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DEPARTMENT OF INTERNATIONAL & EUROPEAN ECONOMIC STUDIES

Blockchain-enabled Local Energy Markets as Climate Resilience Infrastructure: A Welfare-Based Framework for Distributed Flexibility, Storage and Community Energy Trading

Phoebe Koundouri
Efstathios Devves

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Professor Phoebe Koundouri, School of Economics, DIIES Department, Athens University of Economics and Business, Department of Earth Sciences and Peterhouse, University of Cambridge, AE4RIA Research Centers: SDU.AE4RIA at Athena Research Center and ReSEES.AE4RIA at Athens University of Economics and Business. pkoundouri@aueb.gr

Efstathios Devves, PhD Candidate, School of Economics, Athens University of Economics and Business, Athens, devves@aueb.gr

Abstract

Climate change, increasing electrification, energy-price volatility, and growing dependence on variable renewable resources are increasing the exposure of local and regional energy systems to economic and operational disruptions. Strengthening climate resilience therefore requires systemic approaches capable of integrating distributed flexibility, behavioural adaptation, local market coordination, and digital governance. This study develops an integrated behavioural–economic–technical framework for evaluating residential prosumers participating in blockchain-enabled local electricity markets under dynamic pricing. The model operates over an annual 8,760-hour horizon and combines endogenous utility-based demand response, photovoltaic generation, battery storage, grid interaction, peer-to-peer (P2P) energy trading, battery degradation, and multidimensional welfare assessment. Three progressively more intelligent battery dispatch strategies—a fixed rule-based strategy, an adaptive forecast-based strategy, and a 24-hour rolling-horizon optimisation strategy—are evaluated for four storage capacities of 10, 15, 20, and 30 kWh under identical assumptions and performance indicators. Results show that dispatch intelligence is generally more influential than battery size alone in determining grid dependence, renewable self-consumption, price responsiveness, and welfare allocation. Strategy A exhibits strong capacity saturation, Strategy B produces the strongest capacity-dependent response and buyer-oriented redistribution of P2P benefits, while Strategy C provides a more balanced compromise between prosumer welfare, market participation, and storage utilisation. Fourier decomposition further identifies systematic intraday periodicity in elasticity, P2P price reductions, and participant utilities, revealing temporal market dynamics that are not captured by annual indicators alone. A utility-based clearing-price benchmark additionally quantifies the distribution of welfare between buyers and selling prosumers, while a hierarchical welfare decomposition separates behavioural utility, conventional grid-related surplus, and decentralised P2P welfare. Overall, the findings demonstrate that distributed storage, intelligent dispatch, and blockchain-enabled local trading can reduce exposure to wholesale-market volatility, increase local renewable utilisation and energy autonomy, and strengthen the adaptive capacity of energy communities. The framework therefore interprets distributed flexibility not merely as an optimisation resource, but as a form of **local climate-resilience infrastructure** supporting more adaptive, decentralised, and inclusive energy transitions.

Keywords: Climate resilience; Peer-to-peer electricity trading; Battery energy storage systems; Prosumer utility; Blockchain-enabled energy markets; Distributed energy flexibility

1. Introduction

Climate change, increasing electrification, geopolitical uncertainty, and the growing penetration of variable renewable energy sources are transforming electricity systems worldwide. Traditional centralized power systems, historically designed around predictable generation patterns and unidirectional electricity flows, are increasingly challenged by climate-induced disruptions, price volatility, extreme weather events, network congestion, and supply security concerns. Recent energy crises have further highlighted the vulnerability of centralized infrastructures and have intensified the need for resilient energy systems capable of adapting to rapidly changing technical, environmental, and economic conditions.

Within this context, climate resilience has emerged as a central objective of energy transition policies. Resilience extends beyond the conventional notion of reliability and refers to the ability of socio-technical energy systems to anticipate, absorb, adapt to, and recover from disturbances while maintaining essential functionality. At local and regional scales, resilience increasingly depends on the capability of communities to mobilize distributed resources, coordinate flexible demand, and reduce dependence on centralized generation assets and long transmission infrastructures.

The rapid deployment of distributed renewable energy technologies has fundamentally altered the structure of electricity markets. Residential consumers are progressively transforming into prosumers capable not only of consuming electricity but also of generating, storing, and exchanging energy with neighboring users and local communities. Photovoltaic generation, battery energy storage systems, electric vehicles, smart appliances, and home energy management systems are creating new forms of distributed flexibility that can contribute simultaneously to decarbonization, energy security, and climate adaptation.

However, the integration of large numbers of decentralized energy resources introduces significant coordination challenges. Conventional market structures and centralized dispatch mechanisms were not designed to accommodate millions of small-scale actors making autonomous operational decisions in real time. As a result, new market architectures capable of coordinating decentralized flexibility while preserving efficiency, transparency, and trust are becoming increasingly necessary.

Peer-to-peer (P2P) electricity markets and local energy communities have recently emerged as promising mechanisms for addressing these challenges. By enabling direct energy exchanges among neighboring participants, local electricity markets create economic incentives for self-consumption, renewable integration, local balancing, and congestion reduction. Several studies have demonstrated that local trading schemes can improve market efficiency, increase renewable utilization, reduce curtailment, and generate additional economic value for participating consumers and prosumers. The pioneering Brooklyn Microgrid project further demonstrated the practical feasibility of local energy transactions facilitated by digital platforms and distributed ledger technologies.

Despite these advances, significant research gaps remain regarding the integration of behavioral decision-making, energy storage flexibility, welfare economics, and digital governance mechanisms within a unified resilience-oriented framework. Existing studies frequently focus on isolated technical optimization problems or purely economic market mechanisms while neglecting the complex interactions among consumer preferences, battery operation, social behavior, environmental values, and decentralized coordination technologies.

Battery storage constitutes a particularly important component of resilient local energy systems. Storage technologies provide temporal flexibility by decoupling electricity consumption from electricity production, allowing energy to be shifted across time according to market conditions and system requirements. From an operational perspective, batteries enable arbitrage opportunities, increase self-consumption rates, mitigate renewable intermittency, smooth demand peaks, and provide local balancing services. More importantly, storage enhances adaptive capacity by reducing exposure to wholesale market volatility and improving the ability of communities to maintain electricity supply during periods of stress or disruption.

The emergence of blockchain technology further expands the capabilities of decentralized energy systems. Blockchain-enabled smart contracts provide transparent, automated, and tamper-resistant mechanisms for market clearing, transaction settlement, and contractual enforcement without requiring centralized intermediaries. Combined with Internet-of-Things (IoT) devices and trusted data oracles, blockchain infrastructures enable the verification of renewable energy attributes, decentralized coordination among market participants, and the implementation of sophisticated incentive mechanisms based on social, environmental, and behavioral preferences. Such digital infrastructures are increasingly recognized as enabling technologies for resilient and participatory energy systems.

From an economic perspective, the value generated by local energy systems extends beyond simple cost minimization. Local markets influence welfare outcomes through multiple channels, including consumer surplus, prosumer surplus, renewable premiums, congestion reduction, and improved resource allocation efficiency. Furthermore, social trust relationships and environmental preferences may create additional willingness-to-pay for locally produced and blockchain-certified renewable electricity, generating new forms of value that are not captured by conventional wholesale electricity markets.

This study proposes an integrated socio-technical framework for analyzing the contribution of decentralized flexibility to local and regional climate resilience. The proposed model combines utility-based prosumer behavior, dynamic electricity pricing, demand response, battery arbitrage, blockchain-enabled peer-to-peer electricity trading, and social welfare optimization within a unified operational framework over an annual 8,760-hour simulation horizon. Prosumer decisions are modeled endogenously through utility maximization, while battery operation is represented as an intertemporal flexibility resource operating under degradation constraints and real-option considerations. Market transactions are coordinated through blockchain-enabled smart contracts and IoT-based verification mechanisms, allowing social and environmental preferences to influence market outcomes.

The contribution of the study is threefold. First, it develops a systemic framework that jointly integrates technological, economic, behavioral, and institutional dimensions of local energy systems. Second, it explicitly links distributed flexibility and decentralized market mechanisms to the broader concept of climate resilience by quantifying their contribution to adaptive capacity, energy autonomy, and exposure reduction to external shocks. Third, it extends the literature on local electricity markets by incorporating social welfare analysis, blockchain-enabled green preferences, and community-level resilience indicators within a unified modeling environment.

Ultimately, the paper argues that decentralized flexibility infrastructures should not be viewed merely as optimization tools for electricity markets but rather as strategic resilience assets capable of supporting inclusive, adaptive, and climate-resilient regional energy transitions.

2. Theoretical Background

Mathematical Formulation of Prosumer Consumption Utility

The prosumer's utility during each hourly time interval (t) is not solely an economic quantity but rather a multidimensional behavioral construct reflecting the satisfaction derived from electricity consumption and energy management decisions.

2.1 Utility of Electricity Consumption

Electricity directly consumed within the household, denoted by $E_{\{self,t\}}$ generates utility through the provision of energy services such as thermal comfort, lighting, appliance use, and overall household welfare. Following classical microeconomic theory, marginal utility is assumed to be diminishing with increasing consumption levels. This behaviour is represented through a quadratic utility function:

$$(U_{\{cons,t\}(E_{\{self,t\}})} = \omega_{\{t\}} \cdot E_{\{self,t\}} - \frac{\alpha}{2} \cdot \left(E_{\{self,t\}}\right)^2 \ (1)$$

- $\omega_{\{t\}}$ represents the time-dependent preference parameter reflecting the prosumer's willingness to consume electricity during hour (t);
- **α :** is the saturation coefficient controlling the rate at which marginal utility declines as consumption increases.

  The quadratic utility specification is widely employed in demand response and dynamic pricing studies because it captures diminishing marginal utility while preserving analytical tractability. Similar formulations have been adopted by (Fahrioglu & Alvarado, 2000) and (Samadi, et al., 2010) in the context of residential demand response modelling.

- The parameter α governs the curvature of the utility function and is typically calibrated within the range: $\alpha \in [0{,}10 \ldots, 0{,}50]$.

with values between 0.25 and 0.30 frequently reported in the literature (Samadi, et al., 2010) and (Li , et al., 2011).

The preference parameter ωt follows the daily behavioural pattern of residential consumers and varies according to occupancy and appliance usage. Typical values range between: $\omega_t \in [0{,}50 \ldots, 1{,}50]$. Lower values are observed during nighttime hours when only essential loads are active, whereas higher values occur during morning and evening peak periods when household occupancy and electricity service requirements are greatest.

2.2 Typical Daily Calibration of the Preference Parameter ω_t

The time-dependent preference coefficient ω_t reflects household occupancy patterns, electricity service requirements, and the perceived value of electricity consumption throughout the day. Higher values indicate periods during which consumers derive greater utility from electricity usage and are therefore less responsive to price signals. A representative residential daily profile is summarized in the following Table 1.

Table 1. Residential Daily Profile in ω_t

Time Period	**Typical ω_t Range**	**Household Activity Characteristics**
00:00–06:00	0.50–0.60	Night-time base load. Electricity is mainly used for essential appliances such as refrigerators, standby devices, and minimum household services.
07:00–10:00	0.90–1.10	Morning peak period. Increased demand due to breakfast preparation, cooking, water heating, lighting, and household preparation activities.

Time Period	Typical ω_tRange	Household Activity Characteristics
11:00–16:00	0.75–0.85	Midday period. Household occupancy is typically lower as residents may be away from home. Electricity demand is primarily associated with refrigeration and seasonal heating or cooling loads.
17:00–22:00	1.20–1.50	Evening peak period. Most household members are present, resulting in increased demand for cooking, entertainment, lighting, domestic appliances, heating/cooling, and comfort-related services.
23:00–24:00	0.60–0.70	Transition to night-time operation with gradually declining household activity and electricity demand.

The highest values of ω_t occur during the evening peak when household occupancy and comfort requirements are maximized. Conversely, the lowest values are observed during overnight hours when electricity consumption is largely restricted to essential loads. This calibration is consistent with observed residential load profiles and enables the model to capture realistic temporal variations in consumer preferences and demand responsiveness under dynamic electricity pricing.

The Calibration of Hourly Preferences can be done as follows: The hourly preference coefficient is calibrated as:

$$\omega_t = Price_{elec,base} + a * E_{max,t} \quad (2)$$

The first addend denotes the representative daily electricity price while the second one represents the maximum desired consumption level during hour (t).

This formulation links behavioural preferences to both economic conditions and anticipated electricity needs. For example, assuming:

α=0,25 and $Price_{elec,base}$= 0,15 (€/KWh)

the preference coefficient becomes:

$$\omega_t = 0{,}15 + 0{,}25 * 2 = 0{,}65$$

for a midday period with desired consumption equal to 2 kWh, while during evening peak hours with desired consumption of 5 kWh:

$$\omega_t = 0{,}15 + 0{,}25 * 5 = 1{,}40$$

reflecting the increased value that consumers assign to electricity services during periods of high household activity.

2.3 Relation of Price Elasticity with coefficients α and ωt.

Utility maximization occurs when marginal utility equals the electricity price:

Utility finction maximization when $\frac{\partial U}{\partial E_t} = Price_{elec,t} \Rightarrow \ \omega_t - a * E_t = Price_{elec,t}$

and therefore the optimal electricity demand:

$$E_t = \frac{\omega_t - Price_{elec,t}}{\alpha} \quad (3)$$

The resulting point price elasticity of electricity demand is:

$$\varepsilon_t = \frac{dyE_t}{dPrice_{elec,t}} * \frac{Price_{elec,t}}{E_t} = \left(-\frac{1}{a}\right) * \frac{Price_{elec,t}}{\frac{\omega_t - Price_{elec,t}}{a}} \Rightarrow$$

$$\varepsilon_t = -\frac{\mathrm{Price}_{\mathrm{elec,t}}}{\omega_t - \mathrm{Price}_{\mathrm{elec,t}}} \quad (4)$$

This expression highlights three important behavioural properties.
First, the saturation coefficient α determines the slope of the demand function and therefore affects the absolute level of electricity consumption. However, it does not explicitly appear in the elasticity expression.
Second, the preference parameter ωt, directly influences consumer responsiveness. Higher values ωt,typically observed during evening peak hours, reduce the magnitude of elasticity and make demand less price-sensitive because electricity consumption becomes more essential for household welfare.
Third, elasticity varies dynamically over time as electricity prices fluctuate. Consequently, consumer responsiveness is not constant but evolves according to both prevailing market conditions and household consumption preferences, providing a realistic representation of residential demand response behaviour under dynamic pricing schemes.

2.4 Incorporating Export Revenues into the Prosumer Utility Function

In blockchain-enabled peer-to-peer (P2P) electricity markets and decentralized local energy trading systems, prosumer behaviour is influenced not only by electricity consumption preferences but also by the economic value associated with exporting electricity to the grid or local market participants. Consequently, the utility function should explicitly incorporate export revenues, as these revenues constitute a key driver of prosumer decision-making in transactive energy systems.
This approach is supported by the smart grid and demand response literature. (Chavali, et al., 2014) model prosumer utility through a dual economic framework that simultaneously considers electricity purchasing costs and revenues from electricity sales when optimizing appliance scheduling decisions. Similarly, recent studies on blockchain-based local energy markets and P2P trading mechanisms (Zorba, et al., 2014) emphasize that financial incentives associated with energy exports fundamentally shape prosumer participation and market dynamics.
The inclusion of export revenues within the utility function is particularly important because it enables endogenous decision-making. Rather than treating electricity exports as a purely technical outcome of surplus generation, the model represents exports as an economic choice made by the prosumer. In this framework, the prosumer continuously evaluates the trade-off between self-consumption and market participation.
First, export revenues introduce a marginal balancing mechanism. For each additional kilowatt-hour generated, the prosumer compares the marginal utility obtained from self-consumption with the marginal revenue obtainable from selling electricity in the spot or local energy market. Electricity is therefore allocated to the option providing the highest economic benefit.

Second, under periods of elevated market prices, the incentive to export electricity may exceed the utility derived from additional consumption. When spot prices increase substantially, prosumers are expected to reduce discretionary self-consumption and increase electricity exports, thereby maximizing market revenues. Conversely, during low-price periods, self-consumption becomes relatively more attractive because the opportunity cost of consuming locally rather than exporting is reduced.

From a behavioural perspective, the integration of export revenues transforms the prosumer from a passive consumer with distributed generation into an active market participant capable of responding strategically to dynamic price signals. This mechanism is particularly relevant in blockchain-enabled local energy markets, DePIN-based energy networks, and smart grid environments, where real-time price formation and decentralized transactions create continuous economic incentives for flexible prosumer behaviour.

2.5 Impact of Battery Storage on Prosumer Price Responsiveness (elasticity)

Without use of battery the equation form is:, $\frac{\partial U}{\partial E_t} = Price_{elec,t}$

The introduction of battery storage enables temporal energy arbitrage, fundamentally altering the prosumer's response to electricity price signals. During periods of low electricity prices, the prosumer increases electricity purchases not only to satisfy current consumption needs according to (3), but also to charge the battery for future use. As a result, electricity demand increases beyond immediate consumption requirements, making demand highly elastic during low-price periods.

Conversely, when electricity prices rise substantially, the prosumer can discharge the battery to satisfy household demand without reducing comfort levels or increasing demand-shifting disutility. By relying on previously stored energy, the prosumer avoids reductions in utility and maintains the desired consumption level represented by ωt. Consequently, grid electricity demand decreases significantly and may even become zero.

If electricity exports are allowed, battery discharge combined with local generation may exceed household consumption, resulting in net electricity injections to the grid. In such cases, the demand observed by the grid becomes negative, transforming the household from a consumer into a temporary electricity supplier.

From an economic perspective, battery storage breaks the traditional direct relationship between electricity prices and instantaneous demand. The prosumer is no longer constrained to adjust consumption solely through behavioural changes or load shifting. Instead, storage introduces intertemporal flexibility, allowing energy consumption and grid interactions to be optimized across multiple time periods.

As a result, the battery-equipped prosumer behaves as a highly price-responsive economic agent. Electricity is imported when prices are low, stored for later use, and either consumed or exported when prices are high. This mechanism effectively removes demand from the grid during peak-price periods, precisely when the electricity system experiences the greatest stress, thereby enhancing both individual economic welfare and overall system flexibility.

2.6 Grid Demand Function Under Prosumer Energy Management

The next step is to determine the effective demand observed by the electricity grid as a function of the electricity price. Unlike a conventional consumer, a prosumer can simultaneously consume electricity, generate electricity through distributed renewable resources, charge or discharge a battery, and export surplus energy to the grid. Consequently, the demand perceived by the grid differs from the household's actual electricity consumption.

The hourly grid demand is obtained from the energy balance equation:

$E_{grid},t(Price_{spot,t}) = E_{self,t}(Price_{spot,t}) + E_{bat,t}(Price_{spot,t}) - E_{pv,t},$
Where the decision for the self -consumption is given by the criteria:

$$E_{self,t} = \frac{\omega_t - Price_{elec,t}}{\alpha} \quad (5)$$

The battery energy flow is defined as positive during charging and negative during discharging. Its operation is determined endogenously according to electricity price thresholds.

Mathematical Specification of the Grid Demand Function

The net demand observed by the electricity grid at hour (t) is defined as:

$$E_{grid},t(Price_{spot,t})$$

a **Piecewise Grid Demand Function.** The effective grid demand can therefore be expressed as a piecewise function of the electricity price:

1) **When the spot market price is very low and falls below the lower demand threshold, the prosumer increases electricity imports from the grid.** This occurs because electricity is economically attractive both for immediate household consumption and for charging the battery. Consequently, grid demand rises and becomes highly responsive to low-price signals.

$$E_{grid,t}(Price_{spot,t}) = \frac{\omega_t - Price_{spot,t}}{a} + P_{ch,max} - E_{pv,t}$$

$$E_{grid,t}(Price_{spot,t}) = \frac{\omega_t - Price_{spot,t}}{a} + \min(P_{ch,max}; C_{bat} - SOC_t) - E_{pv,t} \quad (6)$$

When the spot market price falls below the lower charging threshold, the battery enters charging mode. The term $P_{ch,max}$ ε represents the maximum charging power that can be absorbed by the prosumer in order to fully exploit temporal arbitrage opportunities. In practice, the actual charging energy is constrained both by the technical charging limit of the battery and by the remaining available storage capacity.

2) For intermediate spot market prices, no economically beneficial arbitrage opportunity exists. Consequently, **the battery remains in standby mode** and no charging or discharging activity occurs: $E_{bat,t}$=0. Therefore, the battery does not contribute to the household energy balance during this period, and the effective grid demand is determined exclusively by electricity consumption, photovoltaic generation, and export decisions:

$$E_{grid,t}(Price_{spot,t}) = \frac{\omega_t - Price_{spot,t}}{a} - E_{pv,t} \quad (7)$$

In this operating regime, the prosumer behaves similarly to a conventional price-responsive consumer with distributed renewable generation, while energy storage remains inactive.

3) **When the spot market price rises above the upper discharging threshold, the battery enters discharging mode**. Under these conditions, the prosumer utilizes previously stored energy to satisfy household demand, thereby reducing electricity imports from the grid. If the market price becomes sufficiently high, battery discharge may completely offset household consumption and, when combined with photovoltaic generation, may even result in net electricity exports. The battery discharge is constrained by both the maximum discharge power and the energy available in storage. Therefore, the discharge decision is expressed as:
:

$$E_{grid,t}(Price_{spot,t}) = \frac{\omega_t - Price_{spot,t}}{a} - P_{disch,max} - E_{pv,t}$$

and

$$E_{grid,t}(Price_{spot,t}) = \frac{\omega_t - Price_{spot,t}}{a} - \min(P_{disch,max};\ SOC,t - SOC,min) - E_{pv,t} \quad (8)$$

the dynamic grid-demand elasticity is defined as:
$(\varepsilon_{grid,t} \sim Price, spot, t)$

$$\varepsilon_{grid,t} = \frac{dE_{grid,t}}{dPrice_{spot,t}} * \frac{Price_{spot,t}}{E_{grid,t}} \quad (9)$$

Since the maximum charging and discharging powers, as well as the available battery energy capacity, are fixed, the battery response at each time step (t) can be represented as a threshold-based operating rule:
$\frac{dE_{grid,t}}{dPrice_{spot,t}} = -\frac{1}{a}$ the dynamic grid-demand elasticity is then defined as:

$$\varepsilon_{grid,t} = \begin{cases} -\frac{1}{a} * \frac{Price_{spot,t}}{\left(\frac{\omega_t - Price_{spot,t}}{a}\right) + P_{ch,max} - E_{pv,t}}, & Price_{spot,t} \le P^*_{low}(C_{bat}) \\ -\frac{1}{a} * \frac{Price_{spot,t}}{\left(\frac{\omega_t - Price_{spot,t}}{a}\right) - E_{pv,t}}, & Price_{spot,t} \text{ in moderate level} \\ -\frac{1}{a} * \frac{Price_{spot,t}}{\left(\frac{\omega_t - Price_{spot,t}}{a}\right) + P_{disch,max} - E_{pv,t}}, & Price_{spot,t} \ge P^*_{high}(C_{bat}) \end{cases} \quad (10)$$

If price thresholds are endogenously adjusted according to battery capacity, the fixed charging and discharging power limits are replaced by the effective available charging and discharging capacities:
$P_{ch,max}$, $P_{disch,max}$ by $\min(P_{ch,max}; C_{bat} - SOC_t)$ και $\min(P_{disch,max};\ SOC,t - SOC,min)$ respectively. Therefore, as battery capacity increases, the discharging threshold becomes less restrictive. The battery does not discharge only during the single highest-price hour, or the second-highest-price hour, but also during adjacent high-price periods with slightly lower market prices. As a result, the evening peak-price “mountain” is smoothed, reducing stress on the grid and providing additional flexibility to the electricity system.

2.7 Supply and Demand Formation as a Function of Storage Capacity

Battery storage capacity plays a fundamental role in shaping both electricity demand and electricity supply decisions in prosumer-based energy systems. As storage capacity increases, the prosumer gains greater flexibility to shift energy consumption across time and to participate more actively in electricity markets through arbitrage and energy exports.
On the demand side, larger storage capacity enables the prosumer to absorb greater quantities of electricity during low-price periods. Consequently, demand becomes increasingly concentrated during hours of low market prices, as the battery can store surplus energy for future consumption or trading.
On the supply side, increased storage capacity allows larger quantities of previously stored energy to be discharged during high-price periods. This expands the prosumer's ability to inject electricity into the grid or local energy market, thereby increasing the effective supply available during periods of system stress and elevated prices.

Mathematically, the maximum energy that can be shifted between periods is constrained by battery capacity. Therefore, the maximum P2P supply of the prosumer is given by:

$$E_{inj,prosum,t} = E_{PV,t} + \min\left(P_{disch,max}, SOC_t - SOC_{min}\right) - E_{self,t} \quad (11)$$

Where the maximum demand of the prosumer, (as a consumer) is given by:

$$E_{buy,prosum,t} = E_{self,t} + \min\left(P_{ch,max}, C_{bat} - SOC_t\right) - E_{pv,t} \quad (12)$$

So, it is derived that the capability of absorption of local energy is higher when the prosumer – buyer has enough capacity in its storage system (battery) with sufficient storage margin available (C_{bat}-SOC_t).

2.8 Dynamic clearing Price of P2P

The community Supply-to-Demand Ratio SDR,t is calculated by aggregating the available energy capacities of all prosumers participating in the local energy market. The indicator provides a measure of the ability of the community to satisfy its electricity demand through local generation and storage resources. The available supply can further represent the fact that charging decreases available supply while battery discharge increases it.
A local supply deficit occurs when:
$0 \leq SDR_t \leq 1$ and the price is defined by:

$$\boldsymbol{Price_{P2P,t}} = \frac{\boldsymbol{Price_{spot,t} * Price_{prosumer,ch-inj,t}}}{\boldsymbol{(Price_{spot,t} - Price_{prosumer,ch-inj,t}) * SDR_t + Price_{prosumer,ch-inj,t}}}$$

(13)

(Price P2P with local deficit)

where

$\boldsymbol{Price_{spot,t}}$, the grid price of the wholesale spot market

$\boldsymbol{Price_{prosumer,ch-inj,t}}$ the highest price of the time window in which PV generation is in the maximum intraday time window, spot market prices are very low and prosumer should charge its generation in order to sell later (when spot market prices are rising up) and inject to the P2P community. Therefore **$\boldsymbol{Price_{P2P,t}}$ tends to lie between $\boldsymbol{Price_{spot,t}}$ (at the same time) and** $\boldsymbol{Price_{prosumer,ch-inj,t}}$ that are corresponding to the earlier intraday time slots, where prosumer is charging a part of its self-generation (except the self-consumption fraction for itself).

Proof of the above formula

The pricing function is derived under the assumption that the P2P market price is inversely proportional to the community Supply-to-Demand Ratio This assumption is consistent with fundamental economic theory, whereby excess supply depresses prices and supply scarcity increases them. A generalized hyperbolic function is therefore specified and calibrated using the boundary conditions of the local energy market, ensuring economically consistent price formation across varying market states.

Boundary Conditions

Under conditions of local energy deficit $0 \leq SDR_t \leq 1$ the P2P electricity price must lie strictly between the grid purchase price $\boldsymbol{Price_{spot,t}}$ and the injection of prosumer price $\boldsymbol{Price_{prosumer,ch-inj,t}}$. When SDR_t= 0 (that means zero local supply), all electricity demand must be satisfied through imports from the main grid (spot market prices). Consequently, the P2P price converges to the grid purchase price:

$Price_{P2P}$=$Price_{spot,t}$

When SDR_t = 1 (local supply exactly matches demand), the energy community achieves local adequacy, and the P2P price reaches its lower bound:

$Price_{P2P}$=$Price_{prosumer,ch-inj,t}$

Mathematical Derivation (Step-by-Step)

Assume the general form of an inversely proportional relationship:

$$Price_{p2p,t} = \frac{1}{a1 * SDR_t + b1}$$

The parameter b1 is obtained by imposing the following boundary condition:

SDR_t=0 and $Price_{P2P}$= $Price_{spot,t}$, therefore $b_1 = \frac{1}{Price_{spot,t}}$

by imposing the following boundary condition: SDR_t=1, the parameter a1 can be also obtained: a1+b1=$\frac{1}{Price_{prosumer,ch-inj,t}}$. Or $a1 = \frac{Price_{spot,t} - Price_{prosumer,ch-inj,t}}{Price_{spot,t} * Price_{prosumer,ch-inj,t}}$

By replacing a1 and b1 with their equivalent formulas in the first assumption formula we can derive the price $Price_{P2P}$ for deficit condition ($0 \leq SDR_t \leq 1$)

End of proof

Then, aggregate community demand exceeds locally available supply. Under this condition, additional electricity imports from the main grid are required to balance the system.

Conversely, in local surplus, when:

$SDR_t > 1$, and the price is defined by:

$$\mathbf{Price_{P2P}} = \mathrm{Price_{prosumer,ch-inj,t}} \quad (14),$$

Price P2P for local surplus

This happens due to the surplus supply, the P2P price lies between the prosumer - injection price and zero (or a minimum compensation price), as supply is excessively high. The community exhibits a local energy surplus, enabling electricity exports to external markets or neighboring communities. The SDR indicator is particularly relevant for blockchain-enabled peer-to-peer markets and local energy communities, as it provides a real-time measure of self-sufficiency, flexibility, and the need for external grid support.

Therefore, when prosumers within a P2P energy community possess large battery capacities, the Supply-to-Demand Ratio (SDR) becomes smoother over time, as storage enables the temporal shifting of energy from periods of surplus generation to periods of scarcity.

This enhanced flexibility reduces local supply shortages and mitigates excess generation, thereby stabilizing the community energy balance. As a result, local electricity prices tend to converge toward more moderate levels, avoiding the extreme fluctuations commonly observed in wholesale spot markets.

From a market perspective, large-scale storage acts as a buffering mechanism that absorbs energy during low-price periods and releases it during high-price periods. Consequently, battery storage dampens price volatility, enhances local self-sufficiency, and improves market efficiency within blockchain-enabled P2P energy trading systems.

Battery storage capacity functions as a market stabilization mechanism, reducing supply-demand imbalances and smoothing electricity price volatility through temporal energy arbitrage. Ceteris paribus, higher aggregate community storage capacity is expected to reduce the temporal variance of the Supply-to-Demand Ratio and Battery storage attenuates peaks and mitigates troughs in the temporal evolution of SDR.

$$\frac{\partial Var(SDR_t)}{\partial C_{bat}^{Community}} < 0$$

The total Social Welfare of the P2P market over the 8,760 hours of the year is defined as the sum of individual utilities, incorporating battery constraints and P2P market parameters.

$$SW_{total} = \sum_{i=1}^{8760} \sum_{n \in N} \left[U_{cons,n}\left(E_{self,n,t}\right) - \frac{\zeta}{2} * \left(\Delta E_{n,t}\right)^2 - C_{degrad}\left(E_{bat,n,t}\right) + \right] + \sum_{t=1}^{8760} \sum_{i} \sum_{j} \left[\theta * \left(1 - \rho_{ij}\right) * E_{P2P,ij,t}\right] - \sum_{t=1}^{8760} \sum_{i,j} \left(\tau_{ij,t} * E_{P2P,ij,t} - TC_{bc}\right) \quad (15)$$

How Larger Batteries Increase the SW_{total} According to the Model:

a) Reduction of Discomfort Costs: The term $\frac{\zeta}{2} * \left(\Delta E_{n,t}\right)^2$ decreases because prosumers use battery storage instead of curtailing their electricity consumption ($\Delta E_{n,t} \to 0$), thereby preserving their comfort levels.

b) Increase in Green Surplus: The term $\theta * \left(1 - \rho_{ij}\right) * E_{P2P,ij,t}$ is maximized because batteries enable larger volumes of green energy $E_{P2P,ij,t}$ to be exchanged among neighboring prosumers throughout the day.

c) Avoidance of Congestion Charges: Batteries discharge locally, reducing the total network load, which keeps the dynamic DSO charge ($\tau_{ij,t}$) at its lowest possible level.

Final Summary of the Study's Findings

This comprehensive mathematical framework demonstrates that battery capacity C_{bat} acts as both an elasticity regulator and a generator of social value during system operation. Furthermore, prosumer behavior—captured through the utility function—and blockchain technology—implemented via smart contracts and P2P oracles—jointly transform a rigid electricity network into a self-regulating, efficient, and equitable local energy market.

2.9 Calibrations for ζ, ($D_{shift}(\Delta E_t)$ ψ and Cdeg

Calibration of the Discomfort Parameter: ζ, $D_{shift}(\Delta E_t)$

In the demand response literature, the discomfort parameter ζ **is not selected arbitrarily but is typically calibrated to reflect the level of economic compensation required for consumers** to modify their preferred electricity consumption patterns. Conceptually, ζ captures the disutility associated with shifting, reducing, or postponing electricity usage and therefore represents the degree of behavioral resistance to demand-side flexibility measures.

For residential consumers and small commercial users, benchmark values reported in the literature generally fall within a relatively broad range. Low values of ζ (approximately 0.01–0.05 €/kWh²) characterize highly flexible consumers who can readily adjust consumption schedules, such as households equipped with smart appliances, automated water heaters, home energy management systems, or electric vehicle charging infrastructure. Medium values (approximately 0.05–0.20 €/kWh²) are typically associated with conventional residential prosumers who **are willing to accept moderate adjustments** to their consumption profile in exchange for meaningful economic incentives but exhibit increasing discomfort as flexibility requirements become more substantial. Higher values of ζ (approximately 0.20–0.50 €/kWh²) represent relatively inelastic consumers whose electricity usage is constrained by fixed schedules, comfort requirements, social circumstances, or critical loads that cannot be shifted without significant welfare losses.

For the purposes of the present case study, the selected value of ζ reflects the behavior of a typical residential prosumer participating in dynamic pricing and P2P energy trading schemes. The chosen calibration therefore represents a balance between economic responsiveness and comfort preservation, allowing the model to capture realistic demand response behavior while avoiding unrealistically high levels of load shifting.

Economic Interpretation of the Discomfort Parameter

This paragraph provides an intuitive interpretation of the discomfort parameter ζ used in the demand response formulation. The parameter quantifies the welfare loss experienced by a prosumer when electricity consumption deviates from the preferred baseline profile. Consequently, ζ represents the degree of behavioral rigidity or flexibility associated with household electricity consumption.

The load-shifting cost is modeled through a convex discomfort function. This formulation implies that progressively larger deviations from the preferred consumption schedule generate disproportionately higher welfare losses, reflecting the increasing inconvenience associated with altering household routines and comfort conditions.

To illustrate the economic meaning of the parameter, consider a representative load-shifting action corresponding to a temporary reduction or postponement of electricity demand during a peak-price period. Such an adjustment may involve delaying appliance operation, modifying thermostat settings, or rescheduling flexible household loads.

For a highly flexible household, characterized by a low value of ζ the resulting discomfort cost remains relatively small. In this case, even modest increases in electricity prices are sufficient to incentivize demand response participation. Such behavior is typically associated with automated homes, smart appliances, electric vehicle charging management systems, and advanced home energy management technologies.

For a representative residential prosumer, corresponding to intermediate values of ζ demand response actions generate a moderate welfare loss. Consumers are willing to modify consumption behavior when meaningful economic savings are available but are unlikely to accept substantial disruptions without adequate compensation.

At the opposite end of the spectrum, large values of ζ characterize highly inelastic consumers. These households experience significant welfare losses when modifying electricity usage patterns and therefore require substantial economic incentives before participating in demand response programs. Such situations may arise when consumption is constrained by fixed schedules, critical household needs, vulnerable consumer groups, or comfort-sensitive loads.

The marginal discomfort cost is obtained from the first derivative of the discomfort function and represents the additional welfare loss associated with shifting one additional unit of electricity demand. According to the optimal demand response framework proposed by (Li , et al., 2011), a utility-maximizing prosumer continues adjusting electricity consumption until the marginal discomfort cost equals the marginal economic benefit provided by prevailing market prices.

This equilibrium condition provides a direct calibration mechanism for the discomfort parameter and establishes a behavioral link between electricity price signals and consumer flexibility. Based on benchmark values reported in the demand response literature, the present study adopts a central calibration of ζ €/kWh² to represent a typical residential prosumer participating in dynamic pricing and peer-to-peer electricity trading schemes. To evaluate parameter uncertainty and behavioral heterogeneity, a sensitivity analysis is conducted over the interval 0.02–0.30 €/kWh², encompassing highly flexible, moderately flexible, and relatively inelastic consumer profiles. Table 2 gives typical calibration ranges for ζ

Table 2. Typical Calibration Ranges for ζ

Consumer Profile	**Typical Range of ζ (€/kWh²)**	**Behavioral Interpretation**
Highly Flexible Prosumer	0.02 – 0.05	Strong willingness to shift demand and participate in demand response programs

Consumer Profile	Typical Range of ζ (€/kWh²)	Behavioral Interpretation
Typical Residential Prosumer	0.05 – 0.20	Moderate flexibility with balanced consideration of comfort and economic incentives
Relatively Inelastic Prosumer	0.20 – 0.50	Limited willingness to modify consumption patterns without substantial compensation

These ranges are consistent with the broader demand response literature and provide a practical basis for evaluating consumer heterogeneity in smart grid and P2P energy market applications.

1. Discomfort Parameter: ζ, $D_{shift}(\Delta E_t)$, **and Disutility/Inconvenience Cost**

Following the formulations proposed by (Fahrioglu & Alvarado, 2000) and subsequently extended by (Samadi, et al., 2010), the discomfort associated with load shifting is represented through a quadratic cost function.

2. Peer-to-peer (P2P) Energy Markets and Utility Functions

The following references establish the theoretical basis for utility-driven market participation in peer-to-peer electricity trading and local energy communities. These studies investigate the economic interaction between buyers and sellers, demonstrating how market-clearing prices emerge from the balance between consumer utility, producer benefits, and transaction constraints. Such interactions generate a region of mutually beneficial exchanges, often described as the market surplus or trading window, where both participants obtain higher welfare than under conventional retail market arrangements:

- (Tushar, et al., 2019) present a highly relevant study for the theoretical formulation of buyer–seller utility interactions, market-clearing conditions, and the identification of mutually beneficial trading regions (Trading Windows) in P2P electricity markets.
- The Brooklyn Microgrid is widely recognized as the pioneering real-world demonstration of blockchain-enabled peer-to-peer electricity trading. Developed by LO3 Energy, the project (Mengelkamp, et al., 2018) provided one of the first practical validations of local energy markets in which prosumers could directly trade surplus photovoltaic electricity with neighboring consumers through a distributed transaction platform. As a result, the Brooklyn Microgrid has become a benchmark case study in the P2P energy trading literature and a reference point for subsequent research on blockchain-based local energy communities.

Regarding the “green preferences” and blockchain interactions, these references provide both theoretical and empirical support for incorporating the consumer preference coefficient $\boldsymbol{\rho_{ij}}$ and the green premium parameter **θ,** as they demonstrate that consumers exhibit a willingness to pay a premium for electricity whose renewable origin and environmental attributes are transparently certified through blockchain technology:

(Sorin, et al., 2019) proved to be a fundamental study to showcase how the “seller differentiation” (the neighbor to be proved as green prosumer) change the P2P clearing price.

(Kloppenburg & Boekelo, 2019) develop their study about the interaction among prosumers, platforms and the role of blockchain technology.

(Wang, et al., 2022)**)** provide the conceptual enhancing of the prosumer utility in P2P microgrids using blockchain-verified green certificates.

2.10 Calibration of Battery Degradation Costs and Real Options Thresholds

Battery Degradation Cost Calibration

To quantify the operational battery degradation cost $C_{\{deg,t\}}$, the model incorporates a throughput-based degradation coefficient ψ representing the marginal depreciation cost associated with each unit of energy charged or discharged through the battery. This approach is widely adopted in operational battery optimization models because it enables degradation effects to be represented without explicitly modeling electrochemical aging processes.

The parameter ψ is calibrated using current lithium-ion battery replacement costs and expected lifetime throughput. Conceptually, the coefficient reflects the ratio between battery replacement cost and the total energy that can be exchanged over the battery's useful life. Consequently, (\psi) can be interpreted as the marginal wear cost incurred for each additional unit of energy cycled through the storage system.

Based on contemporary Lithium Iron Phosphate (LFP) battery technologies (Rangelova & Johnes, 2025) , replacement costs, cycle-life characteristics, and round-trip efficiencies reported in recent studies, typical values of the degradation coefficient fall within the range:

ψ ∈[0.015, 0.050] €/ kWh

For the present case study, a central value of **ψ = 0.03 €/kWh** is adopted. This value represents a conservative calibration that captures not only cycle-related degradation but also additional aging mechanisms, including calendar aging and accelerated degradation associated with higher charging and discharging rates.

The operational degradation cost is subsequently calculated as the product of the degradation coefficient and the absolute energy throughput during each simulation period. This formulation ensures that battery operation is penalized whenever charging or discharging actions contribute to asset wear, thereby preventing unrealistically intensive cycling behavior.

B.2 Calibration of Battery Energy Throughput

The variable $E_{\{bat,t\}}$) represents the quantity of electrical energy exchanged by the battery during time interval (t). Positive values correspond to charging operations, while negative values represent discharging actions.

The magnitude of battery energy throughput depends on the installed battery capacity, the power rating of the storage system, and the duration of the simulation time step. In residential applications, battery capacities typically range between 5 and 15 kWh, while charging and discharging rates are constrained by inverter and battery power limits. Consequently, the battery energy exchanged during each operational interval is determined endogenously by the optimization model subject to these technical constraints.

Integration of Real Options Theory

Beyond degradation considerations, battery operation is also evaluated through the lens of **Real Options Theory**. Following the framework developed by (Dixit & Pindyck, 1994) and subsequently applied to energy storage valuation (Nadarajah & Secomandi, 2023) , the battery is interpreted as a flexible asset that embeds an option to defer operation until more favorable market conditions emerge.

Because electricity prices are inherently stochastic, immediate battery operation is not always economically optimal. The decision to charge or discharge involves an opportunity cost associated with preserving future flexibility. Accordingly, battery arbitrage should only be executed when the expected price spread between charging and discharging periods exceeds both the degradation cost and an additional uncertainty premium reflecting the value of waiting.

Under this interpretation, battery dispatch becomes analogous to exercising a financial option. The battery remains idle when anticipated arbitrage revenues are insufficient to compensate for degradation and foregone future opportunities. Conversely, operation is triggered only when market price differentials become sufficiently large to justify exercising the embedded option.

This Real Options perspective introduces an economically rational threshold for battery activation and prevents excessive cycling in response to marginal price differences. As a result, the storage asset is utilized only when its contribution to system welfare exceeds the combined costs of degradation and uncertainty, yielding more realistic operational behavior and improving the economic robustness of the optimization framework.

$$(C_{\{deg,t\}} = \psi \cdot |E_{\{bat,t\}}|) \ (16)$$

Specialized Literature on Battery Degradation Cost

To substantiate the above parameter values and the mathematical formulation of $C_{\{deg,t\}}$, specialized literature on Battery Degradation Cost can be used, with regards to the **Marginal Degradation Cost Modelling.**

(Miguel, et al., 2022) examine the conversion of battery capital expenditure (CAPEX) into an equivalent operational degradation cost per cycle and evaluates its impact on short-term arbitrage profitability and battery dispatch decisions. (Orbit, et al., 2016) offered a classic reference with regards to the linear modelling of degradation cost in terms of market algorithms. (Rangelova & Johnes, 2025) have given the official market data to indicate the way that the fall of battery capex cost reduces LCOS at the level of **0.065 euro / kWh**, therefore allowing the more frequent operational arbitrage.

3. Research Contributions, Research Gaps and Scientific Novelty

3.1. Positioning of the Study

The present study positions itself at the intersection of residential prosumer optimisation, behavioural economics, distributed energy resources, battery energy storage systems, demand response, blockchain-enabled local energy markets and climate resilience. While each of these research domains has matured considerably during the past decade, the literature remains fragmented. Most existing studies focus on a single objective, such as electricity cost minimisation, battery arbitrage, self-consumption maximisation, peer-to-peer market clearing or blockchain implementation. Consequently, there is still no unified framework capable of evaluating prosumer decisions simultaneously from behavioural, operational, economic and societal perspectives under a common mathematical formulation.

Building upon the attached manuscript and theoretical framework, the proposed research develops a unified 8,760-hour operational model in which utility maximisation, battery dispatch, demand response, peer-to-peer trading and welfare economics are integrated into a single analytical environment. The study therefore shifts the focus from isolated optimisation problems to a comprehensive socio-technical representation of residential flexibility.

3.2. Research Gaps

The literature reveals several persistent gaps. First, battery scheduling models are usually formulated as isolated optimisation problems whose objective is electricity bill minimisation. Second, utility-based demand-response studies generally neglect battery operation and local electricity trading. Third, blockchain studies concentrate on transaction architecture rather than operational behaviour. Fourth, social welfare analyses typically remain at wholesale market level and rarely include residential prosumers. Fifth, studies employing optimisation often compare different algorithms under different objective functions, making comparisons methodologically inconsistent. Finally, monthly and seasonal performance indicators remain underexplored because many publications report only annual averages.

3.3. Overall Scientific Contribution

The proposed framework addresses these limitations by introducing a common mathematical environment (overall set of equations) in which every dispatch philosophy is evaluated using identical behavioural assumptions, operational constraints and economic indicators. Consequently, differences in performance originate exclusively from the decision-making strategy rather than from differences in mathematical formulation.

3.4. Novelty Components (NC1–NC10)

NC1: Unified behavioural–economic–technical framework integrating utility, demand response, battery storage, P2P trading and welfare within one annual operational model. **NC2:** Common evaluation framework (overall set of equations) allowing fair benchmarking of all dispatch strategies using identical KPIs and constraints.

NC3: Three hierarchical battery dispatch philosophies progressing from fixed heuristics to adaptive forecast-based control and finally rolling-horizon optimisation.

NC4: Endogenous prosumer behaviour represented through dynamic utility and time-varying price elasticity rather than fixed demand assumptions.

NC5: Joint quantification of Utility, Consumer Surplus, Producer Surplus, Prosumer Surplus, Grid Welfare and Total Social Welfare instead of electricity cost alone.

NC6: Explicit modelling of storage as an intertemporal flexibility asset balancing arbitrage, self-consumption, exports, degradation and state of charge.

NC7: Operational integration of blockchain-enabled peer-to-peer trading, smart contracts and trusted renewable verification.

NC8: Systematic monthly and annual KPI framework including energy, economic and battery indicators for three strategies and four battery capacities.

NC9: Introduction of aggregate elasticity indicators derived from weighted monthly and annual grid-import behaviour to complement endogenous hourly elasticity.

NC10: Interpretation of distributed flexibility as climate-resilience infrastructure capable of reducing exposure to price volatility while strengthening community autonomy.

Scientific significance: This contribution extends previous work by connecting behavioural decision-making, operational scheduling and welfare assessment within the same analytical framework. It improves reproducibility because every scenario is solved under identical assumptions, enabling causal comparison of strategies.

3.5. Comparison with Existing Literature

Compared with utility-based demand response studies, the proposed framework explicitly incorporates storage, dynamic dispatch and welfare indicators. Compared with battery optimisation literature, it extends the objective from cost minimisation to multidimensional welfare. Compared with peer-to-peer market studies, it embeds behavioural utility and endogenous battery decisions. Compared with blockchain research, it links digital governance with operational optimisation rather than presenting blockchain as a stand-alone technological layer. Finally, compared with resilience studies, it quantifies adaptive capacity using operational indicators instead of conceptual discussion. Tables 3a and 3b describe the comparative advantage of the current study contribution.

Table 3a

Reference	Utility-based Behaviour	Battery Scheduling	Dynamic Pricing / DR	P2P Trading	Blockchain	Welfare Analysis
(Samadi, et al., 2010)	✓	–	✓	–	–	–

(Parag & Sovacool, 2016)	✓	–	✓	Partial	–	Partial
(Tushar, et al., 2019)	Partial	Partial	Partial	✓	–	✓
(Morstyn, et al., 2018)	Partial	✓	Partial	✓	–	Partial
(Sousa, et al., 2019)	Partial	✓	Partial	✓	–	Partial
(Andoni, et al., 2019)	–	–	–	✓	✓	–
(Soto, et al., 2021)	Partial	✓	Partial	✓	Partial	Partial
(Yuan, et al., 2022)	Partial	✓	Partial	✓	Partial	Partial
(Schwidtal, et al., 2023)	Partial	Partial	Partial	✓	Partial	Partial
(Afzali, et al., 2024)	✓	✓	✓	Partial	–	Partial
(Maya & Salam, 2024)	–	Partial	Partial	✓	✓	Partial
(Wang, et al., 2025)	Partial	✓	Partial	✓	–	Partial
This paper	✓	✓	✓	✓	✓	✓

Table 3b

Reference	**Endogenous Elasticity**	**Multi-Strategy Battery Comparison**	**Common Mathematical Framework**	**Monthly & Annual KPIs**	**Climate Resilience**	**Main Limitation**
(Samadi, et al., 2010)	Partial	–	–	–	–	Utility without storage
(Parag & Sovacool, 2016)	–	–	–	–	Partial	Conceptual analysis
(Tushar, et al., 2019)	–	–	–	–	–	P2P focus only
(Morstyn, et al., 2018)	–	–	–	–	–	Market architecture
(Sousa, et al., 2019)	–	–	–	–	–	Market design focus
(Andoni, et al., 2019)	–	–	–	–	–	Blockchain review
(Soto, et al., 2021)	–	–	–	–	–	Review only
(Yuan, et al., 2022)	–	–	–	–	–	Storage review
(Schwidtal, et al., 2023)	–	–	–	–	Partial	Local market review
(Afzali, et al., 2024)	Partial	–	–	Partial	Partial	Focus on prosumer satisfaction
(Maya & Salam, 2024)	–	–	–	–	Partial	Blockchain and transaction losses
(Wang, et al., 2025)	–	–	–	Annual	–	Technical-economic comparison only
This paper	✓	**✓ (Strategies A–C)**	**✓ (complete set of equations)**	✓	✓	**Integrated socio-technical framework**

3.6. Methodological Contribution

Methodologically, the paper contributes a reproducible benchmarking platform. All scenarios use identical hourly demand, photovoltaic production, electricity prices, battery specifications, utility functions and welfare equations. The only changing element is the dispatch philosophy. Strategy A represents fixed heuristic control, Strategy B introduces adaptive forecast-based thresholds and Strategy C explicitly optimises the common economic objective over a rolling 24-hour horizon. This experimental design isolates the value of decision intelligence itself.

3.7. Scientific and Practical Implications

The framework has implications for researchers, system operators, energy communities and policy makers. Researchers obtain a benchmark capable of comparing heuristic and optimisation-based dispatch under identical assumptions. Distribution system operators obtain insights into flexibility utilisation, grid imports, exports and peak reduction. Energy communities can evaluate the value of peer-to-peer trading and blockchain governance, while policy makers can quantify the welfare implications of residential flexibility under dynamic electricity pricing.

3.8. Contribution to Climate Resilience

A distinctive contribution of this work is the explicit interpretation of distributed flexibility as resilience infrastructure. Batteries, demand response and decentralised trading reduce dependence on wholesale electricity purchases, mitigate exposure to price shocks, improve renewable utilisation and increase local energy autonomy. Consequently, resilience is evaluated quantitatively through operational and welfare indicators rather than treated as a qualitative policy concept.

3.9. Why the Paper Advances the State of the Art

The novelty of the manuscript **lies not in proposing only another optimisation algorithm** but in providing an integrated scientific framework where behavioural economics, operational optimisation, distributed flexibility, blockchain-enabled market governance and welfare economics **coexist within a common formulation**. The combination of hierarchical dispatch strategies, common evaluation metrics, endogenous elasticity, comprehensive monthly and annual KPIs and resilience-oriented interpretation substantially broadens the analytical scope of residential prosumer research. This provides a transparent benchmark that future studies can reproduce and extend, thereby offering a meaningful methodological advancement for further research and publishing in journals that are relevant to these topics.

As a further discussion point, the proposed modelling philosophy deliberately separates the optimisation engine from the evaluation framework. This separation enables robust comparison between heuristic and optimisation-based decision making while avoiding bias introduced by different objective functions. Such methodological transparency is **rarely found in the existing literature and improves reproducibility**, interpretability and transferability of results across future studies.

3.10 Fundamental Contribution

A fundamental contribution of this research lies in the introduction of a **hierarchical welfare decomposition framework** that explicitly separates the different economic mechanisms through which residential battery storage creates value. While the majority of existing studies evaluate battery performance using aggregate indicators such as **annual profit**, **self-consumption**, **self-sufficiency**, or **total social welfare**, these metrics provide only a single measure of overall economic performance and do not reveal the underlying sources of value creation. The proposed framework addresses this limitation by distinguishing three complementary layers of economic welfare: **(i) behavioural welfare**, represented by the **Prosumer Utility Function**, which captures the welfare associated with electricity consumption, self-consumption, flexibility and battery scheduling decisions; **(ii) conventional market welfare**, represented by the proposed **Prosumer Surplus with respect to the spot/grid market (PS_to_grid)**, which quantifies the economic value generated exclusively through interactions with the wholesale electricity market before any peer-to-peer transactions occur; and **(iii) decentralised market welfare**, represented by the **P2P surplus and the corresponding social welfare indicators**, which measure the additional value generated through local peer-to-peer electricity trading. Consequently, the overall welfare of the prosumer can be interpreted as the combined outcome of three distinct but interconnected components: the surplus obtained through conventional market participation, the surplus generated through decentralised local energy trading, and the behavioural utility associated with internal household energy management and flexibility. This hierarchical decomposition constitutes an important methodological advance because it identifies **where the economic value created by battery storage actually originates**, rather than reporting a single aggregated measure of economic benefit. In particular, it distinguishes whether improvements arise from **more efficient interaction with the wholesale electricity market**, **additional value created through local peer-to-peer energy exchanges**, or **enhanced internal energy management resulting from intelligent battery scheduling and demand flexibility**. By isolating these individual welfare components, the proposed framework provides a substantially richer interpretation of battery performance and explains why different battery capacities and energy management strategies may produce similar overall economic outcomes while relying on fundamentally different value-creation mechanisms. This decomposition therefore extends conventional battery evaluation methodologies by linking operational decisions directly to the specific economic channels through which storage technologies create value, offering a more transparent and comprehensive framework for analysing residential prosumer systems and local electricity markets.

4. Methodology

4.1 Data Integration and Annual Profile Calibration (8760-Hour Horizon)

The analysis is based on an annual dataset with hourly resolution (8,760 observations), enabling the representation of seasonal and intra-day variations in electricity demand, photovoltaic (PV) generation, and market conditions. The dataset integrates hourly residential electricity consumption profiles, solar availability, PV electricity production, and electricity market prices, providing a consistent framework for the operational simulation of prosumer behavior throughout the year.

Particular attention is given to the seasonal variability of solar irradiation, which directly affects PV generation patterns. Higher PV output is observed during spring and summer months, while reduced solar availability during winter increases dependence on grid electricity and stored energy. The reference consumption profile reflects typical residential demand behavior, characterized by morning and evening peaks and lower demand during nighttime hours.

Battery storage is modeled exclusively from an operational perspective. The objective is to isolate the effects of storage on electricity consumption, demand flexibility, self-consumption, and energy trading decisions. The battery is characterized by its usable storage capacity C_{bat}, charging and discharging power limits (C-rate constraints), round-trip efficiency, and state-of-charge (SOC) boundaries. These technical parameters determine the feasible charging and discharging schedules during the optimization process.

The resulting 8,760-hour calibrated dataset provides the basis for evaluating prosumer decision-making, battery arbitrage strategies, P2P energy trading, and the dynamic interaction between distributed renewable generation, electricity demand, and market prices.
The annual dataset is structured as an 8,760-row time series, where each row corresponds to a specific hourly time step (t). For each hour, the dataset includes the following variables:

1. $\boldsymbol{I_t}$ **:** Solar irradiance ($\frac{W}{m^2}$), representing the solar resource available for photovoltaic electricity generation. The dataset concerning Solar Radiation availability by region, month, and day is obtained from (Koundouris, et al., 2017). The city of Athens is selected as the reference region.
2. $\boldsymbol{E_{PV,t}}$**:** Photovoltaic electricity production (kWh), calculated as a function of solar irradiance, PV system area, and module conversion efficiency, following established photovoltaic performance models (BS EN 15316-4-3:2017, 2026)
3. $\boldsymbol{E_{base,t}}$**:** Baseline electricity consumption (kWh), representing the conventional household demand profile derived from historical consumption data and reflecting typical residential electricity usage patterns. Based on the estimated quantities of electricity consumption in residential households for the 25-year period 2025–2050, according to the National Energy and Climate Plan (NECP), (Greek Ministry of Energy, 2024) and (Koundouri, et al., 2025), the total annual electricity consumption is available. This annual total is allocated to a typical daily load profile (load shape) on an hourly basis throughout the entire year, representing a typical household from (Karamanos, et al., 2019) .
4. $\boldsymbol{Price_{spot,t}}$**):** Hourly spot market electricity price (€/kWh), representing the prevailing market conditions faced by the prosumer when purchasing electricity from or selling electricity to the grid. Electricity price data for 2023 for Greece are downloaded from ENTSO-E (ENTSO-e, 2025)
5. **Battery technical set up:** The operational model incorporates battery storage parameters, including usable storage capacity $C_{bat,t}$ (kWh) and rated charging/discharging power (P_{max}kW). These parameters determine the battery's charging and discharging capabilities and define the feasible energy arbitrage opportunities available to the prosumer. The charging and discharging rate is characterized through the battery C-rate. For example, a battery with a storage capacity $C_{bat,t}$ of 5 (kWh) and a rated power of P=2.5 kW requires exactly two hours to complete a full charging or discharging cycle under nominal operating conditions. More generally, the charging time is determined by the ratio between storage capacity and charging power: $\frac{C_{bat,t}\text{ (kWh)}}{P_{max}\text{ (kW)}}$=2 hrs. This relationship plays a crucial role in determining the battery's operational flexibility and its ability to respond to short-term electricity price fluctuations within the 8,760-hour simulation horizon.

4.2 Behavioral Formulation: Price-Dependent Utility and Endogenous Decision Variables

This section develops the mathematical foundation of the prosumer utility function and the associated demand response behavior under dynamic electricity pricing. The utility derived from electricity consumption is represented through a quadratic utility function, which captures the principle of diminishing marginal utility. The formulation includes both the direct utility obtained from electricity consumption, ($U_{\{cons\}}$), and the discomfort cost associated with load shifting, ($D_{\{shift\}}$), reflecting the trade-off between economic savings and household comfort. The utility function is parameterized by the time-dependent preference coefficient (ω_t), which represents the prosumer's willingness to consume electricity during each hour of the day. Rather than being treated as an exogenous parameter, (ω_t) is calibrated endogenously based

on electricity prices and desired consumption levels, allowing consumer preferences to evolve according to household activity patterns and market conditions.
The optimal consumption decision is obtained by maximizing utility subject to prevailing electricity prices. This yields an hourly demand function from which the dynamic price elasticity of demand, $\boldsymbol{\varepsilon_t}$, is derived. As a result, elasticity becomes time-varying and depends simultaneously on the spot market price and the underlying preference parameter. Higher preference levels, typically observed during morning and evening peak periods, reduce price responsiveness, whereas lower preference levels increase demand flexibility.
Through this formulation, hourly spot market price fluctuations directly influence both consumption decisions and elasticity values, providing a realistic representation of prosumer behavior under dynamic pricing environments and enabling the analysis of demand-side flexibility, battery arbitrage, and peer-to-peer energy trading.
For each hour (t), the endogenous parameters of the utility function are calculated as follows:
Calculation of $\boldsymbol{\omega_t}$: The preference parameter is dynamically determined based on the baseline consumption profile $\boldsymbol{E_{base,t}}$ and a representative electricity price $Price_{elec,base}$, allowing the utility function to reflect the household's actual comfort requirements across different seasons and hours of the day, therefore **calculation of $\boldsymbol{\omega_t}$ is given by equation (2)**.
The parameter α governs the curvature of the utility function and is typically calibrated within the range: $\alpha \in [0{,}10 \ldots, 0{,}50]$, with values between **0.25 and 0.30** frequently reported in the literature (Samadi, et al., 2010) and (Li , et al., 2011).
Let us denote α=0.25 and for ωt Table 1 can be reconfigures as Table 4:
Table 4. Typical ω_tRange per time period

Time Period	**Typical ω_tRange**
00:00–06:00	0.50–0.60
07:00–10:00	0.90–1.10
11:00–16:00	0.75–0.85
17:00–22:00	1.20–1.50
23:00–24:00	0.60–0.70

Calculation of **Dynamic Elasticity $\boldsymbol{\varepsilon_t}$ *is given by equation* (4).**
This indicator informs the model about the degree of prosumer responsiveness to the prevailing spot market price during a given hour. Higher absolute values indicate greater price sensitivity, whereas lower values reflect periods in which electricity consumption is considered more essential and less responsive to market price fluctuations (Samadi, et al., 2010).

4.3: Real-Time Operational Strategy: Decision Making Rule. Hourly Decision Matrix and Battery Arbitrage Strategy

The operational behavior of the prosumer is governed by an hourly decision matrix that determines the optimal allocation of electricity among self-consumption, battery charging, battery discharging, grid imports, and energy exports. At each time step, decisions are made based on prevailing spot market prices, photovoltaic generation availability, battery state-of-charge, and consumer utility preferences.
Battery operation is modeled as an endogenous arbitrage mechanism. During periods of low electricity prices, the battery charges by absorbing surplus photovoltaic generation or low-cost grid electricity, while during high-price periods it discharges to reduce grid purchases or increase electricity exports. The charging and discharging strategy is constrained by storage capacity, power limits, round-trip efficiency, and state-of-charge boundaries.

To capture the economic cost associated with battery cycling, the model incorporates a marginal degradation cost $C_{\{deg,t\}(E_{\{bat,t\}})}$. This parameter reflects battery wear and aging resulting from charging and discharging operations and prevents excessive cycling that would otherwise be economically unrealistic. Consequently, charging or discharging occurs only when the expected arbitrage benefit exceeds both the electricity price differential and the degradation cost.

Special attention is given to negative pricing events. Under negative spot prices, the prosumer adopts an aggressive load absorption strategy, maximizing battery charging whenever spare storage capacity is available. In this situation, the consumer is effectively compensated for absorbing electricity from the grid, transforming battery storage into a flexibility resource that supports renewable energy integration, mitigates curtailment, and stabilizes electricity market operation.

At each hour (t), the **prosumer** does not simply pursue immediate monetary gains. Instead, decisions are made by solving a total **utility maximization problem**, $\boldsymbol{U_t}$**,** which simultaneously considers consumption benefits, comfort preservation, electricity costs, battery operation, and potential market revenues (Li , et al., 2011). Consequently, the decision-making process is driven by overall welfare maximization rather than short-term profit alone.

The operational algorithm follows the hierarchical decision structure outlined below:

$$\max_{E\{self,t\},E_{\{bat,t\}}} \sum_{t=1}^{24} U_{\{cons,t\}(E_{\{self,t\}})} - D_{\{shift,t\}(\Delta E_{\{t\}})} + \beta \cdot \left(W_{\{spot,t\}} + W_{\{PPA,t\}}\right) - C_{\{deg,t\}(E_{\{bat,t\}})} \tag{17}$$

Where $\left(\mathbf{U}_{\{\mathbf{cons,t}\}(\mathbf{E}_{\{\mathbf{self,t}\}})}\right.$ **is given by (1)**

When spot market prices reach sufficiently high levels, the prosumer is incentivized to modify consumption patterns by shifting or curtailing part of the electricity load by an amount ΔE_t This behavioral adjustment reduces exposure to high electricity costs while maintaining the highest possible level of utility. The magnitude of load shifting depends on the trade-off between the economic benefits obtained from avoiding expensive electricity purchases and the associated discomfort cost resulting from deviations from the preferred consumption profile:

$$D_{shift}(\Delta E_t) = |E_{\{base,t\}} - E_{\{actual,t\}}| \text{ (18)}$$

Departures from the benchmark consumption profile generate a discomfort cost that captures the loss of utility associated with modifying preferred consumption behavior. This cost is assumed to increase nonlinearly with the magnitude of load adjustment, reflecting the fact that progressively larger deviations from the desired consumption pattern impose disproportionately higher levels of inconvenience and welfare loss:

$(D_{shift}(\Delta E_t) = \frac{\zeta}{2} * (\Delta E_t)^2$

- **ζ: denotes the inelasticity (discomfort) parameter.** Higher values of ζ imply a stronger preference for maintaining the baseline consumption schedule and a lower willingness to shift appliance operation in response to electricity price signals.

4.4 Spot Market Interaction

If the prosumer is directly exposed to spot market fluctuations (through day-ahead or real-time pricing schemes), the resulting monetary outcome associated with electricity exchanges with the grid is given by:

$$W_{spot,t} = P_{spot,t} * (E_{inj,t} - E_{buy,t}) \ (19)$$

- In other words this is the economic benefit for the interaction with spot market where $E_{inj,t}$ **:** The energy that is injected in the grid from the surplus of self-production of the prosumer or the discharging of the energy restored in the battery in previous time slots.
- $E_{buy,t}$ **:** the energy that prosumer buys when its self-production is not enough to cover its needs.

This operational management under real time spot dynamics is further developed by (Borenstein, et al., 2005).

As far as the Forward Contracts and PPAs are concerned, if the prosumer has entered into a Power Purchase Agreement (PPA) for a fixed portion of electricity production, $E_{PPA,t}$ the corresponding energy is settled at the contracted price $P_{PPA,t}$, As a result, revenue from this share of generation becomes independent of spot market fluctuations, thereby reducing exposure to electricity price volatility and mitigating spot market risk.

:

$$W_{PPA,t} = P_{PPA,t},* E_{PPA,t} + P_{spot,t} * (E_{inj,t} - E_{PPA,t}) \ (20)$$

This represents the principal economic advantage of bilateral and forward contracting arrangements. Under spot market participation, the term $P_{spot,t} * E_{inj,t}$ captures the prosumer's direct exposure to electricity price volatility and therefore represents the spot market risk component of revenues. By contrast, PPAs and other forward contracts replace uncertain spot market revenues with predetermined contractual prices, reducing revenue uncertainty and providing greater income stability. Consequently, these arrangements function as risk-hedging instruments that protect prosumers against adverse price fluctuations while improving the predictability of future cash flows.

4.5 Analysis and Description of the strategies

Strategy A – Baseline Rule-Based Dispatch

The baseline strategy employs a deterministic rule-based dispatch policy using fixed daily electricity price thresholds. Battery charging is activated when the hourly electricity price falls below the daily lower price threshold (25th percentile), while discharging occurs when the price exceeds the upper threshold (75th percentile). Photovoltaic (PV) surplus is preferentially stored in the battery and exported only when the battery reaches its maximum capacity. Battery operation is restricted to serving local demand, grid charging is not permitted, and a constant minimum state-of-charge (SOC) reserve of 10% is maintained throughout the simulation. This strategy represents the reference case against which the more advanced dispatch approaches are evaluated.

Strategy B – Adaptive Forecast-Based Dispatch

The adaptive strategy extends the baseline rule-based controller by incorporating short-term forecasts of electricity prices, PV generation and household demand. Instead of fixed daily thresholds, charging and discharging decisions are determined through dynamically updated thresholds derived from the expected market conditions over the following 24 hours. The battery is allowed to charge from the grid whenever the anticipated price differential exceeds the associated storage losses, enabling profitable energy arbitrage. PV surplus is preferentially stored before being exported, while battery discharge can supply both household demand and electricity market transactions during periods of elevated prices. Furthermore, the minimum battery reserve is dynamically adjusted according to expected demand, renewable availability and anticipated price peaks. Although decisions remain rule-based, they become adaptive to the expected operating conditions, improving battery utilization and increasing the economic value of larger storage capacities.

Strategy C – Rolling Horizon Economic Optimization

The optimal strategy replaces heuristic dispatch rules with a rolling 24-hour optimization framework. At the beginning of each optimization horizon, the controller simultaneously determines the optimal hourly charging, discharging, electricity purchasing, electricity selling and battery state-of-charge trajectory while satisfying all technical battery constraints. The objective function minimizes the overall operating cost by balancing electricity procurement costs, market revenues, battery degradation, peak-demand penalties and incentives for PV self-consumption. A terminal state-of-charge constraint is imposed to eliminate artificial benefits associated with free initial battery energy and to ensure consistent inter-day operation. Unlike the previous strategies, battery operation is no longer governed by predefined charging rules but by endogenous optimization decisions that maximize the overall economic performance of the residential energy system. The characterisitcs of the 3 strategies can be shown in Table 5.

Table 5. Differences among 3 Strategies

Strategy	Decision Logic	Decision Type	Computational Complexity
A	Fixed rule-based thresholds	Deterministic	Low
B	Adaptive forecast-based rules	Predictive / heuristic	Medium
C	Rolling optimization	Optimization-based (endogenous decisions)	High

Rule 1: Negative Price Management $Price_{spot,t}$< 0

When spot market prices become negative, the smart contract temporarily overrides the standard operating constraints and prioritizes energy absorption. Under these conditions, the economic value of electricity consumption becomes positive, as the prosumer is effectively compensated for consuming energy.

Consequently, the optimization algorithm instructs the prosumer to maximize electricity consumption and charge the battery as aggressively as possible, subject only to technical storage constraints. Battery charging continues until the state of charge reaches its maximum allowable capacity SOC_{max}.

From an economic perspective, negative pricing transforms electricity consumption from a cost into a source of revenue. Therefore, the optimal strategy is to absorb as much energy as technically feasible, allowing the prosumer to monetize excess system generation while simultaneously providing flexibility services that help balance the electricity network and reduce renewable energy curtailment.

Rule 2: Endogenous Self-Consumption Decision $E_{self,t}$

When electricity prices are positive, the system determines the optimal level of self-consumption $\boldsymbol{E_{self,t}}$ by balancing household comfort against the opportunity cost imposed by the spot market price and $\boldsymbol{E_{self,t}}$ is given by equation (5).

As spot market prices increase, the optimal level of self-consumption decreases automatically, leading to a controlled demand response through load shifting. In this way, the prosumer reduces electricity consumption $\boldsymbol{E_{self,t}}$ during high-price periods while preserving the highest attainable level of utility and minimizing discomfort costs.

Rule 3: Battery Management (Arbitrage and Degradation Considerations)

Battery discharge is activated only when the prevailing spot market price satisfies the upper discharge threshold condition corresponding to the high-price regime of the **Piecewise Grid**

Demand Function. These price thresholds emerge endogenously from the utility-maximizing consumption decision and the resulting grid-demand formulation.

If the discharge condition is not satisfied, the battery remains in standby mode (Hold). Alternatively, if spot market prices fall sufficiently below the charging threshold, the battery enters charging mode in order to exploit future arbitrage opportunities.

Under high-price conditions, the effective grid demand $E_{grid,t}(Price_{spot,t})$ is expressed by equation (8)

In this operating regime, battery discharge substitutes expensive grid electricity with previously stored energy. Therefore, when the spot market price exceeds the upper discharging threshold, the battery enters discharge mode and supplies part or all of the household demand, thereby reducing grid imports and increasing the economic value of stored energy through temporal arbitrage.

Consequently, battery operation occurs only when the expected arbitrage benefit exceeds both the electricity price differential and the associated degradation cost, ensuring economically rational storage utilization.

To ensure realistic prosumer behavior for Stratgy C, the utility maximization problem is formulated using a 24-hour Rolling Horizon Framework (Model Predictive Control approach). At each hour \(t\), the prosumer optimizes their decision vector (self-consumption, battery flows, grid interaction) over a look-ahead window of 24 hours based on Day-Ahead Market price signals. Crucially, only the decision for the immediate hour is executed, and the optimization window slides forward sequentially across the entire 8760-hour annual horizon.

Rolling-Horizon Optimization Framework

Within the scope of an operational-phase study under dynamic electricity pricing, utility maximization should be performed using a 24-hour rolling horizon (sliding-window) optimization framework rather than through independent hourly decisions or a single annual optimization problem (Conejo, et al., 2010) and (Li , et al., 2011)].

Limitations of Myopic Hourly Optimization

A purely hourly optimization approach fails to capture the intertemporal value of energy storage. If the prosumer were to optimize decisions solely for the current hour (t), battery operation would become economically irrational. For example, the decision to charge the battery at 11:00, when spot prices are negative or exceptionally low, depends on the expectation of higher electricity prices later in the day, such as during the evening peak period. Since battery storage acts as a temporal bridge between charging and discharging events, decisions made at the current time directly affect future energy availability. Consequently, a myopic hourly framework neglects the economic value of storage and is therefore unsuitable for representing realistic prosumer behavior.

Limitations of Annual Optimization

At the opposite extreme, solving a single optimization problem over the entire 8,760-hour horizon implicitly assumes perfect foresight regarding future photovoltaic generation, weather conditions, electricity demand, and spot market prices. Such an assumption is inconsistent with real-world operational decision-making, where market participants typically have access only to short-term forecasts. In most electricity markets, day-ahead prices are announced approximately 24 hours in advance, making annual perfect-information optimization unrealistic for operational studies.

Optimal Approach: 24-Hour Rolling Horizon

To address these limitations, the model adopts a Model Predictive Control (MPC) framework, which is widely applied in the demand response and smart grid literature (Morstyn, et al., 2018). This reference explains how prosumers combine P2P energy trading with rolling-horizon optimization for battery management. At each hour (t), the prosumer receives forecasts of prices, demand, and renewable generation for the following 24 hours ([t,t+23]). The utility-maximization problem is then solved over the entire 24-hour horizon, generating an optimal schedule for consumption, battery charging, battery discharging, and electricity trading. However, only the decision corresponding to the first hour is implemented. In the subsequent hour, the optimization window shifts forward by one-time step, updated forecasts are incorporated, the battery state-of-charge is revised, and the optimization is solved again.

Integration with the 8,760-Hour Dataset

The annual dataset serves as the simulation environment within which the rolling-horizon algorithm operates. The 24-hour optimization procedure is repeated sequentially throughout the 8,760 hours of the year. This approach preserves realistic operational behavior by limiting foresight to a 24-hour horizon while simultaneously producing annual performance indicators, including total social welfare, battery utilization, renewable energy integration, and overall operational efficiency.

4.6 Blockchain-Enabled Peer-to-Peer (P2P) Clearing and Social Welfare Quantification

The local peer-to-peer (P2P) electricity market is modeled using blockchain-enabled smart contracts and IoT-based oracles that facilitate the automated verification, execution, and settlement of energy transactions among participating prosumers. Smart contracts ensure transparent and trustless market operation by automatically enforcing predefined trading rules, while IoT oracles provide real-time measurements of electricity generation, consumption, battery state-of-charge, and energy exchanges.

The market framework incorporates several advanced operational parameters that influence both transaction decisions and welfare outcomes. These include the social and environmental preference parameter ρ_{ij}, which captures the buyer's willingness to prioritize locally generated renewable electricity, dynamic distribution network congestion charges imposed by the Distribution System Operator (DSO), represented by $(\tau_{ij,t})$, and consistency penalties Φi applied to market participants that fail to fulfill their contractual energy commitments.

These parameters are integrated directly into the utility-maximization framework, allowing economic, technical, environmental, and behavioral factors to jointly influence market outcomes. As a result, transaction decisions are determined not only by electricity prices but also by network conditions, renewable energy preferences, and contractual compliance considerations.

The cumulative Social Welfare function is finally formulated as the aggregation of individual utilities, P2P trading benefits, battery flexibility gains, network charges, and contractual penalties over the entire simulation horizon, providing a comprehensive measure of the economic efficiency and societal value generated by the local energy community.

After satisfying its internal electricity requirements, the prosumer participates in the local P2P market through blockchain-based smart contracts.

P2P Market Clearing. If Prosumer (i) has surplus electricity available from photovoltaic generation or battery discharge and Neighbor (j) exhibits an energy deficit, the blockchain automatically matches the transaction and settles it at the local P2P market-clearing price. The clearing mechanism depends on the local supply-to-demand balance. Under local deficit conditions, the P2P price is determined as a function of the community Supply-to-Demand Ratio (SDR), whereas under local surplus conditions the price converges to the feed-in value [Zorba et al., 2021].

a. A local supply deficit occurs when:
$0 \leq SDR_t \leq 1$ and the price is defined by Equation (13)
[Zorba et al., 2021].

b. Conversely, in local surplus, when:

$:SDR_t > 1$, and the price is defined by:

$$Price_{P2P} = \boldsymbol{Price_{prosumer,ch-inj,t}} \text{ , (21)(Price P2P, local surplus)}$$

This can be written in a single expression as:

$$Price_{P2P,t} = \begin{cases} \dfrac{\boldsymbol{Price_{spot,t} * Price_{prosumer,ch-inj,t}}}{(\boldsymbol{Price_{spot,t} - Price_{prosumer,ch-inj,t}}) * SDR_t + \boldsymbol{Price_{prosumer,ch-inj,t}}}, & SDR_t \leq 1 \\ \boldsymbol{Price_{prosumer,ch-inj,t}}, & SDR_t > 1 \end{cases}$$

$$\boldsymbol{E_{inj,prosum,t} = E_{PV,t} + \min\left(P_{disch,max}, SOC_t - SOC_{min}\right) - E_{self,t}}$$

(22)

The resulting energy injection available for trading is determined by the prosumer's renewable generation, battery operation, and self-consumption decisions. Consequently, the prosumer's utility maximization problem incorporates consumption utility, load-shifting costs, revenues from P2P energy sales, and battery degradation costs.

$$\max_{E\{self,t\},E_{\{bat,t\}}} \sum_{t=1}^{24} U_{\{cons,t\}(E_{\{self,t\}})} - D_{\{shift,t\}(\Delta E_{\{t\}})} + (E_{inj,prosum,t} * Price_{P2P}) - C_{\{deg,t\}(E_{\{bat,t\}})}$$

(23)

4.7 Network Constraint Verification

Smart contracts also enforce dynamic network usage charges imposed by the Distribution System Operator (DSO). If local congestion conditions arise, transactions may be restricted in order to preserve network reliability and protect grid operation.

The optimization algorithm is executed over the full 8,760-hour simulation horizon, and the resulting outcomes are aggregated to calculate total social welfare. This metric captures the combined effects of consumption utility, battery flexibility, P2P trading benefits, network charges, blockchain transaction costs, and contractual non-compliance penalties.

Dynamic DSO charges increase with network utilization, reflecting the economic cost of congestion. Typical values depend on the scale of the smart grid or microgrid under consideration, ranging from neighborhood-scale systems to larger distribution networks. Congestion penalty parameters are calibrated to economically discourage excessive loading during peak-demand periods.

Similarly, non-delivery penalties are introduced to account for situations in which participants fail to fulfill their promised energy commitments. These penalties are designed to reflect balancing-market practices and increase nonlinearly with the magnitude of the energy deficit, thereby incentivizing reliable participation in the local energy market:

$$SW_{total} = \sum_{i=1}^{8760} \sum_{n \in N} \left[U_{cons,n}\left(E_{self,n,t}\right) - \frac{\zeta}{2} * \left(\Delta E_{n,t}\right)^2 - C_{degrad}\left(E_{bat,n,t}\right) + \right] + \sum_{t=1}^{8760} \sum_i \sum_j [\theta * \left(1 - \rho_{ij}\right) * E_{P2P,ij,t}] - \sum_{t=1}^{8760} \sum_{i,j} (\tau_{ij,t} * E_{P2P,ij,t} - TC_{bc}) - \sum_{t=1}^{8760} \sum_{i,j} (\lambda_{pen} * max\ (0,\ E_{promised,i,t} - E_{actual,i,t})^2$$

(24)

with

$$\tau_{ij,t} = \tau_{base} + \gamma * \left(\frac{L_{total,t}}{C_{grid}}\right)^2 \text{ (25)}$$

4.8 Typical Parameter Ranges and Calibration

The proposed framework is calibrated using parameter ranges commonly adopted in the smart grid, microgrid, and local energy community literature.

For congestion-related network charges, the baseline network cost parameter τ_{base} typically ranges between **0.05 and 0.30 €/kWh** when interpreted as an economic charge. When representing technical network losses, equivalent values generally correspond to **1–3% of transferred energy**.

The total network load $L_{total,t}$ represents the aggregate electricity demand observed within the local distribution system. Typical values range from **10–500 kW** for neighborhood-scale microgrids and local energy communities, while larger distribution systems may operate at several megawatts. The network capacity parameter C_{grid} reflects the rated transfer capability of transformers and distribution assets. Consequently, the network utilization ratio typically varies from approximately **0.2 under low-demand conditions** to values exceeding **1.0 during temporary overload situations**.

The congestion sensitivity coefficient γ determines the responsiveness of network charges to increasing utilization levels. In practical implementations, γ is commonly selected within the range of **10–50% of the baseline network charge**, providing a sufficient economic signal to discourage excessive loading during peak-demand periods.

The contractual non-delivery penalty coefficient λ_{pen} quantifies the economic consequences of failing to meet contractual energy delivery commitments. Because the penalty function is quadratic with respect to the delivery deficit, the coefficient is expressed in monetary units per squared unit of energy. For microgrid and P2P energy market applications, typical values range between **0.01 and 0.05 €/kWh²**. These values are broadly consistent with balancing-market practices, where non-delivery penalties are often calibrated at approximately **1.5–3 times** the prevailing electricity price. The quadratic penalty structure ensures that larger delivery deviations are penalized disproportionately, thereby promoting contractual compliance, market reliability, and system stability.

Buyer's Utility Function and Social Preference Parameter. P2P participants do not make decisions solely on the basis of economic considerations. Consumers may be willing to pay a premium for electricity supplied by trusted neighbors or from certified renewable sources. To capture this behavior, a social proximity and green preference parameter ((\rho_{ij})) is incorporated into the buyer's utility function.

This parameter reflects the degree of trust, social proximity, or environmental preference between trading partners. Higher values indicate stronger preferences for locally sourced and verifiably green electricity. As a result, buyers derive additional utility from transactions involving trusted or renewable-energy prosumers, creating a social and environmental premium beyond purely economic benefits.

The buyer's utility therefore combines three elements: the intrinsic value of electricity consumption, the economic cost of purchasing electricity, and the additional utility associated with social proximity and renewable energy preferences. This framework explains why consumers may voluntarily choose P2P transactions even when prices exceed those available through conventional retail electricity suppliers.

:

$$(U_{\{P2P,j\}} = U_{\{cons,j\}}\left(E_{\{P2P,ij\}}\right) - \beta \cdot Price_{\{P2P\}} * E_{\{P2P,ij\}} + \theta * \left(1 - \rho_{ij}\right) * E_{\{P2P,ij\}}$$
$$U_{\{cons,j\}}\left(E_{\{P2P,ij\}}\right) = \omega_{\{t\}} \cdot E_{\{P2P,ij\}} - \frac{\alpha}{2} \cdot \left(E_{\{P2P,ij\}}\right)^2 \tag{26}$$

Economic Cost Component. The **second term** of the buyer's utility function captures the direct economic cost of electricity procurement. It is calculated as the product of the traded energy quantity, the P2P market-clearing price, and the price sensitivity coefficient β. This component represents the monetary expenditure associated with electricity purchases and reflects the extent to which transaction costs influence consumer decision-making. When utility is expressed directly in monetary units, **β is typically normalized to 1**

Social and Environmental Benefit Component. The third term incorporates the additional utility derived from social proximity and environmental preferences. This premium reflects the value that consumers assign to purchasing electricity from trusted local prosumers or from verifiably renewable energy sources. By introducing the parameter θ, which monetizes social and environmental preferences, together with the social proximity and green certification index ρ_{ij}, the model captures the non-economic benefits associated with P2P transactions. Consequently, consumers may rationally accept a higher P2P transaction price than that offered by the conventional retail market because they receive additional utility from supporting local renewable generation, strengthening community participation, and purchasing blockchain-verified green electricity.

4.9 Calibration of P2P Market Parameters

The calibration of the P2P matching mechanism requires the specification of economically meaningful parameter values. The P2P market-clearing price is assumed to lie between the feed-in tariff and the retail electricity price, ensuring that both buyers and sellers obtain economic benefits relative to direct interaction with the conventional electricity market. This pricing interval defines the feasible trading window within which mutually beneficial transactions can occur.

The calibration of the **green preference parameter (θ)** is informed by empirical willingness-to-pay studies for renewable electricity. Evidence from German electricity consumers ((Danne, et al., 2021) **suggests a premium of approximately 0.022 €**/kWh associated with greener electricity products, supporting the use of values in the range of 0.01–0.04 €/kWh for representing moderate to strong environmental preferences. Consistent with the willingness-to-pay literature, the parameter θ is treated as a behavioral preference coefficient reflecting consumers' valuation of renewable electricity attributes and local energy participation (Oerlemans, et al., 2016). The parameter operates jointly with the social proximity and green certification index ρ_{ij}, allowing blockchain-verified renewable energy attributes and local trust relationships to generate additional utility beyond purely economic benefits.

Methodological Implications

The inclusion of this calculation at the end of the methodology provides a valuable analytical extension, as it enables the construction of graphical representations demonstrating that buyers may achieve higher utility within the P2P market than through conventional retail electricity procurement, particularly when blockchain technology verifies the renewable origin of the traded electricity.

The analysis of the interaction between buyer and prosumer utility functions constitutes one of the most important aspects of a P2P energy market, as it reveals the existence of a **Trading Window** and the associated **Economic Surplus** generated through local energy exchange.

Unlike conventional supply and demand curves, which intersect at a single quantity-price equilibrium point, the utility functions of the prosumer and the buyer do not necessarily converge to a unique equilibrium. Instead, they evolve in opposite directions with respect to the P2P market-clearing price. Examining both utility functions as a function of the clearing price for a fixed traded energy quantity $E_{\{P2P,ij\}}$ +allows the identification of the range of mutually beneficial transactions.

Trading Window

For a transaction to occur, both market participants must obtain positive utility, or at least a utility level higher than that available through interaction with the conventional electricity network.
The lower bound of the trading window is determined by the prosumer, who will not sell electricity below production cost or below the remuneration available through the feed-in tariff mechanism. Conversely, the upper bound is determined by the buyer, who will not purchase electricity at a price that yields lower utility than purchasing electricity from a traditional retail supplier.

Graphical Representation

The corresponding graphical analysis illustrates how the utility levels of both the buyer and the prosumer vary as the P2P market-clearing price changes. The intersection of the two utility curves represents the price at which both parties obtain an identical level of benefit, corresponding to a balanced win-win outcome and a fair allocation of the economic surplus generated by the transaction.

Interpretation of the Analysis

If this mini-analysis is included in the study, the following conclusions can be drawn:
Fair-Trade Price: The intersection point between the two utility curves represents the fair-trade price, where the economic surplus generated by the P2P transaction is shared equally between the buyer and the seller.
Blockchain Effect: The term ($\theta * \rho_{ij}$) captures the additional social and environmental utility generated when the prosumer provides blockchain-verified green electricity. In this case, the buyer's utility curve shifts upward and to the right, indicating that the buyer is willing to pay a higher price because the transaction provides additional non-monetary value.
Clearing Boundaries: Any market-clearing mechanism, such as Nash bargaining, equilibrium pricing, or centralized optimization, must select a price within the Trading Window. This ensures that both participants obtain positive net utility and remain willing to participate in the P2P market.
The next step is to examine how the fair-trade price shifts when the value of ρ_{ij} changes, for example when moving from an unknown prosumer to a fully blockchain-certified green neighbor.

4.10 Impact of Social and Green Preferences on Market Equilibrium

The updated diagram clearly illustrates the dynamic effect of the social and green preference parameter ρ_{ij} on buyer utility and market equilibrium outcomes.

Analysis of the Shift

1. Shift in the Buyer's Utility Curve

As the green preference index increases from 0 to 1, the buyer's overall utility function shifts upward and to the right. This reflects the additional utility derived from purchasing electricity from a trusted local prosumer or from a blockchain-certified renewable energy source.

2. Increase in the Market-Clearing Price

The intersection point between the buyer's and seller's utility functions, representing the fair-trade equilibrium, moves toward a higher market-clearing price. This result demonstrates that consumers are willing to pay a premium for the same quantity of electricity when additional environmental and social benefits are embedded in the transaction. Consequently, blockchain-verified renewable electricity generates a positive willingness-to-pay premium that is reflected in the equilibrium price.

3. Mutual Welfare Improvement (Win-Win Outcome)

Despite the increase in the equilibrium price, both market participants achieve higher levels of utility at the new equilibrium. The seller benefits from increased revenues, while the buyer obtains additional utility through the satisfaction of environmental and social preferences.

Therefore, the incorporation of blockchain-verified green attributes expands the economic surplus available within the P2P market and improves welfare outcomes for both trading parties. To conclude in this last methodology step for the **Sensitivity Analysis and Market Implications.** The inclusion of blockchain-verified green attributes and social preference indicators expands the economic surplus available within the P2P market. As the green preference parameter increases, buyers become willing to pay higher prices for the same quantity of electricity because they derive additional environmental and social value from the transaction. This mechanism shifts the market equilibrium toward higher clearing prices while simultaneously increasing the utility of both buyers and sellers. Consequently, blockchain-based certification not only improves transparency and trust but also enlarges the feasible trading space within the P2P market.

The interaction between buyer and prosumer utility functions defines a "**Trading Window"** within which both parties achieve positive utility compared with interacting exclusively through the conventional electricity grid. The lower bound of this window is determined by the prosumer's minimum acceptable selling price, while the upper bound is determined by the buyer's maximum willingness to pay.

The intersection of the two utility functions represents the **fair-trade equilibrium**, where the economic surplus generated by the P2P transaction is shared equally between buyer and seller (Sousa, et al., 2019), . Furthermore, the green preference parameter acts as a price premium mechanism: as environmental preferences strengthen, the equilibrium price increases, demonstrating that consumers are willing to pay more for blockchain-certified renewable electricity.

From an operational perspective, if the neighboring prosumer supplies certified green electricity through the blockchain platform, buyer utility increases significantly, thereby justifying a higher P2P transaction price and making the local market more attractive than the traditional retail electricity market.

The equilibrium P2P transaction price (PriceP2P) is obtained by equating the utility functions of the selling prosumer and the buyer.

$$(U_{\{P2P,j\}} = \omega_t * E_{P2P,ij,inj,prosum,t} - \frac{\alpha}{2} \cdot \left(E_{P2P,ij,inj,prosum,t}\right)^2 - \beta \cdot Price_{\{P2P\}} * E_{P2P,ij,inj,prosum,t} + \theta * \left(\rho_{ij}\right) * E_{P2P,ij,inj,prosum,t} = \omega_{\{t\}} * [E_{\{buy,t\}} + E_{\{self,t\}})] - \frac{\alpha}{2} \cdot [E_{\{buy,t\}} + E_{\{self,t\}})]^2 - \frac{\zeta}{2} * \left(\left|E_{\{base,t\}} - E_{\{actual,t\}}\right|\right)^2 + (E_{P2P,ij,inj,prosum,t} * Price_{P2P}) - \psi \cdot (\left|E_{\{bat,t\}}\right|) = U_{prosum,t}$$

(27)

Where,

$$\boldsymbol{E_{inj,prosum,t} = E_{PV,t} + \min\left(P_{disch,max}, SOC_t - SOC_{min}\right) - E_{self,t}}$$

$E_{actual,t}$ =$E_{\{buy,t\}}$+$E_{\{self,t\}}$,

And from the Energy Balance of Theoretical Back-ground paragraph:

$$E_{\{PV,t\}} + E_{\{buy,t\}} + E_{\{dis,t\}} = E_{\{self,t\}} + E_{\{inj,t\}} + E_{\{ch,t\}})$$

Or consequently:

$E_{actual,t}$ =$E_{\{buy,t\}}$+$E_{\{self,t\}}$ =

= $E_{\{self,t\}}$+ ($E_{\{self,t\}} + E_{\{inj,t\}} + E_{\{ch,t\}})$) -$E_{\{PV,t\}}$-$E_{\{dis,t\}}$

(28)

Therefore:

$$Price, eq_{\{P2P\}} = \frac{A}{2 * E_{P2P,ij,inj,prosum,t}} \quad (29)$$

A= $\omega_t * E_{P2P,ij,inj,prosum,t} - \frac{\alpha}{2} \cdot (E_{P2P,ij,inj,prosum,t})^2 + \theta * (\rho_{ij}) * E_{P2P,ij,inj,prosum,t}$ - $\omega_{\{t\}} * [E_{\{buy,t\}} + E_{\{self,t\}})] + \frac{\alpha}{2} \cdot [E_{\{buy,t\}} + E_{\{self,t\}})]^2 + \frac{\zeta}{2} * (|E_{\{base,t\}} - E_{\{actual,t\}}|)^2 + \psi \cdot (|E_{\{bat,t\}}|)$

(30)

Interpretation of the Equilibrium Price Components

The equilibrium price can be interpreted as the combination of two distinct components.

The first component represents the fundamental market value of the transaction and is determined exclusively by the technical and operational characteristics of the trading partners. Specifically, it reflects the interaction between the buyer's intrinsic utility derived from electricity consumption and the seller's underlying electricity generation cost. This component therefore captures the baseline economic equilibrium that would emerge in the absence of any social or environmental considerations.

The second component represents the social and environmental premium embedded in the transaction. This premium arises from consumers' willingness to support locally generated renewable electricity, trusted community members, or blockchain-verified green energy sources. The magnitude of this effect is determined by two factors: the monetary valuation assigned to environmental and social attributes and the degree of social proximity or green certification associated with the seller.

From an operational perspective, stronger social relationships, higher levels of trust, or verified renewable energy attributes increase the buyer's perceived value of the transaction. As a result, consumers become willing to pay a higher P2P market-clearing price for the same quantity of electricity because the transaction provides additional utility beyond its purely economic value. Consequently, blockchain-based certification mechanisms create an economically measurable green and social premium that is reflected directly in market prices and welfare outcomes.

4.11 Social Welfare for P2P

(Samadi, et al., 2010) provides the theoretical foundation for defining grid welfare as the difference between consumers' utility from electricity consumption and electricity generation costs, rather than as a simple balance of monetary transactions.

Derivation of Supply and Demand Curves from Utility and Cost Functions

According to microeconomic theory, supply and demand curves are derived as the first-order derivatives (marginal quantities) of utility and cost functions.

Buyer's Demand Curve (Marginal Benefit – MB)

The buyer's demand curve is obtained from the derivative of the utility function with respect to the quantity of electricity traded through the P2P market. When consumption utility is represented by a quadratic function, the resulting marginal utility function—and therefore the demand curve—is linear and downward sloping. This relationship reflects the principle of diminishing marginal utility, whereby the value assigned to each additional unit of electricity decreases as consumption increases.

$$(U_{\{P2P,j\}} = \omega_t * E_{P2P,ij,inj,prosum,t} - \frac{\alpha}{2} \cdot (E_{P2P,ij,inj,prosum,t})^2 - \beta \cdot Price_{\{P2P\}} * E_{P2P,ij,inj,prosum,t} + \theta * (\rho_{ij}) * E_{P2P,ij,inj,prosum,t}$$

(31)

$$\frac{\partial(U_{\{P2P,j\}}}{\partial E_{P2P,ij,inj,prosum,t}} = P_{DEMAND} = \omega_t - a * E_{P2P,ij,inj,prosum,t} + \theta * (\rho_{ij}) \quad (32)$$

Next, Consumer Surplus CSt is given by:
$CS_t = (\int_0^{E_{P2P,ij,inj,prosum,t}} P_{DEMAND}\,(E)dE)$ - $Price_{p2p,t} * E_{P2P,ij,inj,prosum,t}$
Or finally:
$CS_t = (\omega_t + \theta * \rho_{ij} - Price_{p2p,t}) * \ E_{P2P,ij,inj,prosum,t} - \frac{a}{2} * (E_{P2P,ij,inj,prosum,t})^2$

(33)

Prosumer Supply Curve (Marginal Cost – MC)

The prosumer's supply curve is obtained from the derivative of the total production and operating cost function. When production costs are represented by a quadratic function, the resulting marginal cost curve is linear and upward sloping. This formulation captures increasing marginal costs associated with electricity production, battery degradation, and operational constraints, implying that larger quantities of energy require progressively higher compensation. The overall function of operating cost for the prosumer, for the energy that supplies to the P2P market at time t is given by the formula:

$$C_{prosumer}\left(E_{P2P,ij,inj,prosum,t}\right) = b_i * E_{P2P,ij,inj,prosum,t} + \frac{a_i}{2} \cdot \left(E_{P2P,ij,inj,prosum,t}\right)^2 + \psi \cdot (\left|E_{\{bat,t\}}\right|) + \frac{\zeta}{2} * \left(\left|E_{\{base,t\}} - E_{\{actual,t\}}\right|\right)^2$$

(34)

Therefore, the supply curve (marginal cost) of the prosumer will be:

$$P_{supply}\left(E_{P2P,ij,inj,prosum,t}\right) = \frac{\partial C_{prosumer}}{\partial E_{P2P,ij,inj,prosum,t}} \Longrightarrow$$

$$\boldsymbol{P_{supply}\left(E_{P2P,ij,inj,prosum,t}\right) = b_i + a_i * E_{P2P,ij,inj,prosum,t} + \psi + \zeta * (\left|E_{\{base,t\}} - E_{\{actual,t\}}\right|)}$$

(35)

b_i **(€/kWh):** The linear (fixed) marginal cost of electricity supply, encompassing operating expenses and asset-related costs, such as photovoltaic system wear and maintenance. This parameter represents the minimum supply cost and defines the intercept of the supply curve.
a_i **(€/kWh²):** The production rigidity parameter, corresponding to the slope of the supply curve. It captures the rate at which the prosumer's marginal cost increases as the quantity of electricity requested by the P2P community expands. Higher values indicate a stronger increase in supply costs for additional units of energy delivered.
$\psi + \zeta * (\left|E_{\{base,t\}} - E_{\{actual,t\}}\right|$: This term represents an upward parallel shift of the supply curve arising from battery degradation costs and the discomfort associated with load-shifting actions. Consequently, these operational costs increase the minimum compensation required by the prosumer to participate in energy trading and supply additional electricity to the P2P market.

Next, Prosumer Surplus PSt is given by:
$PS_t = Price_{p2p,t} * E_{P2P,ij,inj,prosum,t} - \ (\int_0^{E_{P2P,ij,inj,prosum,t}} P_{supply}\,(E)dE)$
Or finally:

$$PS_t = \ E_{P2P,ij,inj,prosum,t} * \left(Price_{p2p,t} - \ b_i - \ \psi - \zeta * \left(\left|E_{\{base,t\}} - \ E_{\{actual,t\}}\right|\right)\right) - \frac{a_i}{2} * (E_{P2P,ij,inj,prosum,t})^2$$

(36)

The overall Social Welfare at time t is given by (the sum of PSt and CSt):

$$SW_t = \left(\omega_t + \theta * \rho_{ij} - b_i - \psi - \zeta * \left(\left|E_{\{base,t\}} - E_{\{actual,t\}}\right|\right)\right) * E_{P2P,ij,inj,prosum,t}$$
$$-\left(\frac{a+a_i}{2}\right) * \left(E_{P2P,ij,inj,prosum,t}\right)^2 \quad (37)$$

Economic Interpretation of the Welfare Components

The unified welfare formulation carries a particularly rich economic interpretation and provides valuable insights into the mechanisms through which value is created within a peer-to-peer electricity market.

The Linear Component. $\left(\omega_t + \theta * \rho_{ij} - b_i - \psi - \zeta * \left(\left|E_{\{base,t\}} - E_{\{actual,t\}}\right|\right)\right) * E_{P2P,ij,inj,prosum,t}$

The linear term represents the net marginal benefit generated by the P2P community from the first unit of electricity traded. It indicates that positive welfare can only be created when consumers' willingness to consume electricity and the additional value associated with social and environmental preferences exceed the combined costs borne by the prosumer. These costs include electricity production expenses, battery degradation, and the discomfort associated with demand-side flexibility and load-shifting actions. Consequently, welfare creation emerges from the ability of the market to generate value beyond the technical and operational costs required to deliver electricity.

The Quadratic Component. $\left(\frac{a+a_i}{2}\right) * \left(E_{P2P,ij,inj,prosum,t}\right)^2$

The quadratic term captures the overall rigidity of the market. It reflects the combined effect of demand-side and supply-side constraints on market efficiency. When either consumers become less responsive to economic incentives or prosumers face increasing technical limitations in supplying additional energy, welfare gains grow at a diminishing rate. As a result, the market's ability to generate additional value declines as traded quantities increase. This component therefore represents the aggregate friction embedded within the local energy market and determines how rapidly welfare gains are exhausted as participation expands.

Implications for the Conclusions

The central implication of this framework is that a P2P electricity market can be interpreted as a mechanism for social welfare maximization. Market-clearing prices primarily serve as transfer payments between buyers and sellers and therefore do not constitute net welfare creation in themselves. Instead, the economic value of the local energy market arises from its ability to bridge the gap between consumer utility and prosumer operating costs. This process is further influenced by battery characteristics, flexibility constraints, and blockchain-enabled social and environmental preferences, all of which contribute to the total welfare generated within the energy community.

Accordingly, the effectiveness of a P2P market should be evaluated not solely on the basis of transaction volumes or market prices, but on its capacity to increase aggregate welfare through the efficient coordination of distributed energy resources, consumer preferences, storage flexibility, and trusted local energy exchanges.

4.12 Calibration of Supply Curve Parameters

The parameters a_i and b_i define the operational supply curve of the prosumer and therefore require calibration based on realistic electricity generation and storage economics. Their selection is intended to ensure that the resulting supply function reflects the actual costs and constraints associated with distributed energy resources operating within a P2P market environment.

The parameter b_i represents the fixed marginal cost of supplying electricity and captures the baseline operational cost associated with delivering the first unit of energy to the market. For photovoltaic-based prosumers, this parameter does not reflect fuel costs, since solar irradiation is freely available, but rather incorporates the levelized cost of electricity (LCOE), including the amortization of photovoltaic modules, inverters, balance-of-system components, and associated operation and maintenance expenditures. Based on recent LCOE estimates for small-scale distributed photovoltaic systems, values of b_i are typically calibrated within the range of **0.05–0.08 €/kWh**.

The parameter a_i represents the slope of the supply curve and captures the increasing marginal opportunity cost associated with providing larger quantities of electricity to the local market. Economically, it reflects the degree of supply rigidity faced by the prosumer. Higher values indicate that supplying additional electricity rapidly increases the prosumer's opportunity cost, particularly when battery storage capacity is limited or when available photovoltaic surplus is scarce. Conversely, lower values correspond to prosumers with larger storage systems or substantial excess renewable generation, for whom additional energy exports impose relatively small operational constraints. Consistent with the characteristics of residential prosumers participating in local energy markets, values of a_i are typically calibrated within the range of **0.01–0.04 €/kWh²**.

Together, a_i and b_i determine the economic willingness -to-sell of each prosumer and govern the shape and position of the supply curve used in the market-clearing mechanism. Their calibration directly influences equilibrium prices, traded quantities, prosumer surplus, consumer surplus, and ultimately the social welfare generated by the P2P market.

Literature-Based Justification of Supply Curve Parameters

The selected values of the supply curve parameters are grounded in the peer-to-peer energy trading and distributed energy systems literature.

Justification of the Baseline Cost Parameter b_i. The work of (Long, et al., 2018) demonstrates that electricity supplied by residential photovoltaic systems is associated with a Levelized Cost of Energy (LCOE), which forms the economic foundation of the prosumer's minimum acceptable selling price. This cost component reflects the recovery of capital expenditures (CAPEX), inverter replacement costs, and operation and maintenance expenses over the lifetime of the system. Consequently, b_i can be interpreted as the baseline marginal cost required to ensure the long-term economic viability of prosumer participation in the P2P market.

Justification of the Supply Rigidity Parameter a_i. Studies by (He, et al., 2016) and (Paudel, et al., 2018) show that when battery storage is incorporated into distributed energy systems, the marginal cost of energy provision cannot be adequately represented by a constant value. As battery state-of-charge declines and available flexibility becomes increasingly scarce, the opportunity cost of supplying additional electricity rises. A convex cost structure, represented by the parameter a_i, therefore provides a realistic mechanism for capturing the increasing marginal cost associated with energy exports and storage depletion.

Justification of Market Matching and Clearing Formulation. (Tushar, et al., 2019) employ comparable producer cost formulations within game-theoretic P2P energy trading frameworks and demonstrate that such representations support the existence of mutually beneficial market-clearing outcomes. Their analysis shows that appropriately calibrated producer cost functions facilitate stable peer-to-peer transactions and contribute to the emergence of welfare-improving Nash equilibria within local energy markets.

Collectively, the above-mentioned studies provided the theoretical and empirical support for the proposed calibration of the supply curve parameters and their integration into the market-clearing and welfare evaluation framework adopted in the present study.

Visualization of Economic Surplus

The intersection of the demand and supply curves determines the market-clearing price and the equilibrium traded quantity. At this point, both buyers and sellers maximize their economic gains from participation in the P2P market.

Consumer Surplus corresponds to the area below the demand curve and above the market-clearing price. It measures the economic benefit obtained by buyers because they purchase electricity at a price lower than their maximum willingness-to-pay.

Prosumer Surplus corresponds to the area above the supply curve and below the market-clearing price. It represents the net economic gain obtained by prosumers beyond their marginal production and operational costs.

Integration into the Methodology

Within the proposed framework, consumer surplus and prosumer surplus are calculated after each market-clearing process. Geometrically, these quantities correspond to the areas enclosed between the demand and supply curves and the equilibrium price. Mathematically, they are obtained through the integration of marginal utility and marginal cost functions over the equilibrium quantity traded.

The sum of consumer surplus and prosumer surplus constitutes **Social Welfare**, which represents the total economic value created by the P2P market. Social welfare therefore measures the aggregate benefit generated by local energy trading and serves as the principal indicator of market efficiency within the proposed framework.

Temporal Resolution of Welfare Calculations

The surplus calculations should be performed at each simulation interval individually (e.g., hourly or sub-hourly resolution), reflecting the dynamic nature of electricity markets and consumer behavior. These instantaneous welfare values are subsequently aggregated over longer time horizons, including daily, weekly, monthly, and annual periods.

Because the optimization framework operates under a 24-hour rolling horizon, the daily aggregation constitutes the primary operational performance indicator. However, cumulative weekly, monthly, and annual welfare metrics are also required to evaluate the long-term economic viability of the proposed P2P market and to compare alternative scenarios.

Annual social welfare is particularly important because it quantifies the total economic value generated by the local energy community over the entire simulation horizon and enables comparison against a baseline case in which participants interact exclusively with the conventional electricity market. Furthermore, annual welfare calculations allow the evaluation of whether battery degradation costs are offset by arbitrage revenues and whether the additional value created by P2P trading justifies the deployment of distributed energy resources and blockchain-enabled market infrastructure.

4.13 Social Welfare for the case of prosumer against the Grid

Prosumer Surplus, Grid Surplus and Social Welfare under Alternative Operating Regimes

The proposed model characterizes prosumer behavior under three distinct operating regimes determined by the prevailing spot market price. To quantify the associated economic surplus using the conventional welfare framework, the grid demand functions are first transformed into their corresponding inverse demand functions by solving for the electricity price.

Inverse Demand Curves of the Prosumer

The inverse demand curve represents the prosumer's marginal willingness-to-pay for electricity purchased from the central grid under each operating regime.

Regime 1 – Low Spot Prices (Battery Charging and Consumption). When the spot price falls below the lower charging threshold, the prosumer simultaneously satisfies household demand and charges the battery. Consequently, the inverse demand curve shifts upward and to the right, reflecting the additional value of electricity used for energy storage.

From the theoretical outline we get:

$$E_{grid,t}\left(Price_{spot,t}\right) = \frac{\omega_t - Price_{spot,t}}{a} + P_{ch,max} - E_{pv,t}$$

Then:

$$Price_{spot,t} = \omega_t - \left\{E_{grid,t}\left(Price_{spot,t}\right) - P_{ch,max} + E_{pv,t}\right\} * a$$

Furthermore, for the Consumer Surplus CS_{t1}:

CS_{t1}=($\int_0^{E_{grid,t}} Pdemand(E)de) - Price_{spot,t}$* $E_{grid,t}$ =

= $E_{grid,t}$* $(\omega_t + a * P_{ch,max}$ - $a *$ $E_{pv,t}$ - $Price_{spot,t})$ - $\frac{a}{2} * (E_{grid,t})^2$

(38)

Regime 2 – Intermediate Spot Prices (Battery Standby). Under moderate price conditions, the battery remains inactive and grid demand is determined solely by household electricity consumption net of photovoltaic generation. The inverse demand curve therefore represents the baseline operating condition.

From the theoretical outline we get:

$$E_{grid,t}\left(Price_{spot,t}\right) = \frac{\omega_t - Price_{spot,t}}{a} - E_{pv,t}$$

Then:

$$Price_{spot,t} = \omega_t - \left\{E_{grid,t}\left(Price_{spot,t}\right) + E_{pv,t}\right\} * a$$

Furthermore, for the Consumer Surplus CS_{t2}:

CS_{t2}=($\int_0^{E_{grid,t}} Pdemand(E)de) - Price_{spot,t}$* $E_{grid,t}$ =

= $E_{grid,t}$* $(\omega_t$ - $a *$ $E_{pv,t}$ - $Price_{spot,t})$ - $\frac{a}{2} * (E_{grid,t})^2$

(39)

Regime 3 – High Spot Prices (Battery Discharging and Arbitrage). When the spot price exceeds the upper discharging threshold, the prosumer substitutes grid purchases with stored electricity. The inverse demand curve shifts downward and to the left, reflecting the reduced willingness to purchase electricity from the grid due to battery discharge.

From the theoretical outline we get:

$$E_{grid,t}\left(Price_{spot,t}\right) = \frac{\omega_t - Price_{spot,t}}{a} - P_{disch,max} - E_{pv,t}$$

Then:

$$Price_{spot,t} = \omega_t - \left\{E_{grid,t}\left(Price_{spot,t}\right) + P_{disch,max} + E_{pv,t}\right\} * a$$

Furthermore, for the Consumer Surplu CS_{t3}:

CS_{t3}=($\int_0^{E_{grid,t}} Pdemand(E)de) - Price_{spot,t}$* $E_{grid,t}$ =

= $E_{grid,t}$* $(\omega_t - a * P_{disch,max}$ - $a *$ $E_{pv,t}$ - $Price_{spot,t})$ - $\frac{a}{2} * (E_{grid,t})^2$

(40)

Grid Supply Curve

To evaluate the welfare generated through grid transactions, the supply curve of the electricity market is represented by the marginal cost of electricity supplied through the wholesale market. Assuming that the residential prosumer behaves as a price-taker, the grid supply curve is perfectly elastic and therefore corresponds to a horizontal line at the prevailing spot market clearing price. Under this assumption, the individual prosumer is too small to influence wholesale market prices.

Welfare Calculations

At each simulation interval, the optimization algorithm records both the realized spot market price and the corresponding equilibrium quantity of electricity imported from the grid. Economic surplus is then evaluated ex post using the standard welfare decomposition.

The **Consumer Surplus (CS)** represents the welfare obtained by the prosumer as a consumer purchasing electricity from the grid. Geometrically, it corresponds to the area below the inverse demand curve and above the spot market price, measured over the equilibrium quantity imported during the corresponding operating period.

The **Grid (Producer) Surplus (GS)** is assumed to be zero for the individual transaction because the wholesale electricity market is modeled as perfectly competitive. Since electricity is supplied at marginal cost, the spot market price coincides with the supplier's marginal production cost, leaving no producer surplus attributable to transactions with an individual residential prosumer.

Nevertheless, the electricity system benefits indirectly from battery operation. During high-price periods, battery discharge reduces peak demand and alleviates network congestion, thereby lowering system balancing requirements and avoiding expensive peak generation. This indirect system benefit is quantified as a peak-cost avoidance term, representing the economic value of load smoothing achieved through distributed battery storage.

Then: $GS_{grid,t}$=$(Price_{peak} - Price_{spot,t})* \ P_{disch,max}$ (41)

Accordingly, **Social Welfare (SW)** is obtained as the sum of the prosumer's consumer surplus and the indirect benefit accrued to the electricity system through peak demand reduction.

$$SW_t = \ CS_{pros} + GS_{grid,t} \quad (42)$$

Temporal Resolution

Welfare calculations are performed at every simulation interval (hourly resolution), since battery state-of-charge, photovoltaic generation, and electricity prices evolve dynamically over time. The optimization itself is conducted using a **24-hour rolling horizon**, allowing battery scheduling decisions to anticipate future price signals rather than reacting myopically to current prices. This rolling optimization enables the battery to discharge not only during the single highest-price hour but across consecutive peak-price periods, thereby smoothing the evening demand peak and maximizing cumulative arbitrage benefits.

Hourly welfare values are subsequently aggregated into daily, weekly, monthly, and annual indicators. While the hourly calculations capture instantaneous market behavior, annual cumulative welfare provides the principal performance metric for evaluating the long-term economic value of battery storage and dynamic demand response. Comparing annual welfare across different storage capacities allows the economic contribution of distributed batteries to be quantified in terms of increased consumer surplus, reduced exposure to high spot prices, and improved overall system efficiency.

Graphical Interpretation

The welfare decomposition can be illustrated using three supply-and-demand diagrams corresponding to the three operating regimes. In each case, the grid supply curve is represented by a horizontal line at the prevailing spot price, while the inverse demand curve shifts according to battery operation.

Under **low-price conditions**, battery charging shifts the demand curve upward and outward, substantially enlarging the consumer surplus triangle as the prosumer purchases additional electricity for storage.

During **intermediate-price periods**, the battery remains idle and the consumer surplus reflects conventional household electricity demand.

Under **high-price conditions**, battery discharge shifts the demand curve downward and inward, reducing grid imports and limiting exposure to expensive electricity prices. Although the instantaneous consumer surplus triangle becomes smaller, the battery protects the prosumer from price spikes and generates substantial cumulative welfare over the complete optimization horizon by smoothing electricity demand across time.

5. Results

5.1 SW total (€): Total Social Welfare of the Prosumer–Grid Market

Figure 1 presents the monthly total social welfare (SW total, Eq. 15) for the three operational strategies (A–C) and the four battery capacities (10, 15, 20 and 30 kWh). The indicator represents the overall welfare generated through the interaction between the residential prosumer and the conventional electricity market, including self-consumption, electricity imports from the grid and surplus electricity exports, prior to the introduction of peer-to-peer (P2P) energy trading.

Across all scenarios, Strategy A consistently achieves the highest monthly social welfare, with values ranging from 246.11 € in August to 309.94 € in January. Notably, the four battery capacities produce practically identical results throughout the year, indicating that increasing battery capacity does not provide additional welfare benefits under this operational strategy.

Strategy B exhibits lower welfare values than Strategy A and demonstrates a clear dependence on battery capacity. Monthly welfare decreases progressively as battery capacity increases from 10 to 30 kWh, particularly during winter and summer months. For example, January welfare decreases from 288.42 € (10 kWh) to 252.92 € (30 kWh), while July decreases from 222.33 € to 199.80 €, indicating that larger storage capacities do not improve the overall economic performance of the conventional prosumer–grid interaction under Strategy B.

Strategy C presents an intermediate behaviour between Strategies A and B. Welfare values remain relatively stable throughout the year while exhibiting moderate sensitivity to battery capacity. During periods of higher photovoltaic generation (August–September), larger batteries slightly increase total welfare, reaching 261.77 € in August (30 kWh) compared with 233.32 € (10 kWh). In contrast, winter months show only marginal differences among battery capacities.

Overall, all strategies follow a similar seasonal pattern, with maximum welfare occurring during January and December, declining towards the summer months, and gradually recovering during autumn. However, the magnitude of seasonal variation differs substantially among the three operational strategies.

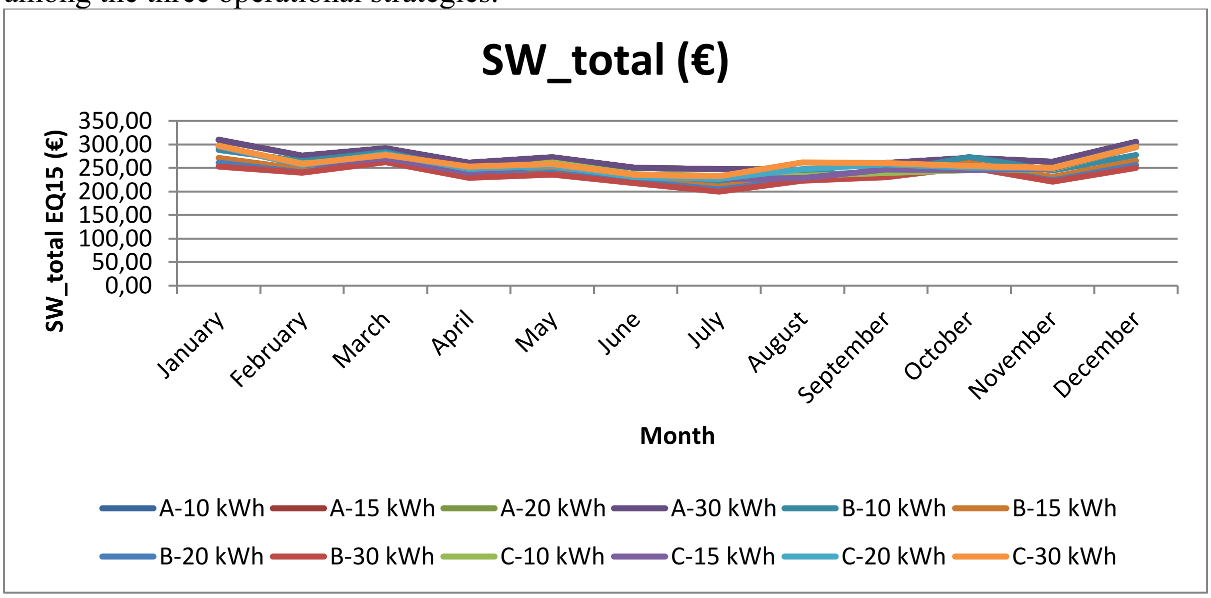

Figure 1. Monthly Social Welfare (with regards to spot market and grid) variation for Strategy A, upon 4 different capacities.

5.2 Annual prosumer utility Uprosumer: Monthly Comparison

Figure 2 presents the monthly values of the annual prosumer utility (U_prosumer) for the three operational strategies (A–C) and the four battery capacities (10, 15, 20 and 30 kWh). The indicator represents the annualized economic utility obtained by the residential prosumer through self-consumption, electricity imports and exports within the conventional electricity market, before participation in peer-to-peer (P2P) energy trading.

Strategy A exhibits remarkably stable behaviour throughout the year. Monthly utility ranges from 305.75 € in November to 409.37 € in July, while the differences among the four battery capacities are practically negligible, remaining below one euro in every month. This indicates that battery size has almost no influence on prosumer utility under the operating principles of Strategy A.

Strategy B demonstrates greater seasonal variability and a moderate dependence on battery capacity. The highest utility is observed during July, reaching 426.32 € (10 kWh), whereas the lowest values occur during November (306.23–316.45 €). In most months, increasing battery capacity results in a gradual reduction in annual utility, with the 10 kWh configuration consistently outperforming the larger storage capacities.

Strategy C achieves the highest utility during periods of increased photovoltaic availability. Monthly utility reaches 454.84 € in July (10 kWh), representing the highest value among all examined scenarios, while elevated values are also observed during May (410.67 €) and June (418.77 €). Unlike Strategy B, Strategy C exhibits moderate improvements for selected months when larger battery capacities are employed, particularly during August and September, indicating a more effective utilization of stored photovoltaic energy under favourable renewable generation conditions.

Overall, all strategies follow a common seasonal pattern characterized by increasing utility from spring towards midsummer, peaking during July, followed by a gradual decline during autumn and early winter. Nevertheless, the magnitude of the seasonal fluctuations differs considerably among the three operational strategies, with Strategy C demonstrating the strongest seasonal response.

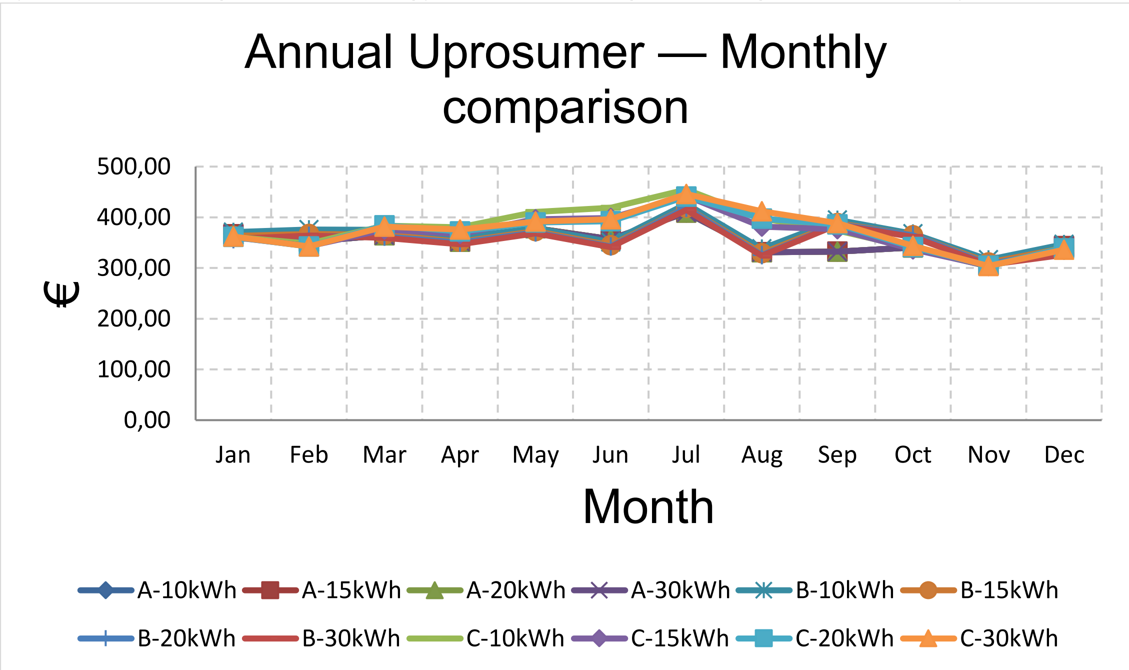

Figure 2 Monthly Utility function of Prosumer (with regards to spot market and grid) variation for Strategy A, upon 4 different capacities.

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5.3 Prosumer Surplus in the Conventional Prosumer–Grid Market

Figure 3,4,5 present the monthly evolution of the **Prosumer Surplus with respect to the conventional spot/grid market (PS_to_grid)** for the three battery management strategies and the four battery capacities. The indicator quantifies the economic surplus retained by the prosumer before participation in peer-to-peer electricity trading.

Under **Strategy A (Figure 3)**, the monthly profiles are **remarkably similar across all battery capacities**. Increasing battery capacity from **10 kWh to 30 kWh** produces only marginal improvements in monthly prosumer surplus, with the annual values differing by less than 2 € over the entire year. The monthly curves almost overlap, indicating that the fixed threshold charging and discharging rules are unable to exploit additional storage capacity to generate significantly higher economic returns within the conventional spot market.

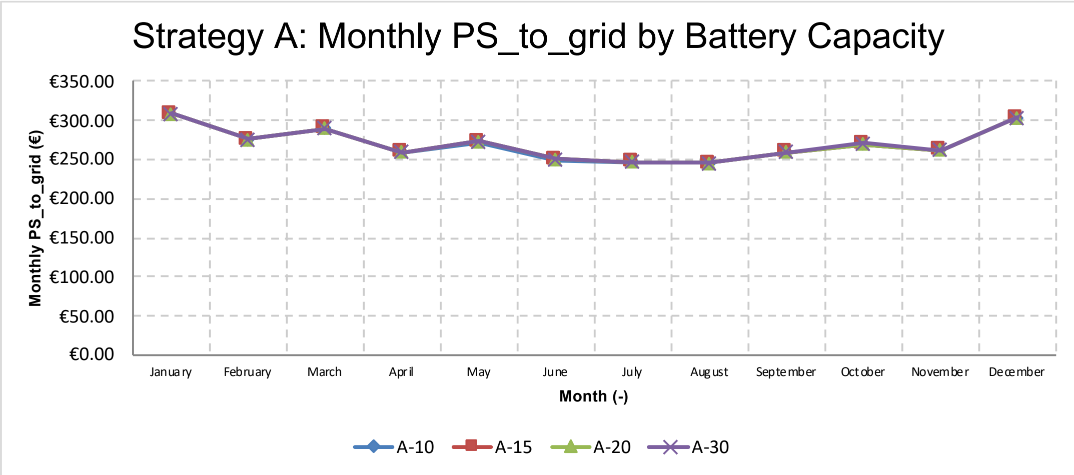


Figure 3. Monthly Consumer Surplus (with regards to spot market and grid) variation for Strategy A, upon 4 different capacities.

In contrast, **Strategy B** (Figure 4)**exhibits a pronounced dependence on battery capacity**. The annual prosumer surplus decreases progressively as storage capacity increases, from approximately **3178 €** for the 10 kWh battery to **2877 €** for the 30 kWh configuration. The reduction is consistently observed throughout the year and becomes particularly evident during the summer months, when photovoltaic generation is highest. Larger batteries under Strategy B therefore reduce the economic surplus retained by the prosumer within the conventional grid market.

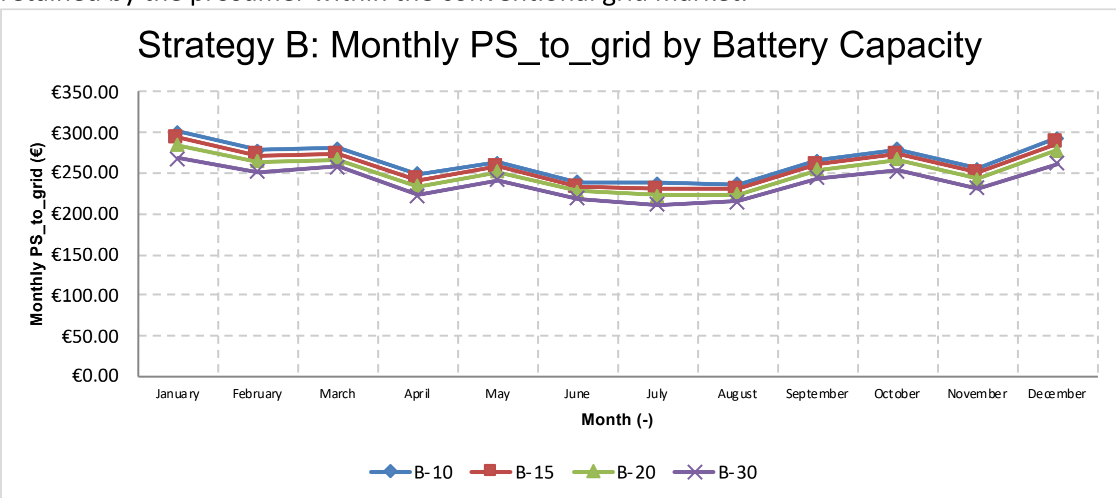


Figure 4. Monthly Consumer Surplus (with regards to spot market and grid) variation for Strategy B, upon 4 different capacities.

Strategy C (Figure 5)presents an intermediate behavior. For small battery capacities (10–15 kWh), annual prosumer surplus remains close to **3066–3068 €**, whereas increasing battery capacity to **20–**

30 kWh leads to a moderate recovery, reaching approximately **3170 €** for the 30 kWh battery. Unlike Strategy B, the monthly profiles remain relatively stable while exhibiting a slight upward trend as storage capacity increases.

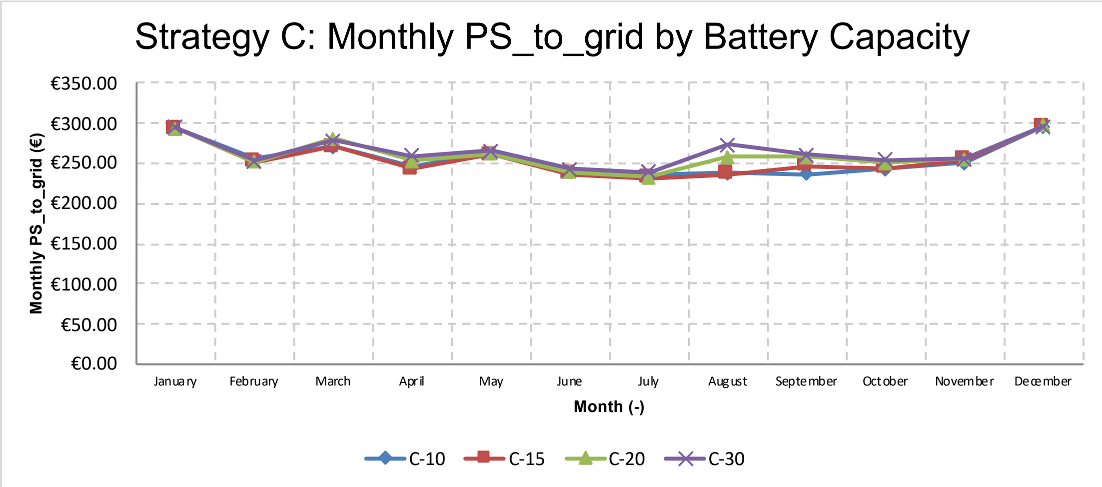


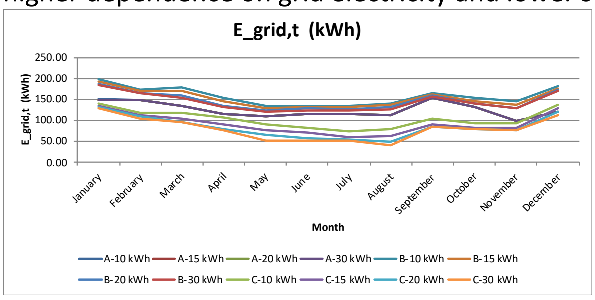
Figure 5. Monthly Consumer Surplus (with regards to spot market and grid) variation for Strategy C, upon 4 different capacities

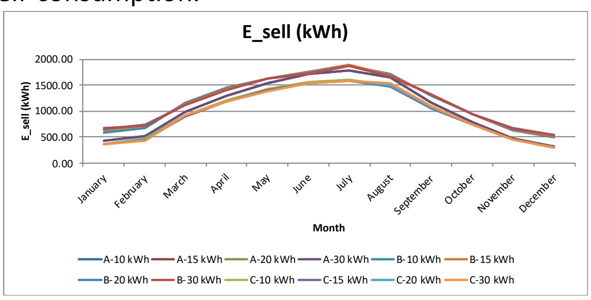
Seasonally, **all strategies exhibit lower prosumer surplus during the summer months and higher values during winter**, reflecting the combined influence of seasonal electricity prices and photovoltaic generation on conventional grid transactions. However, the magnitude of seasonal variation differs among the three strategies, demonstrating that **battery scheduling policies significantly influence the temporal distribution of economic surplus** <u>even before peer-to-peer trading is introduced</u>.

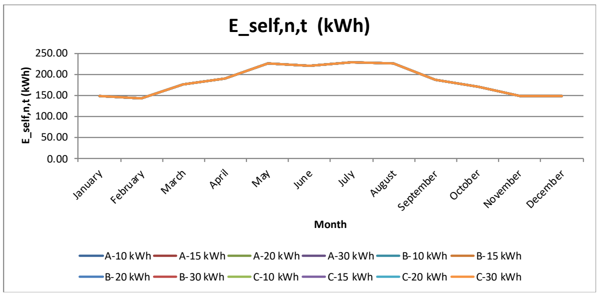
5.4 Energy Balance of the Residential Prosumer

Figures 6(a–c) present the monthly evolution of the three principal energy flow components of the residential prosumer, namely **grid electricity imports (E_grid,)**, **electricity exported to the grid (E_sell)**, and **self-consumed photovoltaic energy (E_self,)**, for the three battery management strategies and the four battery capacities.

The three indicators exhibit consistent seasonal behavior reflecting the annual photovoltaic production profile. During spring and summer, increased solar generation leads to a substantial reduction in grid electricity imports while simultaneously increasing both self-consumption and electricity exports. Conversely, during autumn and winter, reduced photovoltaic production results in higher dependence on grid electricity and lower self-consumption.







Figures 6 a,b,c Demonstration of: a) Monthly Grid Imports (E_grid), b) Monthly Grid Exports (E_sell), **and c)**Monthly PV Self-consumption (E_self)

Strategy A exhibits only **limited sensitivity to battery capacity**. Increasing storage capacity produces relatively small reductions in grid imports and only marginal changes in exported electricity and self-consumption, indicating that the fixed threshold charging and discharging rules are unable to exploit the additional storage flexibility effectively.

Strategy B demonstrates a **much stronger dependence on battery capacity**. Larger batteries substantially reduce grid electricity imports while simultaneously decreasing electricity exported to the grid. The reduction in exports is accompanied by a corresponding increase in self-consumed photovoltaic energy, indicating that additional storage is primarily utilized to retain locally generated electricity rather than injecting it into the conventional electricity market.

Strategy C exhibits the **highest level of internal energy utilization**. The rolling optimization framework consistently minimizes grid imports while maximizing photovoltaic self-consumption across all battery capacities. Compared with Strategies A and B, the monthly **profiles remain smoother** throughout the year, suggesting a **more efficient allocation** of photovoltaic generation between immediate consumption, battery storage and conventional grid interaction.

Overall, increasing battery capacity progressively shifts the residential energy balance from conventional grid dependence towards local utilization of photovoltaic generation, although the **magnitude of this transition strongly depends on the adopted energy management strategy**.

5.5 P2P Revenues and Peer-to-Peer Social Welfare

Figures **7(a) and 7(b**) present the monthly evolution of **P2P revenues** and the corresponding **peer-to-peer social welfare (SWP2P)** for the three battery management strategies and the four battery capacities. Although both indicators exhibit similar seasonal patterns, they represent different dimensions of the local electricity market. P2P revenues quantify the direct financial income received by the selling prosumer through local electricity transactions, whereas SWP2P measures the total welfare generated within the peer-to-peer market by combining both producer and consumer surplus.

Both indicators increase during periods of high photovoltaic production, particularly between late spring and early autumn, reflecting the greater availability of locally generated electricity for peer-to-peer exchanges. Conversely, winter months exhibit lower revenues and reduced social welfare because lower photovoltaic production limits the quantity of electricity available for local trading.

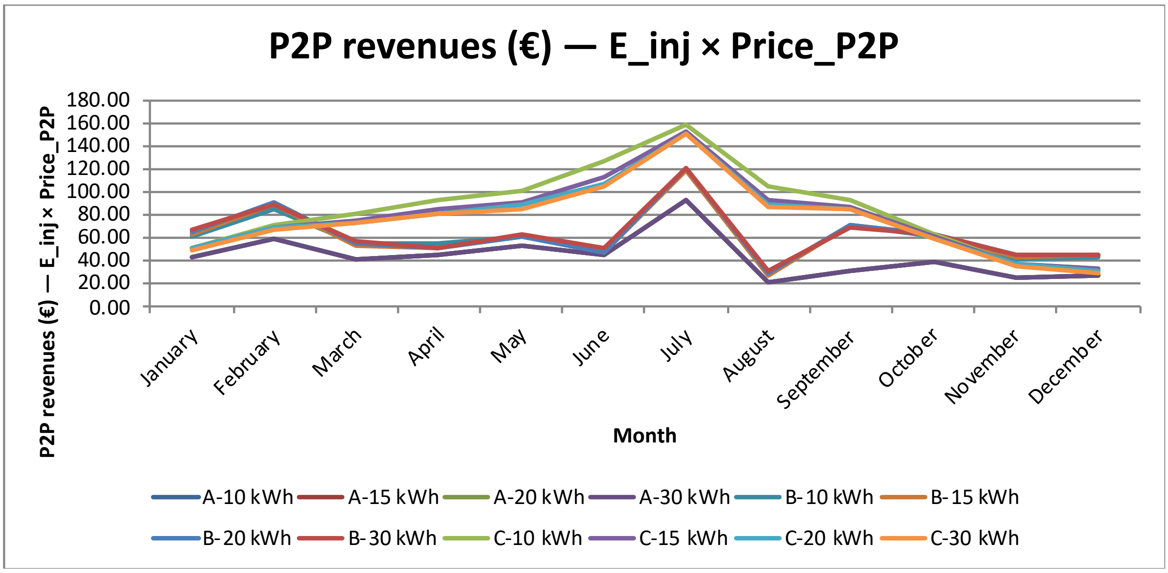


Figure 7a Monthly peer-to-peer (P2P) revenues of the selling prosumer, calculated as the product of the electricity injected into the P2P market (E_inj) and the corresponding P2P transaction price (Price_P2P), for the three battery management strategies (A–C) and four battery capacities (10, 15, 20 and 30 kWh)

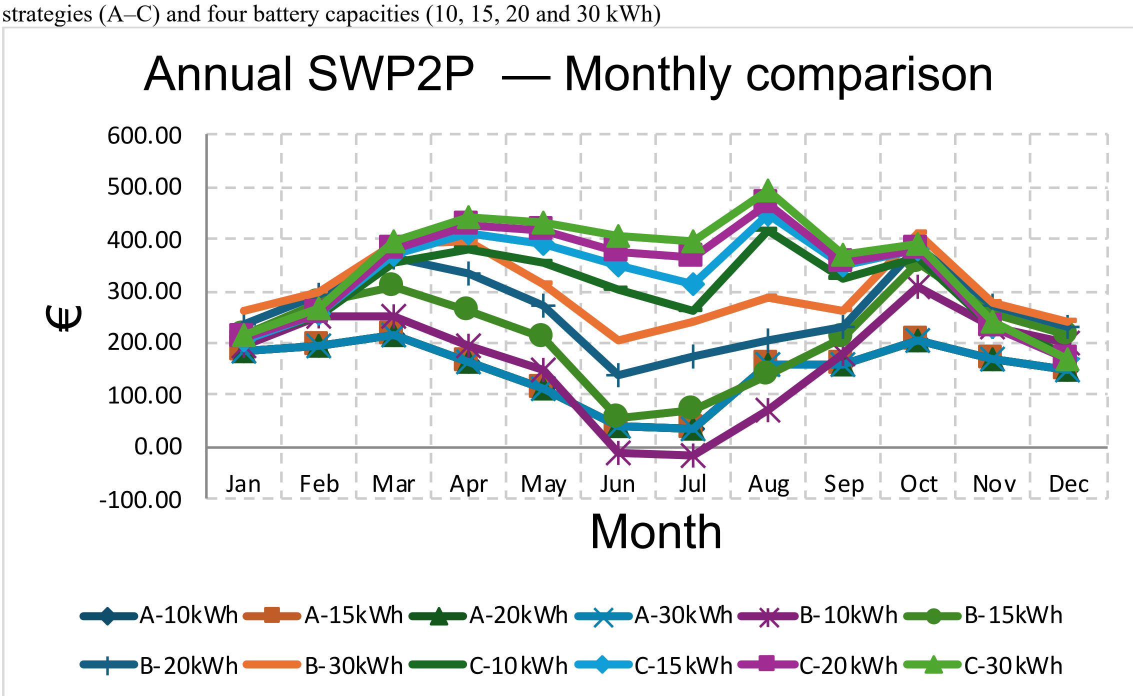


Figure 7b. *Comparison of the monthly peer-to-peer social welfare (SWP2P, EQ25) under the three battery management strategies (A, B and C) and four battery capacities (10, 15, 20 and 30 kWh). The indicator measures the total economic welfare generated by peer-to-peer electricity trading, including both prosumer (producer) and consumer surplus, and is presented as monthly aggregated values.*

Strategy A produces relatively modest variations across battery capacities, indicating that the fixed threshold charging and discharging **rules generate only limited improvements in local trading activity.** Strategy B exhibits the **strongest dependence on battery capac**ity, with larger batteries increasing both monthly P2P revenues and peer-to-peer social welfare throughout the year. Strategy C achieves intermediate but more stable results, **maintaining relatively high revenues and social welfare while reducing seasonal variability** compared with Strategy B.

Although both indicators follow similar seasonal trends, the **increase in SWP2P is consistently greater than the increase in individual P2P revenues**. This reflects the fact that **each additional peer-to-peer transaction** generates value simultaneously for both the electricity seller and the buyer, resulting **in higher total market welfare than individual producer income alone.**

5.6 Monthly Consumer Surplus of P2P Consumers

Figure 8 presents the monthly Consumer Surplus (CS), calculated according to Equation (33), for consumers purchasing electricity through the peer-to-peer (P2P) market under the three battery dispatch strategies (A–C) and four battery capacities (10, 15, 20 and 30 kWh).

Overall, the Consumer Surplus exhibits a pronounced seasonal pattern across all scenarios, with lower values during the winter months (December–February) and progressively higher values during spring and summer, reaching the annual maximum in August before declining towards the end of the year. However, the relative performance of the dispatch strategies varies throughout the year. Strategy B records the highest Consumer Surplus during January, February, October, November and December, whereas Strategy C consistently outperforms the other strategies between April and September, with the highest annual value of **€625.20** obtained for the 30 kWh battery in August.

The influence of battery capacity also differs considerably among the examined strategies. Under Strategy A, increasing battery capacity from 10 kWh to 30 kWh produces only negligible changes in Consumer Surplus throughout the year. By contrast, both Strategies B and C exhibit a clear positive relationship between storage capacity and Consumer Surplus, with progressively larger batteries yielding higher economic benefits for P2P consumers. The strongest capacity-dependent improvements are observed under Strategy C during the high-photovoltaic generation period, whereas the smallest differences occur under Strategy A across all months.

Overall, the results indicate that Consumer Surplus is influenced not only by seasonal conditions but also by the interaction between battery dispatch strategy and storage capacity, with their relative contribution varying throughout the year.

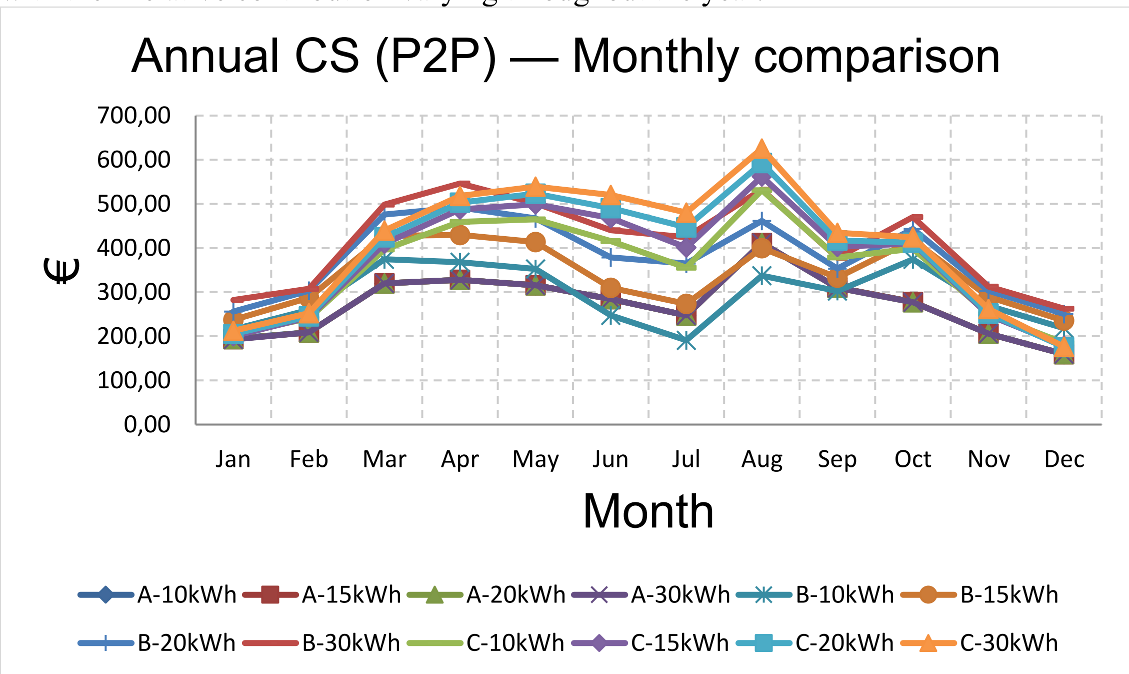


Figure 8. Monthly comparison of Consumer Surplus with regards to P2P network, under 3 strategies and 4 capacities

5.7 Intraday Seasonal Component of Hourly Elasticity

Figure 9, 10, 11 illustrate the intraday seasonal component of the hourly price elasticity of demand obtained using a 24-hour Fourier regression with three harmonic pairs and 95% confidence intervals across all three energy management strategies and the four battery capacities. The Fourier model successfully captures the dominant daily elasticity cycle while smoothing short-term noise observed in the raw hourly data.

Strategy A (Figure 9) exhibits nearly identical elasticity profiles across all battery capacities, confirming that storage size has virtually no influence on the temporal elasticity pattern under this rigid operating framework. The coefficient of determination remains constant ($R^2 = 0.485$) for all four battery capacities, indicating that approximately half of the hourly elasticity variability is explained by the deterministic 24-hour seasonal component. The fitted elasticity profile is most elastic during Hour 2 (approaching -1.18), indicating high price responsiveness) and gradually trends toward a highly inelastic state around Hour 16, where the elasticity coefficient approaches zero. Consequently, **under Strategy A, the intraday elasticity profile is governed primarily by the rigid rules of the operating strategy rather than battery size**.

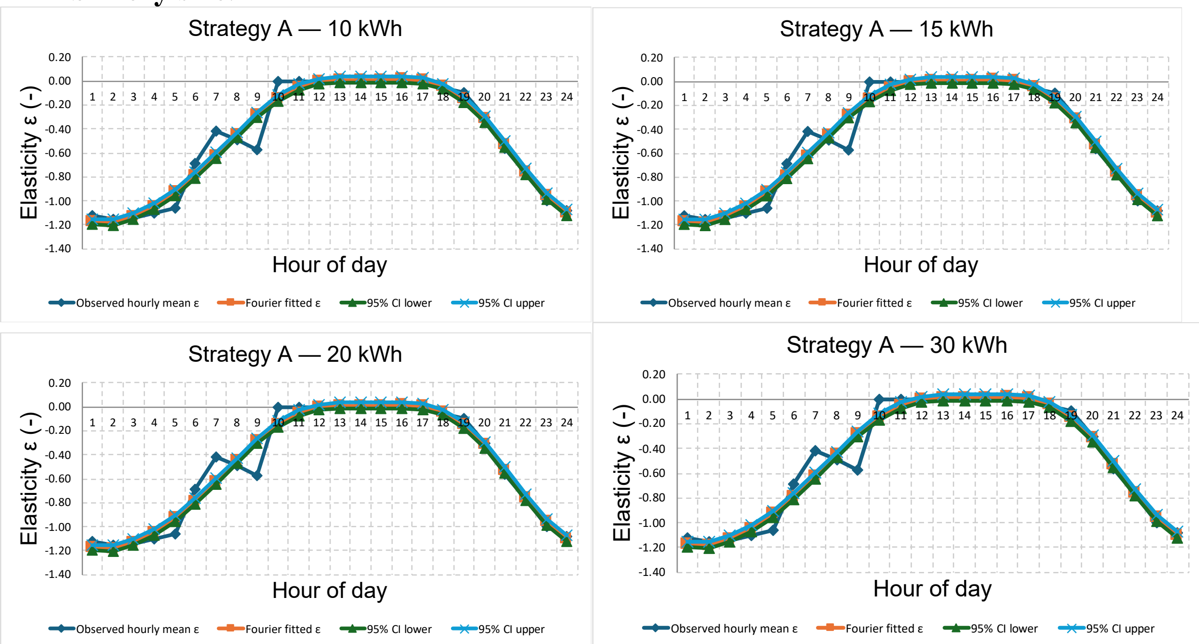
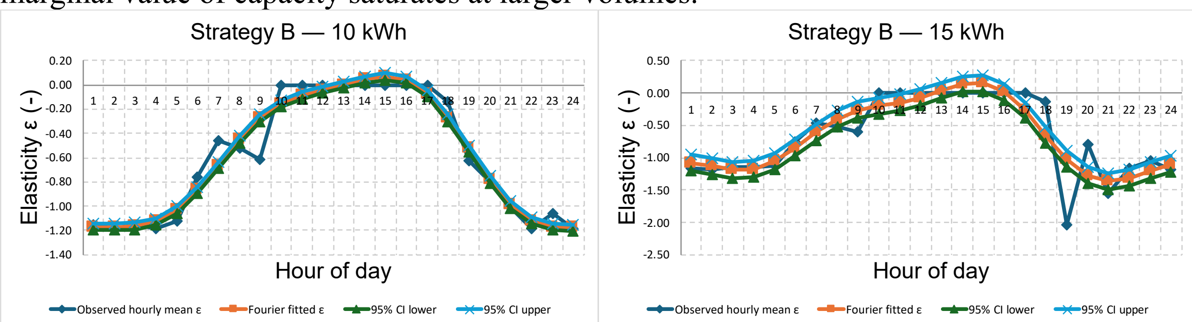


Figure 9. Intraday Seasonal Component of Hourly Elasticity for Strategy A and 4 battery capacities

Strategy B (Figure 10) demonstrates considerably greater structural variability among battery capacities. The explanatory power of the Fourier model drops drastically from $R^2 = 0.469$ for the 10 kWh configuration to $R^2 = 0.051$ for the 15 kWh battery, indicating that the strength of the deterministic daily cycle is highly sensitive to storage capacity. The most elastic demand response generally occurs during the late-night and early-morning hours (Hours 21–24 or Hour 1), while the least responsive, inelastic behavior is consistently observed around Hours 15–16. The largest intraday elasticity range is observed for the 15 kWh battery (1.514), suggesting a heightened sensitivity to daily electricity price variations before the marginal value of capacity saturates at larger volumes.



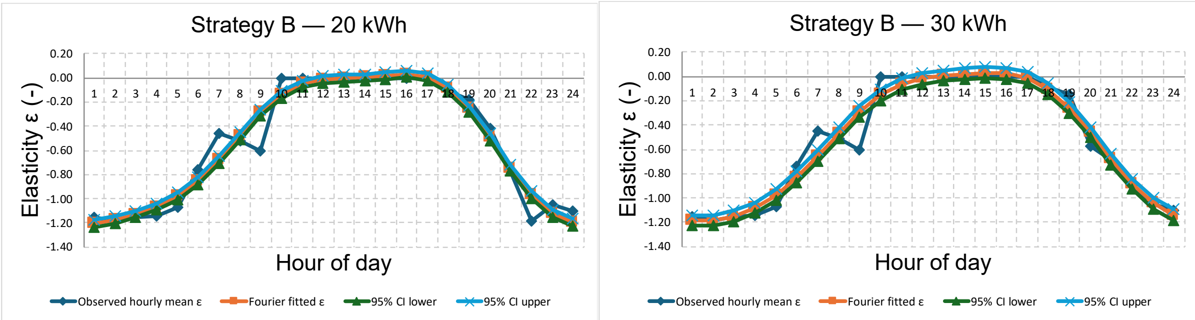


Figure 10. Intraday Seasonal Component of Hourly Elasticity for Strategy B and 4 battery capacities

Strategy C (Figure 11) presents an intermediate behavior between Strategies A and B. The Fourier model explains a moderate proportion of the hourly variability (\(R^2 = 0.094 - 0.276\)), indicating that while a clear daily seasonal component exists, stochastic operational effects account for a substantial share of elasticity fluctuations. Peak price responsiveness consistently occurs around Hour 24, whereas the daily inelastic nadir shifts slightly toward Hours 15–17 as battery capacity increases. The smallest intraday elasticity amplitude is obtained for the 20 kWh battery (1.146), **indicating the smoothest and most stable daily elasticity profile among the Strategy C configuration**s.

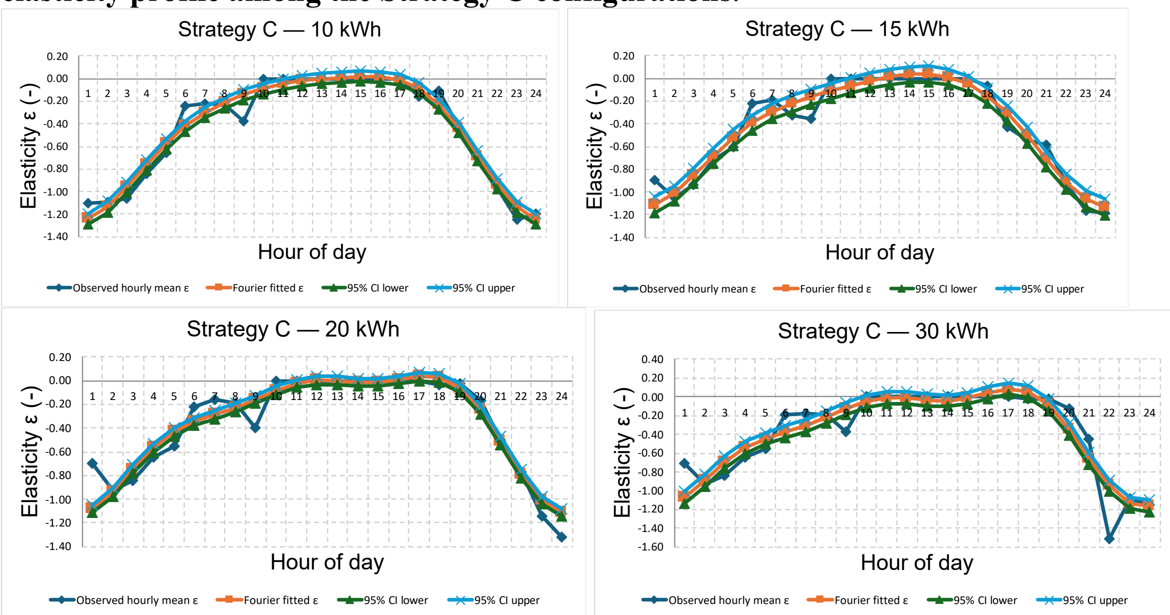


Figure 11. Intraday Seasonal Component of Hourly Elasticity for Strategy C and 4 battery capacities

Overall, all strategies exhibit a **pronounced daily elasticity cycle characterized by robust price responsiveness during overnight hours and reduced grid sensitivity during the afternoon period**. However, the magnitude, timing, and regularity of this daily pattern differ considerably based on the chosen optimization horizon.

5.8 Intraday Seasonal Dynamics of P2P Price, Prosumer Utility and Buyer Utility

To investigate the daily behavior of the proposed P2P market mechanism, a 24-hour Fourier regression with three harmonic pairs and 95% confidence intervals was applied to three key indicators: (i) the hourly price difference between the wholesale spot market and the P2P market, (ii) the reduction in the prosumer utility function resulting from participation in the P2P market, and (iii) the buyer utility function (**U_buyer, Eq. 31).**

The Fourier decomposition reveals a clear and statistically significant intraday seasonal component for all three indicators across the examined strategies and battery capacities.

For the electricity price difference, all strategies exhibit a pronounced daily cycle. **Strategy A (Figure 12) presents the most stable behavior,** with the Fourier model explaining approximately **52–53%** of the hourly variability ($R^2 \approx 0.52–0.53$). The minimum price difference occurs around **23:00**, whereas the maximum price reduction is observed around **17:00**, indicating that the P2P market offers the largest economic advantage during the afternoon peak-demand period. Increasing battery capacity from 10 to 30 kWh slightly enlarges the daily price reduction amplitude from **0.110 €/kWh** to **0.112 €/kWh**.

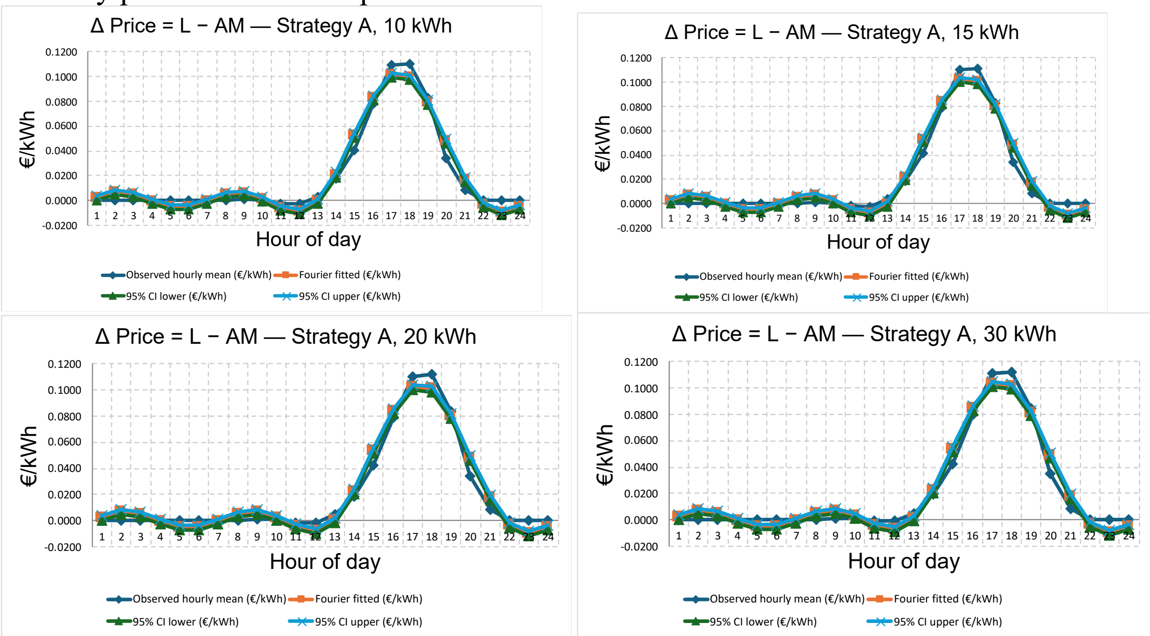


Figure 12. Intraday Seasonal Component of **electricity price difference** for Strategy A and 4 battery capacities

Strategy B (Figure 13) exhibits a stronger dependence on battery capacity. The explanatory power increases from $\mathbf{R^2=0.44}$ to $\mathbf{R^2=0.48}$, while the daily price reduction amplitude increases continuously from **0.115 €/kWh** (10 kWh) to **0.126 €/kWh** (30 kWh). The minimum values occur around midday (Hour 12), whereas the largest price advantage appears during the evening (Hour 18).

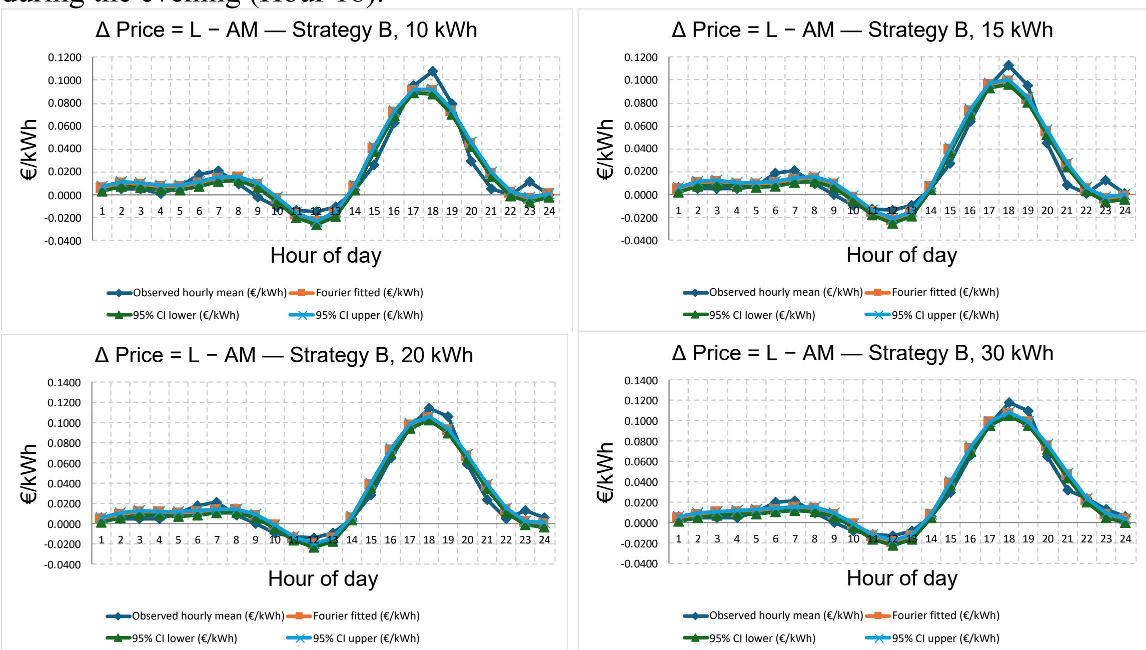


Figure 13. Intraday Seasonal Component of **electricity price difference** for Strategy B and 4 battery capacities

Strategy C (Figure 14) presents a smoother daily profile with lower average price differences but a gradual increase in amplitude as battery capacity increases. The Fourier model explains approximately **41–43%** of the hourly variability, while the daily price reduction reaches **0.107 €/kWh** for the 30 kWh battery.

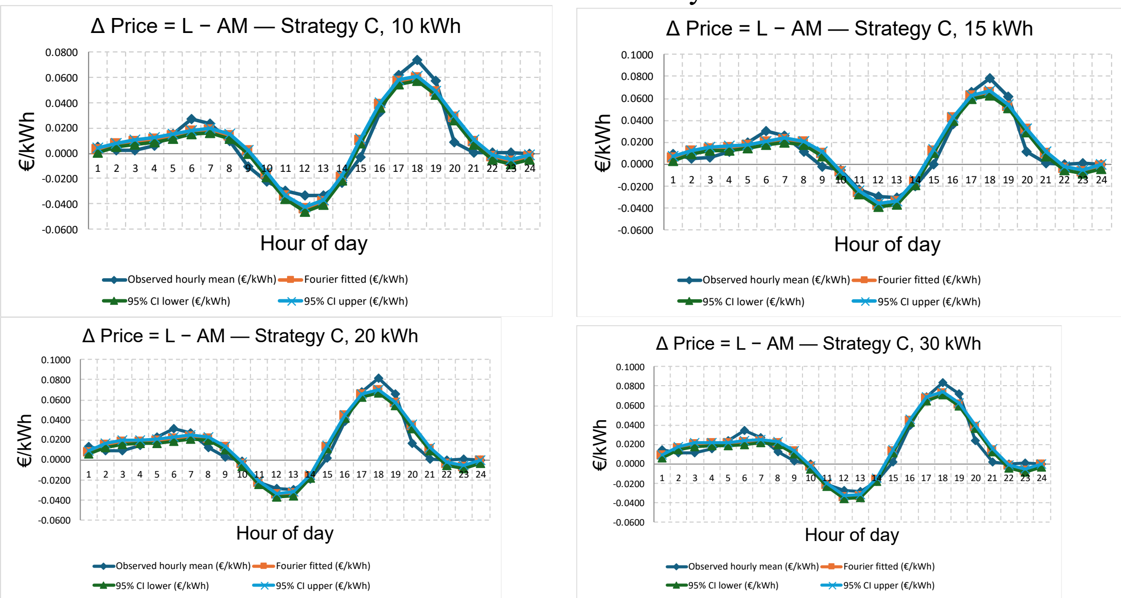


Figure 14. Intraday Seasonal Component of **electricity price difference** for Strategy C and 4 battery capacities

The corresponding differences in the **prosumer utility function** follow a similar intraday pattern. Strategy A (Figure 15) produces relatively small utility reductions, whereas Strategy B (Figure 16) exhibits the largest daily utility differences, particularly for larger battery capacities where the daily amplitude increases from **0.559 €** to **0.610 €**..

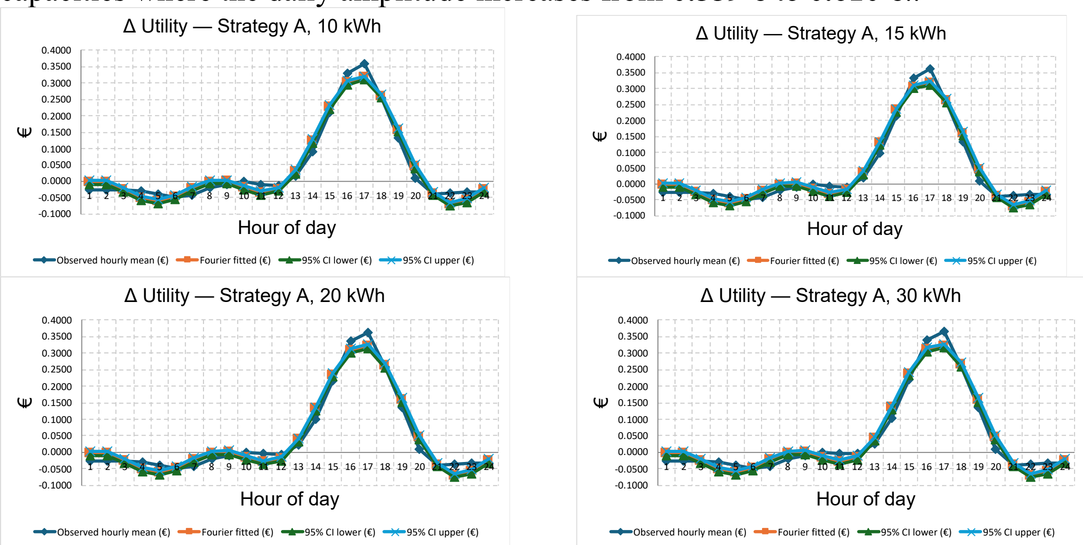
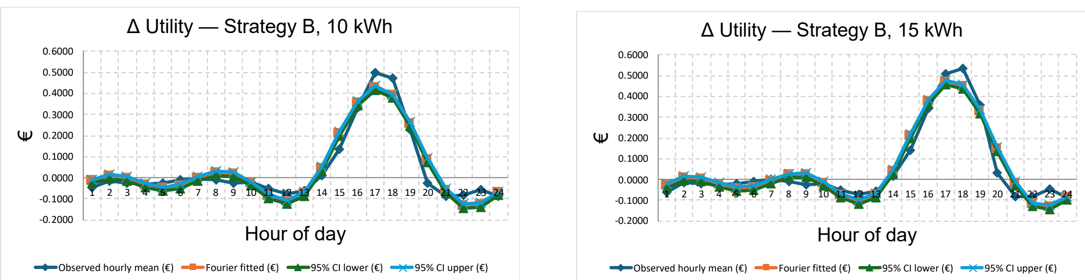


Figure 15. Intraday Seasonal Component of **the prosumer utility function** for Strategy A and 4 battery capacities



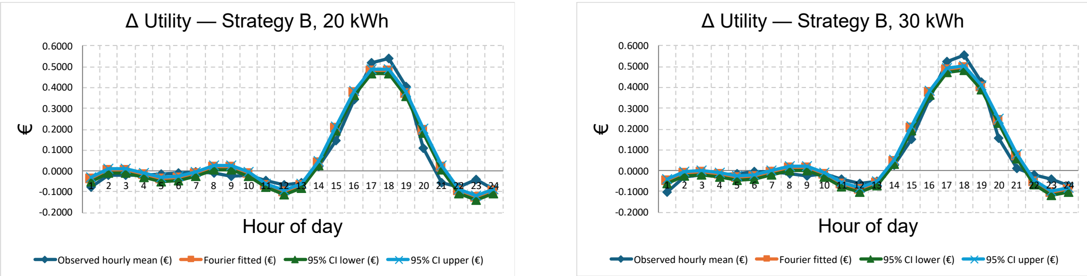


Figure 16. Intraday Seasonal Component of **the prosumer utility function** for Strategy B and 4 battery capacities

Strategy C (Figure 17) demonstrates a more moderate behavior, maintaining considerably smaller daily utility variations than Strategy B.

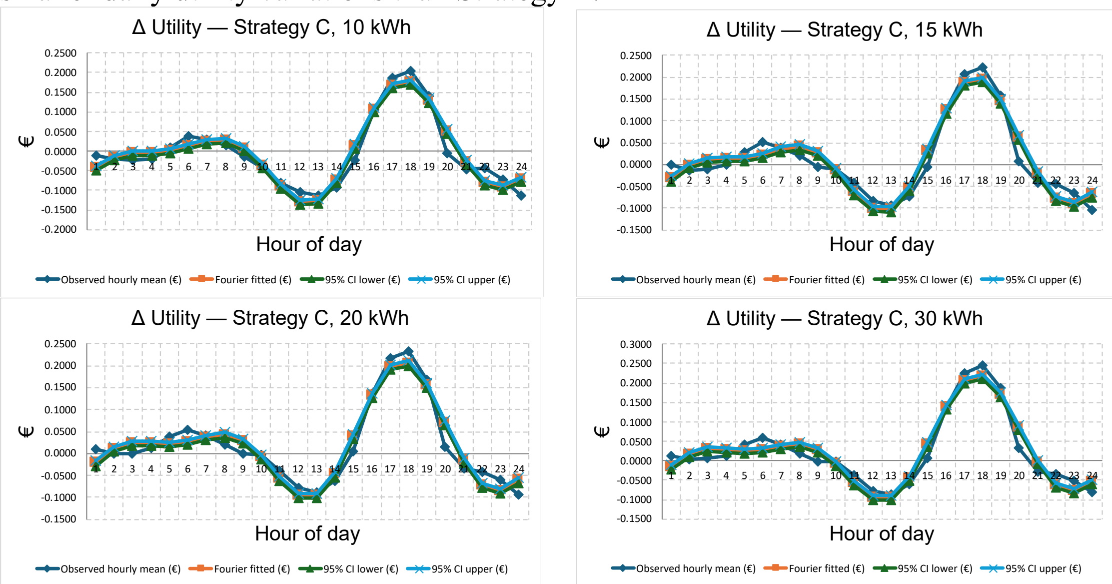


Figure 17. Intraday Seasonal Component of **the prosumer utility function** for Strategy C and 4 battery capacities

Finally, **the buyer utility function (U_buyer)** exhibits the strongest seasonal response among the three analysed indicators. **Strategy A (Figure 18) maintains the most stable buyer utility profile throughout the day.**

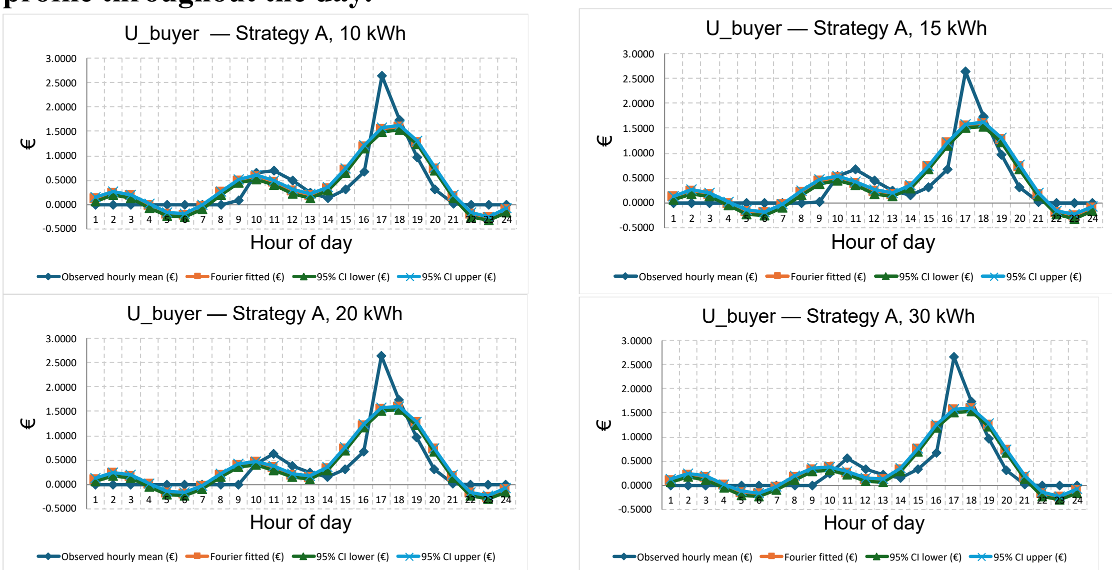


Figure 18. Intraday Seasonal Component of **the Buyer (b2b) utility function** for Strategy A and 4 battery capacities

Strategy B (Figure 19) consistently provides the highest buyer utility, with the daily amplitude increasing from **2.24 €** for the 10 kWh battery to **2.72 €** for the 30 kWh battery.

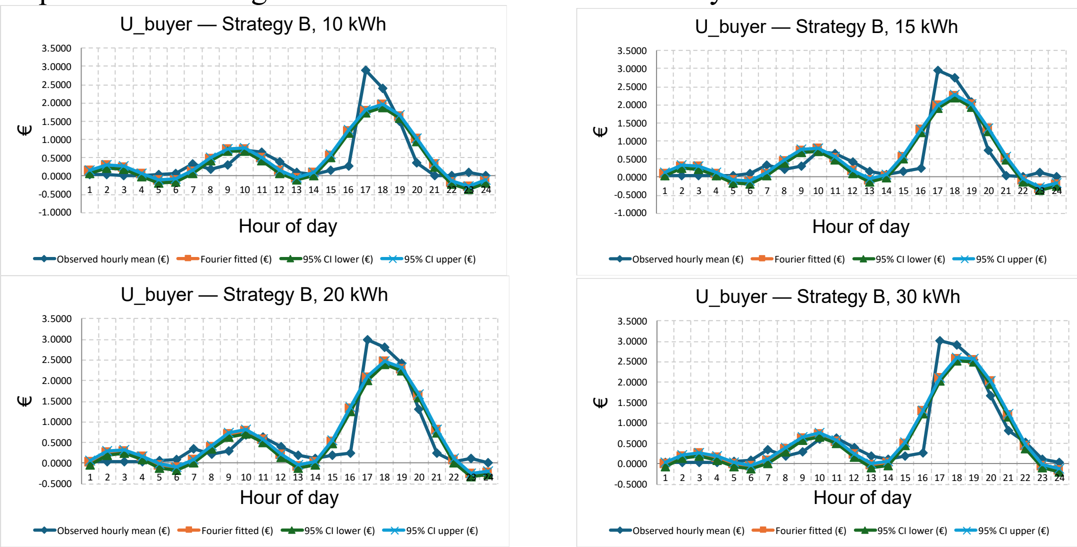


Figure 19. Intraday Seasonal Component of **the Buyer (b2b) utility function** for Strategy B and 4 battery capacities

Strategy C (Figure 20) follows a **similar but smoother trend**.

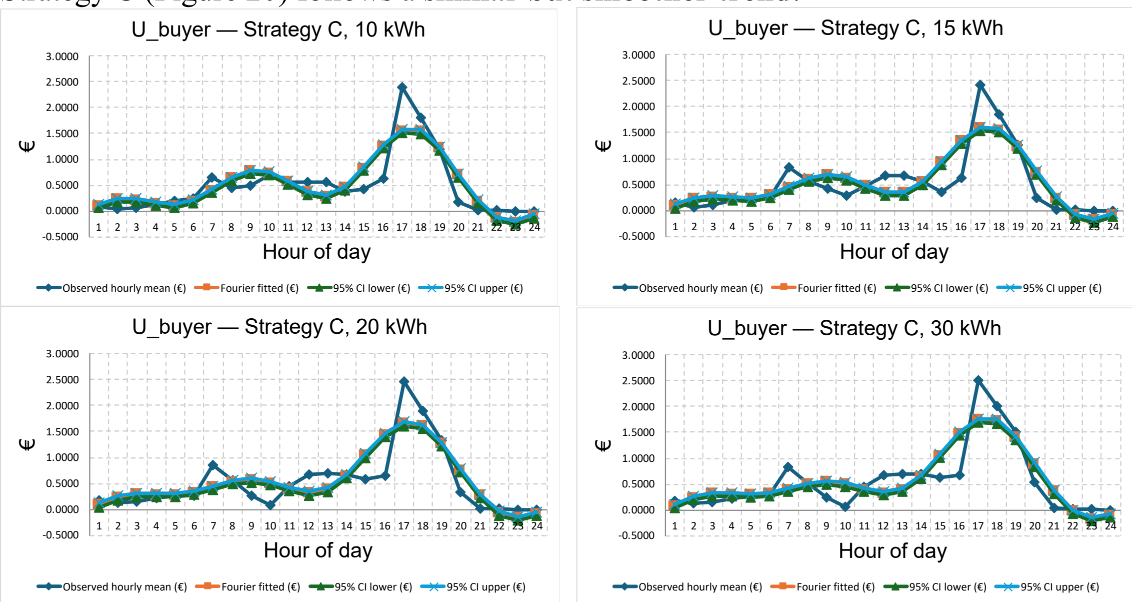


Figure 20. Intraday Seasonal Component of **the Buyer (b2b) utility function** for Strategy C and 4 battery capacities

Overall, the Fourier analysis demonstrates that both battery capacity and operational strategy significantly influence the temporal dynamics of electricity prices and participant utilities within the proposed P2P market.

5.9 Clearing Price Dynamics

The utility-based clearing price $Price, eq_{\{P2P\}}$ (Eq 29) exhibits a clear dependence on battery management strategy, storage capacity, time of day, and season. Across the 47,277 active P2P hourly observations of the 12 examined scenarios, $Price, eq_{\{P2P\}}$ was higher than both the spot price and the implemented P2P price in **57.8%** of cases, lower than the spot price and lower than or equal to the P2P price in **30.5%**, while the remaining **11.7%** corresponded to intermediate price positions. Strategy A showed comparatively weak sensitivity to battery capacity, with high-clearing-price conditions occurring in approximately **53–55%** of active trading hours across all four storage sizes. In Strategy B, the share of observations for which

$Price, eq_{\{P2P\}}$ exceeded both market benchmarks increased from **53.1% at 10 kWh** to **61.9% at 30 kWh**, while the corresponding low-clearing-price share decreased from **35.5% to 27.2%**. Strategy C exhibited the highest prevalence of high-clearing-price conditions, at approximately **61–62%** of active observations, whereas the share of low-clearing-price cases declined from **28.1% at 10 kWh** to **22.1% at 30 kWh**. The intraday analysis (Figure 21) further revealed that high-clearing-price conditions were particularly frequent at **07:00, 10:00–13:00, 17:00–20:00, and 22:00–23:00**, reaching **86.5% at 07:00**, **83.5% at 17:00**, **79.6% at 19:00**, and **92.5% at 23:00**. By contrast, lower clearing-price conditions were more common during **04:00–06:00, 15:00–16:00, and around 21:00**. Seasonally (Figure 22), the frequency of $Price, eq_{\{P2P\}}$ exceeding both reference prices was highest in autumn and winter, reaching **67.5% in October, 72.1% in November, and 73.2% in December**, whereas low-clearing-price conditions became substantially more frequent in summer, particularly in **June (44.4%)** and **July (43.8%)**. The aggregate monthly median $Price, eq_{\{P2P\}}$ also displayed a pronounced seasonal pattern, declining to approximately **0.065 €/kWh in June** and increasing to approximately **0.183–0.188 €/kWh in December–February**.

The strategy- and capacity-specific profiles provided in the Supplementary Material (data restored in the Github link) confirm that the aggregate temporal patterns arise from systematic differences among the individual battery configurations rather than from a uniform market-price effect.

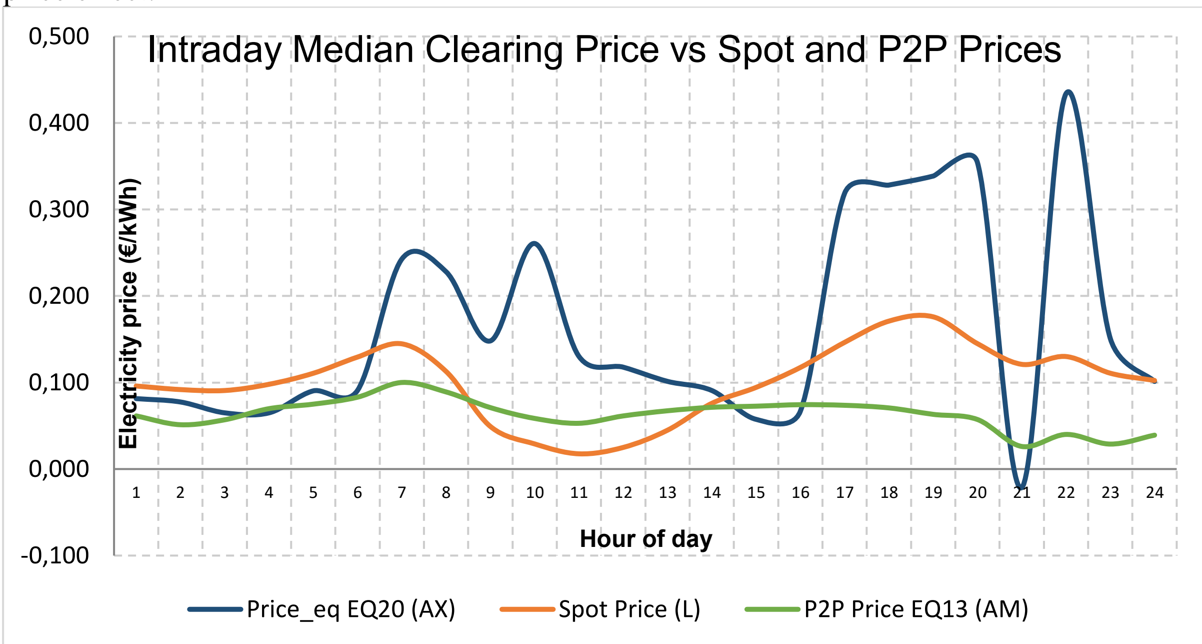


Figure 21. Aggregate intraday variation of the median utility-based clearing price $Price, eq_{\{P2P\}}$ (Eq 29), spot price, and implemented P2P price across the three battery management strategies and four battery capacities. The comparison highlights the hours during which the theoretical utility-equalising price lies above or below the observed market-price benchmarks.

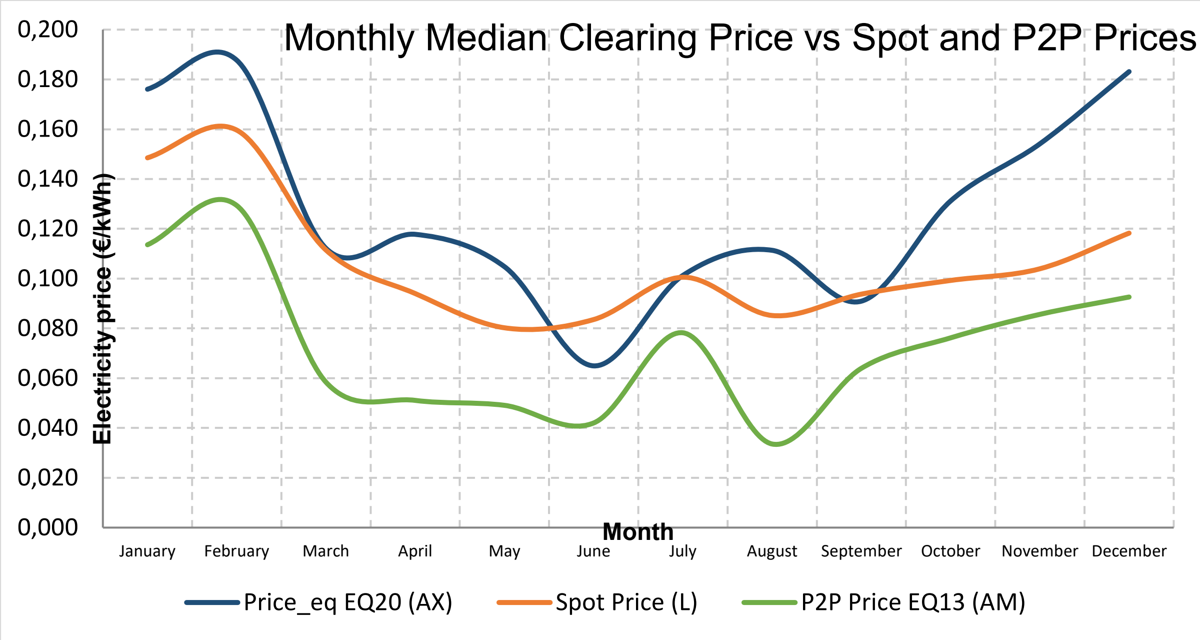


Figure 22. Monthly variation of the median utility-based clearing price $Price, eq_{\{P2P\}}$ (Eq 29), spot price, and implemented P2P price across all examined strategies and battery capacities, illustrating the seasonal evolution of the utility-equilibrium price relative to the conventional and P2P market benchmarks.

6. Discussion

6.1 SW_total (€): Total Social Welfare of the Prosumer–Grid Market

The observed results reveal a nuanced, multi-dimensional interplay between battery storage capacities (10 kWh to 30 kWh), algorithmic operational frameworks (Strategies A, B, and C), and seasonal price fluctuations. A primary finding is that the operational strategy exerts a substantially greater influence on total social welfare than physical battery capacity within the conventional prosumer–grid market. The longitudinal trends of **SW** demonstrate how the look-ahead predictive horizons and seasonal solar availability dictate the micro-system's economic footprint.

Strategy A exhibits a unique phenomenon where the total social welfare remains **completely invariant** across all four battery capacities (10, 15, 20, and 30 kWh) within any given month.

- **The Underlying Mechanism: Strategy A** consistently provides the highest baseline welfare irrespective of storage size. This rigid, fixed-threshold framework implies that its baseline energy management policy already fully exploits the available photovoltaic (PV) generation and grid interaction efficiently. Once these fixed-price conditions are met, the system executes predefined actions, leaving any incremental storage space unutilized.
- **The Welfare Implication:** Consequently, additional battery capacity yields negligible incremental welfare gains, indicating that the marginal economic value of storage has already been saturated under this strategy. The micro-system's (market-grid against one prosumer) welfare remains entirely decoupled from capacity expansions and is instead dictated by exogenous seasonal market shifts.

In direct contrast, **Strategy B** exhibits a systematic, monotonic reduction in total social welfare as battery capacity increases across almost all months.

- **The Underlying Mechanism:** This behavior suggests that larger storage systems do not translate into improved economic performance when operating exclusively within the conventional electricity market under a fixed daily block. Instead, expanding storage capacity to 30 kWh **increases complex internal charging and discharging interactions**. This intensive shifting postpones economically favorable electricity exchanges with the grid and severely curtails the volume of direct, value-capturing market transactions.

- **The Welfare Implication:** While **the prosumer captures private surplus via transaction avoidance,** this dynamic exacerbates the structural cost asymmetry of the micro-system (prosumer and grid). The utility loses its entire profit margin and network cost recovery on a larger volume of foregone or delayed transactions, while its infrastructure costs remain fixed. The larger the battery, **the greater the erosion of producer (established market-grid) surplus, which overpowers private gains and lowers the overall welfare** generated by the prosumer–grid interaction.

Strategy C demonstrates a **more balanced and complex response**, maintaining relatively stable welfare values while **achieving modest improvements during periods of high PV availability**. By utilizing a continuous 24-hour rolling prediction window to update thresholds as new forecast data arrives, it **avoids the rigid blocks of Strategy B, resulting in non-linear welfare trends.**

  - **Summer Volatility and Capacity Inversion:** During peak summer months, higher battery capacities reverse the welfare erosion trend. In August, **SW** increases non-linearly from €233.32 at 10 kWh, to €228.35 at 15 kWh, before surging to €247.42 at 20 kWh and peaking at €261.77 at 30 kWh. A similar upward capacity trend is observable in September (€239.08 at 10 kWh climbing to €260.29 at 30 kWh).
  - **Winter Deficits:** Conversely, during winter months, the traditional welfare contraction re-emerges (e.g., October transitions non-linearly from €245.53 to €254.05, while January hovers relatively flat around €295–€297).

- **The Underlying Mechanism:** This seasonal distinguishing occurs because the rolling 24-hour optimization aligns battery actions with macro-level wholesale price trends and seasonal solar generation profiles. In the summer, wholesale markets experience intense price volatility alongside high PV availability. Larger batteries become economically beneficial only when sufficient renewable surplus exists to justify the additional energy storage, turning the 30 kWh system into an active tool for high-efficiency macro-arbitrage.
- **The Welfare Implication:** The **seasonal variation of total social welfare** closely tracks the availability of solar generation and the corresponding opportunities for economically efficient energy exchange. **In volatile summer months, the systemic efficiency gains from optimizing a 30 kWh storage dispatch over a rolling horizon create genuine economic value that offsets the utility's lost transaction revenues**. Conversely, during winter months when PV generation is limited, the incremental value of storage remains comparatively small. The **flatter winter price profiles offer no extra arbitrage efficiency**, causing the 30 kWh battery to **revert to simple grid-bypassing**, which reduces the marginal economic value of grid transactions and pulls welfare below the 10 kWh baseline.

Table 6. **Summary of Cross-Capacity Trends**

Operational Strategy	10 kWh Capacity Dynamics	30 kWh Capacity Dynamics	Cross-Month Behavior
Strategy A (fixed-threshold rule-based)	Serves as a stable, maximum baseline.	Strands excess capacity; marginal economic value is saturated.	Purely driven by exogenous seasonal market prices and efficient baseline PV exploitation.
Strategy B (Dynamic Intraday,	Preserves higher welfare due to fewer	Postpones favorable grid exchanges;	Systematic, monotonic welfare

adaptive forecast-based rule-based)	delayed grid interactions.	destroys maximum producer surplus.	degradation across all seasons as capacity expands.
Strategy C (24h Rolling horizon optimization)	Limited volume capacity restricts exploitation of macro price shifts.	Unlocks non-linear efficiency gains when supported by high renewable surplus.	High welfare in high-PV, volatile summers; standard contraction in low-PV, flat winters.

6.2Annual prosumer utility Uprosumer: (Monthly Comparison)

The results demonstrate that the operational strategy constitutes the dominant factor influencing annual prosumer utility within the conventional electricity market, while the impact of battery capacity depends strongly on the adopted energy management policy.
The nearly identical values observed for **Strategy A** across all battery capacities indicate that the optimization framework already exploits the available photovoltaic generation efficiently without requiring additional storage capacity. Consequently, **increasing battery size provides negligible incremental utility** because the **operational flexibility offered by larger batteries remains largely unused under this strategy.**
Strategy B reveals a different behavior, where larger battery capacities consistently reduce annual utility. This suggests that **additional storage does not necessarily improve the economic performance of the residential prosumer when interacting solely with the conventional electricity market**. Under these operating conditions, the marginal value of additional stored energy appears insufficient to compensate for storage-related inefficiencies and the altered timing of electricity exchanges with the grid.
In contrast, **Strategy C** demonstrates that battery capacity becomes economically valuable during periods of abundant solar generation. The pronounced utility improvements observed **between May and Septemb**er indicate that larger storage systems enable more effective utilization of locally generated photovoltaic energy, thereby **increasing the prosumer's overall economic benefit. During winter months**, however, when renewable generation is comparatively limited, **the influence of battery size becomes substantially weaker**.
An additional observation concerns the **strong seasonality** exhibited by all three strategies. The highest utility values coincide with periods of elevated photovoltaic production, highlighting the close relationship between renewable energy availability and the economic performance of residential self-generation systems. Although all strategies benefit from favorable seasonal conditions, **Strategy C captures a larger share of this potential, suggesting that its operational policy is more effective in exploiting renewable energy resources**.
Overall, these findings establish the reference performance of the residential prosumer within the conventional electricity market before introducing peer-to-peer transactions. Consequently, the annual utility values reported here provide the baseline against which the additional economic benefits arising from the proposed P2P market mechanism can be assessed in the subsequent analysis.

6.3 Prosumer Surplus in the Conventional Prosumer–Grid Market

The results demonstrate that **battery capacity alone does not guarantee higher economic performance** in the conventional prosumer–grid market. Instead, the realized prosumer surplus **depends primarily on the operational strategy** governing battery charging and discharging decisions.
The nearly identical results obtained under Strategy A indicate that the fixed threshold rules effectively saturate the economic value that can be extracted from arbitrage within the spot

market. Once the battery reaches a moderate capacity, **additional storage remains under-utilised** because charging and discharging decisions are driven by predetermined price thresholds rather than adaptive optimization. Consequently, enlarging battery capacity produces negligible improvements in conventional market surplus.

Strategy B exhibits the opposite behavior. Although this strategy exploits battery flexibility more actively, increasing battery capacity systematically reduces the prosumer surplus associated with conventional grid transactions. This behavior is economically consistent with the adaptive dispatch philosophy adopted by Strategy B. Larger batteries allow more photovoltaic energy to be retained within the local energy system instead of being exchanged with the wholesale market. Consequently, **the prosumer captures a smaller share of value from conventional grid interactions while preserving greater flexibility for alternative energy uses**, including local self-consumption and subsequent peer-to-peer exchanges. The reduction in **PS_to_grid** should **therefore not be interpreted as a deterioration in overall economic performance but rather as a redistribution of value away from the conventional market.**

Strategy C achieves a **more balanced outcome. The rolling optimization framework allocates stored energy dynamically according to** short-term market conditions, preventing the significant decline observed under Strategy B while simultaneously improving the utilization of larger batteries. The gradual increase in prosumer surplus for larger capacities indicates that endogenous optimization is capable of extracting additional value from storage without excessively reducing the benefits obtained through conventional market participation.

Overall, the comparison confirms that the interaction between battery capacity and operational strategy determines not only the magnitude of prosumer **surplus but also its seasonal evolution**. **Intelligent scheduling therefore becomes more influential than storage size itself** in shaping the economic performance of conventional grid participation.

6.4 Comparison between Prosumer Utility and Prosumer Surplus

Although both indicators exhibit similar seasonal behavior, their responses to battery capacity and operational strategy differ substantially.

Both indicators reach **their highest values during the summer months**, particularly between June and August, reflecting the increased availability of **photovoltaic generation**. However, the magnitude of the seasonal variation is **considerably larger for the utility function than for the conventional market surplus.** The utility function exhibits pronounced monthly peaks, whereas PS_to_grid changes more gradually throughout the year.

Under Strategy A, **both indicators remain almost insensitive to battery capacity**. The monthly utility curves and the monthly surplus curves nearly overlap, indicating that enlarging the battery under fixed threshold rules produces only marginal improvements in both behavioural welfare and conventional market profitability.

Strategy B introduces **a clear divergence between the two indicators**. While <u>the utility function generally increases with battery capacity, the conventional market surplus decreases</u>. This **opposite behavior** becomes particularly evident for the **20 kWh and 30 kWh** batteries, where larger storage capacities improve the prosumer's overall utility while simultaneously reducing the surplus obtained from conventional grid transactions.

Strategy C **exhibits the most balanced relationship**. Increasing battery capacity results in **moderate improvements in both utility and conventional market surplus**, suggesting that the **rolling optimization** framework **simultaneously enh**ances prosumer welfare while preserving economic value from conventional market participation.

This comparison demonstrates that **utility maximization and surplus maximization are not equivalent optimization objectives**.

The utility function represents the prosumer's overall welfare**, incorporating self-consumption, flexibility, storage operation and behavioral preferences.** By contrast, PS_to_grid reflects **only the financial benefit obtained through electricity exchanges with the conventional wholesale market**. Consequently, improvements in one indicator do not necessarily imply improvements in the other.

The **strongest evidence** is provided by Strategy B. Increasing battery capacity leads to **higher utility because additional storage** allows better temporal alignment between photovoltaic production, household demand and battery operation. However, the same operational decisions **reduce the quantity of electricity exchanged** with the wholesale market, leading to **lower conventional market surplus**. In economic terms, battery **flexibility shifts value from external market transactions towards internal optimization** of the residential energy system.

Strategy C **exhibits a fundamentally different behavior**. Because charging and discharging decisions are **determined endogenously** through the rolling optimization, <u>larger batteries improve internal energy management without substantially reducing the economic value obtained from conventional market participation.</u> This explains **why both utility and PS_to_grid evolve in the same direction** under Strategy C.

These observations indicate that utility is influenced **primarily by the efficiency of internal energy allocation,** whereas conventional market surplus depends on the interaction between the prosumer and external electricity prices. The two indicators therefore describe **complementary dimensions of prosumer performance** rather than redundant economic measures.

Battery flexibility first changes **how energy is allocated**, and only afterwards changes **how much energy is traded with the grid.** <u>Utility measures internal welfare optimization, whereas PS_to_grid measures external market profitability</u>.

6.5 Energy Balance of the Residential Prosumer

The combined analysis of grid imports, grid exports and self-consumed photovoltaic energy highlights the fundamental role of battery management strategy in determining how locally generated electricity is allocated throughout the residential energy system.

The **reduction in grid imports** observed with increasing battery capacity **reflects the ability of storage systems to shift photovoltaic generation** from periods of surplus production to periods of household demand. However, the results demonstrate that <u>storage capacity alone is not sufficient to maximize this benefit</u>.

Strategy A, despite employing progressively larger batteries, **exhibits only modest reductions in grid dependency** because charging and discharging decisions remain governed by predefined price thresholds rather than adaptive optimization.

Strategy B **utilizes the additional battery capacity much more aggressively.** Larger batteries substantially reduce electricity exports while increasing self-consumption, indicating that photovoltaic energy is preferentially retained within the household rather than being sold to the grid. <u>This behavior increases local energy autonomy but simultaneously reduces participation in the conventional electricity market.</u>

Strategy C further improves this allocation by dynamically optimizing battery operation over the rolling optimization horizon. Instead of maximizing only self-consumption or minimizing grid imports independently, **the optimization balances all available energy pathways according to prevailing market conditions and household demand**. Consequently, Strategy C achieves a more **efficient utilization of photovoltaic** generation while **maintaining stable seasonal energy flows throughout the year**.

These findings demonstrate that **battery intelligence is considerably more influential than battery size itself** in determining the **overall** residential energy **balance**. **Intelligent**

scheduling allows identical storage capacities to produce substantially different levels of grid dependence, self-consumption and electricity exports.

6.6 P2P Revenues and Peer-to-Peer Social Welfare

The joint analysis of P2P revenues and SWP2P demonstrates that financial profitability and market welfare **do not increase proportionally**. While P2P revenues represent the direct monetary return obtained by the selling prosumer, SWP2P captures the total economic value created within the local electricity market through mutually beneficial exchanges between sellers and buyers.

Increasing battery capacity generally raises both indicators because larger storage systems increase the quantity of photovoltaic electricity that can be shifted towards periods of higher local demand. However, the magnitude of improvement depends strongly on the adopted operational strategy. Strategy A **underutilizes additional storage** because predefined charging and discharging thresholds limit the flexibility of local electricity trading. Strategy B exploits larger batteries more aggressively, substantially **increasing local transactions and therefore generating the highest revenues** and peer-to-peer welfare. Strategy C, through rolling optimization, produces a **more balanced allocation** of stored electricity, resulting in stable market welfare gains while avoiding excessive dependence on battery size.

The difference between P2P revenues and SWP2P highlights an **important economic characteristic of decentralized** electricity markets. Additional peer-to-peer transactions do not merely increase seller income; they simultaneously **create consumer surplus** by allowing buyers to purchase electricity below conventional market prices. Consequently, **market welfare grows faster than individual producer revenue**s because each successful transaction generates value for both market participants. This demonstrates that **evaluating local electricity markets solely through producer revenues would underestimate the broader socioeconomic benefits created by peer-to-peer trading**.

6.7 Monthly Consumer Surplus of P2P Consumers

The Consumer Surplus (CS) defined by Equation (23) represents the economic welfare of **consumers purchasing electricity through the peer-to-peer (P2P) market**, rather than consumers supplied directly by the utility grid. Consequently, increases in CS indicate that consumers participating in the local energy market obtain a larger proportion of their electricity demand from neighboring prosumers at prices that are more advantageous than conventional retail electricity prices. Therefore, the magnitude of Consumer Surplus reflects not only electricity price differences but also the effectiveness with which locally generated renewable energy is retained within the community and redistributed through P2P transactions.

The results demonstrate that Consumer Surplus is jointly determined by three interacting factors: **the battery dispatch strategy, the available battery capacity, and the seasonal availability of photovoltaic energy**. However, these factors do not contribute equally throughout the year. Instead, their influence changes according to renewable generation conditions and the operational flexibility available within the local energy system.

One of the most significant findings is that **Strategy A exhibits almost no sensitivity to battery capacity**. Increasing storage capacity from 10 kWh to 30 kWh produces only negligible changes in Consumer Surplus throughout the year. For example, during August the Consumer Surplus remains practically unchanged, decreasing marginally from **€411.20** (10 kWh) to **€411.11** (30 kWh), while similarly insignificant differences are observed in all other months. This behaviour indicates that the fixed-rule charging and discharging policy cannot effectively exploit additional storage resources. Once the predefined charging thresholds have been satisfied, increasing battery capacity provides little additional opportunity to increase the quantity of renewable electricity exchanged through the P2P market. Consequently, under rule-based operation, larger batteries do not translate into higher consumer welfare.

A markedly different behaviour is observed for **Strategy B**, where Consumer Surplus increases systematically with battery capacity. During January, Consumer Surplus increases from **€215.43** for the 10 kWh battery to **€282.19** for the 30 kWh configuration, while in August it increases from **€337.66** to **€532.52**. Similar trends are observed throughout the remaining months. These results indicate that the adaptive threshold mechanism is capable of utilizing additional storage flexibility more efficiently than the fixed-rule approach by dynamically adjusting battery operation according to expected market conditions. As larger batteries become available, greater quantities of surplus photovoltaic generation can be retained and subsequently offered to consumers through the P2P market instead of being exported immediately to the utility grid.

The highest Consumer Surplus values are obtained under **Strategy C**, particularly during periods characterized by abundant photovoltaic generation. Between April and September, Strategy C consistently outperforms the other two strategies for all battery capacities, reaching the annual maximum of **€625.20** in August for the 30 kWh battery. This superior performance can be attributed to the rolling-horizon optimization framework, which continuously updates charging, discharging and electricity trading decisions according to forecasted photovoltaic production, electricity prices and battery state-of-charge. Rather than relying on predetermined thresholds, the optimization algorithm exploits future market opportunities, thereby maximizing the quantity of renewable electricity available for local trading and increasing the welfare of P2P consumers.

The seasonal variation observed in Consumer Surplus is equally important. During spring and summer, higher photovoltaic production generates larger renewable surpluses that can either be stored or exchanged through the local energy market. Under these conditions, larger batteries and more advanced dispatch algorithms substantially increase the volume of renewable electricity available for peer-to-peer transactions, allowing consumers to replace a greater proportion of expensive grid electricity with locally generated renewable energy. Consequently, Consumer Surplus reaches its highest levels during these months. In contrast, during winter months, reduced photovoltaic production limits the availability of renewable electricity for local trading. Under such conditions, the performance differences between dispatch strategies become smaller, while **Strategy B** frequently achieves higher Consumer Surplus than **Strategy C** because its adaptive threshold policy preserves limited battery resources more conservatively when renewable energy availability is constrained. This seasonal transition demonstrates that the effectiveness of battery dispatch strategies depends not only on the optimization algorithm itself but also on the operating conditions of the energy system.

From the perspective of local energy communities, these findings demonstrate that **consumer welfare is primarily determined by the capability of the community to retain renewable energy locally rather than exporting it to the utility grid**. Battery storage increases the temporal availability of locally generated photovoltaic energy, while intelligent dispatch determines how effectively this stored energy is redirected towards neighboring consumers through the P2P market. Consequently, improvements in Consumer Surplus arise from the combined interaction of storage flexibility, operational intelligence and decentralized energy trading rather than from battery capacity alone.

Overall, the results confirm that the value of battery storage in P2P energy communities is **conditional on intelligent operational management**. Simply increasing battery capacity does not guarantee higher consumer welfare, as demonstrated by the nearly constant Consumer Surplus observed under Strategy A. Instead, the benefits of larger batteries emerge only when advanced dispatch algorithms successfully convert additional storage flexibility into greater volumes of locally traded renewable electricity. Therefore, **the relevant equation (33**) captures not only the direct economic benefit experienced by P2P consumers but also the effectiveness with which renewable energy is temporally stored and redistributed within the local energy community, making **Consumer Surplus an integrated indicator of both market efficiency and decentralized energy sharing.**

6.8 Intraday Seasonal Component of Hourly Elasticity

The Fourier analysis demonstrates that the operational strategy exerts a substantially greater influence on the temporal behavior of electricity demand elasticity than battery capacity itself. The nearly identical Fourier coefficients and fitted profiles obtained for Strategy A indicate that enlarging battery storage does not modify the underlying daily elasticity structure. This suggests that the baseline optimization framework already establishes a stable demand response schedule, leaving little opportunity for additional storage capacity to alter consumers' price responsiveness.

In contrast, Strategy B exhibits the strongest non-linear dependence on battery capacity. The severe drop in the coefficient of determination when moving from a 10 kWh (R^2 = 0.469) to a 15 kWh (R^2 = 0.051) configuration suggests a structural break; at 15 kWh, the storage system crosses a critical threshold where the asset size allows the algorithm to decouple from rigid daily routines and aggressively exploit real-time intraday market volatility. Consequently, under Strategy B, elasticity becomes less predictable and less dominated by deterministic daily cycles at intermediate capacities, implying that operational decisions depend on highly dynamic hourly market conditions rather than repetitive intraday patterns.

Strategy C provides a balanced compromise between the previous two strategies. Although the deterministic seasonal component explains only a moderate proportion of total elasticity variability, the relatively small intraday amplitude—particularly for the 20 kWh battery—indicates a smoother and more stable demand response profile. Such behavior suggests that the 24-hour rolling look-ahead horizon under Strategy C distributes charging and discharging actions more evenly throughout the day, mitigating abrupt variations in price elasticity while preserving operational flexibility.

An important observation is that all scenarios consistently identify the highest price responsiveness (most negative elasticity) during the overnight period and the lowest responsiveness (elasticity approaching zero) during the afternoon. This behavior reflects the daily economic optimization of residential prosumers. During low-price overnight periods, consumers exhibit a high willingness to modify grid interactions. Conversely, during the afternoon, abundant photovoltaic generation and high levels of self-consumption insulate the household from the grid. Because behind-the-meter generation satisfies local demand, the prosumer's net grid transactions drop significantly, rendering their net demand mathematically inelastic to external grid price signals during peak solar hours. Consequently, the intraday elasticity pattern is governed by the structural intersection of battery operation, photovoltaic production, and household demand scheduling.

Overall, the Fourier decomposition confirms that the proposed demand response framework generates a stable and repeatable daily elasticity structure. The differences observed among strategies primarily reflect alternative energy management policies rather than changes in battery size, highlighting that optimization algorithms constitute the principal driver of consumer price responsiveness within the conventional prosumer–grid market prior to the introduction of peer-to-peer energy trading.

6.9 Intraday Seasonal Dynamics of P2P Price, Prosumer Utility and Buyer Utility

The Fourier-based decomposition provides important insights into the mechanisms through which the proposed P2P trading framework redistributes economic value throughout the day.

The first important observation concerns the systematic reduction of electricity prices in the P2P market relative to the wholesale spot market. The daily pattern indicates that the largest reductions consistently occur during the afternoon and early evening hours, precisely when electricity demand is typically highest. This demonstrates that local energy trading effectively smooths market prices by matching locally available photovoltaic surplus with residential demand, thereby reducing dependence on wholesale electricity purchases during expensive hours.

A second important finding concerns the reduction in the prosumer utility function (AI−AO). Although participation in the P2P market slightly decreases the individual utility of the selling prosumer, this reduction should not be interpreted as an economic disadvantage. Instead, it represents the transfer of part of the economic surplus from the producer towards buyers through lower transaction prices. In other words, the proposed mechanism intentionally redistributes welfare within the local energy community rather than maximizing the benefit of a single participant. More specifically:

Strategy A: stable price discount, limited capacity effect

Under Strategy A, battery capacity has almost no effect on the three Fourier profiles. The mean fitted price difference increases only slightly, from approximately **€0.0200/kWh** for 10 kWh to **€0.0208/kWh** for 30 kWh. Similarly, the mean prosumer utility difference rises marginally from **€0.0400** to **€0.0431**.

However, mean buyer utility decreases from approximately **€0.3740** to **€0.3420** as capacity increases. The intraday buyer-utility range also falls from **€1.864** to **€1.835**.

This means that Strategy A does not efficiently convert additional storage capacity into additional P2P value. Its fixed dispatch rules produce nearly the same energy-allocation pattern regardless of battery size. Although the price spread becomes marginally larger, the timing or volume of energy supplied to the buyer does not improve sufficiently. Because buyer utility depends on both the P2P price **and the traded energy quantity**, a slightly larger price discount does not necessarily produce greater buyer utility.

Therefore, under **Strategy A, the larger battery does not drive to a greater P2P benefit**. The **principal limitation** is not battery size, but the **rigidity of the dispatch rules**.

This interpretation is confirmed by the behaviour of the buyer utility function. The substantial increase in U_buyer, particularly under Strategy B and larger battery capacities, indicates that buyers capture a considerably larger share of the total economic benefit generated by local electricity exchanges. Therefore, the apparent reduction in prosumer utility is compensated by significantly larger gains at the consumer side, improving the overall efficiency and fairness of the local market.

Battery capacity further amplifies these effects. Larger storage systems enable prosumers to shift larger quantities of photovoltaic energy from periods of excess generation towards periods of higher market value, increasing the temporal flexibility of the local market. Consequently, the magnitude of both price reductions and buyer utility improvements increases with battery capacity, especially under the adaptive Strategies B and C.

Strategy B: strongest redistribution from prosumer to buyer

Strategy B produces the clearest positive capacity effect. As battery capacity increases from 10 to 30 kWh:

- mean ΔPrice rises from **€0.0185/kWh** to **€0.0253/kWh**;
- mean drop of prosumer Utility function rises from **€0.0390** to **€0.0689**;
- mean buyer utility rises from **€0.4447** to **€0.6333**.

The intraday buyer-utility range also increases substantially, from approximately **€2.244** to **€2.723**. The largest buyer benefits occur around **18:00**, while minimum values occur around **23:00–24:00**. The maximum P2P price advantage similarly appears around **17:00–18:00**.

This pattern **indicates a clear welfare-transfer mechanism. Larger batteries allow more energy to be stored during low-price or high-PV periods and supplied to the P2P buyer during the evening demand peak.** This increases the quantity **available for local trading**

precisely when the difference between the spot-market value and the P2P transaction price is **most economically relevant**.
However, the same mechanism also increases the drop of **prosumer Utility** function. In other words, the selling prosumer gives up a larger part of the utility that could have been obtained under the conventional grid-oriented arrangement. The benefit is transferred to the buyer through a more favorable P2P price and a larger traded quantity.
Strategy B therefore produces **the strongest redistribution of economic value toward the buyer**. It maximizes buyer benefit, particularly for the 20 and 30 kWh batteries, but it also imposes the largest relative utility sacrifice on the selling prosumer.
Strategy C: more balanced allocation of P2P value
Strategy C presents a more moderate and balanced relationship. As battery capacity increases from 10 to 30 kWh:

- mean ΔPrice increases from **€0.0072/kWh** to **€0.0146/kWh**;
- mean drop of the Prosumer Utility function changes from **−€0.0044** to **€0.0235**;
- mean buyer utility increases from **€0.4893** to **€0.5547**.

The negative mean of drop of the Prosumer Utility function for the 10 kWh case is especially important. It means that:
$AI-AO<0 \Rightarrow AO>AI$, so <u>the prosumer's P2P-related utility is slightly higher than its utility under the conventional grid arrangement</u>. **At this battery size, Strategy C can therefore improve buyer utility without requiring an average utility sacrifice from the seller**.
As capacity increases, drop of the Prosumer Utility function becomes positive. The prosumer then gives up part of its conventional-market utility, but the magnitude remains considerably smaller than under Strategy B. For the 30 kWh battery, the mean difference is approximately **€0.0235** under Strategy C, compared with **€0.0689** under Strategy B.
Buyer utility under Strategy C exceeds Strategy B for the smaller capacities:

- 10 kWh: **0.4893 vs 0.4447 €**;
- 15 kWh: **0.5137 vs 0.5083 €**.

Strategy B overtakes Strategy C at larger capacities:

- 20 kWh: **0.5636 vs 0.5320 €**;
- 30 kWh: **0.6333 vs 0.5547 €**.

This suggests that **Strategy C is more effective when storage is scarce** <u>because the rolling optimization allocates limited energy selectively among self-consumption, storage, grid interaction and P2P sales</u>. Strategy **B becomes more beneficial to buyers when larger storage is available** because <u>its adaptive rules use the additional capacity more aggressively for local energy trading</u>.
The three indicators do not change proportionally
A larger ΔPrice does not automatically imply an equally large increase in $U_{,buyer}$. Buyer utility depends on more than the difference between the spot and P2P prices. According to its Equation (Eq. 31) , it also depends on:

- the quantity purchased through P2P;
- the buyer's willingness to pay;
- diminishing marginal utility;
- the P2P transaction price;
- the renewable or community premium included in the formulation.

Similarly, the drop of the prosumer utility function is affected not only by the price discount offered to the buyer but also by:

- the volume of P2P sales;
- foregone grid-sale revenues;
- avoided or additional grid purchases;
- battery charging and discharging;

- degradation costs;
- the timing of transactions.

Therefore, **ΔPrice is a price signal, whereas the drop of prosumer utility function and the $U_{,buyer}$ are combined price–quantity–utility outcomes**.This explains why Strategy A can produce a relatively stable price spread but declining buyer utility, and why Strategy C can produce lower price differences than Strategy B while generating comparable or higher buyer utility at smaller battery capacities.

Therefore, an overall comparison can be shown in the following **Table 7:**

Table 7: Overall comparison among results under different Strategies and Capacities

Result	Strategy A	Strategy B	Strategy C
Capacity sensitivity	Very low	Strong	Moderate
P2P price reduction	Stable	Largest at high capacity	Lower, gradually increasing
Prosumer utility sacrifice	Low and stable	Highest	Lowest / sometimes negative
Buyer utility	Declines slightly with capacity	Highest at 20–30 kWh	Strong at 10–15 kWh
Market interpretation	Rigid control	Buyer-oriented redistribution	More balanced allocation

The central finding is therefore that **battery capacity creates P2P value only when the dispatch strategy can use it effectively**. Strategy A largely fails to unlock that value. Strategy **B converts additional storage into the largest buyer benefits**, but with a greater reduction in prosumer utility. **Strategy C generates a more balanced distribution between seller and buyer**, particularly for small and medium storage capacities.

Finally, the relatively high coefficients of determination obtained from the Fourier regressions indicate that these daily patterns are not random fluctuations but constitute stable and repeatable intraday market characteristics. **This finding suggests that the proposed P2P framework produces predictable daily market dynamics** that can be exploited for forecasting, battery scheduling and automated demand response applications.

6.10 Clearing Price Dynamics

The position of the utility-based clearing price relative to the observed market prices can be explained directly by the structure of the prosumer and buyer utility functions. Unlike the spot price and the implemented P2P transaction price, $Price,eq_{\{P2P\}}$ (Eq 29) represents an endogenous utility-indifference benchmark obtained by imposing U,prosumer=U,buyer for the same traded quantity E,inj. Given the opposite signs of the transaction-price term in the two utility functions, the utility difference evaluated at the actual P2P price satisfies $U_{,buyer(PriceP2P)} - U_{,prosumer(PriceP2P)}$ = 2Einj*($Price,eq_{\{P2P\}}$ – $Price_{,P2P}$). Consequently, when $Price,eq_{\{P2P\}}$ (> $Price_{,P2P}$, the buyer obtains greater utility at the implemented transaction price, and an increase in the P2P price towards $Price,eq_{\{P2P\}}$ would redistribute part of the economic benefit towards the selling prosumer until utility equality is reached. Conversely, when $Price,eq_{\{P2P\}}$ < $Price_{,P2P}$,, the prosumer obtains the greater relative utility, and a reduction in the transaction price towards the equilibrium level would shift part of the benefit towards the buyer. The comparison with the spot price has a different interpretation, since the spot price represents an external wholesale-market benchmark rather than the price at which the two P2P utility functions are equalised. The predominance of $Price,eq_{\{P2P\}}$ > $Price_{,P2P}$, therefore indicates that the implemented P2P pricing mechanism generally allocates a larger relative utility benefit

to buyers than would an equal-utility allocation. If a systematically lower utility-equilibrium price were desired, the model would require a higher price-independent utility component for the prosumer and/or a lower price-independent utility component for the buyer—for example, lower buyer-side green or preference premiums, greater seller-side non-price benefits, or lower prosumer discomfort and battery-degradation costs. However, parameters shared by both utility functions, such as common marginal-utility or curvature coefficients, cannot be assumed to shift $Price, eq_{\{P2P\}}$ monotonically in one direction. Similarly, although larger P2P injections are empirically associated with lower clearing prices during high-PV periods in the present results, EQ20 does not imply a purely inverse relationship with Einj, since the traded quantity also appears in the numerator. Therefore, if the objective is to guarantee an executable clearing price below the spot or P2P benchmark, imposing explicit market-price bounds would be methodologically preferable to recalibrating the utility functions solely to obtain a predetermined price ordering.
A key methodological implication is that <u>the utility functions should not be recalibrated merely to force the theoretical</u> clearing price $Price, eq_{\{P2P\}}$ below the spot-market price. If the market-design objective is to ensure that the <u>executable P2P clearing price does not exceed the spot-price benchmark,</u> it is methodologically more **robust to retain Eq 29 as an unconstrained theoretical utility-indifference price** and to **define separately a market-feasible clearing price subject to explicit price bounds.** This preserves the behavioural interpretation of the underlying utility parameters and <u>avoids the appearance of ex post calibration aimed solely at generating a predetermined price ordering.</u> Such a separation also distinguishes clearly between the **welfare-based equilibrium benchmark** derived from participant utilities and the **transaction price that can actually be implemented** under market-design constraints.

7. Conclusions

Regarding the **hourly price elasticity of demand**, this paper investigated the structural determinants within an isolated prosumer-utility micro-system, focusing on the interplay between energy management algorithms (Strategies A, B, and C) and battery energy storage system (BESS) capacities (10 kWh to 30 kWh). Utilizing a 24-hour Fourier decomposition framework, our empirical results reveal that the architectural design of the operational strategy exerts **a dominant, overriding influence on consumer price responsiveness compared to the physical scaling of storage assets**. Strategy A exhibits complete capacity saturation, maintaining rigid, identical deterministic elasticity cycles (\(R^2 = 0.485\)) across all asset sizes. In contrast, Strategy B **introduces acute capacity-dependent non-linearities**, where expanding storage beyond a critical threshold (15 kWh) triggers a structural break (\(R^{2}\) collapses to \(0.051\)), causing the algorithm to abandon repetitive daily routines in favor of volatile intraday market chasing. Strategy C provides an intermediate, balanced optimization paradigm; by utilizing a 24-hour rolling look-ahead forecast, it smooths out abrupt elasticity variations while selectively unlocking non-linear total welfare increase (increase of necessary transactions between prosumer and the market grid) during periods of high photovoltaic availability.
As for the **Theoretical and Methodological Contributions**, this study advances the prosumer modeling literature by demonstrating that the measured elasticity of grid demand is not merely a reflection of structural consumer preferences, but an endogenous outcome of behind-the-meter algorithmic dispatch and transaction saturation. The pronounced diurnal elasticity cycle observed across all scenarios—characterized by robust price responsiveness overnight and absolute inelasticity during peak solar hours—unveils a critical economic paradox: abundant renewable self-generation insulates the consumer from grid price signals, destroying wind-fall transaction revenue volumetric of the established providers. The Fourier decomposition

successfully captures this "transaction saturation" effect, providing a rigorous mathematical diagnostic tool to separate deterministic seasonal habits from stochastic, algorithm-driven load shifting.

Therefore, for the Policy and Regulatory Implications of elasticity and social welfare, From a regulatory and policy perspective, these findings yield vital insights for the next generation of grid tariff designs, reframing the debate around the so-called "utility death spiral." The observed contraction of total social welfare under dynamic forecasting frameworks (particularly Strategy B) should not be misinterpreted as an inherent inefficiency of residential self-generation; rather, it highlights a severe structural misalignment within a spot market prone to price speculation. In conventional market designs, electricity prices are frequently dictated by expensive, marginal natural gas-fired plants rather than zero-marginal-cost renewable power. Consequently, without behind-the-meter optimization of net grid consumption through solar and storage assets, these inflated wholesale prices would simply translate into massive, windfall profits for traditional electricity providers at the expense of end-users.

Therefore, instead of imposing punitive capacity charges that stifle private investment, regulatory authorities should introduce supportive frameworks inspired by advanced storage strategies to safeguard and **accelerate prosumerism**. First**, policy incentives must ensure grid-priority access and guarantee smart compensation mechanisms to protect prosumers utilizing predictive algorithms (like Strategy C)** from arbitrary generation curtailments during peak solar hours. Second, regulators should transition toward dynamic, cost-reflective tariffs that **reward localized battery dispatch** for mitigating system-wide price spikes relevant to the fossil fuel markets, effectively converting residential BESS assets from passive grid-bypassing tools into active systemic stabilizers.

Crucially, these strategic policy shifts should serve as an institutional stepping stone to **empower energy communities and facilitate decentralized** peer-to-peer (P2P) trading markets. By formalizing multi-lateral pledger transaction models, regulators can unlock community-level balancing, allowing prosumers with high-capacity batteries (20–30 kWh) to dynamically trade their renewable surplus with neighboring consumers. Such a regulatory evolution not only reorganizes consumer price responsiveness and locks aggregate economic welfare within the local community ecosystem, but also systematically dismantles the speculative rent-seeking behavior of traditional fossil-fuel dominant utilities prior to full market democratization.

The comparative analysis of **PS_to_grid** demonstrates that the economic value obtained by a residential prosumer from conventional spot-market participation is primarily determined by battery **management strategy rather than battery capacity** alone.

The fixed rule-based **Strategy A** produces nearly identical economic outcomes across all storage capacities, indicating that **additional battery capacity** remains largely **under-utilized**. Strategy **B** exhibits the **strongest sensitivity to battery size**, with larger batteries progressively **reducing** the prosumer surplus associated with conventional grid transactions as energy is **increasingly retained within the local energy system**. Strategy **C** provides the most balanced performance by **combining adaptive optimization with efficient utilization** of larger storage capacities while maintaining **relatively stable conventional market returns**.

These findings indicate that increasing battery capacity **should always be accompanied by an intelligent operational strategy** capable of **exploiting** the additional storage **flexibility**. Otherwise, larger batteries provide <u>only limited improvements</u> in conventional market profitability.

These findings also constitute a distinct research contribution because the literature predominantly evaluates battery sizing using **total annual profit**, **self-consumption**, **self-sufficiency**, or **overall social welfare**. Much less attention has been devoted to isolating the

prosumer surplus generated exclusively through conventional spot-market participation, independently of peer-to-peer trading.
The proposed **PS_to_grid** indicator provides this missing perspective by separating the economic value generated through conventional prosumer–grid interactions from the value redistributed after introducing peer-to-peer transactions. This decomposition enables the economic effects of battery capacity and energy management strategy to be evaluated before and after the transition from centralized electricity markets to decentralized local energy markets. Consequently, the proposed methodology offers a clearer understanding of how storage flexibility modifies the allocation of economic surplus between conventional market participation and local energy trading.
From a methodological perspective, the monthly comparative analysis further demonstrates that identical battery capacities may produce substantially different conventional market outcomes depending solely on the adopted dispatch strategy. This finding highlights that **battery intelligence is economically more influential than battery size alone**, providing new evidence that operational optimization constitutes a critical design variable in residential energy management systems. This separation of **grid-related surplus**, **P2P-related surplus**, and **total welfare** introduces a more comprehensive framework for analyzing the economic impacts of distributed energy resources, extending the performance indicators commonly reported in the current literature on prosumer optimization and peer-to-peer electricity markets.
The comparative analysis of **grid electricity imports (E_grid)**, **grid electricity exports (E_sell)** and **photovoltaic self-consumption (E_self)** confirms that **battery management strategy is the principal factor governing residential energy flows.** While increasing battery capacity generally reduces dependence on grid electricity and increases local utilization of photovoltaic generation, the magnitude of these improvements varies significantly among the examined operational strategies. Strategy A provides relatively limited gains from additional storage, whereas Strategies B and C exploit battery flexibility more effectively by increasing self-consumption and reducing unnecessary electricity exports. Overall, the results demonstrate that **intelligent battery scheduling, rather than storage capacity alone**, determines the **efficiency of** residential **energy management** and the utilization of distributed renewable generation.
The comparative assessment of **P2P revenues and peer-to-peer social welfare** confirms that **intelligent battery scheduling** enhances not only the profitability of individual prosumers but also the **overall efficiency of the local electricity market**. Larger battery capacities increase the quantity of electricity available for local trading, thereby improving both financial returns and collective welfare. However, the realized **benefits depend primarily on the operational strategy governing battery utilization**. Strategy B **maximizes economic activity** within the peer-to-peer market, whereas Strategy C achieves a **more balanced trade-off between revenue generation, market stability and welfare distribution**. Overall, the results demonstrate that evaluating decentralized electricity markets requires both individual financial indicators and aggregate welfare measures, as these **capture complementary dimensions of market performance.**
The Fourier analysis concerning the **Intraday Seasonal Dynamics of P2P Price, Prosumer Utility and Buyer Utility** demonstrates that the proposed P2P trading framework generates consistent and repeatable intraday seasonal patterns in electricity prices and participant utilities. Across all battery capacities and operational strategies, local energy trading systematically reduces transaction prices relative to the wholesale spot market while simultaneously increasing buyer utility. Although the utility of the selling prosumer decreases moderately, this reduction represents an intentional redistribution of economic surplus rather than an efficiency loss. Consequently, the proposed market mechanism enhances the overall economic efficiency

of the local energy community by reallocating welfare from conventional grid transactions towards peer-to-peer exchanges.

Among the examined strategies, Strategy B achieves the largest buyer benefits and the greatest electricity price reductions, whereas Strategy C offers a more balanced compromise between market stability, prosumer benefit and buyer welfare. Increasing battery capacity further strengthens these effects by increasing temporal flexibility and improving the utilisation of locally generated photovoltaic energy.

Overall, the results demonstrate that the combination of intelligent battery scheduling and dynamic P2P pricing produces measurable improvements in local market performance and supports the development of more flexible, consumer-oriented electricity markets.

Beyond evaluating annual economic indicators, this study introduces a novel temporal characterization of peer-to-peer electricity markets through the application of Fourier-based intraday decomposition of market prices and participant utility functions. Unlike existing studies that primarily compare annual welfare or total costs, the proposed methodology quantifies the **daily seasonal behaviour of** (i) the wholesale-to-P2P price reduction, (ii) the redistribution of prosumer utility, and (iii) buyer utility under different battery capacities and energy management strategies. The Fourier analysis demonstrates that these indicators exhibit stable and statistically significant daily periodicity, revealing predictable temporal patterns in local energy trading that are not visible through conventional annual performance metrics. This temporal perspective provides a new analytical framework for evaluating battery scheduling strategies, P2P pricing mechanisms and demand response algorithms, thereby extending the methodological toolkit available for analyzing local electricity markets.

The joint examination of the Fourier-derived **price and utility profiles (for P2P exchanges, with regards to prosumer and buyer P2P utility functions)** reveals that the economic impact of battery capacity depends fundamentally on the adopted dispatch strategy. Under the fixed rule-based Strategy A, **increasing storage capacity produces only marginal changes in the spot-to-P2P price difference and prosumer utility**, while buyer utility slightly declines, indicating that additional storage remains operationally underutilized. Strategy B exhibits the strongest capacity response: larger batteries widen the P2P price advantage, increase buyer utility and simultaneously increase the difference between conventional and P2P prosumer utility, **demonstrating a stronger redistribution of economic surplus from the seller toward the buyer**. Strategy C produces a **more balanced outcome**. At 10 kWh, the **negative mean value of the drop in Prosumer `utility function indicates that P2P participation can improve the prosumer's utility while also providing relatively high buyer utility.** As capacity increases, buyer benefits continue to rise, although less strongly than under Strategy B, while **the prosumer utility sacrifice remains substantially smaller**. These results demonstrate that the **relationship between P2P price reduction and participant welfare is mediated by traded quantities, battery operation and dispatch intelligence**; consequently, <u>a larger price spread does not necessarily translate proportionally into higher buyer utility or lower prosumer utility.</u>

The clearing-price analysis confirms that the utility-based equilibrium price $Price, eq_{\{P2P\}}$ is strongly influenced by battery management strategy, storage capacity, intraday demand conditions, and seasonal renewable availability. In most active P2P trading periods, the theoretical utility-equalising price exceeds both the implemented $P2P_{,price}$ and the spot-market benchmark, indicating that the prevailing P2P pricing rule generally allocates a larger relative utility benefit to buyers than would an equal-utility solution. This tendency becomes more pronounced under larger battery capacities, particularly for Strategies B and C, whereas Strategy A remains comparatively insensitive to storage size. Conversely, periods of high photovoltaic availability and increased local energy injection are associated with more frequent low-clearing-price conditions. Overall, $Price, eq_{\{P2P\}}$ provides a useful welfare-based

benchmark for evaluating not only the level of P2P transaction prices but also the distribution of economic benefits between selling prosumers and buyers. From a market-design perspective, the theoretical utility-indifference price should therefore be distinguished from the executable P2P clearing price, with the latter subject to economically feasible price bounds rather than being obtained through ex post recalibration of behavioural utility parameters.
Ultimately, the operational strategy governs price elasticity by determining the precise timing and magnitude of the prosumer's market responsiveness; this elasticity trajectory, in turn, dictates net grid transactions, which ultimately delineate the distribution of welfare within the micro-system. Regulatory and policy frameworks must therefore intervene to restructure these market rules, ensuring that economic surplus is retained within the local ecosystem through energy communities and peer-to-peer (P2P) trading networks, rather than being captured by fossil-fuel price speculation.
This study is among the first to apply harmonic (Fourier) d**ecomposition to derive the intraday seasonal component of economic response variables in peer-to-peer electricity markets, including dynamic price reductions and participant utility functions**. The proposed methodology reveals stable periodic market behaviors that cannot be identified through conventional annual welfare indicators, **providing a new temporal evaluation** framework for local electricity markets.
Overall, the proposed framework extends existing battery evaluation methodologies by moving beyond aggregate economic indicators towards a **multi-layer welfare assessment** that explicitly separates conventional market surplus, decentralized market surplus, and behavioural utility. This integrated perspective not only improves the interpretation of battery operation under different management strategies but also provides a general analytical framework for evaluating future prosumer-centric electricity markets, peer-to-peer trading mechanisms, and distributed flexibility services. This work therefore contributes both methodologically and conceptually to the economic assessment of residential energy systems undergoing the transition from centralized to decentralized electricity markets.
The distinction between the implemented P2P price and the utility-equalising price offers an additional analytical layer for assessing fairness and welfare distribution in decentralised electricity markets.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes on contributors

Professor Dr. Phoebe Koundouri is a globally renowned mathematical economist who has pioneered human-centered, interdisciplinary modelling systems for the sustainable interaction between nature, society, and the economy. She brings nearly 30 years of academic leadership and research excellence at leading institutions, including the University of Cambridge, University College London (UCL), the London School of Economics (LSE), the University of Reading, and the Technical University of Denmark. She is consistently ranked among the top 2% of world scientists in multiple prestigious international listings, with an academic record that includes 20 books, more than 800 published papers, over 100 large-scale research projects, and measurable impact in more than 120 countries. She is currently Professor at the School of Economics, Athens University of Economics and Business (AUEB); Visiting Professor at the Department of Earth Sciences, University of Cambridge; and Senior Research Fellow at Peterhouse, University of Cambridge—her alma mater. She is the Founder of the Alliance of Excellence for Research and Innovation on Aeiphoria (AE4RIA), a global research and innovation network bringing together more than 200 researchers.

Efstathios Devves Stathis Devves is a Scientific Associate in Sustainable Development Unit of Athena Research Center.He holds a Master's degree in Mechanical Engineering from the Mechanical Engineering & Aeronautics Department and the **MSc specialized in energy – electricity markets modelling**, energy transition Strategies- Economics and EU Regulations. He is a **PhD Candidate** under the Supervision of **Prof. Phoebe Koundouri**, working on his Thesis dealing with the Block-chains and **tokenization of energy – backed assets and renewable technologies, flexibility (demand response) markets for end users and prosumers.** He is also specialized in the monitoring of the achievement in Sustainable Developed Goals, dealing with Energy Transition, Circular Economy -SDG - LCA interplay, as a co-author in relevant research papers and book chapters.

Data availability statement

The data that support the findings of this study are available from the corresponding author Efstathios (**Stathis) Devves**, in the restored Zenodo Github link https://doi.org/10.5281/zenodo.21889948. In this repository link main codes, data set and output files are included into the corresponding folders.

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