A use case assessment method for mobilized heat battery in residential buildings

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Abstract
Mobilized thermal energy storage is a potential way of transporting heat from sustainable sources to buildings for their heat consumption. The heat battery, a novel closed-loop thermochemical heat storage system, can also be integrated into a mobilized configuration. To steer the development of the mobilized heat battery toward this promising application, this paper proposes a method for assessing the use case of mobilized heat battery based on building performance simulation experiments. The method is demonstrated in an investigation into the use case based on two residential communities in the Netherlands. The investigation indicates the method can be used for assessing the use case of the mobilized heat battery, as well as other purposes such as heat battery demand prediction, waste heat scheduling, cost management, and system optimization.

Highlights
- A simulation-based use case framework is proposed and demonstrated.
- A neural-network-based surrogate model is developed and implemented in EnergyPlus simulation.
- The levelized cost of transporting waste heat by the mobilized heat battery is analyzed.

Introduction
Mobilized thermal energy storage
Mobilized thermal energy storage (M-TES) is the concept of using thermal energy storage technology to transport (e.g., by truck or train) thermal energy from its source to the end user. The ideal heat source should be clean, inexpensive, and sustainable, such as solar and industrial waste heat, and geothermal energy (Guo et al., 2018). The possible types of thermal energy storage can be sensible heat storage (Fernandez et al., 2010), latent heat storage (Du et al., 2021), or thermochemical heat storage (Krönauer et al., 2015). The storage material is normally stored in a tank or container and transported by truck, ship, train, or other ways. The end users can be various buildings (Guo et al., 2017; Li et al., 2013), a district heating system (Chiu et al., 2016), or the industrial sector (Miro et al., 2016). The M-TES concept is suggested as a means of overcoming the limitations of traditional heating pipelines. By utilizing transportable storage devices to connect the heat source and end-users, the supply of heat becomes more adaptable, flexible, and robust.

The heat battery and its mobilized configuration

Figure 1: Schematic diagram of the heat battery (left) and its mobilized configuration (right) (Cellicius BV, n.d.; Heat-Insyde, n.d.).

The heat battery (HB) is a thermochemical heat storage system that utilizes the reversible hydration mechanism of potassium carbonate (K2CO3) composites (Houben et al., 2020). This technology comprises a storage module for the composites and an electricity-driven mechanical system that enables continuous thermal power for charging or discharging, as the schematic diagram in Figure 1 shows.

In the mobilized configuration, the storage module is inserted into a standard intermodal container and therefore becomes transportable. The storage capacity of the mobilized heat battery (M-HB) in a standard intermodal container is 10GJ (around 2778kWh), and its maximum discharging power can reach 100kW as is shown in Figure 1 (Cellicius BV, n.d.). The electricity-driven mechanical systems include both the charging and discharging units, and they are coupled with the installation on the site of the heat source and sink.

To start charging or discharging the heat battery, the connected energy system first needs to set a target power for charging or discharging. According to this target, the heat battery adjusts the powers of the fan, the pump, and other components and starts to intake the fluid in the heat exchangers. After the charging or discharging process completes, these components will be turned off to switch the heat battery into standby mode when its heat loss is negligible.

What is the promising use case for M-HB?
As previous literature (Anandan & Sundarababu, 2021; Guo et al., 2018; Miro et al., 2016) pointed out, the feasibility of a mobilized thermal energy storage can be
influenced by the end-user demand, the material storage potential, the investment cost, the operational strategy, the transportation distance, and the waste heat price. Although some studies have already assessed the technical and economic feasibility of other M-TES systems (Fritz et al., 2022; Guo et al., 2017; Li et al., 2013), there is still a lack of a systematic method that can properly combine the mentioned factors for assessing the feasibility and potential of a M-TES system’s use case.

In our previous study (Wang et al., 2022), a use case is defined as the combination of the stakeholder, the utilization goal, the strategy, the facility, and the scenario. These five elements include exactly those mentioned factors. Therefore, this definition is suitable to be used as an assessment framework also for M-HB. Different from a rough estimation (Fritz et al., 2022; Shehadeh et al., 2021), the method used in our previous study can predict the heat demand in a higher resolution due to the usage of BPS tools. However, the assessment of the M-HB’s use case requires more details on the performance of both the M-HB and the buildings. Therefore, this study aims to develop a new use case assessment method with a data-driven surrogate modeling approach and demonstrate it based on the residential communities in the Netherlands.

The use case assessment method

![Flowchart of the proposed method](image)

The proposed method consists of three parts. Part I includes the development and validation of the HB surrogate model. Part II contains the design and verification of the use case simulation experiments. Part III is the simulation experiment and the processing of simulation outcomes. Figure 2 gives an overview of this method. The two decisions in this figure are respectively:

**Decision 1:** The Coefficient of Variation of Root Mean Square Error (CV(RMSE)) between the test and predicted data are below 15% (Ruiz & Bandera, 2017) and the Mean Absolute Percentage Error (MAPE) should be below 5% (Swansons, 2015).

**Decision 2:** the predicted HB performances are in line with the data from lab experiments, and the thermostat setpoints in the building can be reached.

**Part I – HB modelling**
- System and objectives definition
- The objective of modeling the HB is to implement it in BPS and predict the HB’s performance as well as its impact on building performance. The HB mainly interacts with the building energy system via the exchange of fluid and electricity. Therefore, the required HB model should be able to update the HB’s state based on the variable describing these exchanges and generate outputs to the running BPS.
  - Conceptual and communicative model
    The HB’s developer constructed a high-resolution model based on the physical principles and laboratory experiments of a prototype, and it can predict the transient values of some state variables based on several input values and detailed design parameters such as porosity, grain diameter, the dimension of the TCM module, heat exchanger effectiveness, and the air pressure range. This model has been validated to predict HB’s performance, but it is relatively computationally expensive compared to common BPS tools such as EnergyPlus.
    Therefore, we constructed a surrogate model of the high-resolution one. In the case of a mobilized configuration, the surrogate model only represents the discharging process. It takes the temperature and mass flow rate of the fluid entering the HB and the target discharging power as input variables and calculates the outlet temperature of the corresponding fluid, the actual discharging power, and the electric power as output variables.
  - Programmed model
    A dataset is available for training the surrogate model based on lab experiments and data generated by the high-resolution model. The dataset contains thousands of observations for the discharging process (over 391,000 observations) and covers a wide range of values of the input variables and output variables. To train the surrogate model based on the dataset, we need an algorithm to predict the numerical values of multiple output variables based on multiple numerical inputs. Because the inputs and outputs are known in the dataset, the algorithm should be a supervised learning one such as a neural network.
    In the supervised neural network, the predicted outputs of the network are compared with the actual outputs in the training dataset. Based on the error, the parameters are changed and then fed into the neural network again. The neural network fitting tool in MATLAB is used to train the surrogate model for the charging and discharging processes of the HB. The developed surrogate model is expected to be used in the simulation in hourly or shorter timesteps. Therefore, Decision 1 in the flowchart checks if the trained model is capable of predicting the HB performance.

**Part II – use case simulation framework**

In order to perform the use case simulation experiments including all the defined assumptions and the surrogate HB model, we need a simulation engine that allows the embedding of a customized model for the HB. For this...
reason, we selected the open-source BPS tool EnergyPlus for the whole building energy simulation because of its application programming interface (API) (National Renewable Energy Laboratory for the United States Department of Energy, n.d.).

We used the PlantComponent: UserDefined object in the EnergyPlus’s input file to create a shell for the HB and then connect it with the interface of the HVAC system. One branch of the user-defined component was used to represent the HB’s discharging heat exchanger. It was defined to meet load with a nominal capacity and can request flow but cannot initiate it. Based on the created shell, we wrote a python script to define the fundamental energy balance equations and control logic of the discharging model. The script has three derived classes from the EnergyPlusPlugin base class. Two of them override the on user defined component model functions to respectively initialize and simulate the discharging branch, and the remaining class overrides the on end of zone timestep after zone reporting function to update the state of the HB and report desired output variables.

To verify this workflow, Part II also includes a test run of simulation experiments. The test run can be designed based on existing cases with data for reference so that the logic between the simulation result and assumptions could be analyzed. According to the mentioned Decision 2, the performance indicators of the HB would be compared with the test set to check the implementation of the surrogate model. The predicted indoor temperature would also be checked against the setpoints to see whether the whole heating system is functioning properly or not.

Part III - use case assessment

Part III is the assessment of the use case based on the post-processing of simulation results. It mainly has three procedures including the production runs of simulation experiments, the post-processing of simulation results, and sensitivity analysis.

The production runs of simulation experiments are based on the simulation framework verified in Part II. They use the strategy, facilities, and scenarios defined for the use case as assumptions, and deliver the values needed for calculating KPIs.

Post-processing is an optional procedure, and it is unnecessary if the KPI can be directly generated from simulation experiments. Some inputs of the post-processing might be uncertain, such as the inflation rate or energy price, and they can be assumed via literature study, interviews with stakeholders, or some feasible statistic approaches.

Sensitivity analysis is the last but not least procedure in light of all the assumed inputs in both simulation experiments and post-processing. It can be based on the best-worst method, one-at-a-time analysis, factorial design, regression analysis, and other possible methods. In this paper, we use the best-worst method based on the extreme values that are assumed for each uncertain factor.

Use case investigation

The use case is defined as the transporter wanting to use the mobilized heat battery to transport waste heat from different sources to a specific community for covering the heat demand of the building(s), as shown in Figure 3. When using the heat battery, the transporter aims to fully cover the building heat demand while keeping the total cost as low as possible. Two typical Dutch communities are selected in this paper, and they are based on newly constructed apartment buildings or renovated terraced houses. The five basic elements in this use case are:

- **stakeholder:** the waste heat transporter;
- **goal:** technically feasible and low-cost;
- **strategy:** transport waste heat to fully cover the demand;
- **facility:** buildings with heating distribution networks;
- **scenario:** weather, resident, and economic variants.

To quantitively assess the use case and make the results comparable with other literature, this investigation uses the levelized cost of transporting heat (LCOTH) to be the key performance indicator. According to (Fritz et al., 2022), the calculation of LCOTH is based on the annuity of capital expenditure, operational expenditure, and the amount of transported heat.

In this investigation, the capital expenditure includes the investment in the charging units, the heat batteries, and the discharging units. The operational expenditure includes the cost of transporting the heat batteries by trucks, the electricity imported from the grid during the charging and discharging processes, and the general maintenance cost of all the invested devices.

Assumptions

Communities and buildings: community 1 is based on an apartment building with 3 floors above the ground and 50 apartments. It was completed in 2021 and thus is assumed to reach the current Dutch code for insulation. Community 2 is based on 22 terraced houses distributed in two rows, and all the buildings are assumed to be renovated to the low insulation level in our previous study (Wang et al., 2022). Both communities are assumed to have water buffers with backup electric heating elements. The satellite images and model presentations in Design Builder of the two communities can be found in Figure 4.

Waste heat supplier: the location, capacity, and supply profiles of the waste heat supplier are unknown due to
the lack of data. One key advantage of using mobilized thermal storage is the flexibility of choosing different waste heat sources to guarantee a stable supply. Therefore, this case study assumes the waste heat could be continuously supplied and the distance between the supplier and the community remains as a variable for the post-processing in Part III.

Household types: based on the data from CBS in uw buurt (CBS, 2023), the profiles of the residents can be estimated. The assumed household profiles of residents in both communities are listed in Table 1 and Table 2. The S1 in each community is based on the statistical data of a specific Dutch neighborhood, and S2 ~ S6 are the variants to include uncertainties. The test run in Part II only uses S1.

![Satellite image and model presentation](image)

**Figure 4**: Satellite images and model presentations of community 1 (above) and community 2 (below).

### Table 1: Assumed scenarios for households in community 1.

<table>
<thead>
<tr>
<th>Household type</th>
<th>Scenarios</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear family</td>
<td></td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>2 seniors</td>
<td></td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>50</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1 senior</td>
<td></td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>50</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2 adults</td>
<td></td>
<td>9</td>
<td>0</td>
<td>50</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1 adult</td>
<td></td>
<td>24</td>
<td>50</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table 2: Assumed scenarios for households in community 2.

<table>
<thead>
<tr>
<th>Household type</th>
<th>Scenarios</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear family</td>
<td></td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>22</td>
</tr>
<tr>
<td>2 seniors</td>
<td></td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>22</td>
<td>0</td>
</tr>
<tr>
<td>1 senior</td>
<td></td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>22</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2 adults</td>
<td></td>
<td>5</td>
<td>0</td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1 adult</td>
<td></td>
<td>8</td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table 3: Assumed values for uncertain factors for LCOITH calculation.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Unit</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment indicator</td>
<td>€/MWh</td>
<td>low</td>
</tr>
<tr>
<td>Interest rate</td>
<td>%</td>
<td>2</td>
</tr>
<tr>
<td>System life</td>
<td>year</td>
<td>15</td>
</tr>
<tr>
<td>Electricity price</td>
<td>€/MWh</td>
<td>100</td>
</tr>
<tr>
<td>Transportation cost</td>
<td>€/10 km</td>
<td>8</td>
</tr>
<tr>
<td>Maintenance cost ratio</td>
<td>%</td>
<td>1</td>
</tr>
</tbody>
</table>

**Occupant behavior**: the occupancy and heating thermostat patterns of these households are assumed to follow the profiles in (Guerra-Santin & Silvester, 2017). The domestic hot water (DHW) consumptions are assumed to follow the profiles generated from a tool developed by KWR (Pieterse-quirijns et al., 2015). The average consumption is assumed to be 40 liters of hot water per person per day (NEN, 2021). The weather is assumed to vary based on the data of Groningen, Amsterdam, and Beek (National Renewable Energy Laboratory (NREL), n.d.). The test run is based on the weather in Amsterdam.

**Levelized cost**: there are some uncertain factors not included in the simulation experiment but necessary for calculating LCOITH. In this investigation, they are assumed to have two extreme but possible values based on information from literature and the developer of HB. The assumed values for each uncertain factor are listed in Table 3.

The investment indicator denotes the investment cost per storage capacity of the HB. It also includes the cost of a pair of charging and discharging units. The exact numbers are confidential as the HB developer required. The electricity price is assumed to vary in a large range because it is still unclear whether the price for industry or for residents shall be applied. The maintenance cost ratio means the percentage of annual maintenance cost to the total investment cost.

**Validation and verification (Part I and II) Validation results (Part I)**

During the training of the discharging model, we randomly selected 90% of the available data as the training dataset, while the remaining 10% was reserved for validation and testing purposes. We experimented with three different algorithms, namely Levenberg-Marquart, Bayesian Regularization, and Scaled Conjugate Gradient, using five distinct layer sizes (5, 10, 15, 20, 25) for each algorithm. After testing all 15 possible combinations, we found that the most suitable accuracy and prediction speed was achieved by the model trained with Levenberg-Marquart and 15 layers.

Table 4 provides a comparison of the prediction accuracy and the criteria in Decision 1. In this table, $t_{out}$ is the discharging fluid temperature at the heat exchanger outlet, °C. $\eta$ is the thermal efficiency of discharging the HB, and it is the ratio between the actually discharged thermal power and the theoretical
value based on the reaction in the thermochemical storage materials. COP is the coefficient of performance for discharging the HB, and it is calculated based on the actually discharged thermal power and the electric power consumed by the discharging unit. From Table 4, it is clear that the model is capable of predicting the HB’s performance because the calculated CV(RMSE) and MAPE values are all below the acceptable criteria mentioned in (Ruiz & Bandera, 2017) and (Swanson, 2015).

Table 4: Test set prediction accuracy and criteria.

<table>
<thead>
<tr>
<th>Index</th>
<th>$t_{out}$</th>
<th>$\eta$</th>
<th>COP</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>CV(RMSE)</td>
<td>0.1%</td>
<td>0.4%</td>
<td>0.9%</td>
<td>15.0%**</td>
</tr>
<tr>
<td>MAPE</td>
<td>0.1%</td>
<td>0.3%</td>
<td>1.0%</td>
<td>5.0%**</td>
</tr>
</tbody>
</table>

* from (Ruiz & Bandera, 2017), ** from (Swanson, 2015).

Verification results (Part II)

To confirm the implementation of the trained model, we examined the HB’s discharging efficiency and COP by comparing the values predicted in the test run to those of the original dataset that was utilized to train the model. From Figure 5, it is evident that the predicted values in both communities fell within the ranges of the original dataset. This observation indicates that the HB model has been implemented correctly.

To confirm the normal functioning of both the HB and the entire heating system, we randomly chose three households from each community and checked their indoor air temperature in January. Figure 6 indicates that the heating systems in both communities were able to deliver sufficient heat to all of the selected households, suggesting that the models were operating normally.

Figure 5: Comparison of the HB’s performance in the original dataset and simulation (test run) outputs for both communities.

Figure 6: Comparison of the thermostat setpoint and simulated (test run) air temperature in selected living rooms in both communities in the first week of January.

Simulation and assessment results (Part III)

Simulation results

The predicted amount of fully-charged HBs needed by both communities was determined through production simulation runs, and the monthly and yearly results are presented in Figure 7. Under the assumption of continuous HB supply, the backup electric heating elements were barely used in both communities. In community 1, the monthly demand for HBs did not exhibit a clear difference between winter (November to March) and summer (June to September), as depicted in the top left scatter plot in Figure 7. This can be attributed to the relatively high proportion of DHW demand in the total heat demand of the well-insulated apartment building, and the DHW demand is less sensitive to seasonal transition than space heating demand based on our assumptions. The yearly demand reflects a similar trend that the more residents (around 200 in S6) in community 1, the higher demand (134 ~ 146 HBs) it would have.

In community 2, the monthly demand displayed a more evident seasonal pattern, as space heating demand constituted a larger portion of the demand in the 22 renovated terraced houses. The yearly demand also revealed a significant impact from the space heating thermostat setpoint, as S4 (a single senior) had the highest demand range (118 to 130 HBs), while S2 (a single adult) had the lowest demand range (66 to 75 HBs).

In both communities, the assumed household scenarios resulted in larger variations than the assumed weather conditions. On a monthly scale, the variation caused by three weather conditions would be approximately 3 in both communities, whereas the variation based on the assumed household scenarios would be about 5 in community 1 and 10 in community 2.

Based on all the assumptions, community 1 would require 100 to 146 fully-charged HBs annually, equating to around 2 to 3 HBs per household per year. Community 2 would require 66 to 130 HBs throughout
the year, which corresponds to 3 to 6 HBs per household per year.

**Sensitivity analysis**

By combining all the assumed values of the six uncertain LCOTH parameters mentioned in the assumption of levelized cost with the predicted high and low demand of HBs, we obtained 128 sets of inputs. As mentioned in the assumption for the waste heat supplier, the distance between the source of waste heat and each community remains unknown.

Consequently, we defined 40 different distance values between 5 to 50 for each set of inputs, resulting in a total of 5120 sets (128 sets of inputs × 40 distance values) of inputs for calculating the LCOTH for each community, as shown in Figure 8 shows. Each scatter plot in Figure 8 represents the 5120 results with the specific factor present on its top, and the highlighted group denotes the value that can lead to a lower LCOTH.

For instance, the top left scatter plot shows all the 5120 values of LCOTH for Community 1, while the subgroup highlighted in green is the one calculated only with the low value of F1 (investment indicator). It denotes that a lower investment indicator would bring lower LCOTH and the average distance between this green subgroup and the grey one suggests how influential F1 is on LCOTH.

Based on all assumptions in this investigation, the yearly HB demand (F7) has the most impact on LCOTH among all the uncertain factors, and a higher demand could result in a lower LOCTH. The investment parameter (F1) and system life (F3) were also essential factors, and cheaper and longer-lived systems would bring down the LCOTH substantially.

However, the considered price ranges for buying electricity (F4) and transportation services (F5) did not show any significant influence on the LCOTH. Generally, community 1 exhibited a narrower band of LOCTH values than community 2 under all the considered uncertainties.

**Assessment and discussion**

This use case investigation shows that:

- The demand for HBs per household in the newly-constructed apartment community is generally lower than the demand in the renovated terraced house community.
- The levelized cost would be influenced more by the residents' behaviors of consuming heat than the three typical Dutch weather conditions used in this investigation. The influence is more pronounced in the old terraced house community than in the apartment community.
- The investment in the HB (including charging and discharging units) and its system lifetime are more critical to the levelized cost than the cost of buying electricity and transportation services within the considered ranges.

There are some limitations in this investigation. First, the waste heat is assumed to be endlessly supplied due to the lack of data, which is difficult to be achieved in reality. Second, for the same reason, the charging performance of the HB is not discussed, but it would also influence the assessment results. Therefore, a necessary further step is to include the information on waste heat availability in the simulation framework and to model the charging performances accordingly.

**Conclusion**

This paper proposes a method for assessing the use case of mobilized HBs in buildings. The method is
demonstrated to investigate the use case based on two typical Dutch residential communities under various uncertainties from the buildings and other economic factors.

The practice of the method

The investigation in this paper shows that the proposed method has many potential applications, including predicting demand for the mobilized heat battery, scheduling the charging process, managing costs, and optimizing system configuration. This makes it a valuable tool for use during the product development, design, and operation phases of the mobilized heat battery.

Furthermore, the simulation approach created in this method also has the potential to serve as a framework for evaluating the use cases of other innovative building energy technologies that may not be included in the current model library of BPS tools. This could enable researchers and engineers to develop and assess new technologies more efficiently and effectively, leading to more sustainable and energy-efficient building designs.

Limitations and future work

This method is partially dependent on the precision and quantity of input data, which might pose some challenges for emerging thermal energy storage systems and their respective use cases. Furthermore, the verification in Part II is subject to a certain degree, to the user's level of expertise and experience, which can be uncertain in practical scenarios. Despite these limitations, the method still provides a solid foundation for future research into the potential uses and benefits of mobilized thermal energy storage systems such as the heat battery. Further investigation is needed to evaluate more diverse use cases, such as the potential for using the mobilized heat battery to shave peak loads on district heating systems.

Acknowledgment

This research has been supported by project 9.4: development of closed-loop TCM system, which is part of the ‘Integrale Energetiecentrale Bestaande Bouw’ (IEBB). The IEBB project was initiated by the Building and Technology Innovation Centre (BTIC) and is funded by Rijksdienst voor Ondernemend (RVO) Nederland.

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