battery class is responsible for modelling the energy storage system associated with each site. It tracks key parameters such as the State of Charge (SoC), battery capacity, and current limits, while implementing the necessary logic for controlling charging and discharging processes.

The PV and Load classes store data related to energy generation and consumption. The PV class contains the photovoltaic generation profile of a community member,

representing the available solar power based on historical or measured data. The Load class, in turn, stores the building's energy consumption profile, incorporating an uncertainty margin of ±5% to account for potential fluctuations in demand and measurement variability.
A key component of the system is the Controller class, which implements a rule-based system for managing energy flows within the community. The controller returns the optimal charging intensity for each site, ensuring that energy is utilized efficiently. By integrating these various classes, the model allows for the dynamic interaction of components, enabling effective energy management and decision-making at both the individual and community levels.
The interaction and organization of the developed classes can be better understood through the following schematic. This figure provides an overview of the architecture of the simulated energy community, highlighting the relationship between each component. The *Site* class serves as the central element representing an individual member, which can integrate photovoltaic generation (*PV*), consumption data (*Load*), a storage unit (*Battery*), and a local decision-making unit (*Controller*). These modules interact to enable localized energy management. The architecture also reflects the modular and scalable design adopted for simulating larger communities. Figure 2 illustrates the overall structure of the developed energy community model.

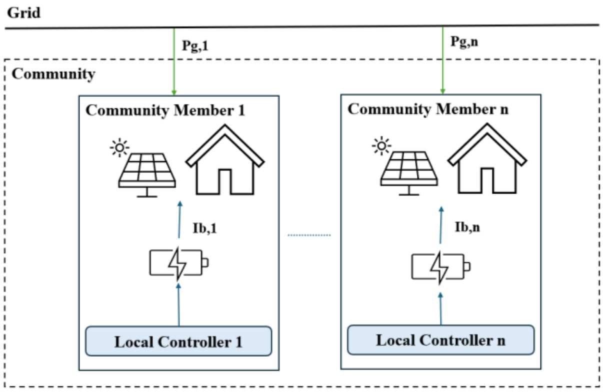

Fig. 2. Schematic Representation of the Energy Community Framework.

2.2. Community Member Rule-Based Controller

The BMS used in this model is defined as a rule-based system. This system requires the current hourly energy cost, the photovoltaic generation and building consumption values as inputs. The rule-based system estimates the optimal charging or discharging intensity to be applied in the next time step, trying to minimise the dependence on the grid. Equation 1 defines the net power exchanged with the grid for the user i at each time step:

$$P_{G,i} = P_{L,i} - \beta_i \cdot P_{PV,tot} - P_{B,i} \tag{1}$$

Where if the battery is charging:

$$P_{B,i} = I_{b,i} \cdot V_{b,i} \, / \, \eta_{chg} \tag{2}$$

And if the battery is discharging:

$$P_{B,i} = I_{b,i} \cdot V_{b,i} \cdot \eta_{dis} \tag{3}$$

Figure 3 illustrates the structure of the BMS together with the EC model.

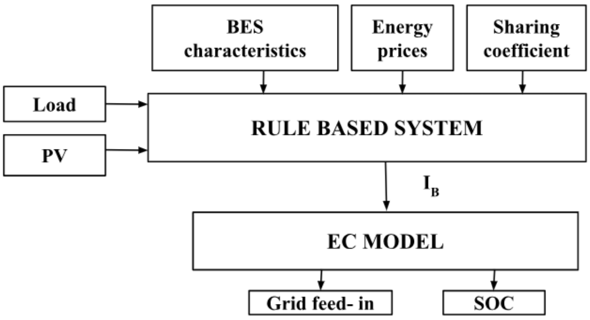

Fig. 3. Structure of the BES control approach.

The rule-based system relies on a series of equations that defines the relationship among the variables of interest. Equation 2 defines the state of charge (SoC).

$$SoC_{k+1} = SoC_k + \frac{Ib_k \cdot \Delta T}{Q} \cdot 100 \tag{2}$$

Furthermore, we know that the battery current must be limited between two values specified in the battery's datasheet.

$$I_{b,min} \leq I_b \leq I_{b,max} \tag{3}$$

Based on Equation 2, the charging and discharging equations of the battery are defined as follows:

$$I_{charge} = \frac{(SoC_{max} - SoC_k) \cdot Q}{100 \cdot \Delta T} \tag{4}$$

$$I_{discharge} = -\frac{(SoC_{min} - SoC_k) \cdot Q}{100 \cdot \Delta T} \tag{5}$$

Additionally, it is important to consider the available or required current ($I_{surplus}$), which results from the difference between the generated power and consumed.

$$I_{surplus} = \frac{\beta_i \cdot P_{PV,Tot} - P_{L,i}}{Vb} \tag{6}$$

The algorithm regulates battery charging and discharging by evaluating power consumption (P_L), photovoltaic generation (P_{PV}), battery state of charge (SoC), and energy cost (C) compared to a low-cost threshold (C_{low}). Additionally, the battery current must comply with the constraint imposed in Equation 3, ensuring that its charging and discharging intensity remains within the allowable limits. Furthermore, the battery capacity must not exceed its maximum or fall below its minimum permissible values, preventing overcharging or deep discharging, which could affect its performance and lifespan.
Based on these factors, different conditions dictate the battery's operation.

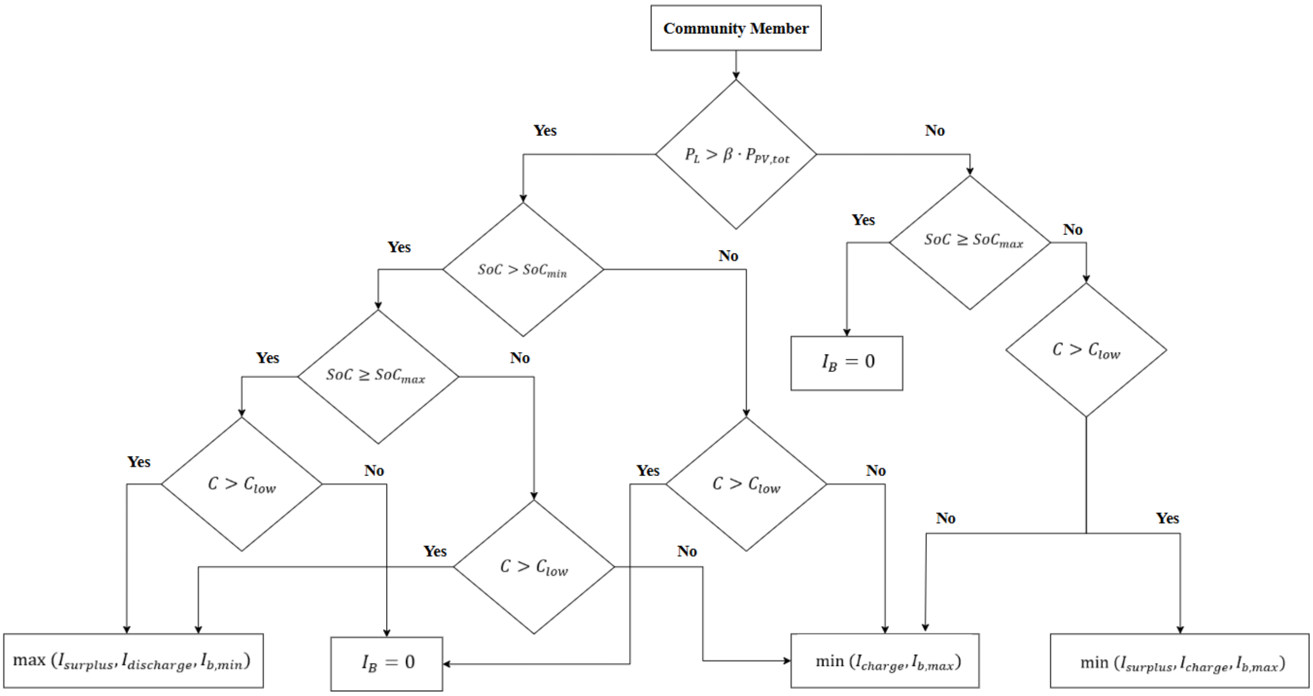

Fig. 4. Flowchart of the Rule-Based Energy Management System (EMS) Implemented.

Case 1: Generation is greater than or equal to consumption.

When photovoltaic generation meets or exceeds consumption, the algorithm first checks if the battery is below its maximum charge. If the energy cost is low, the battery would charge from the grid at its maximum. If costs are high, the battery only charges using available surplus energy. If the battery is already full, no charging occurs.

Case 2: Consumption exceeds generation.

If consumption is higher than generation, the battery's state determines the next step. If the battery is within its operational range $SoC_{min} < SoC < SoC_{max}$, and costs are low, it charges from the grid. When the battery is nearly full, it stops charging, but if costs are high, it may discharge to the grid. If the battery is at its minimum charge, it can only charge if energy costs are low; otherwise, it remains inactive.

Figure 4 shows the implementation of the rules for the BMS.

2.3. Experiment Setup

To evaluate the performance of the proposed rule-based Battery Management System (RBS+), a set of simulation scenarios was designed. These scenarios reflect variations in photovoltaic (PV) generation and electricity pricing, aiming to replicate realistic operational conditions and assess the robustness of the control strategy. The simulation was conducted over a one-week period with data points distributed at 15-minute intervals, providing a high-resolution temporal analysis of the system's performance. The system's effectiveness was assessed based on three main performance indicators: cost reduction, grid dependency, and energy loss. For benchmarking purposes, the proposed system was compared against two reference cases: a baseline scenario without battery storage, and a rule-based control strategy that does not consider energy pricing (RBS_0). In addition, the C_{low} threshold, used to identify periods of low-cost energy, was dynamically adjusted daily to adapt the control strategy to changing price conditions.

Scenario I: Fluctuating Energy Prices and Stable Photovoltaic Generation

In this first scenario, the energy price profile is designed to fluctuate over time, with higher electricity prices coinciding with periods of higher photovoltaic generation, and lower prices during periods of reduced generation. This setup emulates a market-driven pricing model where renewable energy abundance affects energy cost.

Figure 5 illustrates the temporal distribution of electricity prices across one week. Complementarily, Figure 6 shows a typical PV generation profile assumed to remain constant over the seven-day simulation period, alongside a representative consumption profile.

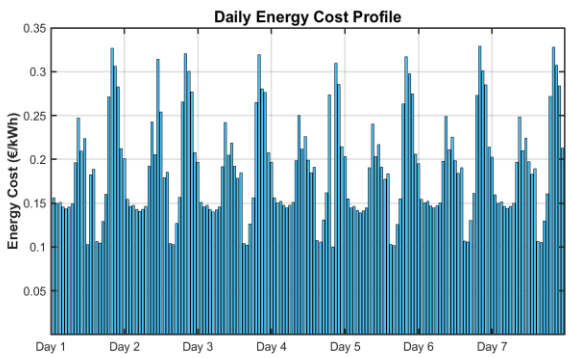

Fig. 5. Energy cost profile.

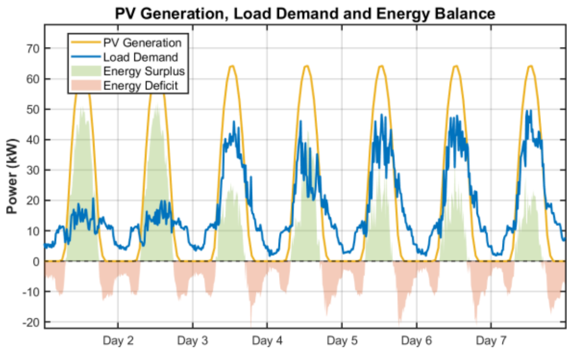

Fig. 6. Photovoltaic generation and consumption profiles for Scenario I.

Scenario II: Fluctuating Energy Prices and Variable Photovoltaic Generation

In the second scenario, the electricity price profile remains unchanged from Scenario I (see Figure 5), maintaining the same temporal variability over the week. However, the photovoltaic generation profile is now subject to variation, introducing more realistic dynamics into the simulation. Specifically, some days exhibit significantly higher consumption than generation, while on others, generation clearly exceeds demand. Additionally, there are periods where generation and consumption are closely aligned. See Figure 7.

This configuration allows for a more in-depth evaluation of the system's ability to optimize battery usage under diverse energy balances, particularly when guided by dynamic pricing signals. By introducing these fluctuations, the influence of considering energy prices in the control strategy becomes more evident, showcasing how the proposed BMS adapts to maximize efficiency and reduce costs even when generation and demand patterns are highly variable.

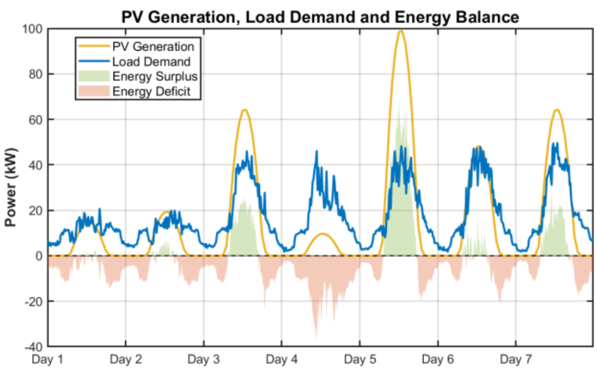

Fig. 7. Photovoltaic generation and consumption profiles for Scenario II.

For all scenarios, the values presented in Table I were applied.

Table I. - Parameter used during the simulations.

Variable	Unit	Value
β	%	90
ΔT	h	0.25
SoC_0	%	44
SoC_{max}	%	90
SoC_{min}	%	10
Q	Ah	100
$I_{b,max}$	A	79
$I_{b,min}$	A	-79
V_b	V	230
η_{chg}	%	90
η_{dis}	%	95

3. Results

This section presents the results obtained from the simulation of the proposed rule-based Battery Management System (RBS+) under the two scenarios described in the previous section.

In both scenarios, the proposed system is compared against two baseline cases: (i) a reference rule-based system that does not consider electricity prices and a (ii) operation without battery storage.

Scenario I: Fluctuating energy cost and stable photovoltaic generation.

Table II summarizes the results obtained for Scenario I, where the energy price profile varies throughout the day while the photovoltaic (PV) generation remains stable.

Table II. - Results for Scenario I.

Metrics	RBS+	RBS_0	No BMS
Total energy cost (€)	144.92	147	159.81
Grid Consumption (kWh)	724.13	696.03	792.32
Energy loss (kWh)	1308.9	1314.35	178.09

As shown in Table II, the proposed RBS achieves the lowest total energy cost, reducing electricity expenses compared to both the reference controller and the no-battery case. Although grid consumption is slightly higher than RBS_0, the inclusion of dynamic pricing in the control strategy allows for more cost-effective decisions. The energy loss associated with the battery operation is similar between both RBS configurations, reflecting the trade-off between energy efficiency and cost savings. Figures 7, 8, and 9 illustrate the system's behavior over the simulation period. Specifically:

- Figure 7 shows the power profile of the battery, indicating charging and discharging patterns.
- Figure 8 presents the evolution of the State of Charge (SoC).
- Figure 9 displays the energy balance, including PV generation, load consumption and grid interaction.

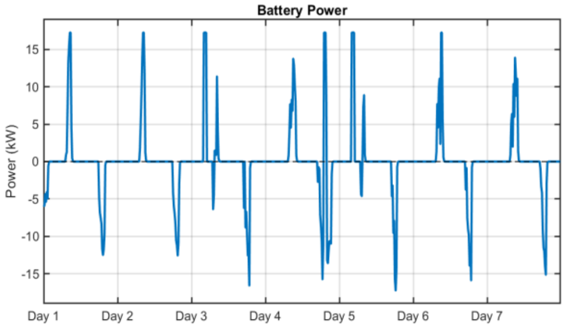

Fig. 8. Battery power profile over time in Scenario I.

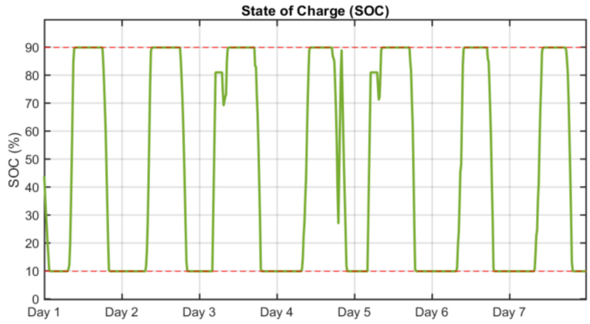

Fig. 9. State of Charge (SoC) evolution in Scenario I.

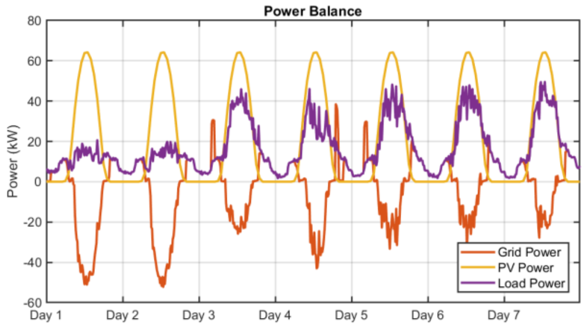

Fig. 10. Energy balance of the system in Scenario I.

Scenario II: Fluctuating Energy Prices and Variable Photovoltaic Generation

Scenario II introduces variability in the photovoltaic (PV) generation profile, while maintaining the same dynamic pricing scheme from Scenario I. Table III presents the performance metrics of the proposed rule-based system (RBS) compared to the reference RBS (RBS0) and the scenario without battery storage.

Table III. - Results for Scenario II.

Metrics	RBS+	RBS_0	No BMS
Total energy cost (€)	204.97	209.15	214.4
Grid Consumption (kWh)	1060.48	1009.24	1062.97
Energy loss (kWh)	651.43	613.84	952.43

As observed in Table III, the proposed RBS again outperforms the other configurations in terms of total energy cost, achieving a reduction of approximately 4% compared to RBS_0 and nearly 10€ compared to the case without battery. Although the grid consumption is slightly higher than in RBS_0, the cost-aware control strategy prioritizes economic efficiency over strict minimization of grid usage. Additionally, energy loss is significantly lower than in the no-battery scenario and remains within an acceptable range compared to RBS0. Figures 10, 11, and 12 illustrate the system's behavior for one week. The results confirm the capability of the proposed system to adapt to changing generation conditions while maintaining efficient and cost-effective energy management.

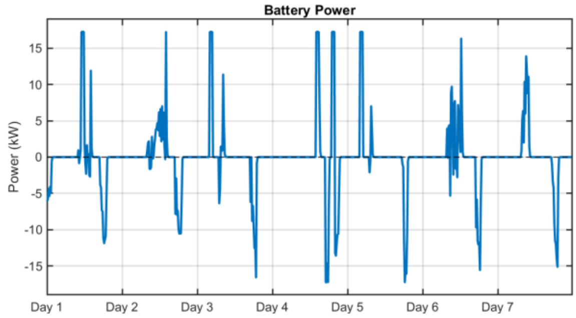

Fig. 11. Battery power profile over time in Scenario II.

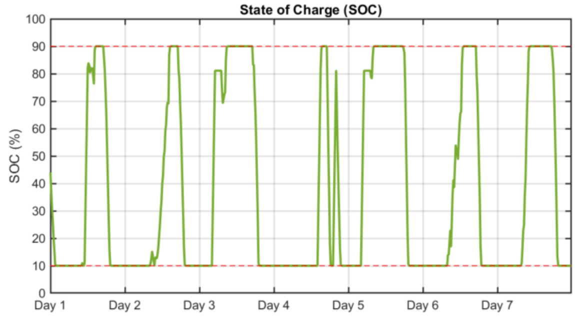

Fig. 12. State of Charge (SoC) evolution in Scenario II.

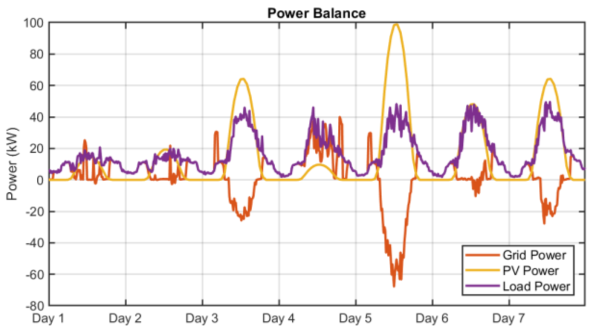

Fig. 13. Energy balance of the system in Scenario II.

These figures demonstrate how the battery operation dynamically adjusts to both pricing signals and generation-consumption mismatches, further validating the benefits of including economic considerations in the battery control logic.

4. Conclusions and Future Works

4.1. Conclusions

This work presents the development and evaluation of a rule-based Battery Management System (BMS) specifically designed to operate within the context of an Energy Community (EC). The proposed system bases its battery charging and discharging decisions on a set of predefined rules that integrate crucial real-time information: hourly electricity prices, instantaneous photovoltaic (PV) energy production, and the user's consumption profile. The primary objectives of this BMS are to maximize the efficiency in the use of local energy resources, reduce dependence on the general power grid, achieve a reduction in final energy costs for community members, and, secondarily, contribute to local grid stability.

The methodology used to evaluate the proposed BMS was based on a modular and scalable simulation model implemented in MATLAB, representing an individual member (prosumer) of the Energy Community. The analysis specifically focused on operational-level control of a single prosumer. To establish a solid comparative basis, the performance of the proposed rule-based system (called RBS) was contrasted with two reference scenarios: a similar rule-based control system that does not consider energy price variations (called RBS_0), and the prosumer's operation without any battery storage system.

The results obtained through simulations, conducted under two different scenarios, consistently demonstrated the economic superiority of the proposed BMS (RBS). In both configurations, the RBS achieved the lowest total energy costs compared to both the RBS_0 system and operation without battery. It is important to highlight that, although the proposed RBS system showed slightly higher net energy consumption from the grid compared to the RBS_0 system (which does not consider prices), its approach oriented toward economic optimization proved more advantageous in terms of total cost. The results validate the system's ability to adapt effectively to the dynamic and variable conditions of both renewable generation and energy prices.

4.2. Future works

For future work, we propose exploring more sophisticated control algorithms, such as Model Predictive Control (MPC) optimization or Machine Learning techniques (especially Reinforcement Learning), to exceed the performance of the current rule-based system and achieve greater cost reduction and operational efficiency. Another key direction is the integration of predictive capabilities. Developing and incorporating accurate models to forecast photovoltaic generation and energy demand will allow the management system to anticipate future conditions and make more proactive and informed battery charging/discharging decisions.

Additionally, it is essential to expand the study approach from analyzing a single member to simulating and optimizing the complete Energy Community. This includes modeling user interactions, optimizing energy sharing, and considering the role of the global coordinator. In parallel, the impact of battery degradation should be incorporated into control strategies for more realistic economic and lifecycle analysis. Finally, to ensure the viability and robustness of the proposed solutions, it will be crucial to conduct experimental validation, either in a controlled real environment or through Hardware-in-the-Loop (HIL) simulations, which would allow comparing simulation results with behavior under conditions closer to real operation.

Acknowledgement

This work is supported by the project Sustainable Atlantic Communities (SAtComm) EAPA 0019/2022 co-funded by the European Union through the Interreg Atlantic Area call. We acknowledge their support for our research.

References

[1] Ahmed, S., Ali, A., & D'Angola, A. (2024). A Review of Renewable Energy Communities: Concepts, Scope, Progress, Challenges, and Recommendations. In *Sustainability (Switzerland)* (Vol. 16, Issue 5). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/su16051749

[2] Kyriakopoulos, G. L. (2022). Energy Communities Overview: Managerial Policies, Economic Aspects, Technologies, and Models. In *Journal of Risk and Financial Management* (Vol. 15, Issue 11). MDPI. https://doi.org/10.3390/jrfm15110521

[3] Marín, L. G., Sumner, M., Muñoz-Carpintero, D., Köbrich, D., Pholboon, S., Sáez, D., & Núñez, A. (2019). Hierarchical energy management system for microgrid operation based on robust model predictive control. *Energies*, *12*(23). https://doi.org/10.3390/en12234453

[4] Chen, H., Cong, T. N., Yang, W., Tan, C., Li, Y., & Ding, Y. (2009). Progress in electrical energy storage system: A critical review. In *Progress in Natural Science* (Vol. 19, Issue 3, pp. 291–312). Science Press. https://doi.org/10.1016/j.pnsc.2008.07.014

[5] Amir, M., Deshmukh, R. G., Khalid, H. M., Said, Z., Raza, A., Muyeen, S. M., Nizami, A. S., Elavarasan, R. M., Saidur, R., & Sopian, K. (2023). Energy storage technologies: An integrated survey of developments, global economical/environmental effects, optimal scheduling model, and sustainable adaption policies. In *Journal of Energy Storage* (Vol. 72). Elsevier Ltd. https://doi.org/10.1016/j.est.2023.108694

[6] Beaudin, M., & Zareipour, H. (2017). Home energy management systems: A review of modelling and complexity. *Lecture Notes in Energy*, *33*, 753–793. https://doi.org/10.1007/978-3-319-26950-4_35

[7] Balasingam, B., Ahmed, M., & Pattipati, K. (2020). Battery management systems-challenges and some solutions. *Energies*, *13*(11). https://doi.org/10.3390/en13112825

[8] N. Voigt, T. Wawer, and T. Albert. (2019). "Optimizing prosumers' battery energy storage management using machine learning," University of Applied Sciences Osnabrueck, Lingen.

[9] Elkazaz, M., Sumner, M., & Thomas, D. (2019). Real-Time Energy Management for a Small Scale PV-Battery Microgrid: Modeling, Design, and Experimental Verification. *Energies*, *12*(14), 2712. https://doi.org/10.3390/en12142712