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Investigating the use cases of a novel heat battery in Dutch residential buildings

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Abstract

Recent advances in thermochemical storage technology have introduced a novel closed-loop thermal energy storage (TES) system, known as the heat battery (HB), which is believed to have great potential for aiding the energy transition in the built environment because of its higher energy density and neglectable storage loss compared to conventional TES systems. In order to investigate the potential use cases of the HB and provide practical feedback for its further development, this research employs a simulation-based approach to analyze its influence on building performance in various use cases within Dutch residential buildings. Stakeholders including the homeowner, distribution system operator, and district heating system operator are identified, and a preliminary list of use cases is defined based on relevant literature and input from the HB developer. The simulation approach is conducted to predict key performance indicators for each stakeholder. The Kruskal-Wallis test was employed to sort and scrutinize the simulation outcomes and discern the significance of each use case element. The findings demonstrated that the HB holds the potential to diminish both the operational energy cost by up to 30% for the homeowners and the peak heating load transmitted from the building to the district heating system.

Keywords

thermochemical storage
building performance simulation
use case
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demand-side management

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1 Introduction

The management of building energy demand and the fluctuations in renewable energy production has posed a growing challenge, prompting significant research efforts towards energy storage in buildings. Energy storage is crucial for managing self-consumption as well as storing surplus energy for later use during periods of insufficiency, especially towards net-zero energy buildings (Ahmed et al. 2022). Different energy storage technologies are being utilized in buildings. Electrical batteries (chemical storage) are used for improving the self-consumption of onsite-generated electricity (Luo et al. 2022) and for reducing buildings' dependency on the grid (Mohammadi et al. 2020). For sensible thermal energy storage, there are both compact systems like water buffers for storing solar energy (Da et al. 2023), and large-scale systems such as aquifer thermal energy storage for digesting massive thermal energy from some sustainable sources (Dvorak et al. 2020). For latent thermal energy storage, many phase change materials are employed for various purposes including stabilizing indoor temperature (Berardi and Soudian 2018) and decreasing buildings' energy demand (Sharshir et al. 2023). Thermochemical energy storage is a promising form of energy storage due to its ability to provide high energy densities (Lizana et al. 2017), exhibit sufficient round-trip efficiencies (Cherrad and Ghiaus 2021), and offer flexibility in terms of charging (Aydin et al. 2016) and discharging (Shkatulov et al. 2020) capacities.

The heat battery (HB) is a closed-loop thermochemical energy storage system. It employs the reversible hydration mechanism of potassium carbonate (K_2CO_3) composites. When being charged, the HB absorbs thermal energy from the hot fluid supplied by an external heat source to dehydrate the composites contained in the storage module (the TCM

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module as shown in Figure 1). When discharged, the composites are hydrated to release thermal energy and heat the cold fluid from an external heat sink. The HB uses air as the heat-transfer media between the external heat source/sink and the composites and employs an electricity-powered circulating system to ensure continuous charging or discharging power of thermal energy. Compared with conventional TES technology, the heat battery has a higher energy density (around 1.0 GJ/m^3 at particle bed level with 25% porosity) and neglectable storage loss. There have been many experiments and demonstrations for the HB available in the literature such as Mazur et al. (2022) and Heat-Insyde (n.d.a).

The current technology readiness level (Hensen et al. 2015) of the HB has reached the phase of prototype demonstration and is moving towards extensive applications, but the direction of applications has not been decided due to the lack of research support. Although researchers have studied the properties of various thermochemical materials (Donkers et al. 2017), the reactor-level (Pan and Zhao 2017) or system-level (Fopah-Lele et al. 2016) performance of different thermochemical storage, and the potential of some thermochemical storage systems in particular use cases including activating building's demand flexibility (Finck et al. 2018) and shaving the electric peak load on the local grid (Hutty et al. 2020), and reducing buildings' operational energy cost (Weber et al. 2022). There remains uncertainty about the types of building applications in which the heat battery can demonstrate promising potential for stakeholders, and how this potential is influenced by varying use environments (such as the building and energy system) and scenarios (including occupant scenarios and energy policy). This leads us to a critical research question that we seek to answer: What is the promising use case of the heat battery?

To address this question, it is necessary to define the potential building applications of the HB with all the mentioned elements included, which needs a more distinct concept such as the use case. According to Jacobson et al. 2011), the use case defines the ways of using a specific system to achieve a particular purpose for the user and illustrates the value that the system can provide. This definition covers the way of using, the studied system, the purpose, the user, and the potential value, but lacks the consideration of some other influential factors when applied to the HB, such as the facility (building and energy system), the scenario (occupancy and policy), and other stakeholders (in addition to the user). Therefore, this research adopts the use case to define the particular way of using the HB under a designated strategy within the facility of building and energy system to achieve a particular purpose for the stakeholder upon certain scenarios of occupant behaviors and energy policies. Based on this concept, this article proposed a simulation-based methodology to define, assess, and compare diverse use cases of thermochemical storage systems in buildings and demonstrated this methodology with the information about the HB's prototype and the assumption concerning Dutch residential buildings in the future.

This work's main contribution is the exploration of various use cases of the novel HB in typical residential buildings in the Netherlands. The investigated use cases involve three stakeholders, six operational strategies, four types of building geometry, three levels of insulation, multiple energy system configurations, and several scenarios of occupant behavior and energy policy. The results include a preliminary list of the HB's use cases, the predicted values of the key performance indicators, the impacts of the use environment and scenario on the predicted results, the promising use cases, and suggestions for the HB's further development. Section 2 of this paper gives an explicit description of the methodology proposed and implemented by this research. It includes the overall workflow and all the specific methods adopted in each essential step. Section 3 presents the results from the first step of the methodology. It includes all the considered stakeholders and their purposes,

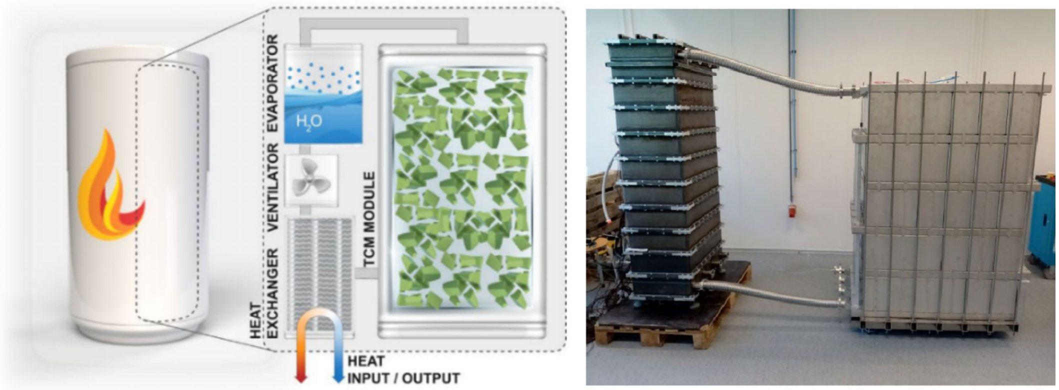


Fig. 1 The schematic diagram (left) (Heat-Insyde n.d.b) and the prototype photo (right) of the HB (Cellcius 2021) (© Cellcius 2021 for Heat-Insyde)

the defined KPIs, variants of buildings and systems, and scenarios of occupants and policies. Section 4 introduces the results from the second and third steps of the methodology. It analyzes the use cases for different stakeholders and briefly discusses the potential of stacking different use purposes. Section 5 is the discussion and conclusion of this study. It includes the results of the methodology's fourth step and a reflection on the whole research process.

2 Methodology

In this study, the use case of the HB is defined as the particular way of using the HB under a designated strategy within the facility of building and energy system to achieve a particular purpose for the stakeholder upon certain scenarios of occupant behaviors and energy policies. A defined use case of the HB includes the following elements:

Stakeholder: who may benefit from the usage of the HB;
Value: the key performance indicator (KPI) representing the stakeholder's purpose;
Strategy: the operational strategy of using the HB;
Facility: the building and energy system where the HB is used;
Scenario: the scenario of occupants' behaviors and energy policy when the HB is used.

Based on the definition mentioned above, this research proposes the following methodology for investigating various use cases of the HB. It consists of four essential steps. The first one is the use case definition. It collects information from literature and the HB developer to define a preliminary list of potential use cases and combine the selected use case elements into detailed modeling and simulation assumptions. The second step uses these assumptions to model the buildings, energy systems, and operating strategies in all use cases. It employs a simulation approach to predict each use case's KPI and includes the verification of the predicted results. The third step includes the classification, comparison, and analysis of the calculated KPIs based on the elements of their corresponding use cases. Use cases with acceptable values of KPI will be delivered for sensitivity analysis while the rest will be analyzed for possible improvement in any use case elements. The fourth step focuses on summarizing the numerical information provided by the third step into either the profile of the valuable use case or suggestions for further developing the HB. Figure 2 shows an overall flowchart of this methodology.

2.1 Step 1: use case definition

This methodology's first step is to confirm a preliminary list of potential use cases and combine the included use case elements into assumptions for modeling and simulation. It studies other thermal storage systems' applications from the literature and identifies the potential stakeholders, their purposes, and strategies for using the HB. The identified content forms an initial set of use cases and will be communicated with the HB's developer.

The second thing is to summarize the content and the feedback provided by the HB's developer to define the preliminary list of the use cases. They include the building and energy system facility that can integrate the HB, the scenario of occupant's behavior and energy policy, and the operational strategy of the HB. According to these elements, assumptions can be defined and sent to the next step. For modeling the buildings and their occupants, assumptions involve buildings' geometry types and insulation levels, occupants' setpoints for space heating, domestic hot water consumption, and other power consumptions (such as lighting, plug-in appliances).

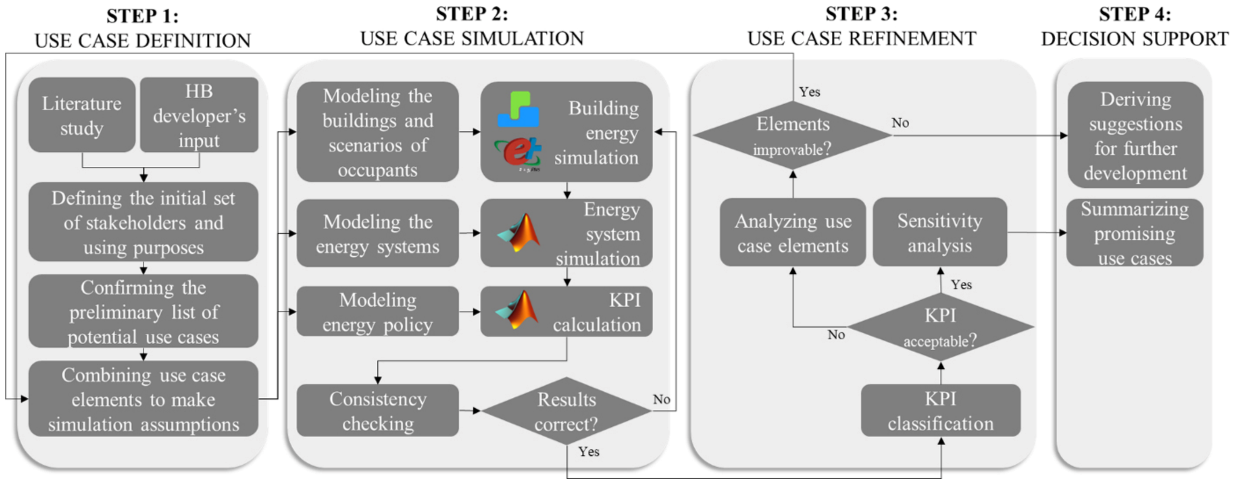


Fig. 2 Methodology of this study

2.2 Step 2: use case simulation

The second step is to virtually predict the KPIs of each use case via a modeling and simulation approach. According to the BEST directory (BEST n.d.), there are currently more than 70 whole building energy simulation tools. DesignBuilder and EnergyPlus are popular because of their high accuracy and ability (Attia et al. 2012). They also fit the requirements of modeling all the aspects of buildings for this research. Therefore, this approach selects DesignBuilder to model the thermal shell of the building in each use case and EnergyPlus for editing the details of occupants' behaviors and for running simulation. In each IDF, the inside surface convection algorithm used is TARP, while DOE-2 is employed for the outside surface. The heat balance algorithm relies on the conduction transfer function. Weather data for Amsterdam is utilized in these simulations. It's worth noting that both TARP and DOE-2 assume that the natural convection heat transfer coefficient remains constant regardless of surface temperature, which could potentially lead to inaccuracies in heat loss estimation. Nevertheless, modeling a residential building in Amsterdam using these algorithms is generally expected to yield reliable results due to the city's moderate climate with no extreme temperature variations. The simulation timestep is set to 15 minutes for calculating required KPIs.

However, current building energy simulation tools are incapable of directly modeling the HB and the energy system with its integration because of the novelty of the HB. Thus, in this research, MATLAB is used to develop numerical models of the HB, the energy system, and the operational strategy. These models use the energy demand time series calculated by EnergyPlus as inputs. The required complexity of the numerical model depends on the purpose of this simulation (for instance, the KPIs). In this research, most of the relevant indicators are related to the building's operational energy performance, such as the operational cost for energy or peak electric or thermal load. They can be estimated based on a model with a "conceptual complexity" level (Hensen 1996). An example of conceptual model complexity is representing a heat pump system with its coefficient of performance (COP) or the heating seasonal performance factor (HSPF).

Table 1 lists all the energy systems and their conceptual models used in this research. This modeling approach can reduce the simulation time that might be unnecessarily long. Combing this with MATLAB's strength in matrix calculation and capability of parallel-loop computing, the entire approach can generate the KPIs of a large group of use cases within an acceptable duration. Therefore, the HB and the energy systems are modeled at this level of model complexity. If the defined KPIs cannot be calculated, the complexity will be adjusted to a more suitable level (Xu 2020).

The HB itself is also represented at a conceptual model complexity. Its heat balance is calculated by:

$$Q_{\mathrm{HB}}(t) = Q_{\mathrm{HB}}(t-\Delta t) + \eta_{\mathrm{c}} \cdot q_{\mathrm{c}}(t) \cdot \Delta t - \eta_{\mathrm{d}} \cdot q_{\mathrm{d}}(t) \cdot \Delta t \tag{1}$$

Here, Q_{HB} is the heat stored in the HB (kWh). η_{c} (η_{d}) are the thermal efficiency of the charging (discharging) process, and they are assumed to be 100% in this screening study. q_{c} and q_{d} are the charging and discharging powers of thermal energy (kW), respectively. The t is the time, and Δt is the simulation timestep. The HB is assumed to have no storage loss and it needs electricity to power the circulation of the air loop. Its electricity consumption is counted by:

$$E_{\mathrm{HB}}(t) = q_{\mathrm{c}}(t) \cdot \Delta t \,/\, \mathrm{COP}_{\mathrm{c}} + q_{\mathrm{d}}(t) \cdot \Delta t \,/\, \mathrm{COP}_{\mathrm{d}} \tag{2}$$

In Eq. (2), E_{HB} is the consumed electricity for the charging and discharging processes of the HB (kWh). The $\mathrm{COP}_{\mathrm{c}}$ or $\mathrm{COP}_{\mathrm{d}}$ are equal to the charged or discharged thermal energy divided by the HB-consumed electricity, respectively, and they are assumed to be 30. The performance of the HB (η_{c}, η_{d}, $\mathrm{COP}_{\mathrm{c}}$, $\mathrm{COP}_{\mathrm{d}}$) can be influenced by many factors which may vary per use case. Therefore, we decided to explore the maximum potential under these ideal

Table 1 Energy system variants and related models

Energy system option		Input variable	Model	Output variable
Electricity source	Photovoltaic	Solar irradiance (kW/m²) Area (m²)	Conversion efficiency	Electric power (kW)
	Electric grid	—	—	Electric power (kW)
Heat source	Solar thermal collector	Solar irradiance (kW/m²) Outdoor temperature (°C) Inlet temperature (°C) Area (m²)	ISO efficiency equation (SRCC 2022)	Thermal power (kW)
	Electric boiler	Electric power (kW)	HSPF	Thermal power (kW)
	Air-to-water heat pump	Electric power (kW)	HSPF	Thermal power (kW)
	District heating system	—	—	Thermal power (kW)

assumption values in all use cases to first exlpore the possible direction of the HB's development. The charge and discharge powers are related to the design of the HB and the defined operating strategy in each specific use case. For a 200 kWh HB, the maximum charging power is set to 5 kW and the maximum discharging power is set to 3 kW. All the above parametric assumptions are based on the developer's previous experiments on HB's prototype, and these values are realizable under certain conditions.

This step also includes consistency checking (Balci 1994) to verify the correct implementation of the models and operational strategies. The consistency of the HB's state-of-charge and the designated operational strategy is checked, and the modeling and simulation will be corrected and re-executed if any errors are recognized.

2.3 Step 3: use case refinement

The third step is to analyze the impacts of various use case elements on the KPIs and identify the promising use cases based on KPI values preferred by each stakeholder. Since different operational strategies stand for different using purposes and ranges of KPI values, it is necessary to first classify the values of each KPI by the corresponding operational strategies and then identify those that can be of interest to the stakeholder. In the use cases with those interesting operational strategies and acceptable KPIs, different facilities and scenarios may have various impacts on the KPIs. Thus a sensitivity analysis is used to understand the influence of these parameters on the KPIs. Statistical methods often used for sensitivity analysis are listed in Table 2.

The options of using environments and scenarios are independent, and there can be more than three options in one aspect (such as four different building geometries), so this study selects the Kruskal-Wallis test. This method compares the medians of variant data groups to determine if the samples come from the same population or different populations with the same distribution. It outputs the p-value to indicate the significance of the option. In this study, if the p-value is smaller than 0.01 ($1 - p > 0.99$), it suggests that the variants in this option (of facility or scenario) have different distributions (Ostertagová et al. 2014). Hence, the trend revealed by these variants needs to be considered. In this research, we compared $1 - p$ values calculated based on the KPIs grouped by different options of each use case element to check the element's impact on the KPI. For use cases without acceptable KPIs, their elements will be further analyzed to figure out the cause. If the elements turn out to be improvable, the second step shall be executed again with adjusted models.

2.4 Step 4: decision support

The final step of the methodology is to convert the quantitative results into conclusions that can support either the further development of the HB and/or the determination of its promising market. The use cases with promising KPI values directly present the operation strategies, facilities of buildings, and energy systems configurations that are appropriate for using the HB. While the remaining part of the use cases also reveals the possible technical gap between the current HB design and the requirement from the market practice.

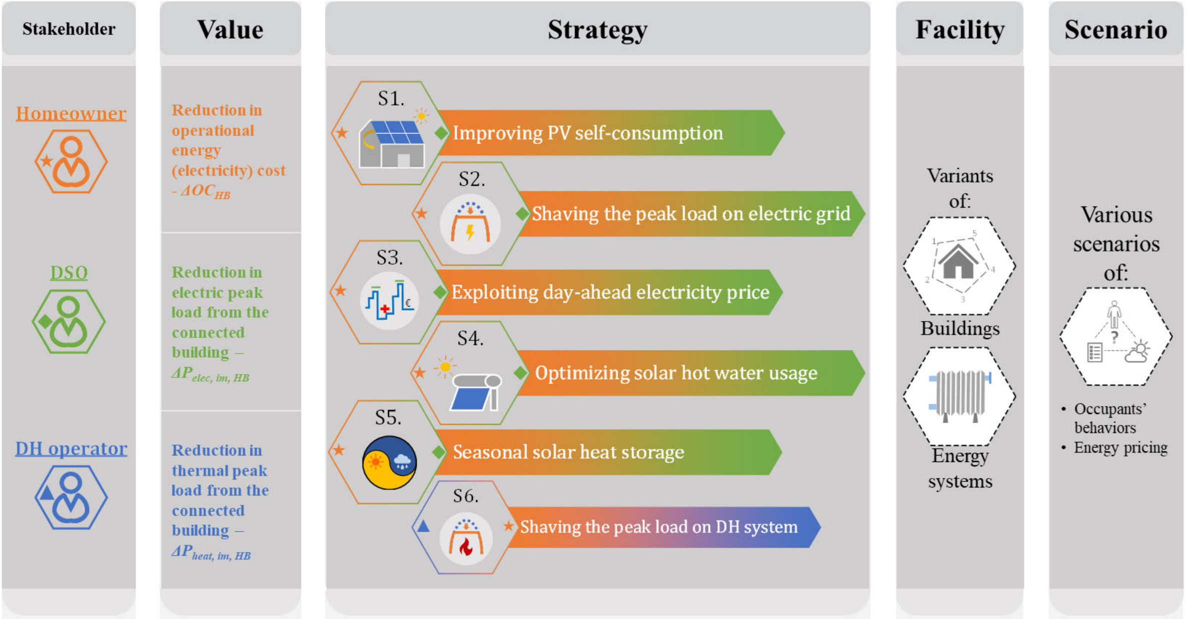
3 Definition of use cases

Based on a literature study, we found various ways of using the HB in residential buildings to form an initial set of use cases. The operational strategies include: improving PV self-consumption (Crespo et al. 2023), shaving the electric peak load on grid (Finck et al. 2018), exploiting day-ahead dynamic electricity price (Fitzpatrick et al. 2020), optimizing solar thermal energy consumption (Gaonwe et al. 2022), seasonal solar heat storage (Weber et al. 2022), shaving the peak load on the district heating system (Ju et al. 2023), optimizing solar absorption cooling (Ahmad and Ding 2021), improving heat pump performance (Da et al. 2023), using the HB's component for space cooling, waste heat recovery (Miró et al. 2016), and so on.

After the discussion with the HB's developer, a preliminary list of use cases is defined as Figure 3 shows. Considered stakeholders include: the homeowner, the distribution system operator (DSO) of electric grid, and the district heating (DH) operator. They are assumed to have six different strategies for using the heat battery (S1 to S6, see also Figure 3). The three colors (orange, green, and blue) and icons (star, rhombus, and triangle) indicate the relations between the stakeholders and other use case elements. For instance, the

Table 2 Four non-parametric statistical test methods for sensitivity analysis (Xu 2020)

Test method	Dependency of option	Number of variants in one option
Mann-Whitney U	Independent	2
Kruskal-Wallis	Independent	2 or more
Wilcoxon signed-rank	Dependent	2
Friedman's	Dependent	2 or more



DSO = distribution system operator, DH = district heating (system).

Fig. 3 The preliminary list of use cases selected in this research

homeowner can use the HB under five operation strategies from S1 to S5, so strategies S1 to S5 share the same color (orange) and icon (star) as the homeowner. The following three parts of this sector give details of the three stakeholders, and the last one illustrates the six strategies.

3.1 The homeowner

It is assumed that the primary motivation for homeowners to adopt the HB is to minimize operational energy expenses. For buildings that are not connected to the local DH system, the majority of these costs are expected to arise from electricity consumption in the future. This is because the residential sector in the Netherlands is gradually transitioning towards electrification (González and Mulder 2018). Therefore, the operational cost of energy is calculated as follows:

$$OC = E_{\mathrm{im}} \cdot p_{\mathrm{im}} + \sum_{m=1}^{12} E_{\mathrm{p},m} \cdot p_{\mathrm{p}} - \left(E_{\mathrm{ex}} \cdot p_{\mathrm{ex}} + E_{\mathrm{self}} \cdot p_{\mathrm{self}} \right) \qquad (3)$$

Here, OC is the annual operational cost for electricity consumed by the building without HB (€). E_{im} is the electricity imported from the local grid (kWh), and E_{ex} is the electricity exported from the building (kWh). The basic importing and exporting prices are assumed to be p_{im} and p_{ex} (€/kWh), respectively. Especially, OC includes the peak load cost (vrt 2020) and the PV-self-consumption incentive. The extra peak load cost is calculated by the electricity consumed with an electric load above 2.5 kW (E_{p}, kWh) in each calendar month (m) and its price rate (p_{p}, €/(kW·kWh)). The extra PV-self-consumption incentive included in OC can be calculated by the onsite-consumed electricity from PV (E_{self}, kWh) and its incentive rate (p_{self}, €/kWh).

Based on Eq. (3), the HB's reduction on the operational cost is:

$$\Delta OC_{\mathrm{HB}} = OC - OC_{\mathrm{HB}} \qquad (4)$$

Here, OC_{HB} denotes the annual operational cost for electricity consumed by the building with a HB (€). It uses the same function as OC. The ΔOC_{HB} is exactly how much annual cost the HB can reduce for the homeowner.

In this study, three scenarios of electricity contracts (both importing and exporting) are assumed, as Table 3 presents.

To reduce the OC, the homeowner can use the HB under the five strategies (from S1 to S5) as mentioned in Figure 3. The first three strategies (S1 to S3) require an air-to-water heat pump and S1 needs PV modules, while S4 and S5 use solar thermal collectors as the main heat source with a backup electric water heater.

According to the current practice and regulations in the Netherlands, various buildings (building geometry and insulation condition) and occupant scenarios (hot water consumption, space heating setpoint, occupancy pattern etc.) are defined. The geometries of the detached house, the mid-terraced house, and the studio are based on the reference building in Ministry of Interior and Kingdom Relations (2017), and the tiny house was based on the one project of Heijmans (Heijmans-ONE n.d.). The occupants' scenarios were based on the information from Guerra-Santin and Silvester (2017) and Kotireddy (2018), and the

Table 3 Scenarios of different electricity policies and dynamic prices refer to the data from (Nord Pool n.d.)

	Importing			Exporting	
Scenario	p_{im} (€/kWh)	p_{p} (€/(kW·kWh))	Scenario	p_{ex} (€/kWh)	p_{self} (€/kWh)
1. Fixed price	0.25	0.00	1. Net-metering	p_{im}	0.00
2. Peak-load penalty	0.20	0.08	2. Low feed-in incentive	0.06	0.00
3. Day-ahead dynamic	Dynamic	0.00	3. Self-consumption incentive	0.00	0.06

domestic hot water consumption value is set according to the Dutch technical agreement (NEN 2021). The used weather file was download from EnergyPlus official website (Amsterdam 062400 IWEC). Figure 4 shows detailed assumptions.

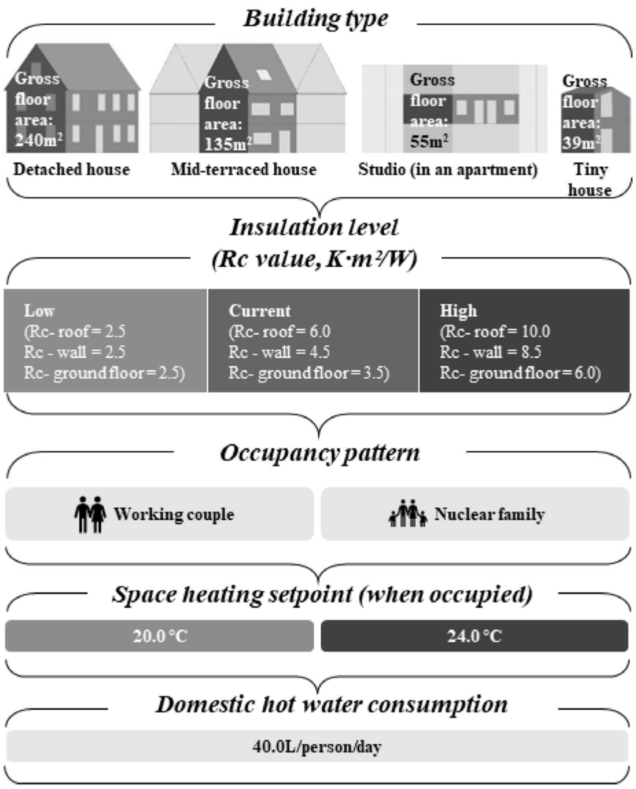


Fig. 4 Building variants and occupant scenarios considered in this research

3.2 The electricity distribution system operator (DSO)

The second stakeholder is the DSO of local electricity grid. Unlike the homeowner, DSO will not directly integrate the HB in its own system. It will define certain pricing strategy to stimulate the end-users to manage their own peak load. The DSO is assumed to encourage the connected homeowners to use the HB to reduce the peak load of importing electricity from the grid ($P_{\text{elec,im}}$, kW). The reduction can be calculated from:

$$\Delta P_{\text{elec,im,HB}} = P_{\text{elec,im}} - P_{\text{elec,im,HB}} \tag{5}$$

The $P_{\text{elec,im}}$ is the peak importing load from the electric grid to the building without HB (kW). It is the maximum value in the annual time series with a 15 minutes timestep as required by many Dutch energy suppliers. $P_{\text{elec,im,HB}}$ is the peak importing load in building with HB (kW), so $\Delta P_{\text{elec,im,HB}}$ is the reduction of the peak load (kW).

3.3 The district heating (DH) operator

The third stakeholder is the operator of the local DH system. It is assumed to directly employ the HB to reduce the peak thermal load on its system, as described in Hutty et al. (2020). In this study, the HB is assumed to be installed in a DH system serving a residential neighborhood consisting of 50 houses. All the houses in one area are assumed to have the same building facilities and occupant scenarios as Fig. 4. The KPI for the DH operator is the reduction on the peak thermal load from the 50 houses in one DH system, and it can be described as:

$$\Delta P_{\text{heat,im,HB}} = P_{\text{heat,im}} - P_{\text{heat,im,HB}} \tag{6}$$

Here, $P_{\text{heat,im}}$ is the peak thermal load of delivering heat from the DH system without HB to the 50 connected houses (kW). It is the maximum value in the annual time series with a 15 minutes timestep and regards a coincidence factor of 0.3 (Knoben 2020). $P_{\text{heat,im,HB}}$ is the reduced thermal peak load of the DH system with HB (kW), and $\Delta P_{\text{heat,im,HB}}$ is the reduction of the peak load (kW).

3.4 The operational strategies

To implement the six operational strategies (S1 to S6) of the HB, the conditions for charging and discharging the HB were defined as shown in Table 4. S1 mainly uses the electric power of PV generation and the predicted electric load of the building to determine the HB's state. S2 requires the comparison between the electric demand power and two defined threshold values for charging and discharging. S3 combines the day-ahead electricity price with the predicted electric demand power and also employs two defined threshold values which are daily updated. S4 and S5 check the predicted solar thermal energy on the collector surface and controls the HB accordingly while S5 considers the

Table 4 Charging/discharging conditions for different operational strategies

Strategy	Charging condition		Discharging condition	
S1	PV generated electricity > electric demand	& HB not full	—	& HB not empty; & Heating demand > 0; & HB not being charged
S2	Predicted electric demand power < a threshold		Predicted electric demand power > a threshold	
S3	Predicted electric cost < a dynamic threshold		Predicted electric cost > a dynamic threshold	
S4	Solar heat available		—	
S5	Solar heat available & outdoor air temp > 20 °C		Outdoor air temp < 10 °C	
S6	Predicted heating demand < a threshold		Predicted heating demand > a threshold	

outdoor air temperature as the indicator for switching HB's state. S6, different from S1 to S5, uses the predicted heating demand power from a group of buildings and compares it with two defined values for controlling the HBs. All the threshold values were defined based on the predicted demand profiles of each building. For charging, all six strategies share the same condition that the HB is not full (state-of-charge is below 100%), while for discharging, they share three conditions including that the HB is not empty (the state-of-charge is above 0%), the building has heating demand, and the HB is not being charged.

4 Simulation and refinement of use cases

The defined preliminary list results in more than thirty thousand combinations of use case elements and thus needs over thirty thousand simulation runs. Over twenty-eight thousand are for the homeowner and DSO, and the rest are mainly for the DH operator.

4.1 Predicted space heating demand

To validate the simulation results from EnergyPlus (DesignBuilder), we compared the predicted space heating demand for each building model to relevant statistic data and existing literature. From the StatLine of CBS (Centraal Bureau voor de Statistiek n.d.), we find the average natural gas consumption of a detached house in Amsterdam was around 1800 to 2300 m^3 from 2017 to 2021. It was around 940 to 1100 m^3 for a terraced house, and 730 to 840 m^3 for an apartment. Excluding a 200 (working couple) to 280 (nuclear family) m^3 consumption for domestic hot water and 20 (working couple) to 40 (nuclear family) m^3 consumption for cooking (van Beijnum et al. 2023), we got the average gas consumption for heating the space in each building type as: 1480 to 2080 m^3 for detached house, 620 to 880 m^3 for terraced house, 410 to 620 m^3 for apartment. Base on a 90% efficiency and the usable floor area of the modeled buildings, we converted the gas consumption data into the annual space heating demand in kWh/m^2 as: 78 to 110 for the detached house, 50 to 70 for the terraced house, and 46 to 65 for the apartment. The simulation results of these three building types with low and current insulation levels fall within the same range of these values, shown in Figure 5.

The tiny house model is based on the ONE residence project which has been investigated in a previous research (Y. Song 2016). The research indicated the annual space heating demand around 20 to 55 kWh/m^2 with a 20 °C heating set point and construction properties similar to current insulation level in our assumptions. The corresponding range in Figure 5 is also closed to the previous research.

4.2 State-of-charge fluctuation in different use cases

From all the finished simulation runs, we chose six typical ones to check the consistency between the results and defined operational strategies. Figure 6 shows how the HB's state-of-charge (SoC) will fluctuate in the chosen use cases with different operational strategies.

The left side of Figure 6 shows the yearly overview of the HB's SoC fluctuation in selected cases. In use cases with S1, S4, and S5, the SoC fluctuation presents an obvious seasonal distribution due to the seasonal variation of solar energy, although S1 and S4 aim originally for short-term storage. In use cases with S2 and S3, the storage capacity of the HB is highly charged most time because these two strategies require the HB to always be ready for any unexpected

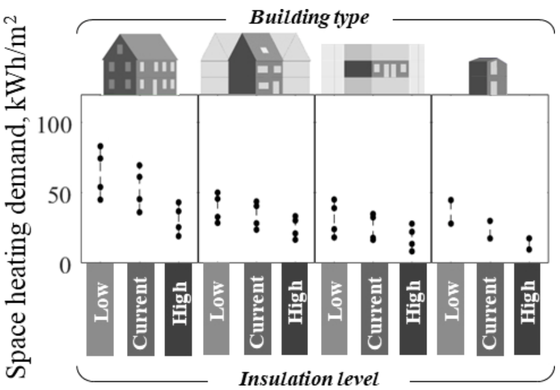


Fig. 5 Predicted annual space heating demand per usable floor area in studied building facilities

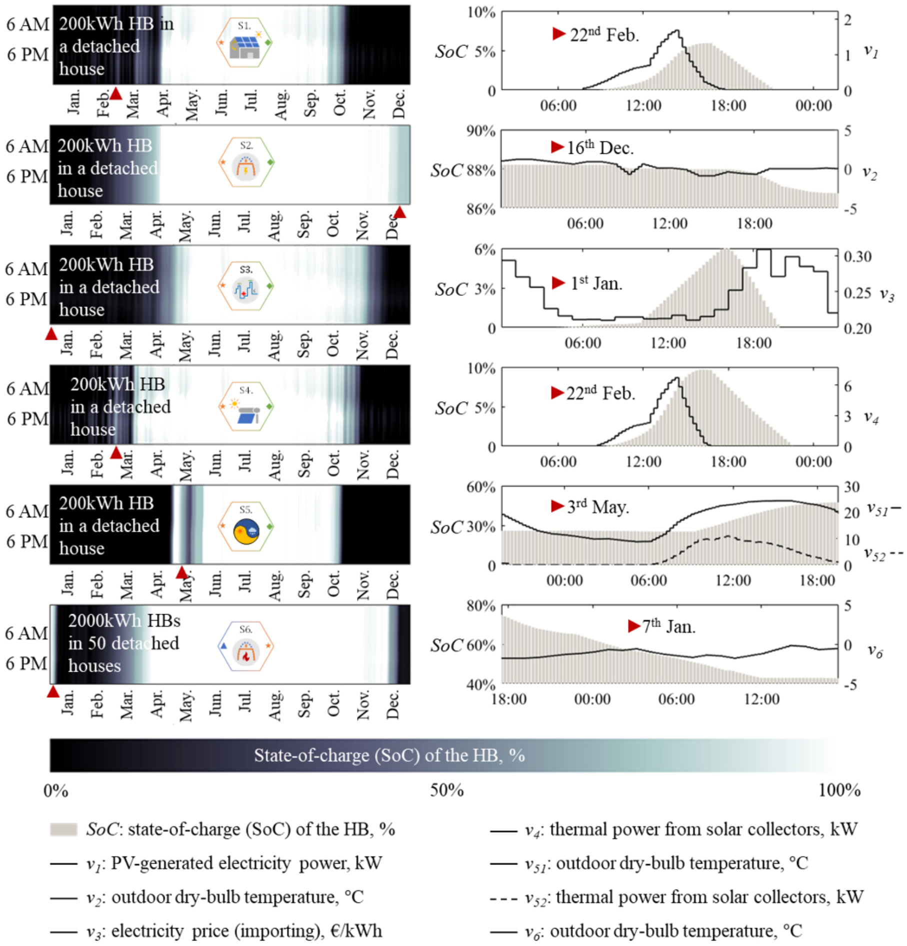


Fig. 6 Predicted state-of-charge fluctuations of the HBs in selected use cases representing six operational strategies (heatmaps on the left) with zoom-in operational variables on typical days (bars and lines on the right)

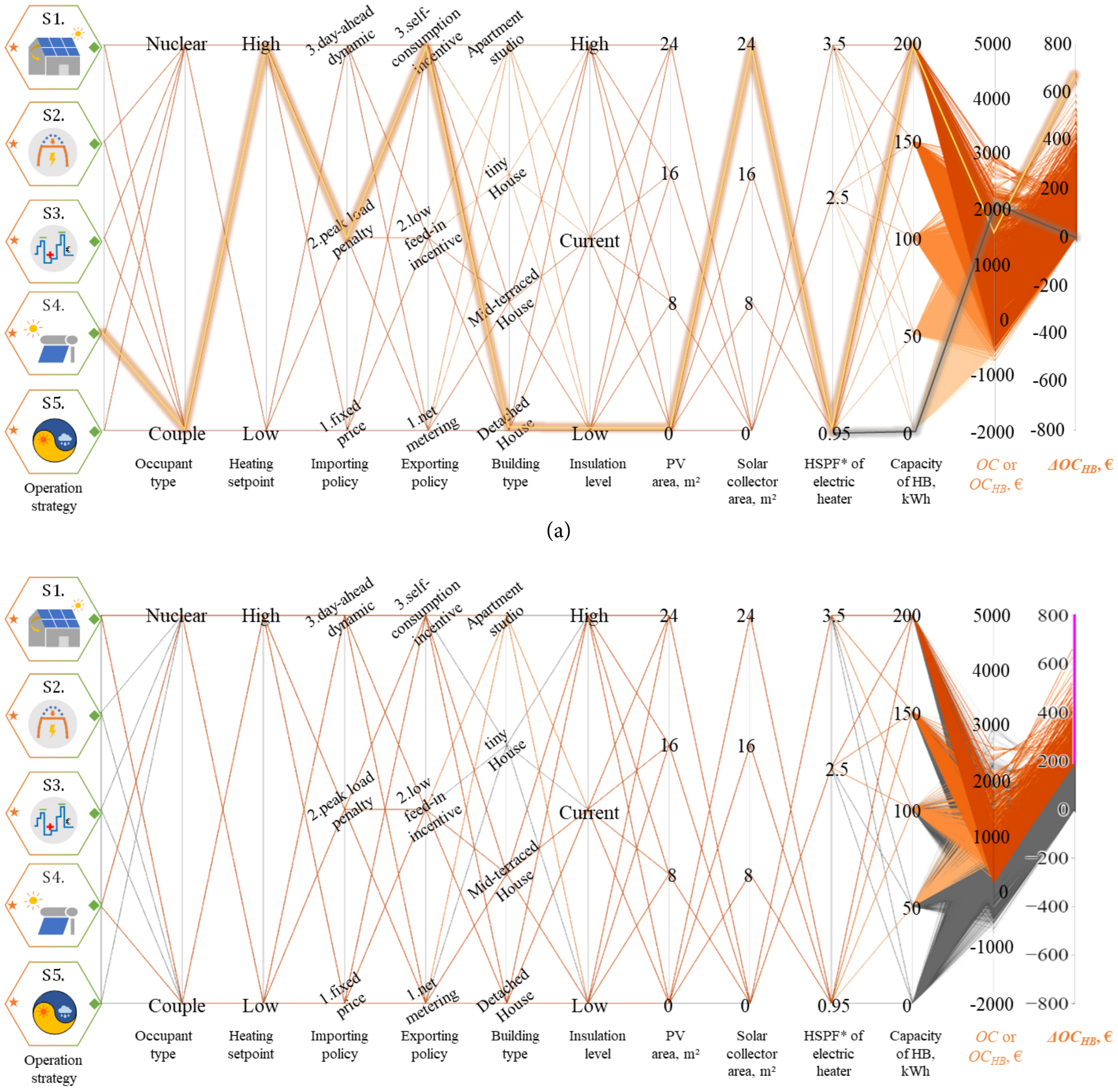
discharging order. In use cases with S6, the HBs were assumed to have a 5 kW maximum charging power and full in the beginning. There are two rapid drops of the SoC in January and December because of possible discharging for shaving the high heat load. Apart from that, the HB is either slowly charged or stands by.

The right side of Figure 6 provides more detailed information of the operational strategies on six typical days for each selected cases. The HB's SoC could follow the energy harvested by PV or solar thermal collectors in use case with S1 and S4, as the graphs on the zoom-in date of 22nd of February illustrate. In the line and bar charts corresponding to S2 and S6, the SoC values gradually drop due to high heating load (indicated by the low outdoor air temperature). In use case with S3, the charging and discharging behaviors of the HB are dominated exactly by the fluctuating electricity price, as the SoC increases at low price and decreases at high one. For seasonal storage (S5), the line and bar graph shows the joint control from the outdoor air temperature and solar energy for charging the HB. Generally, each SoC fluctuation is able to show the designated pattern for each operation strategy and therefore verifies the implementation of the simulation approach.

4.3 Use cases for homeowner and DSO

Figure 7 illustrates the anticipated performance of all the use cases examined, with the homeowner as the primary stakeholder. The storage capacity of the HB is denoted by the line colors, and the blue lines connected to zero capacity indicate the reference cases without the HB. The highlighted lines in Figure 7(a) depict the use case with the greatest reduction achieved by the heat battery (HB), whereby a 200 kWh HB can lower annual electricity expenses from roughly 2100 euros to 1500 euros. The data suggests that the HB has the ability to decrease annual electricity costs by anywhere from 0 to 400 euros, with some extreme cases potentially yielding reductions exceeding 600 euros.

Suppose the homeowner prefers to have more than 200 euros reduction on electricity cost by using the heat battery. In that case, they will find the operation strategies S1 and S4 more interesting than others, as is shown in Figure 7(b).



(a)

(b)

Fig. 7 (a) Parallel coordinate plot of the annual operational cost (OC or OC_{HB}) for electricity and the corresponding reductions (ΔOC_{HB}) in use cases with strategies S1 to S5. The highlighted pair of lines leads to the highest reduction value. (b) Parallel coordinate plot with a filter of the reductions ΔOC_{HB} higher than 200 euros per year

This work selects the use cases using S1 and S4 for further analysis. Most variants of the facility and scenario are still connected (not grey) to the selected range of the KPI, which means that all variants should be considered in the next step.

Figure 8 illustrates how each facility variant (building and energy system) and scenario (occupant and energy price) affect the ΔOC_{HB}. Export contract type 1 is not considered in use cases featuring S1, as it is illogical to store heat generated from PV electricity if the prices of importing and exporting it are the same. Similarly, use cases with S4 do not factor in PV modules as part of their energy system, so exporting contracts are not taken into account.

For use cases under S1, as the $1 - p$ values denote, the building geometry type, HSPF, the HB's storage capacity, PV area, setpoint of space heating, and the policy for exporting electricity can influence the ΔOC_{HB} significantly based on the Kruskal-Wallis tests. Under S1 control, larger buildings equipped with more PV modules and heat pumps with lower HSPF may experience greater electricity cost reductions through the use of the HB. For use cases with S4, all the variants except occupant profiles have a $1 - p$ value higher than 0.99, which means they are all vital to the KPI in the use case.

Both the HB's storage capacity and building geometry type play a role in determining the upper and lower limits of ΔOC_{HB}, while the other two facility variations affect only the upper limit. Therefore, it is more beneficial for homeowners to employ the HB (with S4) in buildings with higher heating demands. The greater the HB's storage

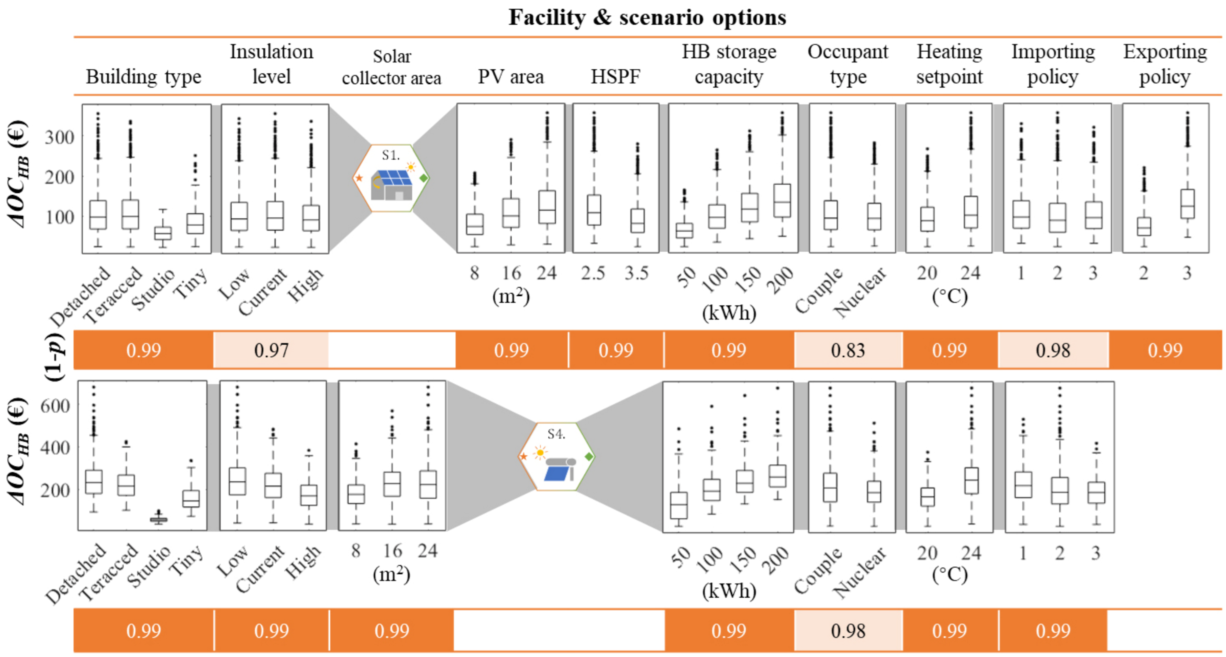


Fig. 8 Boxplots of the reduction of operational electricity costs by HBs (ΔOC_{HB}) with different facilities and scenarios in use cases using S1 or S4, with the $1-p$ value below the boxplot of each option

capacity, the more operational cost (OC) reductions it can achieve. For use cases involving either S1 or S4, the types of occupants and electricity import contracts have less impact on ΔOC than heating setpoints. Particularly under S1, the ΔOC is highly influenced by electricity export policies.

Besides the homeowner, the electric heat sources' interaction with the electric grid in use cases with S1 to S5 may also attract the interest of DSO. Consequently, the 15-minute average peak electric loads $P_{\mathrm{elec,im,HB}}$ and $\Delta P_{\mathrm{elec,im,HB}}$ were also calculated and classified as is presented in Figure 9.

Because of the seasonal performance fluctuations of use cases with S1, S4, and S5, the heat battery cannot effectively deal with the peak load rising in winter. The values of $\Delta P_{\mathrm{elec,im,HB}}$ in use cases with these three strategies are all around 0. Furthermore, in some use cases with S3, the HB may increase $P_{\mathrm{elec,im,HB}}$ due to the discrepancy between the historical day-ahead prices and the predicted electric demand of building models. This situation highlights the potential risk of implementing this pricing strategy for the distribution system operator (DSO) as the low prices may result in an unforeseeable peak load. Conversely, in use cases with S2, where the HB is primarily utilized for reducing electric peak loads, it can significantly enhance peak shaving performance, achieving a peak load reduction of approximately 35%.

4.4 Use cases for DH operator

In addition to the decentralized heating systems referenced earlier, it is assumed that the district heating (DH) system operator installs the HB in their centralized heating system to mitigate the peak load of providing heat to 50 houses with identical design.

Figure 10 displays the predicted $P_{\mathrm{heat,im,HB}}$ and $\Delta P_{\mathrm{heat,im,HB}}$

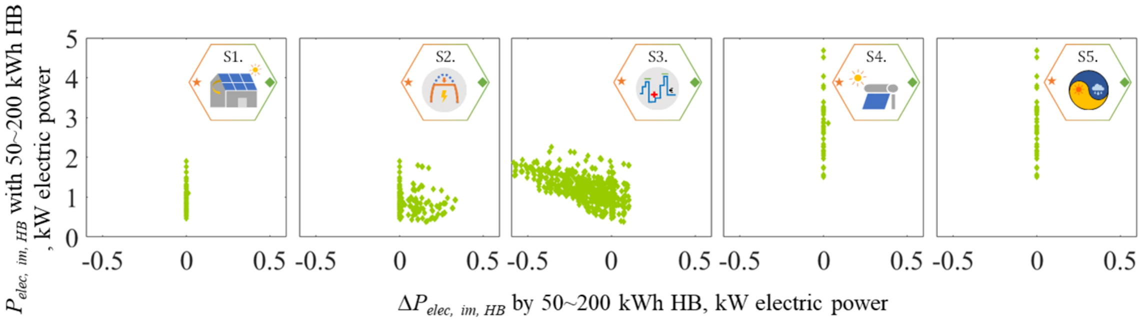


Fig. 9 Scatter plots of the peak electric loads ($P_{\mathrm{elec,im,HB}}$) of importing electricity to houses with HB and the peak load reductions ($\Delta P_{\mathrm{elec,im,HB}}$) by HBs with operation strategies S1–S5

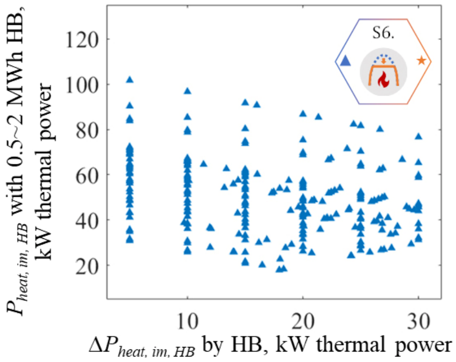


Fig. 10 Scatter plot of the peak thermal loads on the DH system with HB to 50 houses ($P_{\text{heat,im,HB}}$) and the peak thermal load reduction ($\Delta P_{\text{heat,im,HB}}$) in use cases under S6

based on a coincidence factor of 0.3. In this figure, some dots are grouped at such specific values of $\Delta P_{\text{heat,im,HB}}$ as 5 kW, 10 kW, and 15 kW, which are consistent with the maximum thermal discharging powers of different HB configurations. This underscores the significance of HB design parameters. Therefore, the values of $\Delta P_{\text{heat,im,HB}}$ were classified based on the facility options of both buildings and HBs for further examination.

Figure 11 displays that detached and terraced houses have a greater potential for reducing peak loads, with detached houses having the highest value of $\Delta P_{\text{heat,im,HB}}$. Although tiny houses do not exhibit a high upper boundary as the other building types, it can still offer up to 25 kW reduction in peak load. In contrast to building type, the insulation level has a less prominent impact on $\Delta P_{\text{heat,im,HB}}$, and lower insulation levels may lead to slightly higher peak load reductions. The design of the HB also has an effect, but as depicted in Figure 11, the storage capacity and maximum charging power are not crucial to the KPI, as indicated by their low $1 - p$ values. This could potentially be due to an underutilization of the defined storage capacity and charging power, indicating an opportunity for further system optimization. However, thea maximum discharging power of HB shows different trends, and it can be seen in the boxplot that the values of $\Delta P_{\text{heat,im,HB}}$ cannot exceed the maximum limit of discharging power.

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4.5 Use cases with stacked operation strategies

Step 3 of the proposed methodology also includes a check on the possibility of adjusting the promising use cases derived from the former process, and the use cases with S1 and S4 have this possibility. As is shown in Figure 6, the 200 kWh HB used under S1 or S4 was almost empty in winter. It can be interesting to stack other operation strategies on the basis of S1 or S4 so that the HB can both harvest the solar energy in summer and provide other services in winter as those mentioned in the initial set.

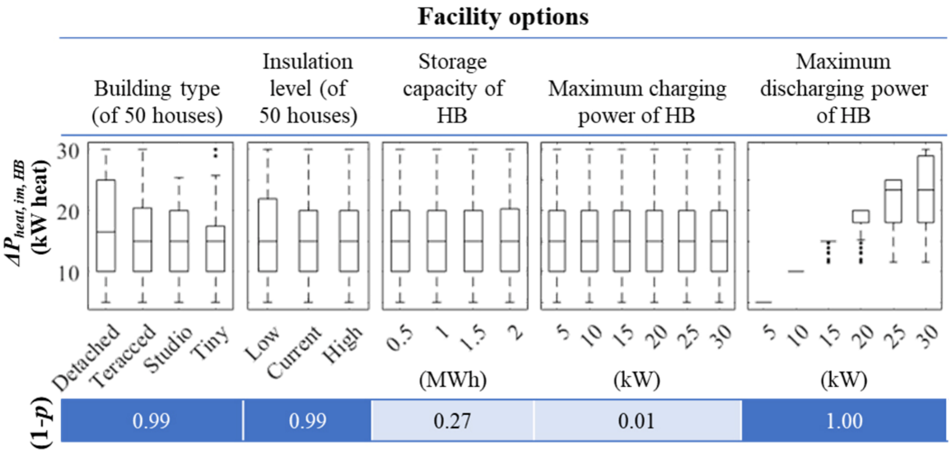

Fig. 11 Boxplots of peak thermal load reduction ($\Delta P_{\text{heat,im,HB}}$) with various facilities in use cases with S6, with the $1 - p$ value below the boxplot of each option

Therefore, a further simulation was implemented based on the use cases with the highest value of ΔOC_{HB} mentioned above. The result shows that there can be a 70-euro further reduction on the OC and a 300 W reduction on the $P_{\mathrm{elec,im}}$ if the HB is controlled mainly under S4 in summer and S2 in winter. However, stacking different operation strategies may also increase the complexity of the use case so there will be no extensive discussion about it in this work.

5 Discussion and conclusion

5.1 The main findings

This study defined three stakeholders for using the HB in Dutch residential buildings: the homeowner, DSO, and DH operator. The homeowner and DH operator will directly install the HB in their systems for such performance improvements as reducing operational energy cost or shaving the peak heating load, while the DSO is interested mainly in the HB's influence on the peak electric load from the building to local grid.

Based on the proposed approach, this research reaches the following findings:

(1) Using the HB for improving the self-consumption of solar energy (both PV-electriciy and hot water) will be more interesting than those for demand-side management (such as the use cases with S2, S3) if the homeowner aims to reduce the energy cost (by more than 200 euros per year in all considered use cases) via using the HB;

(2) The operational cost can be reduced significantly in buildings with higher heating demand (up to approximately 600 euros per year in considered scenarios) and larger PV or solar thermal collector areas. However, the potential of S1 is limited when the contract for exporting electricity doesn't provide sufficient motivation for PV-generated electricity's self-consumption, similar to all types of batteries;

(3) The HB can also reduce peak electric load when coupled with an electric heater, but it may increase electric peak load (by up to 500 W based on assumed price fluctuations) when used with S3 if the electricity price fluctuation differs significantly from the electric demand profile of the building;

(4) When using HB to reduce peak heat load, the DH operator can expect a higher reduction by deploying HB in larger houses' neighborhoods, while apartments with studios can also be interesting;

(5) The peak load reduction value is sensitive to the HB's maximum discharging power and storage capacity, so it would be necessary to optimize these parameters during the integration's design phase.

The proposed methodology aspires to strike a balance between feasibility and practicality. Informed by both literature and the insights from HB developers, our use case definition step attempts to reflect the current understanding of HB usage. The modeling and simulation step tries to predict KPIs, providing an accessible alternative to resource-intensive real-world experiments. This approach involves detailed analysis of each use case, aiming to grasp their respective strengths and areas for potential improvement. This method simplifies complex numerical data into digestible insights to those interested in the field of TES. While this methodology is not without its limitations, it seeks to combine comprehensive exploration with real-world applicability.

5.2 Limitations and future work

This research developed a simulation-based approach to perform a fast investigation and screening of many potential use cases. The approach realizes the analysis of thousands of use cases in a few minutes, while it also shows some limitations. Firstly, the conceptual models of different energy systems including the HB reduce the resolution of the simulation and may cause distortion of the simulation results. Moreover, some practical boundaries, including the indoor thermal comfort condition, were not taken into account in this work because the data could not be fed back from the simulation of energy system model to the building thermal model.

In light of these limitations, we recommend the following for future research:

(1) Develop a more detailed HB model for integration into the building performance simulation tool. This would allow for a more comprehensive analysis of the impact of the HB on energy systems and building performance;

(2) Refine and customize the six operating strategies based on the specific design option and future scenario to maximize the performance improvement of the HB;

(3) Incorporate practical boundaries such as indoor thermal comfort into the model to provide a more realistic representation of building performance;

(4) Conduct further research on how to design HB integration to optimize the maximum discharging power and storage capacity, given their impact on peak load reduction and associated manufacturing cost increase.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author contribution statement

Shuwei Wang: conceptualization, investigation, methodology, writing—original draft, writing—review & editing. Pieter-Jan Hoes: conceptualization, methodology, supervision, writing—review & editing. Jan L.M. Hensen: conceptualization, methodology, supervision, writing—review & editing. Olaf C.G. Adan: supervision, writing—review & editing. Pim A.J. Donkers: resources, writing—review & editing.

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