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Residential Battery Storage Diffusion in Europe Across Electricity Tariff Designs

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Article

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Residential Battery Storage Diffusion in Europe Across Electricity Tariff Designs

Áron Dénes Hartvig[1]

Highlights:

1. CLEARS model projects residential battery adoption across 25 EU countries.
2. Diffusion and grid-level impacts of four electricity tariff designs are assessed.
3. Advanced tariff designs unlock residential battery diffusion in Europe.
4. Residential battery capacity in Europe is projected to reach 356-542 GWh by 2050.
5. Peak operation can cut up to 8.6 Mt CO_2 emissions per year.

Abstract

Europe's transition to a low-carbon energy system is reshaping household electricity generation, consumption, and storage. Residential batteries can increase rooftop photovoltaic self-consumption, support energy autonomy, and provide grid benefits when operated in a coordinated manner. This study applies the Clean Energy Adoption in the Residential Sector (CLEARS EU) model to project residential battery diffusion under four electricity tariff designs of increasing complexity and to assess their grid-level impacts across 25 European countries. The model combines net present value calculations with Bass diffusion dynamics to capture financial and behavioural drivers of adoption. Results show that tariff design strongly affects battery profitability and diffusion. Under self-consumption, investment returns remain weak in some large potential markets, limiting residential battery capacity to 356–424 GWh by 2050. More advanced tariff designs that allow grid interaction and benefit from rapid cost reductions raise projected capacity above 530 GWh. Battery operation also determines system impacts: annual discharge rises from about 65 TWh under self-consumption to 168 TWh with peak-hour feed-in, while coordinated flexibility can reduce peak-load pressures. Estimated emissions savings range from 6.1 to 8.6 Mt CO_2-eq annually. The findings underline the importance of advanced tariff design for integrating distributed storage and supporting power-sector decarbonisation.

Keywords: Technology diffusion; Battery storage; Battery operation; Electricity tariff design

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Nomenclature		*CLEARS*	Clean Energy Adoption in the Residential Sector model
PV	photovoltaic	*BS*	storage capacity of battery (kWh)
NPV	net present value (€)	*BP*	power capacity of battery (kW)
FiT	feed-in tariff (€)	P^{BS}	unit price of battery storage capacity (€/kWh)
η	battery efficiency (%)	P^{BP}	unit price of battery power capacity (€/kW)
DoD	depth of discharge (%)	E^{C}	energy charged into battery (kWh)
Lt	lifetime of battery (years)	E^{SC}	energy used for self-consumption (kWh)
P^{E}	electricity end-user price (€/kWh)	$E^{Feed\text{-}in}$	energy fed into the grid (kWh)
i	interest rate (%)	R^{Flex}	revenue from providing flexible capacity (€)
g	electricity end-user price increase (%)	π	annual profits from the battery ownership (€)
L	labour cost of battery installation (€)	π^{Disc}	discounted value of annual profits (€)
Y^{Adj}	adjustment factor to labour costs (%)	*I*	investment cost of battery (€)
t	value added tax (%)	*AT*	Austria
BE	Belgium	*BG*	Bulgaria
HR	Croatia	*CY*	Cyprus
CZ	Czechia	*DK*	Denmark
EE	Estonia	*FI*	Finland
FR	France	*DE*	Germany
EL	Greece	*HU*	Hungary
IE	Ireland	*IT*	Italy
LV	Latvia	*LT*	Lithuania
LU	Luxembourg	*MT*	Malta
NL	Netherlands	*PL*	Poland
PT	Portugal	*RO*	Romania
SK	Slovakia	*SI*	Slovenia
ES	Spain	*SE*	Sweden

Introduction

The decarbonization of the energy system is reshaping electricity generation, consumption, and storage at the household level. Residential photovoltaic (PV) installations have achieved widespread penetration in many countries, creating opportunities for decentralized energy production but also introducing operational challenges, particularly in distribution grids. Residential battery storage has emerged as a promising response: by aligning local PV generation with demand, batteries increase self-consumption and household energy autonomy, while aggregated operation can support peak load reduction, congestion management, and renewable integration.

Forecasting energy storage deployment has therefore become a central research focus. Top-down system-level models estimate storage requirements to meet climate and policy targets, often highlighting aggregate capacity needs. The European Commission's METIS scenarios, for example, project up to 97 GW of storage across the EU-27 by 2030 depending on demand response and interconnector expansion [1], while the Joint Research Centre projects a cumulative capacity of 80 GW/160 GWh of stationary batteries by 2030 [2]. However, forecasts specifically focusing on residential battery energy storage systems remain scarce.

SolarPower Europe [3] projects annual European residential battery installations to expand from 9.8 GWh in 2025 to 16.5 GWh by 2029, with cumulative capacity reaching approximately 100 GWh by 2029. While in a large-scale analysis, Klingler et al. [4] project residential battery capacity to reach 467.6 GWh in the EU-28, Norway, and Switzerland by 2050.

Regional projections of residential batteries confirm that adoption trajectories depend strongly on context. In Germany, Klingler [5] forecasts 2 GW battery capacity by 2030 and 1.3 million residential PV-battery systems by 2040, while Fett et al. [6] find that residential storage capacity in Germany could exceed 40 GW by 2050. Switzerland's adoption remains sensitive to financial expectations, but

cumulative battery investments are projected to grow from 1 GW/4 GWh in 2020 to 12 GW/58 GWh by 2050 [7]. In the United States, widespread diffusion depends on retail electricity prices and feed-in tariffs (FiTs) [8]. Feed-in tariffs (FiTs) are a widely used policy instrument in Europe to promote investment in renewable energy technologies. Under a FiT scheme, electricity generated from renewable sources is purchased by utilities at a fixed price determined by regulators, typically guaranteed over a long-term contract period, thereby providing revenue certainty for investors [8]. Whereas in Australia, historical policy and FiT eligibility shape market segmentation [9]. In India, commercial use cases and EV applications dominate near-term adoption [10].

Despite recent advances, significant gaps persist. Projections for residential batteries at the multinational grid level are lacking, leaving their system-wide impacts largely unexplored. The number of households willing to adopt residential batteries are strongly influenced by the financial attractiveness of the investment [11]; therefore, electricity tariff design will be a key driver. However, behavioural research also highlights the importance of non-monetary drivers, such as environmental values, social norms, and a desire for self-sufficiency [5], [9], [12]. Moreover, the system impact of batteries depends not only on the number of installed systems but also on electricity tariff designs and operational strategies: using batteries solely for self-consumption can reduce household bills but exacerbate daily load variation, whereas peak shaving may stabilize grids but provide weaker private incentives [13].

This study addresses these gaps by:

1. Assessing the financial feasibility of residential batteries under four electricity tariff designs and integrating net present value (NPV) calculations with a Bass diffusion model to capture both financial and non-financial drivers of adoption. While in other residential battery diffusion models the financial return does not impact diffusion dynamics (e.g.: [4], [6]), in the Clean Energy Adoption in the Residential Sector (CLEARS) model NPV influences the adoption rates [13], [14]. Consequently, the effects of electricity tariff design on the adoption of residential batteries can be assessed at a large scale.
2. Projecting the diffusion of residential batteries under alternative electricity tariff designs and assessing their impacts on the electricity load in 25 European countries using the CLEARS model with country-specific diffusion parameters. To the author's knowledge, only Klingler et al. [4] have conducted residential battery projections at this scale through 2050; however, their analysis modelled a single diffusion trajectory per country and applied identical adoption curves across all countries.

Residential battery energy storage systems are expected to diffuse rapidly as technology costs decline, and regulatory frameworks increasingly support battery installations [3]. However, their diffusion is not discussed extensively in the literature [15]. Existing studies most frequently focus on a single large economy, such as Germany [5], [6], [16], the UK [11], Australia [9], [12], or the US [8], [15].

Existing modelling approaches include techno-economic optimisation, behavioural models, agent-based models (ABMs), and diffusion models. Techno-economic studies evaluate investment profitability under different electricity tariffs and policy settings [8], [12]. Behavioural approaches incorporate financial, technical, sociodemographic, and psychological factors into household adoption decisions [9]. ABMs explicitly represent heterogeneous household decision-making, social

influence, and investment evaluation, allowing the analysis of interactions between behavioural and economic drivers [15].

Diffusion models focus on long-term adoption dynamics. Klingler et al. [4] project residential battery diffusion across Europe using country-specific logistic diffusion curves triggered by economic feasibility, although adoption dynamics are assumed to be otherwise identical across countries. Fett et al. [6] combine a Bass diffusion model with a detailed electricity market model for Germany but assume similar adoption rates across policy scenarios, with regulation mainly affecting battery sizes. Castaneda et al. [11] integrate Bass diffusion into a system dynamics framework, where financial factors influence the pool of potential adopters.

Hartvig and Szabó [14] extend this literature by applying the CLEARS model to simulate regional battery diffusion in Hungary, explicitly linking investment profitability to household adoption decisions under alternative subsidy schemes. Hartvig [13] further applies the model across eight Central and Eastern European countries, demonstrating that feed-in tariffs create a trade-off between rooftop PV and residential battery adoption by simultaneously influencing the profitability of both technologies.

Existing studies offer valuable insights into techno-economic performance, diffusion patterns, and behavioural drivers, yet no large-scale projection jointly captures country-specific adoption dynamics and financial returns, as summarised in Table C.1 in Appendix C. The current study aims to develop multi-country adoption pathways influenced by both financial and non-financial drivers, featuring country-specific diffusion curves.

Electricity tariff designs and battery operational scenarios

This study analyses four distinct electricity tariff designs and operational strategies to evaluate their implications for residential battery diffusion and electricity system outcomes. Each design defines both the financial incentives faced by households and the operational logic governing battery use. For each scenario, battery charging and discharging are simulated on an hourly basis, accounting for the diversity of household archetypes defined by country, load profile, and consumption size. This approach allows for a detailed assessment of how different compensation schemes and operational logics influence both financial returns and broader grid dynamics over time. The scenarios are arranged in order of increasing complexity, determined by the electricity tariff design and the degree of interaction between residential batteries and the grid. Figure 2 presents a schematic overview of the considered operational scenarios.

Self-consumption scenario

The *Self-consumption* scenario represents the baseline and assumes flat electricity prices and purely self-interest-driven operation without opportunity to provide grid services. This configuration is commonly adopted as a reference case in the literature [4], [6], [17].

Under this strategy, PV generation is first used to meet household demand. Surplus generation is stored in the battery until its capacity is fully utilised, after which excess electricity is exported to the grid. When PV output is insufficient, stored energy is discharged to supply household demand, with any remaining deficit covered by grid imports. Direct interaction between the battery and the grid is assumed to be prohibited: the battery cannot be charged from the grid, nor can it feed electricity directly into the grid. Charging from the grid would not be economically rational in this setting, as

households would purchase electricity at the same price that the battery could later offset during consumption, while incurring additional efficiency losses due to storage.

ToU scenario

The *ToU* scenario extends the self-consumption framework by introducing static hourly time-of-use (ToU) electricity prices instead of flat tariffs, while preserving the same operational logic. ToU pricing strengthens incentives for battery adoption by increasing the value of stored electricity during high-price periods.

ToU electricity tariff design is already widespread across the EU. According to Agency for the Cooperation of Energy Regulators (ACER) (2025), some form of ToU pricing is available in 21 European countries. Most commonly, tariffs differentiate electricity prices between weekdays and weekends, as well as between daytime and nighttime periods. According to ACER (2025) 18 out of the 25 analysed countries apply static ToU tariffs for distribution level; however, charges are currently applied almost exclusively for electricity withdrawal from the grid, but not for injection. Further details on electricity pricing schemes across the EU are provided in Appendix C. The scenario assumes a relatively advanced ToU tariff design with recurring daily price profile that varies by country and consumption size. Hourly prices are derived from average wholesale price profiles in 2023 [18], consistent with the year used for solar generation data. To ensure comparability with the flat-price baseline, prices are rescaled such that total annual electricity expenditures for households without battery storage remain unchanged. The average and the range of the calculated hourly electricity prices are shown in Figure 1.

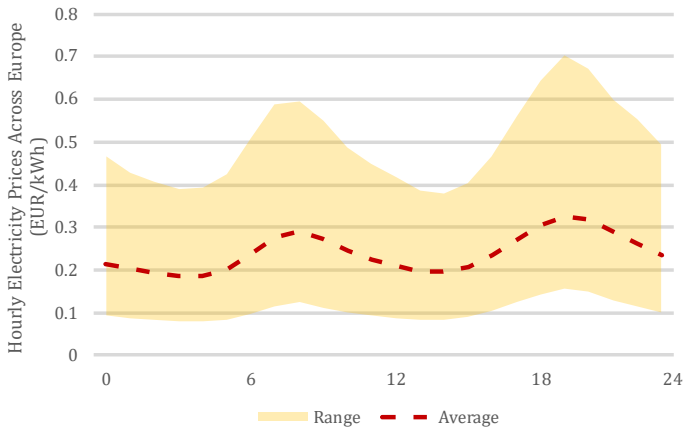

Figure 1. Hourly ToU electricity prices and the range of prices across the analysed countries, source: calculated from [18].

Although ToU pricing would likely lead to more sophisticated battery dispatch in practice, the charging and discharging strategy is assumed to be identical to that of the *Self-consumption* scenario. This simplification allows the isolated assessment of how pricing structures affect battery profitability and diffusion. Under this configuration, batteries predominantly supply household demand during evening peak hours, when electricity prices are typically highest.

FlexPool scenario

The *FlexPool* scenario builds on the *ToU* scenario but introduces partial aggregation of residential batteries through coordinated grid interaction. Households allocate 25% of their battery capacity to

an external operator, while retaining full control over the remaining 75%, which continues to operate under ToU electricity pricing and the standard self-consumption strategy.

In exchange for leasing part of their battery capacity, households receive a fixed daily payment equal to the value of one full cycle of the leased capacity, multiplied by the difference between the flat electricity price and the FiT. This payment reflects the maximum opportunity cost for households and ensures economic neutrality relative to self-consumption.

The operator has exclusive control over the leased capacity and deploys it to provide system-level balancing services. Operation is based on smoothing the national load profile. The operator first computes the mean hourly day-ahead load forecast at national level. When actual load falls below this mean during daytime hours, batteries are charged until the mean load is reached or available capacity is exhausted. Conversely, when actual load exceeds the mean, batteries are discharged until residual load returns to the mean or stored energy is depleted[2]. The battery capacities controlled by the operator are assumed to be able to charge from and feed into the grid. The primary objective of this strategy is to smooth the daily load curve, thereby enhancing peak reduction and potentially lowering carbon emissions. While coordinated battery operation could also contribute to frequency control, this effect is beyond the scope of the present analysis.

Peak scenario

Finally, in the *Peak* scenario, households are allowed to discharge electricity from their batteries to the grid during peak demand periods. Peak hours are identified at national level based on the residual load duration curve of the previous year. The residual load is defined as the hourly system load after subtracting rooftop PV generation, which is then arranged in descending order to form the duration curve. Peak hours are determined as the four hours that most frequently appear among the first 1,000 elements of this curve; corresponding to the periods when the residual load, i.e., the demand not met by rooftop PV generation, is typically at its highest throughout the year. Peak hours most frequently occur between 4 p.m. and 8 p.m., as shown in Figure 5.

To ensure that feeding electricity from household batteries into the grid remains economically viable, it is assumed that during peak hours the FiTs equal the ToU electricity prices. This reflects the maximum opportunity cost for households, as it compensates them at the same rate they would effectively save by using the stored electricity for self-consumption during peak-price periods.

The scenarios assume a uniform operational strategy for all residential batteries. In reality, a mix of strategies is expected: some households use batteries solely to maximize self-consumption, while others participate in coordinated operation schemes. Nevertheless, these extreme scenarios provide a useful framework for exploring the potential advantages and disadvantages of different operational strategies.

[2] Night-time hours between 1 a.m. and 4 a.m. are excluded from the mean calculation, as demand is typically well below average and solar generation is unavailable. Including these hours would lower the daily mean and could prevent charging during periods of high solar output.

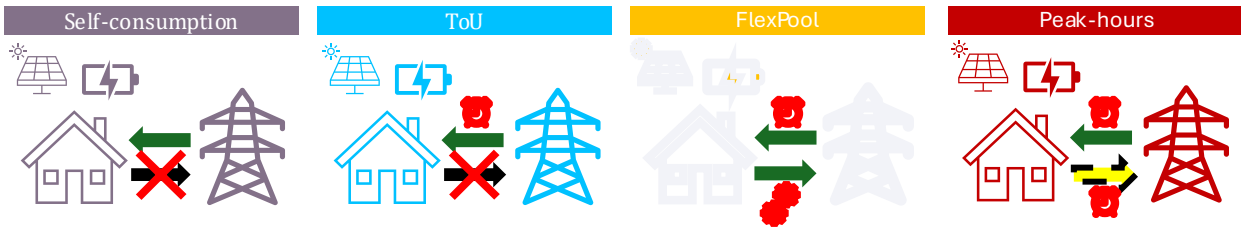

Figure 2 Schematic overview of battery operation strategy scenarios

Results

This section presents the outcomes of the modelling exercise, beginning with the net present value of battery investments and subsequently examining the diffusion of residential batteries and their impacts at the grid level.

Residential battery investment

While non-financial factors play a substantial role in household decisions to invest in residential battery systems, financial performance remains a critical determinant. Consequently, evaluating the financial return, typically measured by the NPV, is essential for analysing the diffusion of residential battery storage technologies.

The calculation of financial returns from residential batteries coupled with rooftop PV systems involves several key components, including solar energy generation, electricity prices, household electricity consumption (both in terms of volume and temporal patterns), battery system cost parameters, and the applicable electricity pricing schemes.

Figure 3 illustrates cross-country variations in some of these key parameters across Europe, revealing substantial heterogeneity. Solar irradiation, for instance, is most abundant in Mediterranean countries such as Spain, Portugal, Italy, and Greece, while Northern European countries receive roughly half of that solar input. Naturally, greater solar radiation translates into higher potential PV generation and, consequently, greater opportunities for battery storage utilization. Electricity prices also represent a major driver of residential battery investment, as they reflect the opportunity cost of grid electricity when storage is unavailable. In the absence of a battery system, households must purchase electricity from the grid whenever PV generation is insufficient to meet demand. Electricity prices are currently highest in Germany, Belgium, and Denmark, whereas the lowest prices are observed in Hungary, Bulgaria, and Croatia.

Finally, household electricity consumption significantly affects the financial viability of battery investments. Since the installation of residential batteries involves fixed costs that are largely independent of storage capacity, such as installation and system integration costs, larger systems benefit from economies of scale, resulting in lower unit costs per kWh of storage. Average household electricity consumption is considerably higher in Northern Europe, particularly in Sweden and Finland.

Considering all these factors and additional relevant components, the NPV of residential battery investments is calculated under the scenario assumptions. In the *Self-consumption* and *ToU* scenarios households utilize the battery solely to increase self-consumption of solar energy; in other words,

they cannot feed electricity from the battery to the grid. However, grid interactions are allowed in the *FlexPool* and *Peak* scenarios that further increases the NPV of the investment.

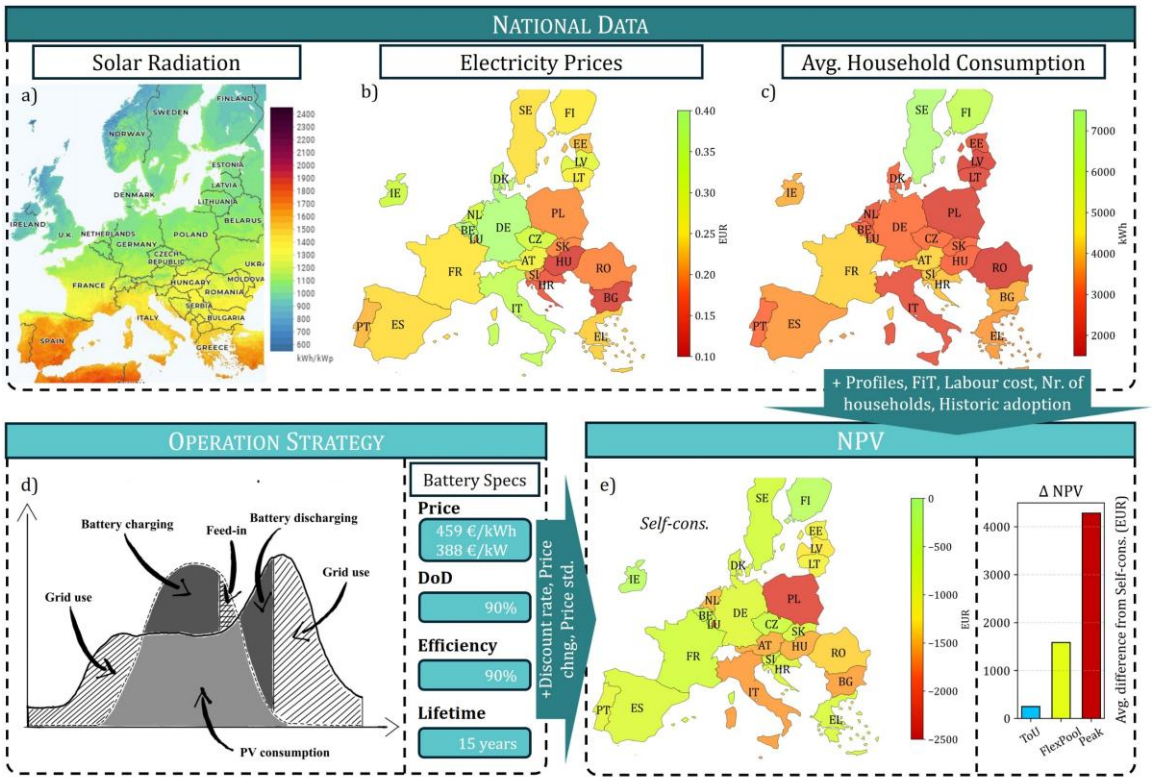

Figure 3 a) Solar radiation map (kWh/kWp), source: [25][3]; b) Electricity prices for medium consumers (€/kWh), source: [26]; c) Average household electricity consumption (kWh), source: [27]; d) Self-consumption battery operational strategy and main battery specifications; e) Battery NPV estimates for 2024 under the *Self-consumption* scenario, and the average deviation from this baseline across the other scenarios (€), source: own calculation.

The results in the baseline *Self-consumption* scenario indicate that, in most European countries, battery investments yield negative or near-zero NPVs, suggesting that such investments are not financially advantageous under flat electricity tariffs in 2024. More advanced electricity tariff designs generate substantially higher economic benefits. While the introduction of ToU electricity prices leads to only a modest increase in average NPV (€251), schemes that enable capacity leasing (*FlexPool*) or battery feed-in during peak hours (*Peak*) significantly enhance battery utilisation and provide more adequate compensation for households. In these cases, average NPV increases by €1,589 and €4,286, respectively, compared to the *Self-consumption* scenario.

However, battery prices are projected to decline rapidly in the coming years [28], while electricity prices are assumed to increase by 2% annually. In their studies [6] and [29] assume that electricity prices for German households rise at this rate, based on historical trends in Germany [30]; the same rate is applied across all countries in the study. Both trends are expected to enhance the economic attractiveness of residential battery investments: declining battery costs reduce upfront capital

[3] Global Solar Atlas 2.0 is a free, web-based application developed and operated by the company Solargis s.r.o. on behalf of the World Bank Group, utilizing Solargis data, with funding provided by the Energy Sector Management Assistance Program (ESMAP). For additional information: https://globalsolaratlas.info

expenditures, whereas rising electricity prices increase the operational profitability of storage systems, as substituting grid electricity with self-generated solar power yields greater savings. However, network operation costs are expected to rise during the transition to clean electricity due to the required grid upgrades to accommodate decentralised energy technologies. Total network costs in Europe, currently accounting for about 25% of the average household's electricity bill, are likely to increase significantly, potentially driving further price increases [31]. Therefore, given the high uncertainty surrounding the future evolution of household electricity prices, high- and low-price increase sensitivity scenarios are also presented in Appendix B along with other sensitivity scenarios.

It is important to note, however, that the NPV captures only the financial dimension of battery adoption and negative NPV does not necessarily imply that no residential battery diffusion happens in a country. Actual adoption behaviour is influenced by a range of sociodemographic and socioeconomic factors, including household income, environmental justice concerns, and ethnicity [32]. Moreover, the diffusion of new technologies, such as rooftop PV systems, often exhibits spatial and temporal disparities due to "peer" and "seeding" effects; in other words, technology uptake accelerates in communities where early adopters are present, as peer influence facilitates information diffusion and reduces perceived adoption barriers [33], [34]. Finally, even when the NPV is positive, non-financial barriers, such as limited access to information, perceived risk, and uncertainty regarding investment costs, may hinder widespread and rapid adoption of residential battery systems [21].

Residential battery storage diffusion in the EU and their impact on the grid

Since European countries are interconnected through a single electricity grid, it is essential to assess grid dynamics not only at the national but also at the EU level, as shocks in one country can rapidly propagate across borders. Cevik and Zhao [35] demonstrated that cross-border volatility spillovers play a dominant role in shaping the dynamics of national electricity markets across Europe.

Residential battery diffusion

The diffusion of residential battery capacity is therefore analysed at the national level for 25 EU countries to capture both localized and system-wide implications. Across the analysed scenarios, total residential battery capacity is projected to reach 109-144 GWh by 2030, up from 32 GWh in 2024 [3], and between 356 and 542 GWh by 2050, with the highest values in the more ambitious *FlexPool* and *Peak* scenarios (see Figure 4.a). The most rapid deployment occurs between 2030 and 2040, corresponding to the steepest phase of the S-shaped diffusion curve. After 2040, the adoption rate slows as most potential adopters have already installed batteries, leaving primarily late adopters and laggards in the market. These results also imply that electricity tariff designs become increasingly important as residential battery markets mature. Once diffusion is less constrained by non-financial barriers, financial incentives and pricing structures emerge as the primary drivers of further adoption.

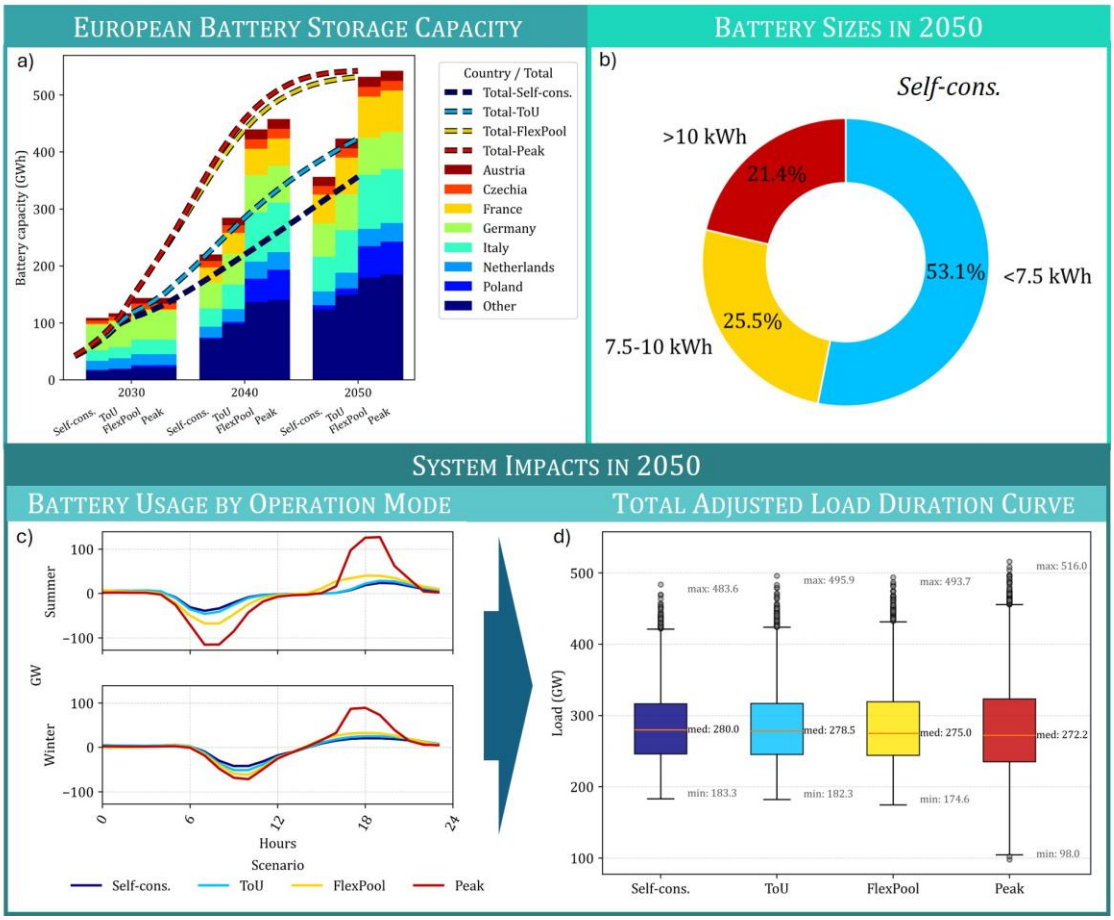

Figure 4 a) Diffusion of residential battery storage capacity in Europe by country under alternative electricity design scenarios estimated by the CLEARS model; b) Distribution of residential battery storage systems by size across Europe in the *Self-consumption* scenario; c) Average total daily battery use in Europe in the summer and winter by scenario in 2050, negative values indicate battery charging, while positive values indicate discharging; d) Boxplot of European hourly load in 2024 adjusted with the calculated battery use impacts for 2050, battery charging is added to the historical hourly load volumes, whereas battery discharging is removed from them.

The results highlight the critical role of electricity tariff designs in determining total residential battery storage capacity by 2050. Introducing hourly electricity tariffs in the *ToU* scenario increases total capacity by nearly 70 GWh compared to the *Self-consumption* scenario, demonstrating that even a relatively small rise in NPV (Figure 3) can have a substantial impact by moving households into the positive NPV range. Further enhancing financial viability through *FlexPool* tariff designs drives even faster deployment, reaching 532 GWh by 2050. However, the effect of increasing NPV exhibits diminishing returns: although battery NPV is substantially higher in the *Peak* scenario than in the *FlexPool* scenario, total storage capacity increases by only 10.4 GWh by 2050. This suggests that, under the *FlexPool* scenario, financial barriers are no longer a significant constraint, and further improvements in viability provide only marginal gains in adoption, potentially indicating overcompensation of battery owners.

Leading markets for residential batteries include Italy, Germany, and France in all scenarios. In contrast, the Polish market size is highly scenario-dependent, as battery NPVs in the *Self-consumption* and *ToU* scenarios are not sufficient to support large-scale diffusion. Countries with relatively low electricity prices also benefit more from advanced electricity tariff designs. In particular, Romania, Bulgaria, and Hungary achieve substantially higher residential storage capacities by 2050 when

households receive more favourable compensation mechanisms. However, there are multiple countries where battery diffusion does not vary substantially across scenarios. In these countries batteries become profitable early in the simulation period even in the *Self-consumption* scenario due to the decreasing battery prices and increasing electricity prices. Consequently, improving the NPV of the investment does not yield further significant adoption as it is constrained by the non-financial drivers. Projected residential battery storage capacity by country in 2050 is shown in Table 1.

Table 1 Residential battery storage capacity by country across scenario in 2050 (GWh).

	AT	*BE*	*BG*	*CZ*	*DE*	*DK*	*EE*	*EL*	*ES*	*FI*	*FR*	*HR*	*HU*
Self-cons.	16.2	21.0	2.5	15.1	58.5	7.5	0.5	7.5	25.0	5.6	50.4	4.3	2.3
ToU	17.0	22.7	4.5	16.2	63.5	8.9	0.6	8.1	32.2	5.8	64.3	5.3	3.9
FlexPool	17.7	23.0	9.3	17.0	65.3	9.9	1.3	8.2	32.7	6.3	72.1	5.6	7.8
Peak	17.7	23.0	9.7	17.0	65.3	9.8	1.3	8.2	32.7	6.3	72.6	5.6	12.4
	IE	*IT*	*LT*	*LU*	*LV*	*NL*	*PL*	*PT*	*RO*	*SE*	*SI*	*SK*	
Self-cons.	8.2	61.2	1.0	0.1	0.6	24.2	7.7	5.9	12.2	14.0	1.9	3.0	
ToU	8.3	74.5	1.2	0.2	0.6	27.6	11.1	9.5	17.0	14.2	2.4	3.9	
FlexPool	9.0	94.7	3.3	0.7	1.3	30.3	55.5	9.9	27.5	16.5	2.5	4.7	
Peak	9.0	94.7	3.3	0.7	1.3	32.5	57.9	9.9	27.7	16.5	2.5	4.7	

The most common residential battery sizes are below 7.5 kWh, accounting for approximately 53% of all installations, with capacities typically ranging between 5 kWh and 7.5 kWh. This is driven by historical installation patterns observed across most countries, likely reflecting the substantial upfront costs associated with larger battery systems. Nevertheless, in countries with relatively high household electricity consumption, larger-capacity batteries (exceeding 10 kWh) are more frequently adopted by large consumer households, for example in Sweden and Austria.

Charging patterns

Examining the charging patterns of the four battery operational strategies (Figure 4) reveals broadly similar temporal trends. Residential batteries are typically charged during the morning hours and discharged in the late afternoon and evening. A seasonal pattern is also apparent: in summer, when sunlight is available earlier and for longer, charging begins earlier and discharging occurs later, as solar energy can supply the system for an extended period. However, in the *Peak* and *FlexPool* scenarios, where battery storage capacity is substantially higher, the overall magnitude of battery usage is greater, particularly in summer when solar generation is abundant. In contrast, in the *Self-consumption* and *ToU* scenarios, batteries operate solely to meet household demand and do not respond to higher summer generation levels, resulting in underutilisation.

Allowing batteries to feed electricity back into the grid increases the utilisation of stored solar energy during evening hours. In the *Peak* scenario, battery discharging surpasses that of the *Self-consumption* scenario after 4 p.m., which is considered a peak hour in several countries, and reaches its maximum at 5 or 6 p.m., which is a peak hour in 19/22 countries, as shown on Figure 5. Later in the evening, discharge levels decline as battery charge is depleted, even though 7 p.m. is considered a peak hour in the most countries. This highlights a limitation of the *Peak* scenario: batteries feed electricity into the grid up to their capacity, without any coordinated control. As a result, most batteries are fully discharged by 10 p.m.

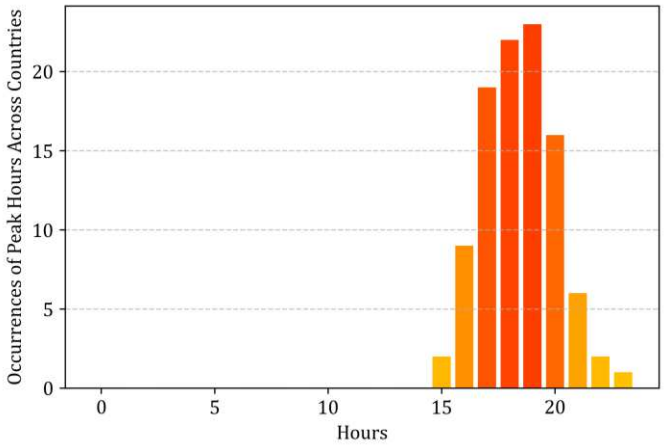

Figure 5 Occurrences of peak hours by hour of the day across 25 European countries in the *Peak* scenario for 2050. In the majority of countries (23), 7 p.m. is identified as a peak hour, followed by 6 p.m., which is a peak hour in 22 countries.

The maximum discharge in the *Peak* scenario during an average summer day approaches 130 GW, and 90 GW in winter, representing a substantial contribution during periods of highest demand. Charging patterns in this scenario are similar to those in the *Self-consumption* case, as households begin charging once rooftop PV generation exceeds consumption, but require greater recharging during the day due to higher evening use. Limiting the charging power of batteries can help delay morning charging and reduce the midday peak in solar power exports [36]. Peak-shaving schemes can also improve the NPV of residential batteries if appropriate financial incentives are provided [17] and can generate substantial system level cost savings [37]; however, this is not considered in the current study.

In the *FlexPool* scenario, the discharging profile is similar to that of the *Peak* scenario, although the curve is overall smoother. Unlike in the *Peak* scenario, where discharging during peak hours occurs without coordination and households feed electricity into the grid up to the power capacity of their batteries, the *FlexPool* scenario features centrally controlled discharging managed by the operator. This coordinated approach prevents a pronounced evening peak and allows energy reserves to be retained for later hours, with discharging extending beyond midnight. Furthermore, the scenario responds to local morning peak loads, causing battery charging to begin slightly later than in the other two scenarios.

Load impacts

By adjusting the current load curves of European countries to account for the operation of residential batteries in 2050, their impact on the European electricity system can be assessed. This analysis is conducted at the national level for each country, after which the results are aggregated to evaluate impacts at the European level. The *Self-consumption* scenario has the smallest effect on system load, primarily because total storage capacity is also the lowest in this case. In the *ToU* scenario, where storage capacity is nearly 70 GWh higher, maximum load increases by about 12 GW, while the median load is nearly 1.5 GW lower than in the *Self-consumption* scenario. The higher maximum load is driven by increased demand in the morning hours, when batteries are charged.

The highest maximum load occurs in the *Peak* scenario, reaching 516 GW. This outcome is expected, as storage capacity is largest in this case and battery charging substantially increases demand during morning hours. Moreover, the load range is widest in this scenario, because batteries discharge

during peak periods regardless of actual system demand, reducing the minimum load to 98 GW compared with 183 GW in the *Self-consumption* scenario.

In the *FlexPool* scenario, total battery storage capacity is similar to that in the *Peak* scenario, but the maximum load is reduced by 22.3 GW compared with the *Peak* scenario and by 2.2 GW compared with the *ToU* scenario, as battery operation is designed to reduce demand whenever it exceeds the daily average. By lowering peak demand, this strategy reduces the need for high-cost peak power plants, meaning that peak shaving can generate considerable economic benefits [38], [39]. This operational logic also results in a slightly lower median system load.

Emissions savings

Residential batteries can yield significant environmental benefits by enabling the use of solar energy during evening hours. Assuming that batteries replace gas power plants with 90% efficiency, and an emission factor of 12.8 g CO_2-eq/MJ for natural gas [40], while being charged with solar energy during the day (as shown in Table 2), they could save 473,976 TJ of natural gas in the *FlexPool* scenario and 673,463 TJ in the *Peak* scenario, corresponding to saving 56.1 and 8.6 Mt CO_2-eq emissions, respectively. However, a more detailed analysis is needed to accurately assess the extent to which batteries can substitute gas power plants and their resulting emission reduction potential. In the *Peak* scenario, which yields the highest emissions savings, charging and discharging occur in an uncontrolled manner. This may require additional generation capacity in the morning hours to meet grid demand while batteries are being charged from rooftop PV systems.

Table 2 Emission reduction potential of residential batteries by electricity tariff design mode in 2050. The simple calculation assumes that batteries are charged exclusively with zero-emission solar energy and discharge electricity that substitutes gas-fired power generation.

2050	*Total annual battery discharge (GWh)*	*Natural gas savings (TJ)*	*Emissions savings (Mt CO_2-eq)*
Self-cons.	64,781	259,125	3.3
ToU	77,629	310,516	4.0
FlexPool	118,494	473,976	6.1
Peak	168,366	673,463	8.6

Conclusions

This paper examined the diffusion of residential battery storage and its system level impacts across 25 European countries under four electricity tariff design scenarios: *Self-consumption*, *ToU*, *FlexPool*, and *Peak*. The analysis integrated financial evaluation and behavioural diffusion modelling within the CLEARS framework, enabling a comprehensive assessment of how household decision making and battery operation jointly shape future energy system outcomes.

While this study has limitations, it offers valuable insights and a foundation for future research. Distribution grid constraints like feeder limits or voltage issues were not explicitly modelled, though calculated battery capacities provide useful inputs for more detailed grid models. The hourly resolution overlooks ancillary services such as frequency regulation, an area for future work. This study simplifies residential tariffs and does not consider alternative grid tariff structures, such as demand charges (€/kW) based on monthly peak demand. Assuming a single battery size per household type, based on historical data, simplifies adoption but establishes a clear baseline.

Emissions calculations assume solar-only charging without hourly generation data, yielding conservative estimates to guide refined assessments.

The results demonstrate that residential battery adoption in Europe strongly depends on electricity tariff designs available to households. Across all scenarios, residential battery capacity is projected to expand substantially by 2050, reaching 356–542 GWh depending on electricity pricing structures, feed-in tariffs, and grid interaction mechanisms. Scenarios that enable greater household interaction with the grid enhance the economic attractiveness of batteries, leading to significantly higher levels of deployment. In contrast, without grid interaction, adoption is largely concentrated in countries with already favourable financial conditions, particularly Germany and the Netherlands, while in markets such as Poland, Bulgaria, Romania, and Hungary, residential battery uptake remains limited unless households are supported through more advanced electricity tariff designs. However, financial metrics alone cannot fully explain adoption behaviour, as social and psychological factors, such as environmental values and community effects, also influence investment decisions. Enhancing the financial attractiveness of residential battery investments yields diminishing returns and fails to drive significant additional installations beyond a certain threshold.

The comparative analysis of operational strategies highlights that battery management strongly determines system impacts. The *Peak* strategy enables households to discharge during high demand hours, slightly reducing the maximum load but increasing volatility due to uncoordinated behaviour. The *FlexPool* strategy offers system benefits by coordinating charging and discharging to align national load with daily averages, producing a flatter load curve and retaining energy reserves for later hours. These findings emphasise that widespread adoption of residential batteries alone does not guarantee system level advantages. Coordinated operation schemes and appropriate financial incentives are necessary to fully realise the potential of distributed storage. When effectively integrated, residential batteries can enhance self-consumption, stabilise electricity demand, lower greenhouse gas emissions, and support the large-scale integration of variable renewable generation across Europe.

Several avenues exist for future research to build on this work. First, the assessment of residential battery profitability could be extended to consider additional policy instruments, such as Feed-in-Premiums or Contracts-for-Differences. Second, integrating the model with an EU-level electricity market simulation would allow for incorporating grid constraints, and endogenizing electricity prices and emissions savings, providing a more comprehensive understanding of the interaction between residential storage adoption and the wider electricity system. Such extensions would enhance the policy relevance and robustness of the findings.

Methods

The CLEARS model estimates national-level adoption pathways for residential batteries by combining economic evaluation with diffusion dynamics [13], [14]. The analysis proceeds in five steps, as outlined on Figure 6: first, the assumptions of the electricity tariff design are incorporated into the model, including electricity prices, feed-in tariffs, grid interactions, and, consequently, battery operational strategies. Second, the NPV of battery investments connected to rooftop PVs is calculated for heterogeneous households, accounting for country-specific load profiles, electricity prices, consumption levels, and solar radiation. Third, households for which the investment is financially beneficial are quantified as the potential population in the Bass diffusion models. Fourth, Bass diffusion models are used to simulate cumulative adoption trajectories, capturing non-financial

drivers and producing an S-shaped growth curve. Finally, the aggregated charging and discharging profiles are assessed.

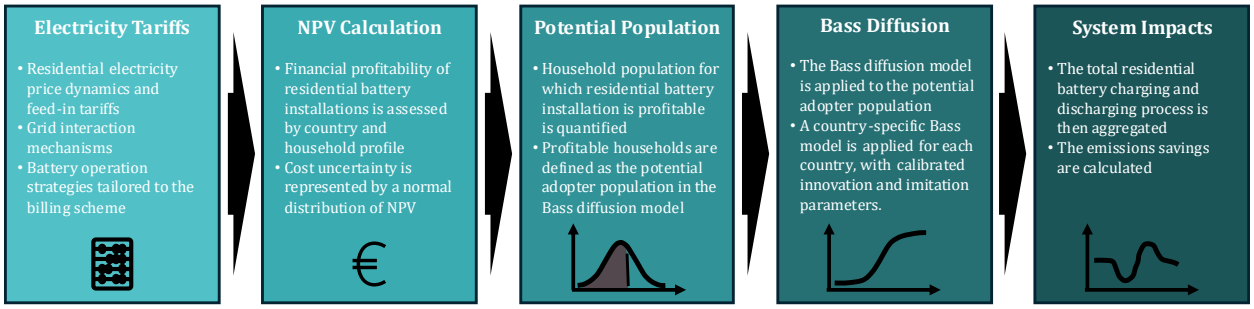

Figure 6. Model logic overview

3.2 NPV calculation

Household investment decisions are influenced by the NPV of the battery installation, as only households that perceive the investment to be profitable are considered potential adopters. The NPV is calculated in two steps. First, the discounted annual profit of the battery installation is estimated. Second, the upfront installation costs are calculated. The NPV is then obtained as the difference between these two components. Nine distinct household types are considered in the analysis, differentiated by annual electricity consumption s (small, medium, large) and load profile p (normal, heating, cooling).

Annual profits from residential batteries are calculated based on self-consumption, E^{SC}, which depends on household load, solar generation, and battery efficiency (η), multiplied by the hourly electricity price (P_h^E). In addition, battery owners under specific electricity tariff designs can earn revenue by exporting stored electricity to the grid ($E^{\text{Feed-in}}$), which is multiplied by the applicable hourly feed-in tariff (FiT_h). Alternatively, households may offer a portion of their battery capacity to an operator to provide flexibility for a fixed payment (R^{Flex}). The total cost of energy charged into the battery is then determined by multiplying the charged energy (E^C) by the hourly feed-in tariff (Eq. 1). These profits are then discounted over the system lifetime (Lt) with interest rate i and growth rate g (Eq. 2).

$$\pi_{c,p,s} = E_{c,p,s}^{SC} \times \eta \times P_{s,h}^{E} + E_{c,p,s}^{Feed-in} \times \eta \times FiT_h + R^{Flex} - E^{C} \times FiT_h, \quad (1)$$

$$\pi_{c,p,s}^{Disc} = \frac{\pi_{r,p,s}}{i-g} \times \left(1 - \frac{1+g}{(1+i)^{Lt}}\right). \quad (2)$$

The upfront investment costs (I) account for battery capacity, power electronics, and installation (Eq. 3).

$$I_{c,p,s} = \left(P^{BS} \times BS_{c,p,s} + P^{BP} \times BP_{c,p,s}/2\right) \times (1 + t_c) + L \times Y_c^{Adj}) \quad (3)$$

where BC denotes the unit price of battery storage capacity per kWh; $BS_{c,p,s}$ represents the assumed battery size (in kWh) for the given country (c), consumption profile (p), and consumption size (s); t_c is the value-added tax rate in country c; PC is the unit price of battery power per kW; $BP_{c,p,s}$ indicates the assumed power capacity of the battery system (in kW); L refers to the installation labour cost; and Y_c^{Adj} is an adjustment factor applied to labour costs based on the average income level in country c.

The NPV is then calculated as the difference between discounted benefits and costs (Eq. 4).

$$NPV_{c,p,s} = \pi_{c,p,s}^{Disc} - I_{c,p,s} \quad (4)$$

Once the NPV is calculated for battery storage systems, the adoption simulation proceeds. A normal distribution with mean $I_{,c,p,s}$ and relative standard deviation σ_I is generated. The potential population in the Bass diffusion model is determined from the probability that the discounted benefit exceeds the investment cost. It is further assumed that 2.5% of households are considered as innovators [19], [20] who adopt the technology regardless of NPV. In summary, the NPV estimation defines the proportion of households for which adoption is financially beneficial, which then serves as the potential population in the Bass diffusion model.

3.3 Bass diffusion model

Financial profitability alone does not fully explain technology adoption dynamics, as households often face uncertainty and limited access to information [21]. To account for these behavioural and informational factors, CLEARS incorporates national-level Bass diffusion models to simulate the temporal evolution of adopters [11], [22], [23], [24].

In each simulation year (t), a country-specific Bass model estimates the number of residential battery adopters ($N_{c,t}$) in country c, considering the potential population of adopters ($M_{c,t}$), and the innovation (p_c) and imitation (q_c) coefficients (Eq. 5).

$$N_{r,t} = M_{r,t} \times \frac{1-e^{-(p_r+q_r)(t-t_0)}}{1+\frac{q_r}{p_r}e^{-(p_r+q_r)(t-t_0)}} \quad (5)$$

The potential adopters identified by the NPV analysis are used in Bass diffusion models to simulate the cumulative adoption trajectory, capturing non-financial drivers and producing an S-shaped growth curve. The S-shaped curve represents how a new technology spreads over time, starting with slow adoption, followed by rapid growth after an inflection point, and eventually slowing as the market becomes saturated. It reflects cumulative adoption driven by interactions between adopters and non-adopters, similar to the spread of an epidemic [5]. Similar approach was applied by Fett et al. [6] and Klingler et al. [4] but in their analysis financial profitability does not impact the number of residential battery adopters.

Since the potential population in the Bass model evolves dynamically each year, the hypothetical S-shaped diffusion curve also changes annually. Consequently, in each year, the model aligns the previous year's number of residential batteries with the S-curve corresponding to the current potential population. It then determines the additional adopters from this segment of the curve, thereby preserving the overall diffusion pattern.

3.4 Model calibration

The model is calibrated to the 2025–2029 forecast of SolarPower Europe [3]. In countries where national residential battery storage capacity estimates are available, the FiT levels are adjusted to approximately reproduce the 2029 forecast values. For countries without national projections, calibration is performed to align the aggregate European capacity with the continent-wide forecast for 2029. FiTs are selected for calibration because they are a widely implemented policy instrument across Europe [8]. The model considers only FiT support schemes for residential batteries, which represents a necessary simplification for the modelling exercise; however, alternative support mechanisms may become more relevant over time.

According to SolarPower Europe [3], the total cumulative battery storage capacity in Europe is expected to reach 399 GWh by 2029, of which the residential sector accounts for approximately 25%

or 100 GWh. The CLEARS EU model is calibrated to achieve approximately the same total residential battery storage capacity by 2029. Beyond 2029, the diffusion process is governed solely by the internal dynamics of the model.

More details on parameters and data sources are provided in Appendix A.

Statement of exclusive submission

This paper has not been submitted elsewhere in identical or similar form, nor will it be during the first six months after its submission to the Publisher.

Data availability

The model codes used in this study, along with selected data generated for 2050, are available in the CLEARS-EU repository (https://github.com/CLEARS-Diffusion-Model/CLEARS-EU_public). Data prior to 2050 are not publicly available due to data storage constraints and the inclusion of proprietary information from SolarPower Europe on historical residential battery and rooftop PV installations, system sizes, and total capacities. Some of the remaining data may be made available upon request.

Declaration of generative AI in scientific writing

During the preparation of this work the author used ChatGPT in order to improve readability. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of Competing Interest

Declarations of interest: none

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