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Hierarchical Energy Management for Renewable Energy Communities Using MPC and Rule-Based Control with Peer-to-Peer Energy Trading

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Abstract

Islanded and weakly interconnected power systems face increasing operational challenges as the penetration of renewable energy grows, particularly in environments with limited flexibility and reserve support. This study investigates a residential energy community in Cyprus using real-time prosumer data and proposes a hierarchical decentralized Energy Management System (EMS). The EMS was initially implemented as a rule-based Minimum Viable Prototype (MVP), enabling practical validation of system operation and data integrity under realistic conditions. Building on this foundation, the final EMS adopts a three-layer control architecture in which rule-based household storage operation and peer-to-peer energy trading are complemented by a community-level Model Predictive Control (MPC) strategy for shared battery management. The MPC leverages short-term net-energy forecasts to proactively schedule charging and discharging of the community battery with the objective of reducing grid energy imports and improving local renewable energy utilization, while respecting battery operational limits and regulatory constraints. Simulation results based on measured data demonstrate consistent improvements over the rule-based baseline, achieving up to 23.4% reduction in electricity cost, approximately 6–7% reduction in grid energy imports, and a 1–2% increase in community self-sufficiency. Although the reduction in imported energy is moderate, its cumulative impact over long-term operation leads to significant economic benefits under time-varying tariffs. These results demonstrate that even when MPC is applied exclusively at the community battery layer, coordinated system-level energy management can deliver stable and economically meaningful improvements under realistic operating conditions.

Keywords: energy management system; renewable energy communities; real-time data acquisition; islanded power systems; multi-objective optimization; minimum viable prototype; model predictive control

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1. Introduction

Modern power systems are experiencing continuously increasing integration of large-scale renewable energy. However, the inherent variability, intermittency, and forecasting uncertainty associated with renewable energy sources pose significant challenges in maintaining system stability, balancing real-time supply demand and achieving economically efficient operation [1,2]. As a major Distributed Energy Resource (DER), solar PV introduces continuous and rapid power fluctuations that must be absorbed and balanced by the grid in real-time [3]. These challenges become substantially more critical in geographically isolated and non-interconnected power systems. Cyprus, an island country in the eastern Mediterranean Sea, lacks energy storage, neighboring grid support, and cross-border balancing

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mechanisms [4,5]. Under such conditions, the power system must independently manage power imbalances, frequency deviations, reserve shortages, and power quality disturbances [6].

The European Union (EU), through the Renewable Energy Directive, attempts to address these challenges through regulatory frameworks for renewable and citizen energy communities. This is achieved by enabling consumers to control their own energy, the deployment of distributed intelligence, the expansion of Advanced Metering Infrastructures (AMI), and the implementation of flexible market mechanisms [4,7,8]. The fundamental EU objective is to establish a decentralized and resilient energy ecosystem. In this framework, consumers, prosumers, and aggregators actively participate in energy markets [4]. Within this broader European energy transition, Cyprus continues to face significant technical and operational constraints. These limitations arise from the island's non-interconnected and isolated power system [5,9].

Cyprus operates a fully isolated power system with no interconnection to the European synchronous grid [5]. As a result, the EU has granted Cyprus several regulatory derogations. These exemptions reflect the increased difficulty of achieving full market liberalization and transparent compensation operations in non-interconnected power systems [10]. Despite these structural limitations, Cyprus has introduced a series of market reforms. These include the Forward Market (FM), the Day-Ahead Market (DAM), and the Balancing Mechanism, aiming to gradually develop a multi-actor and competitive electricity trading ecosystem [11].

Within the broader European energy transition, both Cyprus and the EU are advancing strategic initiatives to enhance system flexibility, strengthen operational stability, and accelerate decarbonization [12]. At the system level, large-scale infrastructure projects such as the Great Sea Interconnector (GSI) aim to reduce Cyprus' long-standing electrical isolation. This is achieved by enabling regional synchronization and cross-border electricity exchange with neighboring power systems [13,14]. In parallel, national energy planning emphasizes complementary flexibility solutions at community and urban levels. These include renewable energy communities and emerging electrification initiatives in coastal energy hubs, such as cold ironing at ports [15]. These developments indicate a broader shift toward data-driven, flexible, and locally optimized energy management approaches. In this context, residential communities equipped with distributed PVs and shared energy storage provide an appropriate testbed to evaluate advanced control strategies under realistic operating conditions [16].

Despite these regulatory and market developments, a critical gap persists in the existing literature. Real-time, data-driven, and decentralized Energy Management System (EMS) frameworks tailored specifically for isolated power systems, such as Cyprus, remain limited [17]. Most existing studies rely on synthetic datasets, simplified operational assumptions, or purely simulation-based environments. These limitations restrict practical applicability and reduce relevance for real-time deployment [18]. Moreover, multi-objective coordination strategies that simultaneously address electricity cost, PV utilization, battery health, and grid interaction remain largely underexplored in non-interconnected isolated power systems. As a result, there is a clear need for localized and data-driven EMS solutions, especially before the realization of large-scale interconnection projects such as the GSI [19].

In this research, an intelligent and decentralized EMS is proposed for a real residential community in Cyprus. The EMS performs adaptive energy scheduling based on real-time PV generation and household demand. In this work, decentralization refers to the adoption of a layered and modular control structure, without centralized optimization at the household level. The Model Predictive Control (MPC) strategy is applied exclusively at the community battery layer. This design choice reflects a fair and unbiased comparison with the rule-based baseline.

The key contributions and novelties of this work are summarized as follows:

- Development and validation of an EMS using a full-year, high-resolution real-time dataset collected from a multi-house residential community.
- A hierarchical hybrid EMS framework in which rule-based household control and P2P energy trading are combined with a predictive control layer applied exclusively at the community battery level.
- A controlled and methodologically consistent benchmarking framework, where the impact of predictive control is isolated by maintaining identical household-level and P2P operations across all scenarios.
- Integration of deployment-oriented system design, including data-driven PV and battery sizing under realistic operational constraints.
- Demonstration that partial deployment of MPC at a single coordination layer can yield consistent reductions in grid dependency and significant long-term economic benefits.

The central research question addressed in this work is whether real-time prosumer data obtained from an isolated power system such as Cyprus can support efficient energy management and P2P energy trading under practical operational constraints. The study investigates to what extent the integration of MPC can reduce grid dependency and electricity costs under time-of-use tariffs compared to conventional rule-based strategies.

This study bridges the gap between regulatory requirements for advanced metering infrastructure in isolated EU power systems and the practical feasibility of data-driven energy management using real prosumer datasets. Unlike existing studies that rely on synthetic datasets or purely simulation-based environments, the presented methodology evaluates the practical effectiveness of energy management strategies using one-year high-resolution real-time data collected from a residential community.

Building on this, the primary scientific novelty of this work lies in the controlled isolation of the marginal contribution of predictive control within a hierarchical EMS architecture. The proposed framework intentionally applies MPC exclusively at the community-battery layer in order to isolate and evaluate the contribution of predictive coordination toward minimizing community grid import under identical household-level operating conditions, while also enabling the evaluation of the community battery sizing methodology. This hierarchical residual-balancing approach preserves household autonomy while enabling coordinated community-to-grid interaction through supervisory community-battery scheduling.

In the context of Cyprus and other isolated power systems with increasing PV curtailment challenges, the proposed framework further demonstrates that coordinated battery sizing methodologies, P2P energy trading between prosumers, and decentralized household battery storage systems have the potential to mitigate renewable energy curtailment and improve local renewable energy utilization using full-year real-time consumption and production datasets.

Table 1 provides a comparative overview of recent EMS and MPC-based community energy management studies, highlighting their methods, strengths, and limitations. In contrast to existing approaches, this work distinguishes itself through the use of one complete year's real-time IoT dataset, a hierarchical PV-centric EMS architecture, and integrated P2P energy trading, with MPC applied only at the community battery layer for fair benchmarking.

Table 1. Comparative Review of Recent EMS and MPC-Based Community Energy Management Studies.

Category	Ref.	Method	Key Contributions	Main Limitations
Rule-Based PV Community EMS	2024 [20]	Rule-Based	(A) Practical EMS for collective PV self-consumption, (B) Transparent and deployable logic	(A) Heuristic thresholds, (B) No forecasting, (C) No optimization
Rule-Based Hybrid Microgrid	2024 [21]	Rule-Based	(A) Reliable PV–battery–grid coordination, (B) Easy real-time implementation	(A) Static decision rules, (B) No community battery
Community Storage MPC	2021 [22]	MPC	(A) MPC-based shared battery dispatch, (B) Increased PV utilization	(A) Centralized control, (B) No P2P trading layer
Electro-Thermal Microgrid EMS	2024 [23]	MPC	(A) Constraint-aware MPC with degradation modeling, (B) Cost and lifetime optimization	(A) No energy community context, (B) High modeling complexity
Distributed Community MPC	2022 [24]	Distributed MPC	(A) Uncertainty-aware coordination, (B) reduced grid dependency	(A) Communication overhead, (B) No hardware validation
Grid-Connected Microgrid EMS	2025 [25]	MPC	(A) Cooperative MPC under grid constraints, (B) Reduced operational cost	(A) No P2P trading layer, (B) Centralized grid interaction
AC/DC Microgrid EMS	2025 [26]	MPC	(A) MPC for hybrid AC/DC systems, (B) Improved power compensation	(A) Sensitive to forecast errors, (B) No layered EMS architecture
Hybrid Rule–MPC EMS	2022 [27]	Rule + MPC	(A) MPC-assisted rule-based dispatch, (B) Improved system stability	(A) Synthetic datasets only, (B) Short evaluation horizon
Neural Approximate MPC	2023 [28]	NN–MPC	(A) Fast online control, (B) reduced computational burden	(A) Risk of constraint violations, (B) reduced interpretability
Building-Level MPC	2025 [29]	MPC	(A) MPC framework for smart buildings, (B) Energy cost reduction	(A) Single-building focus, (B) No community coordination
Multi-Energy District MPC	2025 [30]	MPC	(A) Long-horizon multi-energy optimization, (B) Grid-aware dispatch	(A) No residential prosumers, (B) No P2P trading layer
Hierarchical Community MPC	2023 [31]	Hierarchical MPC	(A) Two-level hierarchical EMS architecture, (B) Grid-interaction optimization	(A) Synthetic demand profiles, (B) No rule-based baseline
Rule-Based vs MPC Residential EMS	2022 [32]	Rule vs MPC	(A) Fair benchmarking of rule-based and MPC EMS, (B) Transparent comparison	(A) Single-house case, (B) Short simulation horizon
Export-Constrained Battery MPC	2024 [33]	MPC	(A) Explicit export-cap modeling, (B) Curtailment-aware scheduling	(A) Centralized EMS architecture, (B) No P2P trading layer
Practical Residential EMS	2023 [34]	Rule-Based	(A) Deployable EMS for energy communities, (B) Improved PV self-consumption	(A) No optimization layer, (B) No forecasting
Grid-Interactive Community EMS	2025 [35]	MPC	(A) Long-horizon grid-aware dispatch, (B) reduced grid stress	(A) No real IoT dataset, (B) Centralized EMS architecture
AI-based Robust Nonlinear PHEV EMS	2024 [36]	I-GWO +NL-Control	(A) Improved GWO tuned robust nonlinear controller for G2V PHEV EMS, (B) Better SOC regulation, stability and energy efficiency under uncertainties	(A) Results validated mainly in simulations no real-time deployment, (B) Centralized control design scalability and real-time constraints not fully addressed
This Work	—	Hierarchical Hybrid EMS (Rule + MPC)	(A) Three-layer EMS: household, P2P, and community battery–grid layers. (B) Fair benchmarking between fully rule-based EMS and hybrid EMS. (C1) MPC applied only at community battery–grid layer. (C2) Full transparency: household dispatch and P2P trading remain identical across controllers. (D) Full-year evaluation using real IoT-based data from 5 households. (E) Reduced grid import and operational cost	

Recent studies continue to demonstrate the growing interest in MPC-based energy management for residential and community energy systems. For example, the recent work of [35] proposed a grid-interactive community EMS using MPC and reported improved operational performance under dynamic grid conditions. However, the framework relied on a centralized EMS architecture and did not investigate the controlled isolation of predictive control at a dedicated community-battery layer. Furthermore, household-level dispatch logic and P2P trading mechanisms were not preserved across baseline and MPC scenarios, making it difficult to isolate the specific contribution of predictive control. These limitations highlight an important research gap that motivates the hierarchical EMS framework proposed in this study.

The remainder of the paper is organised as follows. Section 2 provides a detailed description of the datasets utilised, along with their relevance to the analysis. Section 3 outlines the EMS architecture framework underpinning the study. Section 4 presents the complete mathematical formulation of the proposed work. Section 5 reports the performance evaluation of the proposed EMS under MVP and

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MPC-based community battery control. Finally, Section 6 highlights the discussion and future aspects of the proposed work. For ease of reference, all frequently used abbreviations are summarised in Table 2.

Table 2. Nomenclature.

Abbreviation	Description
AMI	Advanced Metering Infrastructure
CB	Community Battery
DAM	Day-Ahead Market
DER	Distributed Energy Resource
DoD	Depth of Discharge
DSO	Distribution System Operator
EMS	Energy Management System
EU	European Union
FM	Forward Market
GSI	Great Sea Interconnector
MPC	Model Predictive Control
MVP	Minimum Viable Prototype
P2P	Peer-to-Peer
P90	90th Percentile
PV	Photovoltaic
QP	Quadratic Program
RES	Renewable Energy Sources
SoC	State-of-Charge
ToU	Time-of-Use
TSO	Transmission System Operator

2. System Description and Real-Time Data Acquisition

2.1. Community Context and System Scope

This study is motivated by the operational philosophy of the EU Renewable Energy Communities. It focuses on geographically isolated regions without interconnection to larger power systems, such as Cyprus. For such systems, localized energy management is critical. Community-level coordination may support ancillary service provision and contribute to improved grid operation in isolated power systems. It may help reduce operational costs and increase renewable energy penetration and utilization.

2.2. Residential Community and Data Sources

Real-time data was collected from multiple residences equipped with smart meters and inverters. Each participating household was continuously monitored over a one-year period, resulting in a comprehensive dataset capturing variations in PV generation and consumption on a daily basis.

This long-term measurement horizon enables accurate characterization of realistic operating conditions, including periods of high PV penetration, demand variability, and seasonal effects. Such characteristics are often inadequately represented in short-term or synthetic datasets.

Figure 1 illustrates the hardware-based data acquisition and summarizes the complete data acquisition, preprocessing, and logging workflow adopted in this study. The collected datasets were subjected to timestamp synchronization, missing-value handling, outlier filtering, unit conversion, and consistency checks before being used in the EMS simulations.

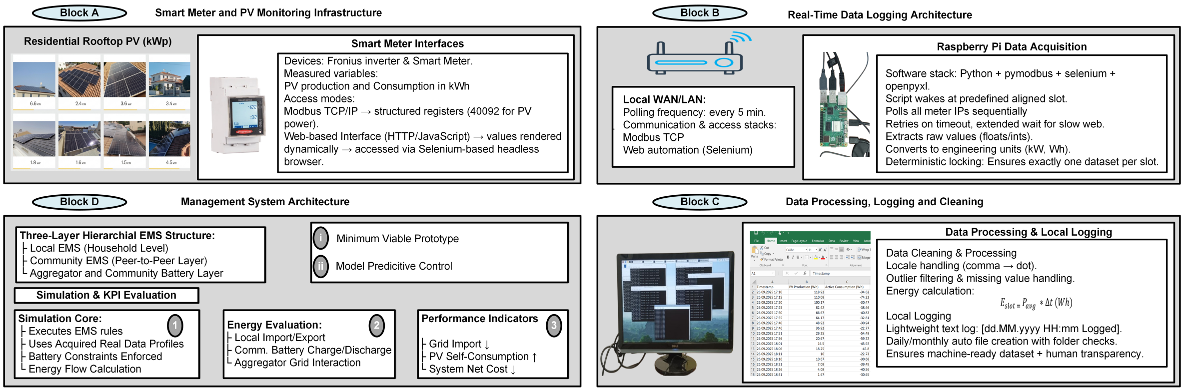

Figure 1. Real-time data acquisition testbed and EMS integration framework showing residential PV installations, smart metering interfaces, Raspberry Pi–based logging infrastructure, hierarchical EMS architecture, and performance evaluation pipeline.

2.3. Hardware Platform and Logging Architecture

To establish a reliable and autonomous monitoring infrastructure, a dedicated hardware-based data acquisition platform was developed using a standalone Raspberry Pi as the central processing unit. The Raspberry Pi executed Python-based scripts continuously (24/7), with data acquisition triggered at fixed five-minute intervals to ensure synchronized and deterministic logging.

Data were collected using Modbus TCP communication for direct access to inverters and smart meters, complemented by Selenium-based web automation for dynamically rendered measurements not accessible through structured registers. This hybrid architecture enables fully automated and uninterrupted data logging.

The recorded dataset consists of three primary variables: timestamp (date and time), PV energy production, and household electricity consumption, all measured in watt-hours. All measurements were stored locally in lightweight CSV files, facilitating transparent inspection, reproducibility, and compatibility with subsequent processing and analysis pipelines.

Figure 2 presents the annual electricity consumption profiles of the five residential households. Significant variations can be observed among the households due to differences in occupancy patterns, lifestyle characteristics, and seasonal electricity usage. Higher consumption levels are generally observed during winter and summer periods, reflecting increased heating and cooling requirements. The figure further demonstrates the diversity of demand patterns within the community and highlights the importance of coordinated energy management strategies capable of adapting to varying residential load conditions.

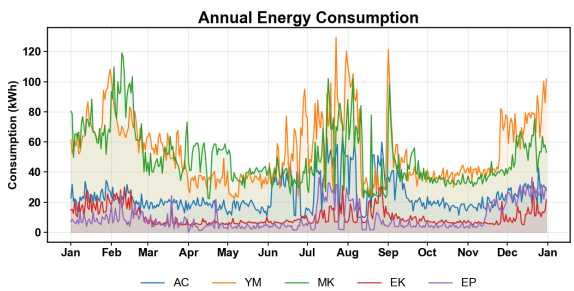

Figure 2. Annual daily electricity consumption profiles of residential households.

2.4. Data Cleaning and Validation

Prior to the analysis and controller development, the complete dataset underwent a rigorous data cleaning and validation procedure to ensure accuracy, consistency, and reliability. The process included timestamp alignment, abnormal value detection and filtering, handling of missing values, and verification of unit consistency across all measurements.

The collected dataset was subjected to standard preprocessing and validation procedures to ensure data quality and consistency. Missing values, which may occur due to temporary communication interruptions, were handled using short-term interpolation or by carrying forward the last valid measurement, depending on the duration of the data gap.

Abnormal values were identified through range-based checks and consistency verification across consecutive measurements. Any detected anomalies were either corrected when possible or excluded from the analysis to prevent distortion of results.

All data streams, including PV generation and household consumption, were synchronized to a uniform 5-minute sampling interval to ensure temporal consistency across all households. The dataset used in this study represents a full-year real-time measurement campaign. Due to privacy considerations, the dataset is not publicly shared in its raw form, but it can be made available in anonymized format upon reasonable request for research purposes.

These preprocessing steps ensure that the dataset is reliable and suitable for data-driven modeling and control design.

2.5. Forecasting Framework for MPC

To enable predictive scheduling at the community battery layer, the MPC controller requires a short-term forecast of the aggregated community net-grid imbalance after household-level dispatch and P2P exchange. In the implemented MATLAB-based framework, this forecast is provided to the MPC controller as an external input vector over the prediction horizon.

The MPC controller itself does not explicitly perform forecasting of PV generation or demand. Instead, since the study is conducted in an offline simulation environment using measured time-series data, the required forecast over the prediction horizon is directly obtained from the available dataset.

A prediction horizon of $N = 12$ steps is considered, corresponding to a one-hour ahead horizon with a five-minute sampling interval. At each control step, only the first optimal action is applied, and the optimization is repeated at the next time step using updated system information.

This assumption enables evaluation of the theoretical performance limits of the MPC framework under ideal forecasting conditions. Forecast uncertainty is acknowledged as a limitation and is considered as a direction for future work.

Forecasting inputs used in this study represent an idealized scenario based on measured data. In practical implementations, forecast errors are inevitable and may influence the performance of predictive control strategies. However, the primary objective of this work is to evaluate the theoretical performance limits of the MPC framework under controlled conditions. Therefore, the reported performance should be interpreted as an upper-bound estimate obtained under ideal forecasting conditions.

Future work will incorporate realistic forecasting models, such as machine learning-based approaches (e.g., LSTM), and explicitly assess the impact of forecast uncertainty on system performance.

3. EMS Architecture

3.1. Hierarchical Dispatch Framework

The decentralized EMS architecture is adopted in this study to ensure modular implementation and compatibility with real-time deployment constraints. Unlike centralized EMS approaches, decentralized control allows independent household-level operation while preserving system-level coordination, reducing computational complexity and communication overhead.

The proposed EMS follows a PV-centric dispatch philosophy that aims to maximize local renewable utilization and prosumer economic benefits [31]. Each residential unit is equipped with rooftop PV generation, and control decisions prioritize the use of locally generated energy before interaction with external resources. The EMS explicitly accounts for temporal mismatches between generation and demand and employs a structured dispatch sequence to allocate available PV energy across multiple flexibility layers.

At the household level, locally generated PV energy is first utilized to satisfy the instantaneous residential load, ensuring maximum direct self-consumption whenever PV generation is available. During periods of surplus PV generation, excess energy is allocated to the household battery energy storage system, subject to minimum and maximum SoC limits defined between 10% and 90%. Unlike conservative strategies that restrict battery operation around a fixed SoC target, the proposed EMS allows full operational flexibility within these bounds, enabling effective utilization of available storage capacity during both surplus and deficit periods.

When household-level demand and local battery charging requirements are satisfied, any remaining PV surplus is shared within the residential community through P2P energy exchange [40]. This mechanism enables surplus energy from one household to be traded directly with neighboring households or to contribute to charging their local storage systems. By prioritizing intra-community energy exchange over grid interaction, the EMS enhances collective self-sufficiency while preserving household-level autonomy.

3.2. Community Battery and Grid Interaction

In scenarios where PV surplus persists after household-level utilization and P2P exchange, excess energy is allocated to a shared community battery. The community battery aggregates surplus energy at the community level and provides an additional layer of flexibility by compensating for the temporal mismatch between PV generation and electricity demand. Similarly to household batteries, the community battery operates within predefined SoC limits, allowing flexible charging and discharging without enforcing fixed SoC targets.

The community battery is coordinated at the supervisory level to mitigate remaining residual community-level power imbalances prior to interaction with the external grid [25]. By absorbing surplus energy and supplying energy during deficit periods, the community battery reduces reliance on grid imports and enhances overall system efficiency. Grid interaction occurs only after household-level self-consumption, P2P energy trade, and community battery operation have been exhausted, ensuring that local resources are efficiently utilized.

Grid export and import are treated as residual interactions, meaning the remaining community-level power imbalance after household self-consumption, P2P exchange, and community battery operation. This design choice enables transparent evaluation of the impact of community battery coordination on grid dependence without imposing artificial export or curtailment constraints within the control logic. Any observed differences in grid interaction therefore arise solely from differences in community-level storage scheduling, rather than from externally imposed limits.

3.3. System Equipment Sizing and Design

All equipment sizing and preliminary system design analyses presented in this section were performed using Python-based scripts. The sizing approach is based on measured household consumption and PV generation data. It is implemented using a simulation-validated methodology rather than heuristic or purely theoretical assumptions [42]. Python was selected because of its flexibility in handling large time-series datasets and its suitability for iterative evaluation of PV and battery sizing scenarios. The sizing procedure adopts a P90-based criterion to ensure conservative and robust equipment dimensioning under realistic operating conditions.

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3.3.1. PV Capacity Sizing

A fundamental observation is that the total PV capacity required to meet a given annual energy offset target remains approximately unchanged whether households operate individually or as part of a P2P energy-sharing community. This is because PV sizing is primarily driven by long-term energy balance:

$$P_{\mathrm{PV}} = \frac{\alpha\, E_{\mathrm{year}}}{Y_{\mathrm{site}}}, \tag{1}$$

The PV sizing formulation presented in Equation 1 follows conventional residential PV system design methodologies [41] where E_{year} is the annual household electricity demand (kWh/year), Y_{site} is the site-specific PV yield (kWh/kWp/year), and α is the targeted annual offset factor typically close to unity when grid import minimization is desired. Under community operation, P2P sharing primarily influences how PV is utilized and distributed among households, rather than the annual PV energy required at the community level. This formulation reflects standard residential PV design practice, where system capacity is selected based on annual energy balance rather than instantaneous power matching.

3.3.2. Battery Sizing Based on P90 Evening (Non-PV) Load

The battery sizing methodology is based on the statistical analysis of household energy demand during evening (non-PV) hours (18:00–08:00), when solar generation is negligible. Using full-year measured data, the daily evening energy demand is computed, and the battery capacity is determined based on the 90th percentile (P90) of this distribution.

This approach ensures that the battery is sized to meet typical high-demand conditions without oversizing for rare extreme events. In practical terms, the selected capacity is sufficient to meet evening demand on approximately 90% of operating days, while higher-demand days are supplied by the grid.

The nominal battery capacity is further adjusted to account for depth of discharge and round-trip efficiency. To validate the selected size, a time-series simulation is performed using multiple candidate battery capacities, and performance metrics such as grid import, export, and self-sufficiency are evaluated. The final battery size is selected based on a trade-off between performance improvement and diminishing returns.

The use of the P90 criterion provides a practical balance between reliability and economic efficiency, as it captures typical high-demand scenarios while avoiding excessive system oversizing.

Case Study Application: YM Household

To demonstrate the practical application of the proposed sizing methodology, the YM residential dataset is analyzed using full-year load and PV production data. The daily evening demand is computed, and the P90 percentile is used as the reference for battery sizing.

$$E_{\mathrm{P90}}^{(\mathrm{YM})} = 42.7\ \mathrm{kWh/day},$$

indicating that on approximately 90% of days over the year, the evening demand does not exceed 42.7 kWh. Equation 2 shows that the nominal battery capacity is calculated using standard battery sizing practices [42] accounting for depth-of-discharge and round-trip efficiency η_{rt}, the nominal battery capacity becomes:

$$C_{\mathrm{bat}}^{(\mathrm{YM})} = \frac{E_{\mathrm{P90}}^{(\mathrm{YM})}}{\mathrm{DoD}\, \eta_{\mathrm{rt}}}. \tag{2}$$

Typical values of $\mathrm{DoD} = 0.9$ and $\eta_{\mathrm{rt}} = 0.9$ are adopted, which results in a nominal capacity of approximately 50 kWh for YM. The selected rating is subsequently validated through a time-series PV–battery–load simulation, confirming that the storage size meaningfully reduces grid imports without unnecessary oversizing.

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Table 3 illustrates the impact of different battery-sizing criteria on the operational performance of the YM case study under full-year evaluation horizons. The comparison includes no-battery operation together with P70-, P80-, and P90-based storage sizing configurations.

Table 3. Battery storage sizing comparison evaluation for the case study building [With-Battery (WB) and No-Battery (NB) cases].

Metric	Full year			
	NB	**WB-P70**	**WB-P80**	**WB-P90**
PV	17.423	17.423	17.423	17.423
Consumption	19.927	19.927	19.927	19.927
Grid-Imp	12.999	6.764	6.283	6.070
Grid-Exp	10.495	3.599	3.071	2.839
Cost-(€)	2410.05	1403.09	1325.12	1290.45

The results show that increasing battery capacity consistently reduces annual grid-import dependence and operational electricity cost while also decreasing unnecessary grid export. Although larger battery capacities improve operational performance, the results also indicate diminishing returns between consecutive sizing levels, particularly between the P80 and P90 configurations.

These observations support the practical suitability of the adopted P90-based sizing methodology, which provides a balanced trade-off between operational improvement and excessive battery oversizing under realistic residential operating conditions.

The same P90-based methodology is consistently applied to the remaining residences to derive their individual baseline battery sizes.

Battery Model and SoC Dynamics

In this work, a lithium-ion battery model is used. The battery behavior is represented using an energy-based formulation, which is commonly employed in energy management and optimization frameworks due to its simplicity and accuracy at system level.

A battery is characterized by two fundamental parameters:

- Energy capacity E_{bat} [kWh] defines how much energy the battery can store.
- Power capacity $P_{\text{bat}}^{\text{max}}$ [kW] represents how fast this energy can be exchanged with the system, i.e., maximum charging/discharging power.

A battery power rating of 0.4C is selected in this study, referring to the maximum allowable charging or discharging rate of the battery. In C-rate notation, 1C corresponds to a full charge or discharge within one hour; therefore, a 0.4C rating implies a full charge or discharge duration of approximately 2.5 hours. This moderate power rating is well suited for energy management applications, as it allows flexible multi-hour charging and discharging while avoiding aggressive battery operation. The selected power limit represents an operational constraint rather than a continuously sustained operating rate, with the actual charging or discharging determined by PV availability, household demand, and EMS decisions.

The SoC is defined as the ratio between the stored energy and the nominal energy capacity. The battery model follows the commonly adopted energy-balance formulation used in energy management and storage optimization studies [22,37]:

$$SoC(t) = \frac{E(t)}{E_{\text{bat}}} \tag{3}$$

The battery energy behavior over a discrete time step Δt is given by:

$$E(t + \Delta t) = E(t) + P_{\text{bat}}(t)\,\Delta t \tag{4}$$

where $P_{\text{bat}}(t) > 0$ indicates charging, $P_{\text{bat}}(t) < 0$ indicates discharging, and Δt is expressed in hours.

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Using the energy balance, the SoC dynamics are expressed as:

$$SoC(t + \Delta t) = SoC(t) + \frac{P_{\text{bat}}(t)\,\Delta t}{E_{\text{bat}}} \tag{5}$$

For a battery with $E_{\text{bat}} = 25$ kWh, $P_{\text{bat}}^{\text{max}} = 10$ kW, and $\Delta t = 0.75$ h, charging at rated power yields:

$$\Delta SoC = \frac{10 \times 0.75}{25} = 0.3 \tag{6}$$

Similarly, discharging at the same power and duration results in a SoC decrease of 30%.

3.3.3. Extension to Community and P2P Operation

When households operate outside an energy community, battery storage sizing must consider that evening consumption is supplied entirely from the battery, subject to financial constraints. This may require a larger battery capacity. When households participate in an energy community, however, with P2P taking place, battery storage sizing can be smaller. This is because households can exchange energy through P2P trading, allowing surplus energy from one residence to supply another.

Moreover, when a community battery is also introduced, surplus and deficit energy can be aggregated and centrally balanced. Due to the diversity of household loads, the aggregated evening demand exhibits a smoother profile than individual load curves, which reduces the total storage capacity required compared to the sum of standalone batteries.

Table 4 summarizes the PV capacities and battery specifications adopted for each household and for the community-level storage under the proposed configuration. The PV capacities are selected based on annual household electricity demand to achieve near-complete yearly energy offset. Household battery capacities are sized while also considering their role within the P2P community environment, aiming to minimise imported grid energy through short-term mismatch mitigation rather than addressing each daily demand profile independently. Residual surplus and deficit energy is handled at the aggregate community level through the shared community battery, which provides centralized longer-term energy compensation.

Table 4. Specifications of installed residential PV capacity and battery energy capacity under standalone and community-based operation.

Residence name	Annual Load (KWh/yr)	P90 Evening Load (KWh/yr)	PV Capacity (kWp)	Standalone battery (P90-based) (kWh)	Reduced Battery under Community Participation (kWh)
AC	10,102.7	22.2	6.12	30	15
YM	19,925.6	42.7	12.08	50	25
MK	5132.2	29.0	3.11	20	10
EK	3,925.9	10.3	2.38	20	10
EP	3,416.1	15.1	2.07	20	10

Battery ID	Battery Capacity (kWh)	Power Rating (kW)	Efficiency %	SoC min (%)	SoC max (%)
Comm. Batt.	50	40	92	10	90

Accordingly, household batteries are intentionally kept modest and primarily assigned the role of local smoothing and short-term mismatch compensation, while the community battery is sized to perform longer-duration compensation at the aggregate level. This hierarchical allocation improves overall storage utilisation and avoids redundant storage capacity at the household level.

The dataset consists of five residential households monitored over a full-year with a 5-minute resolution. The aggregated annual consumption and PV generation are approximately 42.75 MWh/year and 53.59 MWh/year, respectively (equivalent to 42,751 kWh/year and 53,593 kWh/year). All annual energy values are reported in kWh/year. The P90 evening load represents the 90th percentile of daily non-PV consumption demand (kWh/day).

3.3.4. Sizing Interpretation

The adopted sizing framework leads to the following practical insights:

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- PV capacity is governed by annual consumption and is only weakly affected by the presence of P2P sharing.
- Battery capacity is strongly dependent on the level of cooperation: individual operation results in larger household batteries, while P2P exchange and community-level storage reduce the total capacity requirement.
- The selection of the P90 percentile represents a practical trade-off between system reliability and economic efficiency. Lower percentile values (e.g., P70 or P80) may lead to insufficient battery capacity during high-demand days, while higher percentile values (e.g., P95 or P100) may result in oversized and economically inefficient storage systems. Therefore, the P90 criterion provides a balanced design choice that ensures high coverage of typical demand conditions while avoiding excessive system oversizing.
- It should be noted that battery degradation effects and long-term aging are not explicitly modeled in this study, as the focus is on operational energy management performance. Incorporating detailed degradation models and life-cycle cost analysis is considered as an important direction for future work.

3.4. Control Objectives and Optimization Perspective

Although the EMS addresses multiple objectives, the primary control goal is the minimization of grid energy imports. Reducing grid dependency inherently promotes higher PV utilization and more effective use of locally available energy resources. Consequently, secondary outcomes such as improved energy sufficiency and reduced net electricity cost occur from this primary objective.

Figure 3 presents a simple Time-of-Use (ToU) pricing scheme. The grid import price varies between off-peak, base and peak price at the periods shown. The base import price is set to 0.25 €/kWh, the peak price at 1.5 times the base price and the off-peak price at 0.7 times the base price. Additionally, electricity exported to the grid is compensated through a fixed feed-in tariff of 0.08 €/kWh. These timing windows are selected to reflect typical residential demand patterns, where electricity consumption typically peaks during the evening period, when household activity increases.

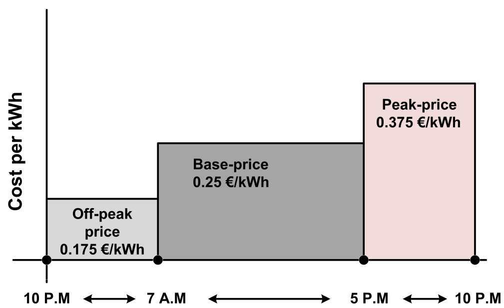

Figure 3. ToU electricity pricing scheme used in this study.

This multi-objective structure forms the basis for the MPC strategies introduced in Section 4.

4. Mathematical Formulation

The mathematical formulation and EMS implementation described in this section were implemented in MATLAB using custom-developed `.m`-files. The MATLAB-based framework enabled consistent implementation of household-level dispatch rules, P2P coordination, and the evaluation of MPC.

All quantities are defined in discrete time with a sampling interval $\Delta t = 5$ minutes. Power variables are expressed in kW, while energy quantities are obtained by time integration over Δt.

4.1. Household Net Power Balance

For each household $h \in \{1, \ldots, H\}$, the instantaneous net power prior to local battery compensation is defined as:

$$p_h^{\text{net}}(t) = p_h^{\text{load}}(t) - p_h^{\text{pv}}(t), \tag{7}$$

where $p_h^{\text{load}}(t)$ denotes the household electrical demand and $p_h^{\text{pv}}(t)$ denotes the rooftop PV generation. A positive value represents a power deficit, while a negative value corresponds to surplus PV generation.

4.2. Household Battery Operation

Each household is equipped with a local battery operated using a rule-based strategy that prioritizes direct PV self-consumption. Let $B_h(t)$ denote the battery power, where $B_h(t) > 0$ indicates charging and $B_h(t) < 0$ indicates discharging.

Following the standard battery dynamics formulation in [22,37], the household battery evolves according to The effective discharging and charging components are defined as:

$$B_h^+(t) = \max(B_h(t), 0), \qquad B_h^-(t) = \max(-B_h(t), 0). \tag{8}$$

The SoC evolves according to

$$\text{SoC}_h(t+1) = \text{SoC}_h(t) - \frac{B_h^+(t)\Delta t}{E_h^{\text{cap}}\eta_h} + \frac{B_h^-(t)\eta_h\Delta t}{E_h^{\text{cap}}}, \tag{9}$$

subject to

$$\text{SoC}_h^{\min} \leq \text{SoC}_h(t) \leq \text{SoC}_h^{\max}, \qquad |B_h(t)| \leq \bar{B}_h. \tag{10}$$

The resulting post-battery residual power is denoted $p_h^{\text{post}}(t)$ and is passed to the P2P trading layer.

4.3. P2P Energy Trading

After household-level compensation, P2P trading is performed among households with residual surplus and deficit:

$$S_h(t) = \max(-p_h^{\text{post}}(t), 0), \qquad D_h(t) = \max(p_h^{\text{post}}(t), 0). \tag{11}$$

The total power traded within the community is

$$p^{\text{p2p}}(t) = \min\left(\sum_h S_h(t), \sum_h D_h(t)\right). \tag{12}$$

Energy is allocated proportionally among participants. Any remaining residual power after P2P trading is exchanged with the external grid and forwarded to the community battery controller.

4.4. Community Battery Model

Let $B_c(t)$ denote the power of the shared community battery, where $B_c(t) > 0$ indicates charging to the community and $B_c(t) < 0$ indicates discharging. The community battery adopts the same energy-balance representation commonly used in MPC-based storage scheduling frameworks [22,31]. The SoC dynamics are

$$\text{SoC}_c(t+1) = \text{SoC}_c(t) - \frac{B_c^+(t)\Delta t}{E_c^{\text{cap}}\eta_c} + \frac{B_c^-(t)\eta_c\Delta t}{E_c^{\text{cap}}}, \tag{13}$$

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subject to

$$\mathrm{SoC}_c^{\min} \leq \mathrm{SoC}_c(t) \leq \mathrm{SoC}_c^{\max}, \qquad |B_c(t)| \leq \bar{B}_c. \tag{14}$$

Equation (13) describes the discrete-time SoC evolution of the community battery, accounting for asymmetric charging and discharging efficiencies and the usable battery energy capacity.

4.5. Community Net-Grid Power Balance

Let $p^{\mathrm{agg}}(t)$ denote the aggregated post-P2P community imbalance. The net power exchanged with the external grid after community battery intervention is

$$p^{\mathrm{grid}}(t) = p^{\mathrm{agg}}(t) - B_c(t), \tag{15}$$

where positive values represent grid import and negative values represent grid export.

4.6. MPC Design

The proposed MPC framework is applied exclusively at the community-battery layer after household-level self-consumption, local battery operation, and P2P energy exchange have been completed. Therefore, the MPC coordinates only the shared community battery to compensate for the remaining community-level power imbalance before external grid interaction.

At each sampling instant ($\Delta t = 5$ minutes), the controller receives the current community-battery SoC together with a forecasted residual community imbalance over a prediction horizon of $N = 12$ time steps (1 hour). The optimization problem is solved in a receding-horizon manner, where only the first optimal control action is applied before updated measurements and forecasts are acquired at the next sampling instant.

In the conceptual EMS framework, the community-battery power is represented using a single signed variable $B_c(t)$, where positive values indicate discharging and negative values indicate charging. For the MPC optimization formulation, this representation is reformulated, as shown in (16), using two separate non-negative decision variables:

$$B_c(t) = P_c^{dis}(t) - P_c^{ch}(t) \tag{16}$$

where $P_c^{dis}(t) \geq 0$ and $P_c^{ch}(t) \geq 0$ denote the community-battery discharging and charging powers, respectively.

This reformulation preserves the physical interpretation of the EMS framework while enabling the optimization problem to be expressed in a standard Quadratic Programming (QP) form compatible with convex optimization techniques.

Figure 4 illustrates the workflow of the MPC-based community battery controller. The controller receives input data including battery parameters, forecasted residual community imbalance, and weighting coefficients together with the selected prediction horizon. Based on these inputs, the optimization model defines the decision variables and operational constraints of the battery system. The cost function and system constraints jointly formulate the MPC optimization problem. At each time step, the solver computes the optimal charging/discharging command for the community battery. The applied battery power command is sent to the system, while the planned power and SoC trajectories are stored for monitoring and analysis. The MPC is applied exclusively at the community-battery layer, while household storage and P2P trading remain rule-based, ensuring a controlled and methodologically fair comparison between the two EMS architectures. The optimization problem is continually updated using newly acquired measurements and forecast information, thereby enabling adaptive real-time scheduling under continuously varying operating conditions [38].

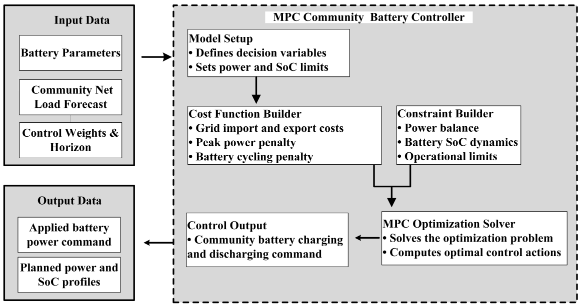

Figure 4. Workflow of the MPC-Based Community Battery Controller.

QP refers to a class of optimization problems in which the objective function contains quadratic terms while the system dynamics and constraints remain linear. In the proposed framework, quadratic penalties are used to regulate grid import, battery operation, and SoC behavior, whereas the battery dynamics and power-balance equations remain linear. This structure preserves convexity and enables efficient numerical optimization.

The forecast vector represents the predicted aggregated residual community imbalance after household-level dispatch and P2P energy exchange have already been completed. Therefore, the MPC schedules only the shared community battery to compensate for the remaining community-level deficit or surplus before external grid interaction.

QP Formulation of the MPC

The adopted MPC formulation follows the standard receding-horizon optimization framework widely used in community energy management and battery scheduling applications.

The problem is formulated as a constrained QP problem in which quadratic penalty terms are minimized subject to linear battery dynamics, power-balance equations, and operational constraints [22,31,43].

Decision Variables

The optimization is solved repeatedly over a prediction horizon of $N = 12$ time steps using MATLAB's `quadprog` solver. For a prediction horizon of length N, the stacked decision vector is expressed as:

$$\mathbf{x} = \left[P_c^{dis}, P_c^{ch}, P^{imp}, P^{exp}, s_c \right]^T \tag{17}$$

where:

- $P_c^{dis} = [P_{c,0}^{dis}, \ldots, P_{c,N-1}^{dis}]^T$ represents the community-battery discharging trajectory,
- $P_c^{ch} = [P_{c,0}^{ch}, \ldots, P_{c,N-1}^{ch}]^T$ represents the charging trajectory,
- P^{imp} and P^{exp} represent grid import and export powers over the prediction horizon,
- $s_c = [s_{c,0}, \ldots, s_{c,N}]^T$ denotes the predicted community-battery SoC trajectory.

The optimization problem therefore predicts the future evolution of the battery SoC while simultaneously determining the optimal grid interaction and battery operation over the prediction horizon.

Dynamics and Power Balance

The optimization problem predicts the future evolution of the community-battery SoC while simultaneously enforcing power-balance consistency between battery operation, community imbalance, and grid interaction.

The community-battery SoC dynamics are expressed as:

$$s_{c,k+1} = s_{c,k} + \frac{\eta_c \Delta t}{E_c^{cap}} P_{c,k}^{ch} - \frac{\Delta t}{\eta_c E_c^{cap}} P_{c,k}^{dis}, \quad k = 0 : N-1 \tag{18}$$

where E_c^{cap} denotes the community-battery energy capacity and η_c represents the round-trip efficiency parameter.

This equation predicts how the battery energy state evolves over time depending on the applied charging and discharging commands.

The aggregated post-P2P residual community imbalance is defined as:

$$P_{c,k}^{net} = \sum_{h=1}^{H} p_{h,k}^{post} - p_k^{p2p} \tag{19}$$

where $P_{c,k}^{net}$ denotes the remaining aggregated community-level imbalance after household battery operation and P2P energy exchange have already been completed. Accordingly, the MPC schedules the community battery together with the grid interaction variables to compensate for the remaining imbalance.

The corresponding community-level power-balance relationship is given by:

$$P_{c,k}^{net} = P_{c,k}^{dis} - P_{c,k}^{ch} + P_k^{imp} - P_k^{exp} \tag{20}$$

Equation (20) shows that the MPC controller operates on the aggregated post-P2P residual imbalance rather than directly controlling household-level resources. Consequently, the community battery acts as a supervisory balancing layer that compensates for the remaining community deficit or surplus prior to external grid interaction.

Unlike fully centralized MPC formulations, the proposed optimization framework does not directly manipulate household appliances, household batteries, PV generation, or P2P trading decisions. These layers are resolved independently before the MPC stage. Therefore, the proposed formulation preserves prosumer autonomy while reducing communication and computational complexity.

Battery self-consumption and internal losses are implicitly considered through the round-trip efficiency parameter used in the battery model. Therefore, no separate metric is reported, as these effects are already embedded within the charging and discharging dynamics.

Operational Constraints

The optimization problem is subject to battery and grid operational constraints:

$$0 \le P_{c,k}^{ch} \le P_c^{ch,max} \tag{21}$$

$$0 \le P_{c,k}^{dis} \le P_c^{dis,max} \tag{22}$$

$$s_c^{min} \le s_{c,k} \le s_c^{max} \tag{23}$$

$$0 \le P_k^{imp} \le P^{imp,max} \tag{24}$$

Although charging and discharging powers are represented as separate non-negative decision variables, the final command applied to the physical community battery is reconstructed as a single signed power command presented in Equation 16.

Therefore, the physical battery operates only in one mode at each sampling instant: charging, discharging, or idle operation.

In addition, the discharging upper bound is linked to the positive component of the forecasted residual deficit, ensuring that battery discharge is only activated when the predicted community imbalance requires support. Concurrent charging and discharging would also increase cycling-related penalties without improving the power-balance objective [33].

It should be noted that the proposed formulation does not employ a strict mathematical complementarity constraint or binary decision variables to explicitly prevent simultaneous charging and discharging. Instead, such behavior is naturally avoided through the adopted optimization structure, operational constraints, and cost-function formulation. Furthermore, no instances of simultaneous charging and discharging were observed in the conducted simulations.

Cost Function

The MPC objective function is designed to minimize the long-term operational cost of the community while maintaining stable and feasible battery operation. The cost function penalizes excessive grid import, unnecessary export, aggressive battery cycling, and large deviations from desired SoC trajectories through a combination of linear and quadratic terms:

$$\begin{aligned} J_k = w_{\text{imp}} \left(p_k^{\text{imp}} \right)^2 + w_{\text{exp}} \left(p_k^{\text{exp}} \right)^2 \\ + w_{\text{dis}} \left(p_{c,k}^{\text{dis}} \right)^2 + w_{\text{soc}} \left(s_{c,k} - s_c^{\text{ref}} \right)^2 \end{aligned} \tag{25}$$

where:

- w_{imp} penalizes grid import,
- w_{exp} penalizes unnecessary export,
- w_{dis} penalizes aggressive battery discharge activity,
- w_{soc} regulates SoC smoothness and stability.

It is important to note that the adopted quadratic objective function acts as a surrogate formulation of the original economic objective. Instead of directly minimizing electricity cost, the use of quadratic penalties ensures convexity and computational tractability, while closely approximating the minimization of grid dependency and associated operational cost under the considered tariff structure. In particular, under ToU tariffs, reducing grid import during high-price periods directly contributes to lowering the total electricity cost [43].

To reduce abrupt control variations and improve battery-operating smoothness, an additional smoothing penalty is included:

$$J_k^{sm} = w_{sm}(P_{c,k}^{ch} - P_{c,k-1}^{ch})^2 + w_{sm}(P_{c,k}^{dis} - P_{c,k-1}^{dis})^2 \tag{26}$$

The overall horizon cost is therefore:

$$\min_x \sum_{k=0}^{N-1} J_k \tag{27}$$

which is finally expressed in the compact QP form:

$$\min_x \frac{1}{2} x^T H x + f^T x \tag{28}$$

subject to:

$$Ax \leq b \tag{29}$$

$$A_{eq} x = b_{eq} \tag{30}$$

The cost function is formulated in a QP framework, consisting of both linear and quadratic terms as given in Equation (28), following standard MPC formulations [43]. The formulation is defined as follows:

- The matrix **H** is a block-diagonal positive definite matrix constructed from the weighting coefficients associated with grid import, grid export, battery charging/discharging power, and SoC deviation.

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- The vector **f** captures linear terms arising from SoC reference tracking and the initial battery state. Since all weighting coefficients are strictly positive, the resulting optimization problem is convex and admits a unique global optimum [43].

Weight Selection and Sensitivity Analysis

The weighting coefficients were selected using a priority-based simulation tuning procedure guided by the operational objectives of the study rather than arbitrary trial-and-error selection.

- Grid import minimization was assigned the highest priority because imported electricity represents the dominant contributor to operational cost under the adopted ToU tariff structure.
- Peak-import reduction was treated as a secondary objective to smooth short-duration high-power grid dependency and improve community-level grid interaction during high-demand periods.
- Export penalties were included to discourage unnecessary export while still allowing beneficial surplus exchange.
- Smaller support weights were assigned to battery discharge penalties, SoC smoothing, and terminal SoC regulation to avoid aggressive cycling, maintain feasible SoC trajectories, and ensure stable battery operation.

The final coefficients used in the implementation were:

$$\begin{aligned} w_{imp} &= 5.0, \quad w_{peak} = 2.0, \quad w_{exp} = 1.0, \\ w_{soc} &= 0.02, \quad w_{dis} = 0.05, \quad w_{term} = 0.5 \end{aligned} \tag{31}$$

To evaluate robustness against controller tuning, a sensitivity analysis was conducted as presented in Table 5 by perturbing the primary weighting coefficients around their nominal values while keeping the prediction horizon, battery constraints, tariff structure, and dataset unchanged. The analysis shows that the MPC controller maintains consistent operational behavior across all tested cases, with only minor variations in annual grid import and operating cost. The selected nominal configuration achieved the lowest annual operating cost while preserving stable battery operation and smooth SoC behavior. Overall, the results confirm that the proposed MPC framework is not overly sensitive to coefficient tuning and that the reported economic benefits mainly arise from the predictive scheduling capability of the controller.

As shown in Table 5, substantial variations in the weighting coefficients result in only minor changes in annual grid imports and operating costs. This indicates that the MPC framework exhibits robust behavior and that the selected nominal weighting coefficients provide a balanced trade-off between operational performance and economic benefit.

Table 5. Sensitivity analysis cases for MPC weighting coefficients.

Case	Purpose	w_{imp}	w_{peak}	Grid Import (MWh)	Annual Cost (EUR)
Selected	Selected	5.00	2.00	7.49	477.79
Analysis-1	Import-priority ↓	4.00	2.00	7.49	479.32
Analysis-2	Import-priority ↑	6.00	2.00	7.49	478.12
Analysis-3	Peak-priority ↑	5.00	5.00	7.49	478.00
Analysis-4	Import priority +80%	9.00	2.00	7.50	485.51
Analysis-5	Import priority -80%	1.00	2.00	7.51	491.43

Table 6 summarizes the notation used for the power-flow variables, SoC states, grid-interaction terms, and weighting coefficients appearing in the MPC formulation and in the wider energy-management framework.

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Table 6. Notation and symbols used in the mathematical formulation.

Symbol	Description	Unit
t	Discrete time index	–
Δt	Sampling interval (5 minutes)	h
H	Number of households	–
N	MPC prediction horizon	steps
$P_h^{load}(t)$	Household electricity demand	kW
$P_h^{pv}(t)$	Household PV generation	kW
$P_h^{net}(t)$	Net household power ($P^{load} - P^{pv}$)	kW
$B_h(t)$	Household battery power	kW
E_h^{cap}	Household battery energy capacity	kWh
$SoC_h(t)$	Household battery state of charge	–
$S_h(t)$	Household surplus PV power	kW
$D_h(t)$	Household deficit demand	kW
$P_h^{p2p}(t)$	P2P traded power	kW
$B_c(t)$	Community battery power	kW
E_c^{cap}	Community battery energy capacity	kWh
$SoC_c(t)$	Community battery state of charge	–
$P^{grid}(t)$	Net community grid power	kW
$P^{imp}(t)$	Grid import power	kW
$P^{exp}(t)$	Grid export power	kW
w_{imp}	Weight on grid import	–
w_{exp}	Weight on grid export	–
w_{soc}	Weight on SoC smoothness	–
w_{term}	Weight on terminal SoC	–

5. Results and Performance Evaluation

This section evaluates the proposed hierarchical EMS under two control configurations: Rule-Based control (baseline MVP) and MPC-based community battery control-using real data over a one-year period from the residential community. The analysis focuses on seasonal operating conditions, community-level power flows, battery behavior, renewable energy utilization, and aggregate performance indicators. Both controllers were tested under identical assumptions, including household-level dispatch rules, P2P energy exchange, tariff plans, and identical grid import and export limits, ensuring a fair comparison between strategies.

5.1. Annual Community PV Generation and Electricity Demand

Figure 5 presents the cumulative annual PV energy generation and total community electricity demand for the five-house residential energy community over a full-year simulation period. The PV generation curve represents the total electrical energy produced by all rooftop PV systems in the community, accumulated over time. The community load curve shows the cumulative electricity demand of all households over the same period. Both quantities are expressed in megawatt-hours (MWh), allowing a direct comparison between annual energy production and consumption at the community level.

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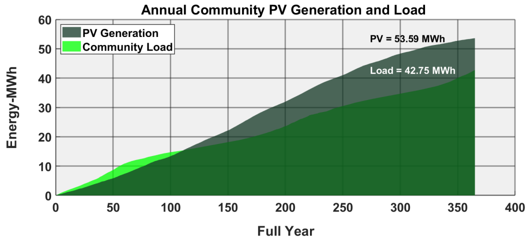

Figure 5. Cumulative annual PV generation and total electricity demand of the residential energy community.

By the end of the year, the community produces approximately 53.59 MWh of PV energy, while the total electricity demand amounts to 42.75 MWh. This reflects that, on an annual basis, PV generation exceeds the aggregate community load, highlighting the strong renewable potential of the community. The seasonal slope variations observed in both curves reflect typical PV availability and consumption patterns, with higher PV accumulation during periods of increased solar irradiance and a steadier growth in demand driven by household electricity use throughout the year.

Overall, Figure 5 demonstrates that the installed PV capacity is sufficient to meet the community's annual energy demand, thereby providing a favourable foundation for high self-consumption and self-sufficiency, subject to the effectiveness of energy management, storage, and P2P coordination strategies.

5.2. Annual Community Grid Import and P2P Trading

Figure 6 shows the cumulative annual electricity imported from the external grid for the residential energy community under the rule-based and MPC-based EMS. The values are accumulated over the full-year simulation period and expressed in MWh, allowing a direct comparison of total grid dependency under both control approaches.

The rule-based system results in a total annual grid import of 8.09 MWh, while the MPC-based system reduces the imported energy to 7.49 MWh. This difference demonstrates the reduced dependence of the MPC-based approach on the external grid over the annual operating horizon. The reduction is achieved by coordinating community battery operation using short-term forecasts, which allows more effective use of locally available PV energy before importing power from the grid.

The shape of the cumulative curves also highlights periods of higher grid reliance, particularly during times of low PV availability, where both strategies show increased import. However, the MPC-based profile consistently remains below the rule-based profile throughout the year, confirming lower collective grid dependence.

Overall, Figure 6 demonstrates that MPC-based community battery coordination leads to a measurable reduction in annual grid energy imports compared to the rule-based approach, thereby improving community self-sufficiency.

Figure 7 illustrates the annual P2P energy trading of each house using bar charts. From the figure, it can be clearly observed that different houses play different roles in the P2P market. The YM house mainly acts as a P2P buyer, indicating higher electricity demand relative to its local PV generation, whereas the MK and EP houses act as strong P2P sellers by exporting a larger amount of surplus PV energy to the community. This variation reflects the heterogeneous consumption and generation profiles of the houses and shows how the P2P mechanism enables energy exchange between surplus and deficit households within the community.

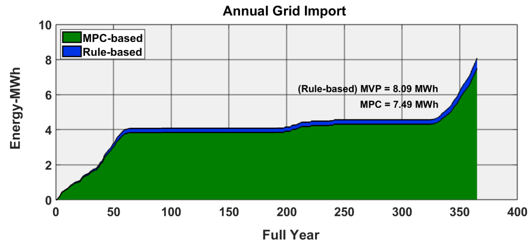

Figure 6. Cumulative annual grid electricity import under rule-based and MPC-based operation.

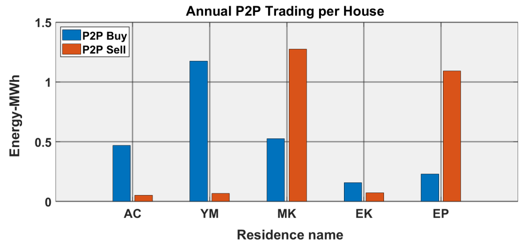

Figure 7. Annual P2P energy trading per house.

5.3. Weekly SoC of Community Battery

Figure 8 shows the community battery SoC during the first week of August for both the rule-based and MPC-based EMS. The SoC is expressed as a percentage of usable battery capacity and is presented over the same time window to allow a direct comparison between the two approaches.

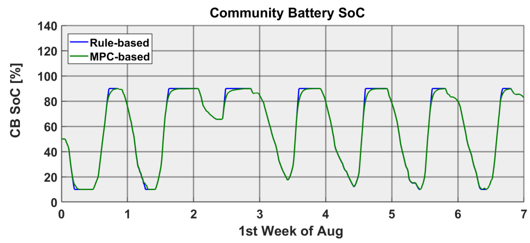

Figure 8. Community battery SoC during the first week of August under rule-based and MPC-based operation.

In the rule-based case, the battery SoC profile exhibits relatively sharp increases and decreases, as charging and discharging actions follow the instantaneous power imbalance of the community. As a result, the battery responds directly to current conditions without considering how demand or generation may evolve over the next hours.

In contrast, the MPC-based approach results in a smoother SoC profile over the same period. Charging and discharging actions are distributed more gradually over time, since the controller accounts for short-term forecasts of community net power and schedules battery operation accordingly. This leads to fewer abrupt SoC variations while maintaining operation within the same minimum and maximum limits.

The similarity observed in the SoC profiles between the rule-based and MPC-based strategies during certain periods is primarily due to similar operating conditions, particularly when PV generation is either consistently high or negligible. Under such conditions, both strategies tend to converge to similar charging and discharging behaviors, resulting in comparable SoC trajectories.

However, the key advantage of the MPC-based approach lies in its anticipatory and predictive capability, which enables more efficient scheduling during transitional periods, such as the shift from PV generation to evening demand. These benefits may not always be directly visible in short-term SoC comparisons but become more evident when evaluating long-term system performance and economic outcomes.

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Additionally, the use of ideal forecast inputs in this study may reduce the observable performance gap between the MPC and rule-based strategies. In real-time scenarios, where forecast uncertainty is present, the predictive capability of MPC is expected to provide more pronounced advantages over reactive rule-based control.

Collectively, Figure 8 shows that both control approaches operate within a similar SoC range; however, the MPC-based strategy achieves smoother battery operation and improved temporal energy management. This contributes to more stable community-level energy balancing and more effective utilization of locally generated PV energy and storage resources.

5.4. Aggregated Performance over Extended Horizons

Table 7 reports the absolute community-level performance of the Rule-Based (MVP) and MPC-based community battery controllers across three evaluation horizons (Jan–Feb, July–Aug, and the full-year). The results show that the MPC-based controller consistently improves key operational and economic indicators relative to the baseline while operating under identical household-level dispatch rules and P2P coordination mechanisms.

Table 7. Community-level absolute performance of the Rule-Based (MVP) and MPC-based community battery controllers across different evaluation horizons.

Metric	Jan-Feb		July-Aug		full-year	
	MVP	MPC	MVP	MPC	MVP	MPC
Grid import (MWh)	3.96	3.73	0.48	0.45	8.09	7.49
Self-sufficiency (%)	62.99	64.51	94.44	94.83	81.09	82.47
Total cost (EUR)	1003.29	940.61	-111.19	-114.97	623.56	477.79

Across all horizons, the MPC-based strategy consistently achieves lower grid energy imports compared with the Rule-Based controller. While the absolute reduction in imported energy is moderate, the improvement is systematic and becomes more evident over longer evaluation horizons, reflecting the cumulative benefit of predictive community battery scheduling. These reductions directly translate into higher community self-sufficiency levels under MPC, with gains remaining incremental due to the already strong baseline performance enabled by local storage and P2P energy sharing.

Grid export volumes remain practically unchanged between the two controllers, indicating that the observed improvements are not driven by increased export activity but rather by more effective utilization of locally available energy through coordinated community battery operation. Similarly, P2P energy exchange remains identical across both control strategies, confirming that performance gains are attributable exclusively to the community battery control layer and not to changes in intra-community trading behavior.

From an economic perspective, the MPC-based controller consistently yields lower total system costs across all horizons. Notably, although the reduction in grid import appears modest in absolute energy terms, its cumulative effect over a full-year, combined with time-varying electricity prices, results in a substantial reduction in total operating cost. These results demonstrate that localized MPC deployment at the community battery layer can deliver persistent system-level economic benefits without modifying household-level control rules or P2P coordination logic.

Table 8 summarizes the relative performance improvements of the MPC-based controller with respect to the Rule-Based baseline. The results indicate grid import reductions in the range of approximately 6–7% across the considered horizons, accompanied by self-sufficiency improvements of around 1–2%. The most pronounced relative gains are observed in total system cost, particularly over a year, highlighting the ability of predictive community battery scheduling to convert modest operational improvements into meaningful long-term economic benefits.

Although formal statistical hypothesis testing is not performed in this study, the consistency of performance improvements across all evaluation horizons suggests that the observed gains are operationally meaningful and not driven by isolated or random conditions.

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To further strengthen the performance evaluation, additional variability analysis was conducted across different seasonal horizons. The consistent improvement trends observed in all considered periods indicate that the proposed MPC-based control strategy provides robust and repeatable performance gains rather than scenario-specific advantages.

Table 8. Relative performance improvements of the MPC-based community battery controller with respect to the Rule-Based baseline.

Metric	Jan-Feb	July-Aug	full-year
Import reduction (%)	5.8	6.3	7.4
Sufficiency (%)	2.4	0.4	1.7
Cost reduction (%)	6.3	3.4	23.4

Table 9 reports the house-level results of P2P energy trading and the corresponding annual net cost for each community member. P2P-buy and P2P-sell values represent the total energy exchanged internally within the community over the full-year. When multiple buyers and sellers coexist at the same timestep, energy allocation is performed proportionally, i.e., buyers receive energy in proportion to their demand and sellers contribute energy in proportion to their available surplus. Since a uniform internal community price is assumed, no bidding or priority-based selection is applied; instead, a fairness-based proportional sharing mechanism is used.

The reported net cost is calculated per house and reflects the actual economic participation of each household, including local PV self-consumption, battery operation, P2P buying and selling, and residual grid imports or exports. Consequently, the final annual cost is not equally divided among households, as each house contributes differently to energy production and consumption. Houses with higher PV surplus and P2P selling tend to achieve lower (or even negative) net costs, while houses with higher demand and P2P buying incur higher costs.

This accounting approach demonstrates a fair and transparent allocation of costs and revenues, where each household is rewarded or penalized according to its real energy behavior rather than an equal cost-sharing assumption.

Table 9. House-wise P2P energy exchange and annual net cost under rule-based (MVP) and MPC-based community battery control.

Residence name	PV (MWh/yr)	Load (MWh/yr)	P2P-Buy (MWh/yr)	P2P-Sell (MWh/yr)	MVP Net Cost (€/yr)	MPC Net Cost (€/yr)
AC	10.07	10.10	0.47	0.05	193.53	175.24
YM	17.42	19.93	1.18	0.07	891.62	811.34
MK	8.88	5.35	0.53	1.27	-95.67	-120.81
EK	5.86	3.93	0.16	0.07	7.37	-0.92
EP	11.36	3.45	0.23	1.09	-373.29	-387.06

6. Discussion and Future Aspects

6.1. Key Findings

It should be emphasized that the present work is conducted as a detailed case-study validation based on a real-time residential energy community consisting of five households. While the system size is limited, the use of a full-year high-resolution dataset enables capturing a wide range of realistic operating conditions, including seasonal variability, PV intermittency, and demand fluctuations.

Therefore, the objective of this study is not to claim universal generalization, but rather to provide a controlled and data-driven evaluation of the proposed EMS framework under realistic conditions. The consistency of the observed performance improvements across multiple seasons and evaluation horizons shows that the proposed control strategy captures representative operational trends in

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residential energy communities. The use of real measured data further strengthens the practical relevance compared to studies based solely on synthetic datasets.

Although the improvements in grid import reduction and self-sufficiency appear moderate in percentage terms, the economic impact of the proposed MPC strategy is significantly more pronounced. The controller achieves up to 23.4% reduction in operational cost over a full-year horizon, demonstrating that even modest improvements in energy balancing can translate into substantial financial benefits under time-varying tariff structures. The MPC controller does not directly optimize electricity cost. Instead, the controller minimizes a surrogate quadratic objective associated with community battery scheduling and power-balancing performance. The reported economic savings are subsequently evaluated using the adopted ToU tariff structure applied to the resulting energy flows.

The results across seasonal scenarios, evaluation horizons, and aggregated performance indicators confirm that the proposed MPC-based community battery controller delivers consistent operational and economic benefits compared to the Rule-Based baseline [32]. These benefits are particularly evident during periods of active PV generation and storage utilization, where the MPC proactively schedules charging and discharging actions based on anticipated net-load conditions. Conversely, during low-generation periods, the MPC effectively moderates grid import peaks and preserves battery availability.

Analysis of the battery SoC further highlights the fundamental difference in control philosophy between the two approaches. The MPC exhibits forecast-driven scheduling behavior, whereas the rule-based controller operates in a purely reactive manner. This distinction leads to systematic reductions in grid energy imports and incremental improvements in community self-sufficiency across all evaluation horizons.

Importantly, although short-term improvements may appear limited, their cumulative effect over long-term operation becomes economically significant. This suggests that the value of MPC in community energy systems lies in persistent system-level improvements achieved through coordinated and anticipatory use of shared storage resources.

The analysis also reflects that MPC performance is inherently linked to seasonal variability, with greater benefits observed when flexibility resources are available. Collectively, the proposed approach achieves a favorable trade-off between implementation complexity and economic performance, making it suitable for practical deployment in emerging residential energy communities.

In comparison to existing EMS approaches summarized in Table 1, which often rely on centralized control, synthetic datasets, or simultaneous modification of multiple control layers, the proposed framework offers a distinct advantage by enabling a controlled and unbiased evaluation of predictive control. Unlike prior works, the MPC is applied exclusively at the community battery layer while preserving identical household-level control and P2P trading mechanisms. Furthermore, the use of a full-year real-time dataset enhances the practical relevance of the results, distinguishing this study from simulation-based or short-term analyses commonly reported in the literature.

This study has several limitations that should be acknowledged.

- First, the use of ideal forecasting inputs based on measured data does not account for real-time forecast uncertainty.
- Second, battery degradation and long-term aging effects are not explicitly modeled, which may influence long-term operational and economic performance.
- Third, the analysis is conducted on a limited number of residential units within a specific community, which may affect the generalizability of the results.

6.2. Future Research Directions

Although the proposed framework suggests strong potential in real residential community settings, several extensions remain open for future research:

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- Integration with price-adaptive and market-participation strategies. Future work will investigate MPC formulations that co-optimize operation with dynamic pricing, ancillary-service participation, and demand-response programs.
- Scalability toward multi-community and hierarchical coordination. Extending the framework toward inter-community cooperation and distribution-level aggregation would enable assessment of system-level behavior at larger scales [39].
- Inclusion of uncertainty-aware and learning-enhanced control. Future work may incorporate stochastic MPC, probabilistic forecasting, and learning-assisted supervisory layers to better handle uncertainty.
- Life cycle-aware storage operation and techno-economic considerations. Incorporating battery degradation models and long-term cost analysis will further enhance practical applicability.
- Cyber-physical reliability and deployment readiness. Future investigations should consider communication delays, measurement noise, and cybersecurity aspects for robust real-time implementation.

6.3. Closing Remark

Collectively, the study suggests that targeted MPC deployment at the community battery layer can measurably reduce grid dependency and improve operational efficiency, without altering decentralized household-level control. The findings position MPC as a coordinating intelligence layer that enhances system-level performance, providing a practical pathway toward more efficient and resilient energy communities.

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