

Hierarchical Mathematical Optimization Model for Grid-Oriented Management of Aggregated Prosumer Communities

Iraide López¹, Julen Gómez-Cornejo¹, Itxaso Aranzabal¹, Elvira Fernandez¹, Angel Javier Mazón¹

¹Department of Electrical Engineering
Bilbao Scholl of Engineering, University of the Basque Country (UPV/EHU)
Ingeniero Torres Quevedo Plaza, 1, 48013 Bilbao, Biscay (Spain). 946014013, iraide.lopez@ehu.eus

Abstract. This work presents a hierarchical mathematical optimization model for grid-oriented management of aggregated residential prosumer communities, equipped with photovoltaic (PV) generation and battery energy storage systems (BESS). Beyond maximizing individual self-consumption, the proposed Energy Management Strategy (EMS) targets power system operation by enabling aggregated storage to provide flexibility services to the grid.

The model operates through a three-level control architecture (Local Edge Level, Collective Balancing Layer, and Virtual Power Plant Interface) using real irradiance data and actual demand patterns. Local energy excesses and shortages are first matched internally to maximize collective efficiency and reduce power exchanges. At the upper level, the aggregated community is managed as a single flexible asset through a global community state of charge, reserving 10% of the total storage capacity for secondary regulation (Frequency Restoration Reserves, FRR). The fixed 10% band is defined based on criteria aimed at maximizing participation in grid stability services without compromising the physical integrity of the storage systems or the continuity of user supply.

Simulation results demonstrate that the hierarchical strategy achieves collective energy autarky levels above 80% while maintaining the aggregated storage within a secure operational range suitable for frequency control. The proposed approach establishes a technically viable framework for the integration of residential prosumers as active grid-supportive resources in future decentralized power systems.

Key words. Aggregated Prosumers, Photovoltaic Energy, Battery Storage, Grid Stability.

1. Introduction

The global energy sector is currently immersed in a paradigm shift driven by the urgent need for decarbonization to mitigate the effects of the climate crisis [1]. This transformation is built upon three fundamental pillars: decarbonization, digitalization, and decentralization. As traditional hierarchical power systems, based on large-scale centralized generation, evolve toward decentralized smart grids, the role of the final consumer is being redefined [2]. The newest legislation provides the administrative and technical basis for photovoltaic self-consumption, allowing prosumers not only to generate their own energy but also to share it within communities and inject energy excesses into the grid [3]. While European and Spanish regulations, such as Directive (EU) 2019/944 (as amended by Directive (EU) 2024/1711 [4] and Spanish

Royal Decree 244/2019 and its subsequent amendments, have enabled collective self-consumption and energy communities, the operational integration of these resources remains a major technical challenge for Distribution and Transmission System Operators [5].

These updates facilitate aggregated management and expand the operational radius for energy communities, providing a solid legal foundation for the hierarchical model proposed in this work. Hierarchical control architectures offer a scalable solution to address the complexity of managing these interconnected assets while ensuring grid stability [6]. However, the massive integration of intermittent renewable sources poses significant challenges for grid stability, as generation must match demand in real-time to avoid frequency fluctuations [7].

To address these challenges, the deployment of BESS at the low-voltage level has become essential. While individual BESS units enhance local autarky, their potential to support the electrical system remains largely untapped when managed in isolation [8]. Most existing management models focus strictly on individual economic optimization, often neglecting the technical needs of the Distribution System Operator (DSO) and the Transmission System Operator (TSO) [9].

This conceptual framework highlights the aggregator's dual role: first, as a local coordinator that harmonizes the distributed energy resources within the community to achieve collective autarky; and second, as a technical and economic interface with the grid. As shown, the aggregator manages the community's flexibility as a single consolidated asset, enabling participation in wholesale markets and the provision of ancillary services. This structure ensures that local energy needs are prioritized while simultaneously generating revenue through energy trading and grid stability support.

This paper presents an advanced hierarchical mathematical optimization model for the management of aggregated prosumer communities. The proposed EMS, developed in Matlab/Simulink [10], coordinates five residential prosumers through a three-level control structure: Local Edge Level, Collective Balancing Layer, and Virtual Power Plant Interface. The model integrates real irradiance data and predictive load patterns to optimize energy flows.

The primary contribution of this research is the dual-purpose nature of the optimization algorithm. On one hand, it maximizes local efficiency and minimizes energy losses by matching energy excesses and shortages internally within the community. On the other hand, it transforms the community into a grid-supportive asset by participating in secondary regulation services, reserving 10% of the total battery capacity for frequency control. Through the calculation of a community state of charge (SOC_{agg}) and the implementation of real-time adjustment strategies, the model ensures that prosumer aggregation strengthens grid stability while reducing the overall cost of energy over a 15-year horizon.

2. Methodology

The methodology is based on a hierarchical control architecture designed to manage a cluster of five residential prosumers as a single, coordinated entity. To ensure the robustness of the model, it has been validated using demand and irradiance datasets from five distinct profiles in north of Spain. These profiles, characterized by oceanic climate patterns, provide a representative diversity of local excess and demand gaps, ensuring the scalability of the proposed EMS.

A. Algorithm Workflow and Strategy

The mathematical optimization model is executed through a hierarchical and multi-stage EMS designed to balance local consumption efficiency with grid-side stability requirements. The workflow is divided into four critical temporal phases that ensure the technical viability of the aggregated community as a single market unit:

- Stage 1: Predictive data integration (D-1). The algorithm initializes by processing predictive patterns of availability and demand. This includes hourly solar irradiance forecasts and historical load profiles from smart meter data [11]. These inputs allow the model to anticipate energy excesses and shortages with high accuracy.
- Stage 2: Day-ahead collaborative scheduling (D-1). Before market gate closure at 12:00h, the system runs the Local Edge Level and Collective Balancing Layer sub-algorithms. The first stage calculates individual battery charge/discharge cycles to maximize local PV usage, while the second stage performs an internal matching of energy flows among prosumers. This process minimizes transport losses by prioritizing local energy sharing before committing bids to the daily market.
- Stage 3: Real-time grid support (D). During the operation day, the individual battery states are aggregated into a community state of charge (SOC_{agg}). The algorithm manages the 10% capacity reserve dedicated to secondary regulation, responding to real-time frequency restoration signals from the system operator to strengthen grid stability.
- Stage 4: Continuous adjustment and optimization (D t+2). To maintain the system within a safe zone (35-65% SOC), the EMS performs a re-scheduling every hour. It implements advanced control strategies such as Dynamic Operating Point Control (DOPC) and Nocturnal Arbitrage Optimization (NAO) to correct

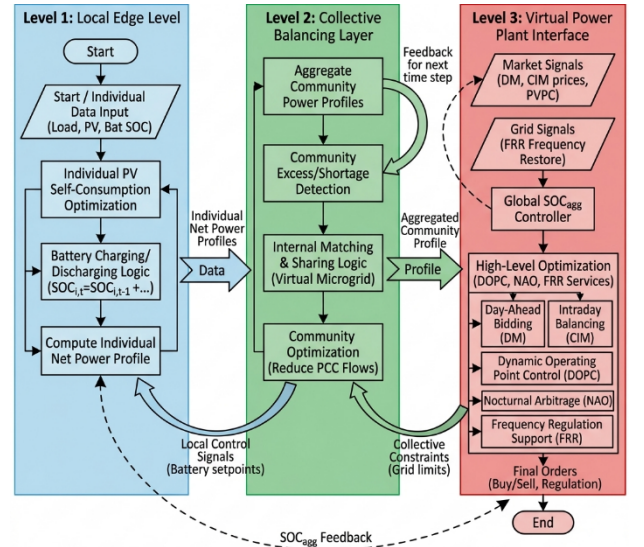


Fig. 1. Integrated three-level hierarchical control architecture for aggregated prosumer communities.

deviations and optimize energy purchases during minimum price hours in the continuous intraday market.

B. Hierarchical Control Levels

The management of the aggregated prosumer community is governed by a three-layer hierarchical control strategy [12], designed to ensure that local energy needs are met with maximum efficiency before providing services to the grid.

- Layer-1. Local Edge Level (local home-scale optimization): At the base of the hierarchy, the algorithm performs an individual energy balance for each household. The primary objective is to maximize the utilization of local PV generation.
 - Balance logic: The system calculates the hourly difference (E_{dif}) between PV production (E_{PV}) and household load (E_{load}). If $E_{dif} > 0$, the battery charges; if $E_{dif} < 0$, it discharges to meet demand. The energy balance for each prosumer i at time t is governed by:

$$P_{PV,i,t} + P_{bat,i,t}^{dis} \cdot \eta - \frac{P_{bat,i,t}^{ch}}{\eta} + P_{grid,i,t} \quad (1)$$

$$= P_{load,i,t} + P_{excess,i,t}$$

Where $P_{bat,i,t}^{ch}$ and $P_{bat,i,t}^{dis}$ are the charging and discharging powers, and $\eta=0.90$ represents the round-trip efficiency. The state of charge evolves as follows:

$$SOC_{i,t} = SOC_{i,t-1} + \frac{P_{bat,i,t}^{ch} \cdot \eta - P_{bat,i,t}^{dis}}{C_{nom,i}} \cdot \Delta t \quad (2)$$

Subject to $15\% \leq SOC_{i,t} \leq 85\%$.

- Efficiency and constraints: A 90% efficiency factor ($\eta=0.90$) is applied to both charging and discharging processes to account for conduction and inverter losses.
- Safety limits: To preserve battery health (State of Health, SoH) and ensure grid band availability, the SOC is restricted between a lower limit ($SOC_{lim}=15\%$) and an upper limit ($SOC_{max}=85\%$).
- Output variable: Any energy that cannot be stored or locally provided is identified as

interchangeable energy (E_{int}), which serves as the input for the next level.

- Layer-2. Collective Balancing Layer: This level manages the five prosumers as a virtual microgrid, coordinating energy exchanges to maximize collective autarky (see Fig. 1).
 - Internal matching: The algorithm identifies members with energy excesses and members with shortages within the same hour. It implements an "aggregated cloud" logic where energy excesses are proportionally shared among users with shortage.
 - Collaborative storage: If internal demand is still not met, users with a SOC above 70% are authorized to discharge their batteries to cover the collective shortage, provided their own future needs are guaranteed.
 - Loss minimization: By matching generation and demand at the local low-voltage level, the model reduces the energy flows crossing the Point of Common Coupling (PCC), thereby minimizing transport losses and grid stress.

The net community aggregation balance ($E_{agg,t}$) is the algebraic sum of individual interchangeable energies ($E_{int,i,t}$):

$$E_{agg,t} = \sum_{i=1}^n E_{int,i,t} \quad (3)$$

This aggregation allows the community to cancel out internal imbalances before interacting with the DSO.

- Layer-3. Virtual Power Plant Interface (Grid Stability): The top layer coordinates the community's external participation [13], [14]. Once local balances are settled, the community acts as a single entity in the energy markets (see Fig. 1).
 - Global aggregation: Individual battery states are merged into a weighted SOC_{agg} , allowing the operator to manage the community's total flexibility as a single asset.

The aggregated flexibility is characterized by the SOC_{agg} , defined as the capacity-weighted average of all community members:

$$SOC_{agg,t} = \frac{\sum_{i=1}^n SOC_{i,t} C_i}{\sum_{i=1}^n C_i} \quad (4)$$

Where $SOC_{i,t}$ represents the state of charge of the i -th prosumer during the time step t , C_i is the nominal battery capacity of the user i , and N is the total number of prosumers.

This parameter is the control variable for the high-level Optimizer to determine the community's participation in the ancillary services market.

- Secondary regulation: The unit reserves 10% of its total capacity to provide frequency restoration reserves to the System Operator. This 10% reserve is strategically defined to ensure a symmetric upward and downward regulation band without reaching the physical limits of the BESS (SOC_{min}/SOC_{max}). By keeping the SOC_{agg} within a "Safe Zone" (35%, 65%), the DOPC algorithm guarantees that the community can respond to a frequency restoration signal for at least 30 minutes,

complying with typical TSO requirements for secondary regulation participation.

- Market interface: The algorithm manages bids for the Daily Market and adjusts them in real-time through the continuous intraday market to correct any deviations caused by the grid stabilization services.

The high-level optimization follows a cost-minimization objective function (J):

$$\min J = \sum_{t=1}^{24} (P_{grid,t} \cdot \lambda_{buy,t} - P_{inj,t} \cdot \lambda_{sell,t} - R_{FRR,t}) \quad (5)$$

Where $R_{FRR,t}$ represents the hourly remuneration for the reserved capacity band.

C. Predictive Patterns and Data Acquisition

To fulfil the optimization requirements, the model integrates a resolution data processing framework to characterize local energy availability and demand patterns. The specific technical parameters for each of prosumers are detailed in Table I.

The solar irradiance data are retrieved from the Basque Weather Agency (Euskalmet). The algorithm converts 15-minute raw irradiance data into hourly power production (E_{PV}) by applying solar array configurations based on the solar peak hours criterion, aiming for a 100% annual solar coverage ratio.

The load profiles (E_{load}) are extracted from smart meter readings provided by the DSO (i-DE). The model treats these inputs as predictive patterns, assuming that advanced statistical or neural network-based forecasting provides the algorithm with a successful horizon for the day-ahead scheduling.

To maximize energy efficiency, a 90% system efficiency factor ($\eta_{syst} = 0.90$) is integrated into the calculations to account for conduction and module losses. The model prioritizes Layer-2 local exchanges (Virtual Microgrid) to minimize energy transport across the point of common coupling, effectively reducing distribution grid stress and transport losses.

Table I. – Technical characterization of the aggregated prosumer community.

User	PV (kW)	BSS (kWh)	Annual Consumption (kWh)	Annual PV Production (kWh)
User 1	2.7	3.0	2086.7	3425.0
User 2	4.5	6.0	3881.4	5293.1
User 3	2.4	3.0	1387.9	2808.8
User 4	2.4	3.0	1533.6	2882.4
User 5	8.1	12.0	7495.9	9126.4
Total	20.1	27.0	16385.5	23535.7

D. Grid Stability and Secondary Regulation Interface

The model transforms the prosumer community from a passive load into an active grid-supportive asset. This is achieved through a coordinated interface with the system operator and the participation in ancillary services.

- 1) Global aggregation: The individual batteries are managed as a single consolidated entity through the calculation of a SOC_{agg} . This variable is determined by a weighted average of the SOC of the whole participants, as shown in equation (4).
By utilizing a capacity-weighted aggregation, the EMS prevents smaller storage units from distorting the perception of total available energy, allowing for a more reliable commitment of frequency restoration bands to the system operator.
- 2) Frequency restoration reserve: The algorithm manages hourly "up" and "down" flexibility bands to correct real-time imbalances between generation and demand in the national grid.
- 3) Uninterrupted supply commitment: Unlike traditional demand-response models, this EMS guarantees that grid-side services never compromise the prosumer's local comfort. The algorithm prioritizes household supply, utilizing the storage flexibility to balance the community's market obligations.

E. Real-time Optimization and Intelligent Adjustment

To ensure technical viability and economic efficiency, the model implements a two-stage scheduling process: a Day-ahead planning (D-1) and a Continuous re-scheduling (D t+2). Two advanced adjustment strategies are executed within the continuous intraday market:

- 1) DOPC: This strategy monitors the SOC_{agg} to prevent deep discharges or overcharges that would disable the frequency control service. A safe zone is established between 35% and 65% SOC. Depending on market prices, the algorithm applies a control matrix to buy or sell energy and return the SOC_{agg} to a secure operating point. The DOPC strategy acts as the technical enabler for frequency services; by dynamically adjusting the community's energy balance in the continuous intraday market, it ensures the SOC_{agg} remains flexible enough to absorb or inject power as requested by the system operator without violating battery safety limits.
- 2) NAO: To optimize energy costs, the algorithm identifies the minimum price hour (typically between 3:00 and 5:00 AM) using market price signals. During this hour, the community performs an energy arbitrage purchase to ensure the SOC_{agg} is near 50% by 6:00 AM, preparing the storage systems for the morning peak demand and maximizing the use of renewable energy generated during the day.
- 3) Corrective bidding: Any deviation caused by real-time frequency regulation is recalculated every hour. The algorithm adjusts the bids in the continuous intraday market to correct the initial day-ahead schedule, ensuring that the final energy balance minimizes technical constraints and maximizes the community's profitability.

F. Definition of Study Scenarios

To evaluate the technical and economic performance of the proposed hierarchical management model, four distinct scenarios were defined and simulated over a 15-year time horizon. This period was selected based on the estimated battery life cycle under the proposed operational conditions, ensuring no replacement costs are required during the analysis.

- Scenario A (Business as Usual - BaU): This scenario represents the conventional energy consumer who lacks local generation or storage assets.
 - Operational logic: The user relies entirely on the utility grid for power supply.
 - Economic framework: All consumption is billed under the current Spanish regulated tariff (PVPC), incorporating real-time electricity market price signals. This ensures that the baseline accurately reflects the modern volatility and energy cost structure of the Spanish power system.
 - Objective: It serves as the baseline reference for comfort and cost comparison, as it requires no initial investment but is subject to high market volatility.
- Scenario B (PV-Only Prosumer). This stage introduces renewable generation without storage flexibility.
 - Operational logic: Solar arrays are sized to achieve a 100% annual solar coverage ratio.
 - Regulatory framework: It operates under the simplified energy excesses compensation mechanism defined in the Spanish RD 244/2019.
 - Economic strategy: Excess energy is injected into the grid and compensated at the wholesale market price minus deviations.
- Scenario C (Individual PV+BSS). This scenario integrates individual storage to enhance self-consumption.
 - Operational logic: Each prosumer manages their own Battery Storage System (BSS) to decouple generation from consumption hours.
 - Management: Control is purely local, aiming to maximize household autarky without interacting with other users or providing grid services.
 - Economic impact: While it increases self-consumption levels, it faces challenges regarding profitability due to the high initial investment in battery.
- Scenario D (Virtual aggregated community). This is the core research scenario, implementing the full hierarchical three-level EMS.
 - Operational logic: Prosumers are clustered into a virtual aggregated community that acts as a single market unit.
 - Grid interaction: Beyond self-consumption, the community participates in ancillary services, specifically providing a 10% capacity band for secondary regulation to the system operator.
 - Optimization strategies: The model utilizes real-time DOPC and NAO in the continuous intraday market to maintain grid stability and optimize energy purchase costs. This scenario is technically superior for strengthening the power grid, despite current fiscal barriers.

The overall economic performance of the four simulated scenarios over a 15-year horizon is summarized in Table II. These results provide the basis for the subsequent analysis of operational stability and market interaction

Table II. – Comparative economic results over a 15-year horizon.

User	Scenario A	Scenario B	Scenario C	Scenario D
User 1	8071 €	6860 €	7180 €	6210 €
User 2	12948 €	10870 €	11200 €	9840 €
User 3	5671 €	4930 €	5120 €	4590 €
User 4	5942 €	5110 €	5340 €	4730 €
User 5	22347 €	18556 €	19200 €	16980 €
Average Saving	0 %	+14.2 %	+11.5 %	+22.8 %

3. Results and Discussion

A. Operational Performance and SoC Stability

The mathematical model was tested using a continuous one-year simulation with hourly granularity. A key performance indicator is the stability of the SOC_{agg} , which represents the collective energy buffer available for grid services. Results indicate that the DOPC strategy effectively maintains the aggregated state of charge within the safe zone (35-65%) during most of the operating hours. This stability ensures that the community can reliably provide the 10% secondary regulation band to the system operator without compromising the local demand of prosumers. Technical verification shows that individual batteries respect the State of Health limits, staying within the 5-95% range even during periods of high frequency regulation demand.

The economic breakdown in Table III details the community's performance within the energy and ancillary service markets. Unlike traditional self-consumption models, the proposed EMS leverages the frequency restoration reserves as a primary revenue stream. While participating in the continuous intraday market incurs operational adjustment costs to maintain the SOC_{agg} within the safe zone, these are effectively offset by the remuneration for providing flexibility to the system operator. The positive annual market balance across all prosumers demonstrates that the aggregated management unit successfully transforms technical flexibility into financial sustainability, providing a clear incentive for the formation of energy communities.

Note that revenue from FRR services in Table III is identical for prosumers with the same storage capacity (User 1, User 3, and User 4). This is due to the proportional allocation logic of the aggregator, which remunerates participants based on their contributed flexibility band (10% of nominal capacity) rather than their individual consumption profiles

Table III. - Grid-oriented performance and flexibility revenue.

Economic Concept	User 1	User 2	User 3	User 4	User 5
DM* Balance	-42 €	-85 €	-42 €	-42 €	-170 €
CIM* Balance	-58 €	-116 €	-58 €	-58 €	-232 €
FRR* Revenues	+210 €	+420 €	+210 €	+210 €	+840 €
Annual Market Balance	+110 €	+219 €	+110 €	+110 €	+438 €

*DM. Day-ahead market

CIM. Continuous Intraday Market

FRR. Frequency Restoration Reserve

B. Community Balancing and Efficiency

The hierarchical management shows a significant improvement in local energy utilization. By implementing the community level balancing, energy excesses from certain members are matched with the shortages of others before any grid interaction occurs. This internal matching reduces the energy flows crossing the point of common coupling, which technically translates into a reduction of distribution grid stress and a minimization of transport losses. The data confirm that the virtual community logic achieves a higher collective autarky than the sum of individual self-consumption facilities operating in isolation.

The economic analysis demonstrates that under current market conditions, Scenario D is the most cost-effective solution. This is driven by two main factors: the significant reduction in BESS CAPEX observed in recent years and the increased spread between peak and valley electricity prices. While Scenario B (PV only) offers a lower initial investment, the aggregated model (Scenario D) provides higher long-term stability and superior savings due to its ability to provide ancillary services and maximize internal community matching.

Table IV. - Comparative summary of technical and economic performance.

Feature / Scenario	Scenario A	Scenario B	Scenario C	Scenario D
Grid Stability Support	None	Low - Energy excesses injection	Medium-Peak shaving	High - FRR & SOC_{agg}
Local Energy Autarky	0 %	~35 %	~65 %	>80 %
15-Year Savings	Baseline	+14.2 %	+11.5 %	+22.8 %
Payback Period	N/A	8.2 years	11.4 years	8.5 years
Operational Reliability	Low-Market Exposure	Medium	High	Maximum-DOPC Strategy

It is worth noting that while Scenario B (PV-Only) presents a slightly shorter payback period (8.2 years) due to its significantly lower initial CAPEX, Scenario D (Aggregated) emerges as the most robust investment. Despite the 8.5-year payback, the hierarchical model achieves a substantially higher net saving of 22.8% over the 15-year horizon. This is explained by the dual revenue stream: the drastic reduction in grid dependency (over 80% autarky) and the constant flow of FRR revenues from grid-support services, which eventually outweigh the initial cost of the battery storage systems.

This research demonstrates the technical and financial viability of a hierarchical mathematical optimization model for aggregated prosumer communities. By integrating a three-level EMS, the system ensures a balance between individual comfort and grid stability.

As summarized in Table IV, the aggregated model (Scenario D) provides superior performance in all analysed metrics. Unlike previous historical contexts where high battery costs limited profitability, the current market framework (characterized by a significant reduction in BESS CAPEX and increased price volatility)

positions the proposed model as the most cost-effective solution.

The implementation of the SOC_{agg} and the 10% reserve for frequency restoration reserve services creates a new revenue stream that, combined with the 80% autarky level achieved through local matching, ensures a positive return on investment within a competitive timeframe. The results confirm that shifting from individual management to a collaborative, grid-oriented aggregated model is essential for the transition toward resilient and decentralized smart grids.

The main contributions of this work are highlighted below:

- **Grid stability support:** The community transforms from a passive load into an active system asset by providing secondary regulation services. The use of the SOC_{agg} and a coordinated 10% battery capacity reserve allows for effective frequency control, strengthening the national power grid.
- **Energy efficiency and autarky:** The hierarchical internal matching logic achieves collective energy autarky levels exceeding 80%. By prioritizing local energy sharing within the community, the model minimizes energy flows across the point of common coupling, effectively reducing distribution grid stress and transport losses.
- **Economic and future viability:** The results confirm that the proposed aggregated management (Scenario D) achieves the highest financial performance, with an average saving of 22.8% compared to the baseline. This model leverages the current drop in storage costs to bridge the gap that previously existed in residential BESS investments. By acting as a single market unit, the community not only reduces its energy bill through an 80% autarky rate but also creates a new revenue stream from grid-support services. The 10% reserve for frequency restoration reserve, coordinated through the SOC_{agg} , ensures that the community is a key asset for future grid stability while maintaining a payback period below 9 years.

Accordingly, to the results, the proposed mathematical model fulfills the objectives of optimizing local consumption through predictive patterns while ensuring grid stability.

Acknowledgement

This work is financially supported by the Basque Government under the Grant IT1647-22 (ELEKTRIKER research group), and by the Grant KK-2025/00093 (Project SAGE) funded by the Basque Government (Collaborative Research Support Program ELKARTEK).

References

- [1] J. Blumberg et al., "Decarbonization of the energy sector: A review of pathways and technologies," *Renewable and Sustainable Energy Reviews*, vol. 162, p. 112408, 2022.
- [2] M. Farmanbar et al., "A Review on Smart Grid Modernization and Blockchain Technology," *IEEE Access*, vol. 7, pp. 127173-127196, 2019.
- [3] T. Bauwens et al., "What is the 'energy community'? A review and conceptual framework of collective self-consumption," *Energy Research & Social Science*, vol. 90, p. 102627, 2022.
- [4] European Parliament and Council of the European Union, "Directive (EU) 2019/944 on common rules for the internal market for electricity and amending Directive 2012/27/EU", *Official Journal of the European Union*, 2019.
- [5] Ministerio para la Transición Ecológica, "Real Decreto 244/2019, de 5 de abril, por el que se regulan las condiciones administrativas, técnicas y económicas del autoconsumo de energía eléctrica", *BOE*, 2019.
- [6] J. M. Guerrero et al., "Hierarchical Control of Microgrids via Secondary and Tertiary Control," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 1, pp. 158-173, 2011.
- [7] F. Blaabjerg et al., "Role of Power Electronics in Future Smart Grids," *IEEE Transactions on Power Electronics*, vol. 32, no. 7, pp. 5055-5071, 2017.
- [8] B. P. Bhattarai et al., "Big data analytics in smart grids: State-of-the-art, challenges and opportunities," *Renewable and Sustainable Energy Reviews*, vol. 101, pp. 243-264, 2019.
- [9] S. Parhizi et al., "A Review of Microgrid Control and Management Strategies," *IEEE Access*, vol. 3, pp. 1767-1783, 2015.
- [10] M. S. Ahmed et al., "Real-time optimal energy management of a grid-connected hybrid microgrid system using Matlab/Simulink," *Applied Energy*, vol. 263, p. 114565, 2020.
- [11] A. S. Ahmad et al., "A review on applications of ANN and SVM for building electrical energy consumption forecasting," *Renewable and Sustainable Energy Reviews*, vol. 33, pp. 102-109, 2014.
- [12] J. M. Guerrero et al., "Hierarchical Control of Microgrids via Secondary and Tertiary Control," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 1, pp. 158-173, 2011.
- [13] H. K. Nguyen et al., "Optimizing intensity and location of energy storage systems in low-voltage distribution networks," *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 2509-2518, 2017.
- [14] Y. Zheng et al., "Optimal Operation of Battery Energy Storage System for Multi-Service Provisioning," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 3, pp. 1013-1021, 2015.