2025 European Conference on Computing in Construction

CIB W78 Conference on IT in Construction

Porto, Portugal
July 14-17, 2025

OPTIMIZING PEAK LOAD MANAGEMENT IN DUTCH RESIDENTIAL NEIGHBORHOODS USING SHORT-TERM ENERGY STORAGE SOLUTIONS: A CASE STUDY IN THE NETHERLANDS

Dujuan Yang, and Luuk Hupkens
Eindhoven University of Technology, Eindhoven, The Netherlands

Abstract

Heating and cooling account for 50% of the EU's energy consumption, with over 70% sourced from fossil fuels. Decarbonizing residential heating by electrifying systems presents challenges such as increased demand and grid instability. Energy storage systems (ESSs) offer a solution, but tools for selecting optimal ESSs at the neighborhood scale are lacking. This paper introduces a decision-support method that evaluates ESSs using dynamic neighborhood-level energy demand simulation. A case study in Eindhoven, Netherlands, demonstrates how this approach helps stakeholders make informed decisions, enhancing grid stability and promoting effective energy storage integration for residential decarbonization.

Introduction

Heating and cooling account for 50% of the European Union's (EU) energy consumption, with over 70% of this energy still sourced from fossil fuels (European Commission, 2023). In the Netherlands, residential heating alone contributes significantly to CO_2 emissions, as approximately 80% of final energy consumption is used for space and water heating (European Commission, 2023). To address this, the Dutch government has set ambitious targets, including a 49% reduction in CO_2 emissions by 2030 compared to 1990 levels (Rijksoverheid, 2019). A key strategy to achieve this goal is the electrification of heating systems, replacing gas and oil-fired boilers with electric heat pumps and other renewable solutions. This shift has already increased the share of renewable energy in heating and cooling from 4% in 2010 to 15% in 2022 (Eurostat, 2024).

However, the electrification of heating systems presents significant challenges. Increased electricity demand during peak hours can strain the grid, leading to instability and potential overloads (Wang et al., 2023). This issue is exacerbated by the intermittency of renewable energy sources like solar and wind power, which can create mismatches between supply and demand. In densely populated urban neighborhoods, the combination of fluctuating renewable energy generation, heating demand, and other electrical loads—such as electric vehicle charging—further intensifies these challenges. These issues underscore the need for grid flexibility and effective energy storage solutions (ESSs) to balance demand and supply. Energy storage systems (ESSs) are recognized as a promising solution to mitigate peak load strain and balance supply and demand. Existing ESS technologies can be broadly categorized into short-term and long-term storage. Short-term storage solutions, such as batteries, flywheels, and supercapacitors, are ideal for managing daily fluctuations and immediate load balancing (Castillo & Gayme, 2014). Long-term storage options, like pumped hydro and hydrogen storage, address seasonal variations but often face economic and spatial constraints.

Despite technological advancements, stakeholders—including policymakers, energy communities, and urban planners—lack effective decision-support systems (DSSs) to guide them in selecting the most appropriate storage solutions. Current DSS tools, such as ES-Select™ and multi-criteria decision-making (MCDM) frameworks, provide preliminary insights based on economic feasibility and broad technical characteristics (Akhil et al., 2013; Gamal et al., 2024). However, these tools often fall short in evaluating real-world performance scenarios, such as the specific impact of ESSs on peak shaving or their suitability within neighborhood-scale energy systems.

This research addresses these gaps by developing a DSS that evaluates and compares short-term ESSs based on simulated dynamic neighborhood-level energy demand. The proposed DSS aims to provide stakeholders with evidence-based guidance on selecting suitable ESS technologies to alleviate peak load strain while supporting business case development. The contribution of this research lies in bridging the gap between theoretical ESS evaluations and practical, real-world applications, particularly in the context of urban energy transition and grid stability.

The remainder of this paper is organized as follows. Section 2 outlines the research methodology and the proposed decision-support system (DSS) framework for evaluating energy storage solutions. Section 3 presents a case study conducted in Eindhoven, the Netherlands, demonstrating the application of the DSS at the neighborhood level. Section 4 discusses the results and key insights derived from the case study. Section 5 concludes the paper by summarizing key findings and suggesting directions for future research.

Methodology

DSS System Architecture

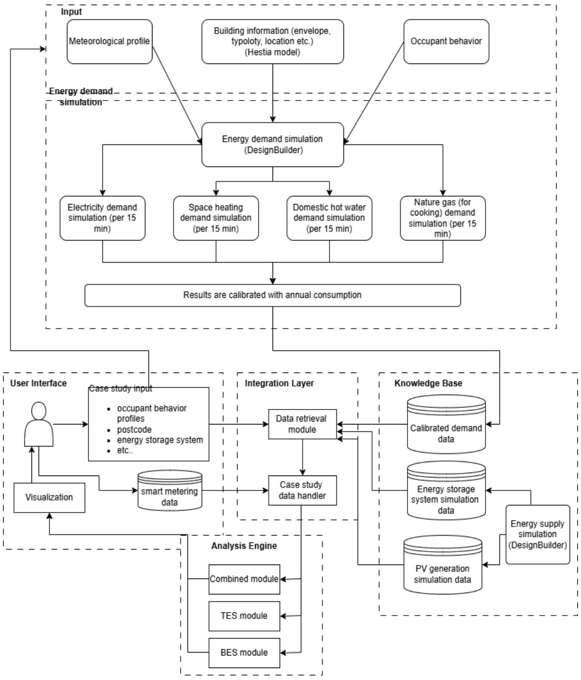

Figure 1: System architecture of the DSS

The proposed decision support system (DSS) adopts a modular architecture comprising a User Interface, Energy demand simulation engine, Integration Layer, Knowledge Base and Analysis Engine to enable robust analysis of case studies in energy systems. As shown in Figure 1, at its core, the user interface enables users to submit relevant data such as geographic parameters (e.g., postal codes), occupant behavior profiles, requirements of energy storage system, existing number of PVs and smart metering data if it is available. Part of these inputs are processed through Energy demand simulation engine to produce calibrated demand simulation results. These inputs are also processed by the integration layer, where the data retrieval module fetches pre-simulated PV performance data and energy storage system data from the knowledge base. The Data Handler harmonizes case profiles (e.g., both smart metering data and simulated energy demand and PV generation data) with user-defined inputs of energy storage systems. The Analysis Engine include domain-specific TES (Thermal Energy System) and BES (Battery Energy System) modules to process the integrated datasets to generate insights based on predefined KPIs. Results are visualized dynamically in the user interface layer, bridging theoretical simulations with real-world observations. This architecture ensures scalability, reproducibility, and cross-domain applicability, particularly for energy optimization tasks. Detailed explanations of each component are provided in the subsequent sections.

Demand side simulations

The demand-side simulation begins with data acquisition from the Hestia model based on user input. The Hestia model developed by TNO and PBL is an open-source and open-access spatial energy model (TNO & Planbureau voor de Leefomgeving, 2023), which provides building typology and thermal properties for the target neighborhood. These inputs, queried via Python, drive DesignBuilder simulations of electricity, heating, and domestic hot water demand at 15-minute intervals. Meteorological profiles (Eindhoven, 2022) and occupant behavior patterns (Guerra-Santin & Silvester, 2017) were incorporated to capture dynamic demand fluctuations.

Electricity demand was simulated to capture variations throughout the weekdays and weekend. Space heating demand was also modeled to account for thermal dynamics and heating requirements based on occupant behavior and building characteristics during winter period. Domestic hot water demand was modeled based on stochastic end-user patterns based on household data from the Netherlands in 2014. Natural gas demand for cooking was simulated to reflect typical household usage patterns for cooking activities.

For this research, the 2022 Eindhoven meteorological profile (NLD_EID_EPW_YR2022.epw) was used as input for DesignBuilder. Occupant behavior encompasses usage patterns and schedules that affect electricity, heating, and gas consumption. These behaviors include heating schedules (setback and setpoint temperatures), thermostat settings, lighting and occupancy schedules. Five typical household types were identified, and their occupant behaviors were modeled using data derived from previous research (Guerra-Santin & Silvester, 2017). This approach ensures an accurate representation of typical household energy consumption patterns within the simulation. We calibrated the simulated demand profiles against CBS (Statistics Netherlands) data. DesignBuilder generated electricity and heating demand profiles were compared with annual aggregated energy consumption data from CBS for residential buildings. Discrepancies between simulations and reference datasets were minimized through parameter adjustments (e.g., thermostat schedules, appliance usage), ensuring alignment within a 10% margin of error. This validation confirms the reliability of demand profiles used for battery storage analysis.

Energy generation by Solar panels

Due to limited information about solar panels, the integration of solar panels into the DesignBuilder model required a careful selection process to ensure that the chosen panels reflected realistic options for any simulated neighborhood. The source Greenchoice (2024), a Dutch energy supplier known for its focus on providing renewable energy solutions to residential and commercial customers, was consulted to make the selection. For this study, the Jinko 54HL4R-B model was selected for the simulation. This panel features a power output of 430 watts and utilizes n-type mono-crystalline cells with a module efficiency of 21.5%. To validate this choice, these specifications were compared with data from the National Renewable Energy Laboratory (NREL, 2025) that compiles results from credible test institutions evaluating the performance of different PV panel technologies. NREL (2025) reported an efficiency of 23.2% for n-type mono-crystalline cells, closely aligning with the efficiency of the selected Jinko model.

Battery storage solution

A battery storage system was incorporated into the model using the 'Simple Battery' function in DesignBuilder. Since early design stages often require broad assumptions rather than detailed system models, this function provides sufficient accuracy for preliminary assessments, while reducing the need for intricate data inputs. The function configures a direct current DC storage system. Additionally, an inverter was added. To maintain simplicity, a simple inverter that utilizes a fixed conversion efficiency was assumed. The battery system was configured to operate using the "base load" algorithm. This algorithm ensures that the battery charges only when there is surplus energy generated by the solar panels, and discharges energy only when the energy generated by the solar panels falls short of the energy demanded by the building.

Thermal storage solution

For the thermal energy storage solution, a water heater equipped with an electric heating element was added to the DesignBuilder model. To simulate the heating process, the water heater was equipped with an electric heating element, ensuring that the system could respond dynamically to demand while allowing for detailed analysis of the behavior of the tank. Multiple simulation runs were conducted to evaluate the performance of the thermal storage solution, particularly focusing on overall energy usage and operational behavior. The analysis of the simulation results focused on the temperature differences of the water during operation, the energy losses and how the heater maintained and responded to variations in demand, and the overall energy usage of the water heater.

KPIs

The evaluation of energy storage solutions within the DSS is guided by a set of Key Performance Indicators (KPIs) derived from the literature and expert interviews. A summary of KPIs from previous studies is shown in Figure 2. Among the most frequently cited KPIs are charge/discharge power rating, cycling capacity, and efficiency, which play a key role in determining ESS effectiveness (e.g., Castillo & Gayme, 2014; Ibrahim et al., 2008; Luo et al., 2015). Additional important factors include capacity, cost, and energy density, which influence the economic and technical feasibility of storage solutions (e.g., Aneke & Wang, 2016; Del Pero et al., 2018). These KPIs provide essential benchmarks for assessing the suitability of ESS technologies in grid applications.

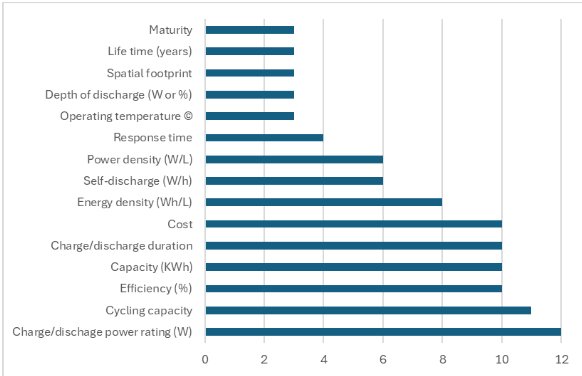

Figure 2: KPIs cited in the literature for assessing energy storage solutions

For this study, which focuses on residential peak shaving using short-term battery storage solutions. Based on literature, expert interviews and available functions of simulation tools, the following KPIs have been selected to evaluate the peak shaving potential:

- Efficiency: The round-trip efficiency, representing the ratio of energy output to energy input, is essential for minimizing energy losses.
- Capacity: The amount of energy that can be stored in the system and is made available after charging.
- Discharge Power Rating: the rate at which energy can be charged into or discharged from an energy storage system.

Efficiency is a crucial key performance indicator (KPI) because it directly affects the economic viability of ESSs. Systems with higher efficiency minimize energy losses, resulting in better utilization of the input energy (Aneke & Wang, 2016; Koohi-Fayegh & Rosen, 2020). Capacity is a fundamental metric that helps determine the performance and potential of storage systems (Castillo & Gayme, 2014; Elalfy et al., 2024). Charge/discharge power rating is crucial in determining the system's ability to store and release energy efficiently under specific operational conditions (Ibrahim & Ilinca, 2013). It represents the maximum power that the system can deliver or absorb during discharging or charging (Airò Farulla et al., 2020; Elalfy et al., 2024).

These KPIs are applied within the DSS Analysis Engine to evaluate the performance of a specific ESS technology (i.e., batteries) in achieving residential peak shaving potential.

Case study and data preparation

Case area

To demonstrate and evaluate the Decision Support System (DSS) for battery storage, a case study was conducted in the Joriskwartier neighborhood, a residential area characterized by aging housing stock. The selection of study area was guided by three criteria which are, ownership, construction year (energy efficiency) and type of dwelling. The study area comprises 654 houses, with 46% owner-occupied and 54% rental properties. Notably, approximately 90% of these residences were constructed before 2000, suggesting a prevalence of buildings with suboptimal insulation and thermal performance. Further, the housing stock includes a mix of dwelling types, with corner houses accounting for 15.3% and terraced houses for 29.8% of the total. An analysis of energy labels revealed that around 75% of the houses are rated C or lower, indicating poor thermal efficiency and a significant potential for renovation and energy performance improvements. These characteristics underscore the suitability of Joriskwartier for this case study.

To ensure that the simulations were both representative and manageable within the scope of the research, 4 corner houses were selected from a single block within Joriskwartier. While the case study focuses on a single building type (corner houses) for consistency in thermal performance assumptions, the research will focus on intra-type variation since variated occupant profiles will be applied to the same building archetype.

Data preparation

Details about these houses' thermal envelopes were required to simulate their energy demand. The necessary data were obtained from the Hestia model. The average Rc-value, U-values, and infiltration rate were calculated and presented in Table 1.

Tabel 1: Average thermal properties of building elements

Building element	U-value	Rc-value	qv;10
Windows upstairs	3.94	-	-
Windows downstairs	2.80	-	-
Doors	3.45	-	-
Panels	-	0.94	-
Floor	-	1.26	-
Cavity walls	-	1.41	-
Roofs	-	0.79	-
Roofs dormer	-	0.86	-
Gaps	-	-	3.00

Note: qv;10 represents airflow rates (infiltration) at 10 Pa

The intra-type variation is assumed based on the statistic of the WoON data 2018. It has been found that couple households and couple with child(ren) are more likely to live in a terraced corner houses. Therefore we assigned the four corner houses with one for 2-adult type, one for 2-senior and 2 for nuclear family type. The occupant behavior are based on the results from Guerra-Santin and Silvester (2017), including thermal setting, heating schedules and lighting profiles.

To quantify the natural ventilation in households, we assumed that all homes consistently ventilate based on findings from Guerra-Santin and Silvester (2017). To quantify indoor lighting and equipment usage, assumptions were made due to the absence of measured electricity data for the neighborhood. Lighting profiles for different household types, developed by Guerra-Santin and Silvester (2017), were directly adopted in the simulation model. Additionally, the living room was assigned extra gains to account for indoor equipment commonly used by residents, such as televisions and radios.

The kitchen was modeled using a catering setting, providing a specialized framework for simulating energy usage in kitchen spaces. The power density, representing energy consumption for catering activities, was defined in W/m², with natural gas set as the fuel source to reflect real-world energy usage patterns. Data from Milieu Centraal was used to determine the input parameter for power density, with annual gas consumption for cooking estimated at approximately 37 m³. Using a conversion factor of 1 m³ of natural gas equaling 9.77 kWh, this corresponds to an annual energy consumption of 361 kWh, which served as the reference for defining energy demand attributed to catering activities in the simulation. Additionally, a schedule was implemented to reflect the kitchen's operational hours, with catering activities set to occur daily from 18:00 to 19:00. This ensured that the simulated energy demand accurately represented the temporal dynamics of kitchen usage.

PV generation assumptions

Since the selected neighborhood currently lacks houses equipped with solar panels, no real-world data was available to model solar energy generation profiles. For the PV generation simulation, each house was equipped with four pre-selected solar panels as explained in methodology section, measuring 2.38m by 1.13m, to reflect a realistic setup for assessing solar energy potential.

Results and Discussion

Weekly Electricity demand for three house types

Figure 3-5 summarizes one week of electricity demand recorded at 15-minute intervals for three household types: two-adult, two-senior, and nuclear family, under both summer and winter conditions. Across all profiles, a stable baseline of approximately 12W–15W is observed during late-night hours, reflecting minimal activity from essential appliances or standby loads.

Notably, the early morning period shows a rapid increase in consumption. In summer, all household types exhibit a steep rise in demand, reaching a peak of around 879 W by approximately 7:15 AM. In contrast, the corresponding winter profiles show lower morning peaks - around 806 W, indicating a less pronounced surge in activity. The nuclear family and two-adult households display very similar peak magnitudes during summer, suggesting that their morning routines and appliance usage patterns are closely aligned. Meanwhile, the two-senior household, although reaching comparable peak levels in the morning, presents a somewhat different overall daily profile, with a more subdued increase during other parts of the day compared to the other household types.

These peak comparisons underscore the influence of both seasonal variations and household composition on electricity demand. The higher peaks observed in summer may be attributed to increased daytime activities and appliance usage, while the slightly lower winter peaks could reflect altered daily routines.

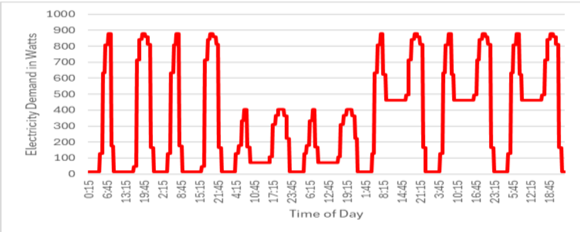

Figure 3a: Energy simulation of a corner house with 2-adult family type in a typical summer week.

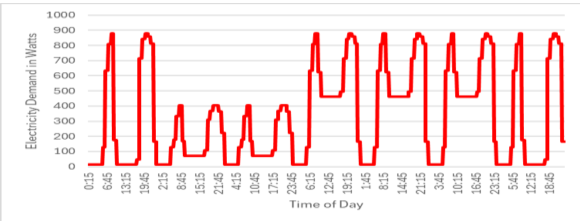

Figure 3b: Energy simulation of a corner house with 2-adult family type in a typical winter week.

To be more specific, as shown in Figure 3, the energy simulation for a 2-adult household in a corner house during a typical summer week in July reveals distinct electricity patterns. Electricity demand remains stable at night (~12.6W) but surges in the morning (~05:00), likely due to morning routines. A peak electricity demand pattern emerges, with rises between 06:00–08:00 and 17:00–21:00, aligning with residential activities. In contrast, a typical winter week in Feb., as shown in Figure 5b, reveals electricity consumption peaks in the morning (~07:00, 634W) and evening (~18:00, 879W).

For a 2-senior family household in a corner house during a typical summer week in July (Figure 4a) indicates that electricity consumption remains low and stable overnight (~12.6W) until early morning, when a gradual increase begins around 04:15, peaking between 06:00 and 08:00 (~879W), likely due to morning routines such as appliance use and meal preparation. Throughout the day, electricity demand remains moderate, with a slight midday dip before rising again in the evening (17:00-21:00) to around 879W, corresponding to evening household activities. The simulated energy consumption and production during a typical winter week in Feb (Figure 4b). demonstrates a stable daily pattern of electricity consumption, with moderate morning and evening peaks, averaging 800-900W in the evening, primarily due to lighting and appliance use.

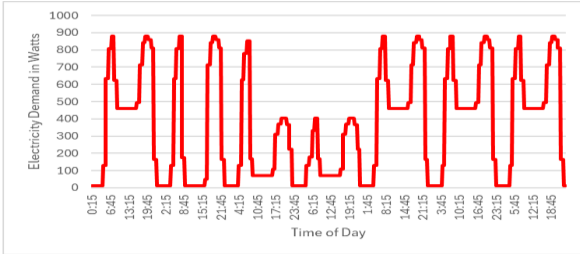

Figure 4a: Energy simulation of a corner house with a 2-senior family type in a typical summer week.

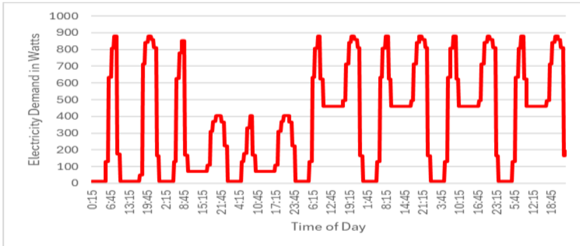

Figure 4b: Energy simulation of a corner house with a 2-senior family type in a typical winter week.

The energy simulation for a nuclear family household in a corner house during a typical summer week reveals steady electricity demand with peaks in the early morning and evening, aligned with typical household activities like cooking and entertainment, as shown in Figure 5a.

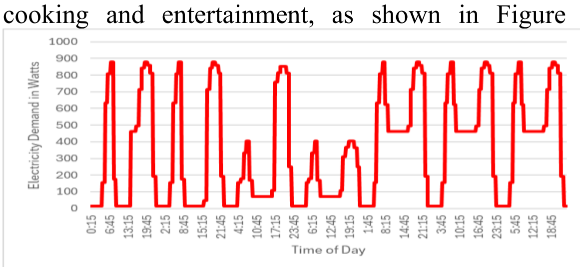

Figure 5a: Energy simulation of a corner house with nuclear family type in a typical summer week.

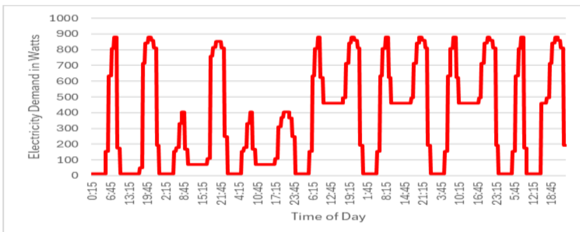

Figure 5b: Energy simulation of a corner house with nuclear family type in a typical winter week.

In contrast, during a typical winter week, as shown in Figure 5b, electricity demand increases in the morning and evening, driven by lighting, and appliances.

The demand-side simulations provide insight into the annual and daily electricity consumption patterns of different household types. Across all three household types, the 2-adult household has the lowest annual electricity demand. While the nuclear family exhibits the highest variation in seasonal energy consumption due to variated schedule of adults and kids, as expected.

PV generation

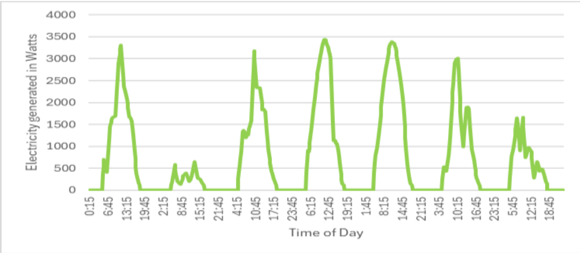

Figure 6a: PV generation in a typical summer week.

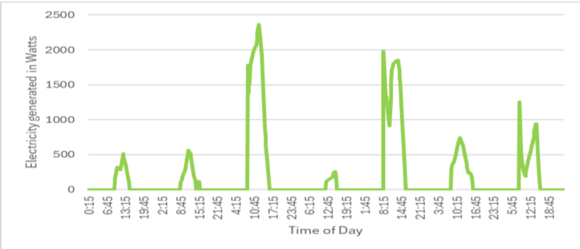

Figure 6b: PV generation in a typical winter week.

For this case study, we assumed a standardized photovoltaic (PV) system was installed on the roofs of each household type, and its performance was simulated under summer and winter conditions. Figure 6 presents the resulting PV generation profiles, measured at 15-minute intervals, over the course of one week.

In both seasons, overnight values remain at zero, reflecting the absence of solar irradiance. Generation typically begins around sunrise—between 5:00 and 6:00 AM, then rises sharply to reach midday peaks. In summer, these midday peaks frequently exceed 2,500W, and can approach or surpass 3,000W, depending on the specific day's irradiance and atmospheric conditions. By contrast, winter production is generally lower, often remaining below 1,000 W at midday. This seasonal discrepancy is largely attributable to shorter daylight hours, lower sun angles, and reduced overall irradiance during winter months. Despite the variation in absolute output, the daily production profiles follow a characteristic "bell-shaped" curve in both seasons, with generation ramping up after sunrise, peaking around noon or early afternoon, and tapering off in the late afternoon as the sun sets. Minor day-to-day fluctuations can be observed in the data, indicating changing weather conditions such as intermittent cloud cover.

Evaluation results of DSS for battery storage technologies

To assess the decision support system (DSS) evaluation potential for battery storage technologies, three distinct battery system scenarios were tested. We assumed the battery would always be at max capacity when the peak starts. The combined electricity demand of 4 corner households served as the cast study for three peak shaving configurations, each varying in battery capacity, discharge power, and target baseline power (i.e., the peak shaving goal).

Scenario 1: Moderate Peak Shaving (10 kWh, 1700 W Discharge, 1600 W Baseline)

In scenario 1, two sub-configurations were evaluated: Scenario 1a employed a 10 kWh battery system with 85% efficiency, and Scenario 1b used the same capacity at 80% efficiency. In both cases, the battery was used to lower an evening peak of approximately 3500 W, down to a baseline of 1600 W. The discharge power was set at 1700 W, enabling the system to actively lower the peak load during high-demand periods.

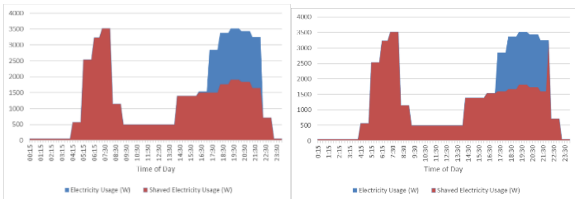

Figure 7: Impact of Battery Storage on Peak Demand in Scenario 1(left for 7a, right for 7b)

As illustrated in Figure 7 (left panel for 1a, right panel for 1b), between 18:15 and 21:00, the battery consistently discharged energy. However, the peak demand remained slightly above the 1600 W baseline at certain intervals. This occurred because the discharge power (1700 W) was insufficient to fully compensate for peak loads exceeding this threshold. Despite this, the peak demand occasionally exceeded the 1600 W baseline because the fixed discharge power was insufficient to counteract momentary surges beyond its limit. Scenario 1a achieved a peak shaving potential of 95.13%, while Scenario 1b achieved 91.09%. These results indicate that even a modest reduction in battery efficiency leads to a slight decrease in peak shaving performance. This scenario demonstrates that a moderate battery capacity can significantly reduce peak demand, but the discharge power setting plays a critical role. When the demand momentarily exceeds the battery's discharge limit, minor peak shaving gaps persist. Nevertheless, this configuration offers a high degree of peak load mitigation while maintaining system stability, making it a viable option for moderate peak shaving applications.

Scenario 2: Aggressive Peak Shaving (10 kWh, 3000 W Discharge, 1000 W Baseline)

In this scenario, a more ambitious baseline of 1000 W was introduced, while the battery capacity remained at 10 kWh with 85% efficiency. To meet this stricter peak reduction target, the discharge power was increased to 3000 W, enabling faster and more aggressive peak load reduction.

As shown in Figure 8, this approach initially proved effective, preventing power demand from exceeding 1000 W. However, by 20:45, the battery was fully depleted, leaving the household reliant on the grid for the remaining energy needs. Consequently, peak demand began to rise again, as no stored energy was available for further peak shaving. This resulted in a peak shaving potential of 69.76%, significantly lower than in Scenario 1. This scenario highlights the trade-off between aggressive peak shaving and battery endurance. While a higher discharge power effectively reduces peaks in the short term, it also accelerates battery depletion, limiting the system's ability to sustain peak shaving throughout the entire demand period. To address this, either a larger battery capacity or a more conservative discharge strategy would be required to maintain the effect over extended durations.

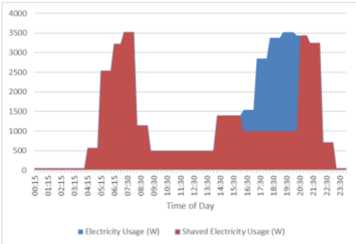

Figure 8: Impact of Battery Storage on Peak Demand in Scenario 2

Scenario 3: Conservative Peak Shaving (5 kWh, 1100 W Discharge, 2500 W Baseline)

In this scenario, a smaller 5 kWh battery system with 85% efficiency was deployed. Unlike the previous cases, a higher baseline of 2500 W was set, aiming for a less aggressive but more sustainable peak shaving strategy. A discharge power of 1100 W was selected to ensure gradual and controlled peak reduction.

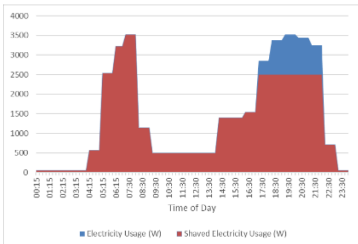

Figure 9: Impact of Battery Storage on Peak Demand in Scenario 2

As depicted in Figure 9, this configuration proved highly effective, successfully reducing almost all peak demand above the 2500 W baseline. The system achieved a peak shaving potential of 99.25%, the highest among the three scenarios. Unlike Scenario 2, where battery depletion was a significant issue, this setup maintained peak shaving throughout the entire peak period without depleting energy reserves too quickly. This scenario demonstrates that even a smaller battery system can deliver high peak shaving efficiency when the baseline is set at a reasonable threshold. By optimizing the relationship between discharge power, capacity, and target baseline, this approach achieves near-complete peak mitigation with minimal resource investment, making it an attractive option for sustainable peak shaving applications.

Table 3 compares the performance of the three scenarios, highlighting the impact of different battery configurations on peak shaving. Scenario 1 achieved a peak shaving potential of 95.13%, but minor gaps persisted due to insufficient discharge power. Scenario 2, with a higher discharge power, initially reduced peak demand effectively but depleted the battery by 20:45, resulting in a lower peak shaving potential of 69.76%. In contrast, Scenario 3 demonstrated that even a smaller battery system can achieve near-complete peak shaving (99.25%) when paired with a conservative baseline and moderate discharge power. These results highlight the trade-offs between discharge power, battery capacity, and baseline targets.

Table 3: results of the DSS

KPIs	Sce 1a	Sce 1b	Sce 2	Sce 3
Baseline Power (W)	1600	1600	1000	2500
Start of Peak	16:15	16:15	16:15	16:15
End of Peak	23:00	23:00	23:00	23:00
Duration of Peak (hrs)	6,75	6,75	6,75	6,75
Time Interval (hours)	0,25	0,25	0,25	0,25
Storage Capacity (Wh)	10000	10000	10000	5000
Storage Efficiency	0,85	0,80	0,85	0,85
Usable Storage Energy (Wh)	8500	8500	8500	4250
Total Peak Energy (Wh)	8782,3	8782,3	12185,2	4282,3
Discharge Power (W)	1700	1700	3000	1100
Max Energy Discharged (W)	1916,21	1916,21	2516,21	1016,21
Energy Discharged (W)	8354,49	8354,49	8500,00	4250,00
Peak Shaving Potential (%)	95,13	91,09	69,76	99,25

Conclusions

This study examined the role of battery storage in managing peak loads in Dutch residential neighborhoods using a decision-support system (DSS) to evaluate three battery configurations. By integrating detailed demand-side simulations with PV generation profiles, we captured distinct consumption patterns across three household types under both summer and winter conditions. Importantly, the proposed DSS offers a versatile framework that can support stakeholders such as energy communities in exploring and selecting suitable storage solutions tailored to their specific needs. By providing detailed insights into demand profiles, PV generation, and storage performance under varying conditions, the DSS empowers communities to design strategies that maximize renewable self-consumption and mitigate grid stress.

Despite these promising findings, several limitations need attention. First, the electricity demand simulations were based on a simplified load profile and personal usage data, which may underestimate real-world peak demands that could be captured with comprehensive smart metering data. Future studies should validate demand simulations against both annual consumption figures and observed daily peak loads. Second, while the system architecture considered the role of gas, it was not directly integrated into the storage scenarios. As the Netherlands transitions away from natural gas, future research should explore the combined impacts of electrification and battery storage on grid stability. Finally, scaling the DSS to encompass larger neighborhoods and extended timeframes would provide deeper insights into demand-side management, collective storage strategies, and their broader implications for grid resilience.

AI Usage Disclaimer

Artificial Intelligence tools especially Grammarly and ChatGPT were used during the writing process of this paper for rewriting text to improve clarity and coherence. All final content and critical analysis reflect the authors' own understanding and judgment.

References

Abbas A. Akhil, Georgianne Huff, Aileen B. Currier, Benjamin C. Kaun, Dan M. Rastler, Stella Bingqing Chen, Andrew L. Cotter, Dale T. Bradshaw, & William D. Gauntlett. (2013). DOE/EPRI 2013 Electricity Storage Handbook in Collaboration with NRECA.

Aneke, M., & Wang, M. (2016). Energy storage technologies and real life applications – A state of the art review. Applied Energy, 179, 350–377.

Beyers, I., Bensmann, A., & Hanke-Rauschenbach, R. (2023). Ragone plots revisited: A review of methodology and application across energy storage technologies. Journal of Energy Storage, 73, 109097.

Castillo, A., & Gayme, D. F. (2014). Grid-scale energy storage applications in renewable energy integration: A survey. Energy Conversion and Management, 87, 885–894.

Elalfy, D. A., Gouda, E., Kotb, M. F., Bureš, V., & Sedhom, B. E. (2024). Comprehensive review of energy storage systems technologies, objectives, challenges, and future trends. Energy Strategy Reviews, 54, 101482.

European Commission. (2023). European Commission. Heat Pumps. https://energy.ec.europa.eu/topics/energy-efficiency/heat-pumps_en#:~:text=According%20to%20Eurostat%20data%2C%20about,for%20space%20and%20water%20heating.

Eurostat. (2024, April 5). Share of renewable energy in gross final energy consumption by sector. https://ec.europa.eu/eurostat/databrowser/view/sdg_07_40/default/line?lang=en

Gamal, A., Abdel-Basset, M., Hezam, I. M., Sallam, K. M., Alshamrani, A. M., & Hameed, I. A. (2024). A computational sustainable approach for energy storage systems performance evaluation based on spherical-fuzzy MCDM with considering uncertainty. Energy Reports, 11, 1319–1341.

Greenchoice. (2024, September). Zonnepanelen. https://www.greenchoice.nl/zonnepanelen/

Guerra-Santin, O., & Silvester, S. (2017). Development of Dutch occupancy and heating profiles for building simulation. Building Research & Information, 45(4), 396–413.

Ibrahim, H., & Ilinca, A. (2013). Techno-Economic Analysis of Different Energy Storage Technologies. In Energy Storage - Technologies and Applications. InTech.

Ibrahim, H., Ilinca, A., & Perron, J. (2008). Energy storage systems—Characteristics and comparisons. Renewable and Sustainable Energy Reviews, 12(5), 1221–1250.

Koohi-Fayegh, S., & Rosen, M. A. (2020). A review of energy storage types, applications and recent developments. Journal of Energy Storage, 27, 101047.

Li, L., Zhou, T., Li, J., & Wang, X. (2022). A machine learning-based decision support framework for energy storage selection. Chemical Engineering Research and Design, 181, 412–422.

Luo, X., Wang, J., Dooner, M., & Clarke, J. (2015). Overview of current development in electrical energy storage technologies and the application potential in power system operation. Applied Energy, 137, 511–536.

Milieu Centraal. (2025). Inductie kookplaat. https://www.milieucentraal.nl/energie-besparen/apparaten-in-huis/inductie-kookplaat/

Ministry of Economic Affairs, TNO-AGE, & NLOG. (2021, January 1). Olie en gas overzicht. https://www.nlog.nl/olie-en-gas-overzicht#:~:text=Aardgasvoorraad,nog%20%C3%A9%C3%A9n%20gasopslag%20in%20zoutcavernes).

NREL. (2025). Best Research-Cell Efficiency Chart. Crystalline Silicon Cells. https://www.nrel.gov/pv/cell-efficiency.html

Rijksoverheid. (2019). Klimaatakkoord. https://www.rijksoverheid.nl/documenten/rapporten/2019/06/28/klimaatakkoord

TNO, & Planbureau voor de Leefomgeving. (2023). Functioneel ontwerp Hestia 1.0.

Wang, S., Hoes, P. J., Hensen, J. L. M., & Adan, O. C. G. (2024). Quantifying the decarbonization potential of mobile heat battery in low-temperature district heating. Sustainable Cities and Society, 113, 105657.