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A hierarchical design of distributed battery system in PV power shared building community

Pei Huang[1*], Xingxing Zhang[1], Marco Lovati[1]

[1] Department of Energy and Built Environment, Dalarna University, Falun, 79188, Sweden (Corresponding author. E-mail: phn@du.se)

ABSTRACT

Proper energy storage system design is important for performance improvements in solar power shared building communities. Existing studies have developed various design methods for sizing the distributed batteries and shared batteries. For sizing the distributed batteries, most of the design methods are based on single building energy mismatch, but they neglect the potentials of energy sharing in reducing battery capacity, thereby easily causing battery oversizing problem. For sizing the shared batteries, the existing design methods are based on a community aggregated energy mismatch, which may avoid battery oversizing but cause another severe problem, i.e., excessive electricity losses in the sharing process caused by the long-distance power transmissions. Therefore, this study proposes a hierarchical design method of distributed batteries in solar power shared building communities, with the purpose of reducing the battery capacity and minimizing the energy loss in the sharing process. Case studies on a building community show that compared with an existing design method, the proposed design can significantly reduce the battery capacity and electricity loss in the sharing process, i.e. 36.6% capacity reduction and 55% electricity loss reduction. The proposed method is helpful to improve the cost-effectiveness and energy efficiency of energy storage systems in solar power shared building communities.

Keywords: PV; Distributed energy storage; Design; Energy Sharing; Building Community

1. INTRODUCTION

Existing studies have developed many design methods for distributed energy storage systems (named 'individual design' in this study). For instance, Baniasadi et al. [1] developed a particle swarm optimization (PSO) algorithm-based design method to size the electrical energy storage and thermal energy storage system in a building with the purpose of reducing life-cycle cost of the PV-battery system. Considering the demand prediction uncertainty, battery degradation and maintenance, in [2] a genetic algorithm-based design optimization method was developed, which uses the energy system life-cycle costs as the fitness function and the users' performance requirements as the constraints. Considering the possible energy sharing among different buildings, Sameti and Haghighat [3] developed a mixed-integer linear programming (MILP) optimization-based method to design the distributed energy storages of a net-zero energy district in Switzerland. Pareto analysis was used to identify the best integrated district energy system which minimizes both the total annualized cost and equivalent CO_2 emission while ensuring the reliable system operation to cover the demand. This study considers the surplus sharing (i.e. use one building's surplus power to meet other buildings' electricity demand), but the storage sharing (i.e. store one building's surplus power in other buildings' batteries) is not considered.

Some studies have investigated the community shared energy storage system design (named 'group design' in this study) and its performances. For instance, Parra et al. [4] designed a method to calculate the optimal community energy storage (CES) systems for end-user applications based on the levelized cost, which considers round-trip efficiency and durability. Their case studies showed that the application of a community energy storage to 100 houses could reduce the levelized cost by 56% by shifting demand compared to a single house energy storage installation. Based on the results, they concluded that the application of a community shared energy storage could result in a good solution to facilitate the usage of distributed renewable energy generation and manage the loads. Sardi et al. [5] developed a framework for designing CES in an existing residential community system with rooftop solar PV units, considering the optimization of CES location, capacity and operation. Their study results indicated that 22% of community energy storage could reduce the annual purchased energy cost from the grid by 11.1% and the annual energy loss cost by 36.9%.

In the CES, there are actually two forms of energy sharing: surplus sharing (i.e. use the surplus PV power to meet the electricity needs in other buildings) and storage sharing (i.e. store or take electricity from other buildings' batteries) [6]. The buildings first share their surplus PV power with other buildings with insufficient PV power production (i.e. surplus sharing). Then, the remaining surplus PV power will be stored in the shared CES (i.e. storage sharing) if the aggregated surplus power is larger than the aggregated deficiency, or the remaining power shortage will be taken from the shared CES if the aggregated deficiency is larger than the aggregated surplus power. Contributed by such energy sharing, the CES typically performs better than the conventional HES which do not enable energy sharing or only enable very limited energy sharing [7]. In recent years, with the development of advanced energy storage controls for energy sharing, the HES can achieve nearly the same level of energy sharing and thus the similar performances as the CES system. In fact, due to the frequent low-voltage energy exchanges with the CES system which can be located in a long distance from the buildings, there can be significant amount of electricity losses due to such long-distance power charging/discharging. The HES, on the other hand, can store most of the electricity near the buildings and thus reduce the energy losses due to long-distance power transmission.

Therefore, this study proposes a hierarchical design method of distributed batteries in solar power shared building community, with the purpose of reducing the required battery capacity by applying energy sharing and reducing the electricity loss in the energy sharing process. The developed design method first considers all the distributed batteries as a virtual 'shared' battery and searches the optimal capacity of the virtual 'shared' battery using genetic algorithm. Based on the optimized aggregated capacity at community-level, the developed method then optimizes the capacity of the distributed batteries installed in each building using non-linear programming with the objective of minimizing the storage sharing (and thus the associated power loss due to long-distance power transmission). For validation, the developed design method is compared with two existing design methods based on a virtual building community located in Sweden. The proposed design will combine the merits of both individual design (i.e. low energy loss due to power transmission from/to battery) and group design (i.e. reduced battery capacity due to energy sharing).

2. METHODOLOGY

The hierarchical design consists of four steps, see Fig. 1. In Step 1, the PV power production and electricity demand of each individual building and is evaluated and then aggregated to obtain the power supply/demand of the whole building community. In Step 2, using the aggregated-level power supply/demand as inputs, the capacity of a virtual 'shared' battery is optimized using genetic algorithm (*GA*) according to the user-required energy performance (e.g. a specific self-consumption). In Step 3, the capacity of the distributed batteries installed in each building is optimized using non-linear programming (*NLP*) to minimize the storage sharing (i.e. power exchanges with other batteries) and thus the associated energy loss. The aggregated capacity of all the distributed batteries should equal the capacity of the virtual 'shared' battery obtained in Step 2. In Step 4, the performances of the proposed hierarchical sizing are compared with the two common designs, namely individual sizing and group sizing. The details of each step are introduced below.

Step 1: Evaluation of the aggregated electricity demand and supply of the building community

In this step, the aggregated electricity demand and supply of the building community are evaluated. The hourly electricity demand ($[E^c_{d,1}, E^c_{d,2}, \dots, E^c_{d,8760}]$ (*kW·h*)) of the building community equals the aggregated hourly electricity demand of each single building ($[E^j_{d,1}, E^j_{d,2}, \dots, E^j_{d,8760}]$ (*kW·h*)) (*j* indicates the *j*th building), and its hourly PV power production (($[E^c_{s,1}, E^c_{s,2}, \dots, E^c_{s,8760}]$ (*kW·h*)) equals the aggregated hourly PV power production of each single building (($[E^j_{s,1}, E^j_{s,2}, \dots, E^j_{s,8760}]$ (*kW·h*)), as depicted by Eqs. (1) and (2). The electricity demand and PV power generation of each individual building is calculated using the TRNSYS.

$$E^c_{d,i} = \sum_{j=1}^{n} E^j_{d,i} \qquad \textit{(i=1,2,…,8760 hr)} \qquad (1)$$

$$E^c_{s,i} = \sum_{j=1}^{n} E^j_{s,i} \qquad \textit{(i=1,2,…,8760 hr)} \qquad (2)$$

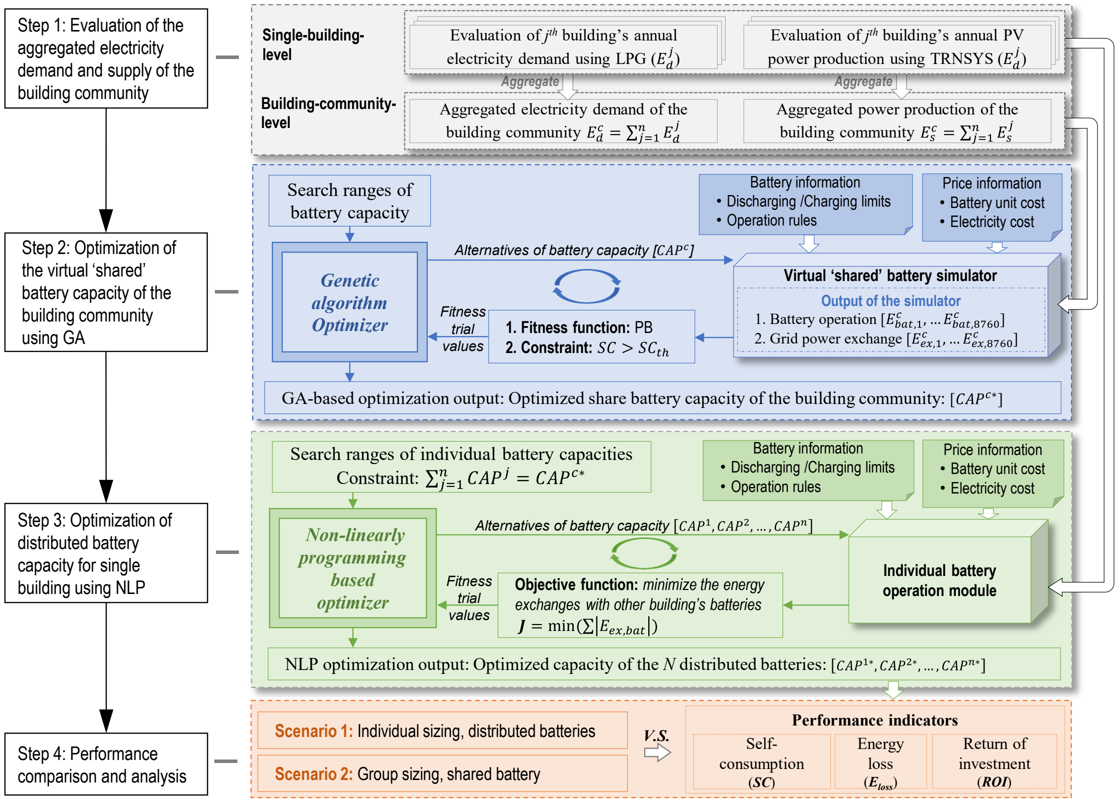

Figure 1 Flowchart of the hierarchical design of distributed batteries for solar power shared building community.

Based on the aggregated power generation and power demand, the hourly power mismatch ($E_{m,i}^c$ ($kW{\cdot}h$)) at the building-community-level is calculated using Eq. (3).

$$E_{m,i}^c = E_{d,i}^c - E_{s,i}^c \qquad (i=1,2,...,8760\ hr) \qquad (3)$$

Step 2: Optimization of the virtual 'shared' battery capacity of the building community using GA

This step uses the GA to search the optimal battery capacity (CAP^{c*} ($kW{\cdot}h$)) that minimizes the payback period (*PB*) of battery while meeting the user-required PV power self-consumption rates (SC_{th}). In this study, minimizing the payback period is set as the fitness function as an example, see Eq. (4). Note that the fitness functions can be flexibly changed according to the users' needs.

$$J_{fitness} = \min(PB) \quad \text{s.t. } SC \geq SC_{th} \qquad (4)$$

The PB is calculated as the by Eq. (5), which is calculated as the ratio of the investment of the battery and electricity cost savings contributed by battery installation.

$$PB = \frac{CAP^c \cdot \rho}{Cost^{c,0} - Cost^{c,1}} \qquad (5)$$

CAP^c ($kW{\cdot}h$) is the aggregated battery capacity; ρ (€/($kW{\cdot}h$)) is the unit cost of the battery. $Cost^{c,0}$ (€) and $Cost^{c,1}$ (€) are annual electricity costs before and after installing battery, which is calculated by Eq. (6).

$$Cost^{c,0/1} = \sum_{i=1}^{8760} E_{grid,i}^{c,0/1} \times \chi_i, \begin{cases} \chi_i = \chi_{buy}, if\ E_{grid,i}^c > 0 \\ \chi_i = \chi_{sell}, if\ E_{grid,i}^c \leq 0 \end{cases} \qquad (6)$$

$E_{grid,i}^c$ ($kW{\cdot}h$) is the building community's energy exchange with the power grid in the i^{th} hour, which is calculated as the deviation between the energy mismatch ($E_{m,i}^c$, as calculated by Eq. (3)) and the battery charging/discharging rates ($E_{bat,i}^c$), see Eq. (7). χ_i (€/$kW{\cdot}h$)) is the hourly electricity price. χ_{buy} (€/($kW{\cdot}h$)) is the price of purchasing electricity from the power grid, and χ_{sell} (€/($kW{\cdot}h$)) is the feed-in-tariff.

$$E_{grid,i}^c = E_{m,i}^c - E_{bat,i}^c \qquad (7)$$

In this study, the battery is considered to be continuously operating. The calculation of the charging/discharging states of the virtual 'shared' battery are described as follows.

- ***Discharging state:*** When the community-level power mismatch ($E_{m,i}^c$) is larger than zero, the battery is in discharging state. The battery discharging rate is calculated by Eq. (8).

$$E_{bat,i}^c = \begin{cases} \min(\phi_i, E_{charge,limit}^c), if\ E_{m,i}^c > \min(\phi_i, E_{charge,limit}^c) \\ E_{m,i}^c, \qquad if\ E_{m,i}^c \leq \min(\phi_i, E_{charge,limit}^c) \end{cases} \qquad (8)$$

$E_{charge,limit}^c$ ($kW{\cdot}h$) is the maximum charging/discharging rates of the battery in each hour. ϕ_i

($kW{\cdot}h$) is the amount of electricity stored in the battery, which is calculated by Eq. (9).

$$\phi_i = \sum_{i=1}^{i} E_{bat,i}^{c} \tag{9}$$

- ***Charging state:*** When the community-level power mismatch ($E_{m,i}^{c}$) is smaller than zero, the battery is in charging state. The battery charging rate is calculated by Eq. (10).

$$E_{bat,i}^{c} = \begin{cases} -\min(CAP^c - \phi_i, E_{charge,limit}^{c}), & if \ -E_{m,i}^{c} \geq \min(CAP^c - \phi_i, E_{charge,limit}^{c}) \\ E_{m,i}^{c}, & if \ -E_{m,i}^{c} < \min(CAP^c - \phi_i, E_{charge,limit}^{c}) \end{cases} \tag{10}$$

The self-consumption rate (SC), i.e. the percentage of PV power that is consumed on-site, is calculated by Eq. (11), in which $\left|\sum E_{grid,i,-}^{c}\right|$ is the aggregated amount of electricity exported to the grid ($E_{grid,i}^{c}$ with negative values).

$$SC = \frac{\sum_{i=1}^{8760} E_{s,i}^{c} - \left|\sum E_{grid,i,-}^{c}\right|}{\sum_{i=1}^{8760} E_{s,i}^{c}} \tag{11}$$

The output of the GA search is the optimal capacity of the virtual 'shared' battery (CAP^{c*}) which has the minimal *PB* while meeting a user-required *SC*. The aggregation of the distributed battery capacities, to be optimized in Step 3, should be equal to CAP^{c*}.

Step 3: Optimization of distributed battery capacity for single building using NLP

In this step, the capacity of distributed batteries ($[CAP^1, CAP^2, \ldots, CAP^n]$ ($kW{\cdot}h$)) installed in individual buildings is optimized using NLP based on the virtual 'shared' battery capacity. The objective function of the NLP is expressed by Eq. (12), which aims at minimizing the amount of storage sharing (i.e. the required energy exchanges with other buildings' batteries). By minimizing the required storage sharing, the energy loss due to long-distance low-voltage power transmission can be significantly reduced.

$$J_{NLP} = \min\left(\sum_{i=1}^{8760} \sum_{j=1}^{50} \left|E_{bat,other,i}^{j}\right|\right) \tag{12}$$

$E_{bat,other,i}^{j}$ ($kW{\cdot}h$) is amount of energy stored-in/taken-from other buildings' batteries. Fig. 2 displays the operation logic of battery operation and energy sharing in the proposed hierarchical design in the i^{th} hour for each individual building.

- $E_{m,i}$ ($kW{\cdot}h$): the hourly energy mismatch.
- $E_{cluster,i}$ ($kW{\cdot}h$): the amount of surplus power sharing with other buildings in the power grid.
- $E_{m,i}^{1}$ ($kW{\cdot}h$): the hourly energy mismatch after surplus sharing.
- $E_{bat,own,i}$ ($kW{\cdot}h$): the amount of energy stored-in/taken-from its own battery.
- $E_{m,i}^{2}$ ($kW{\cdot}h$): the hourly energy mismatch after surplus sharing and own battery regulating.
- $E_{bat,other,i}$ ($kW{\cdot}h$): the amount of storage sharing, i.e. energy stored-in/taken-from other buildings' batteries.
- $E_{grid,i}$ ($kW{\cdot}h$): the hourly energy exchanges with the power grid.

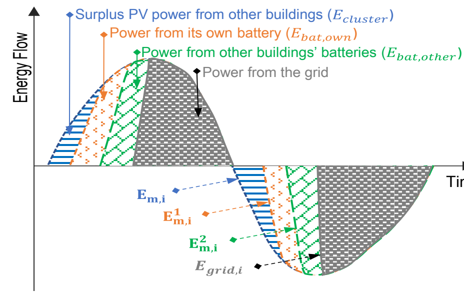

Figure 2 Operation logic of battery and energy sharing in the proposed hierarchical design

The hierarchical design will minimize the aggregated storage sharing (i.e. aggregated $E_{bat,other,i}$) and thus maximize the usage of the buildings' own batteries (i.e. aggregated $E_{bat,own,i}$).

Step 4: Performance comparison and analysis

After obtaining the optimized design of the distributed batteries, the building-community-level performances are analyzed and compared with the two existing design approaches: individual design of distributed batteries and group design of shared battery.

3. CASE STUDIES

In the case studies, 50 case buildings were used to test the performances of the proposed hierarchical design method. The weather data of Ludvika was used to model the local PV power productions. The PV system capacity was sized to achieve the zero-energy goal that its annual aggregated PV production equals the annual aggregated electricity demand.

3.1 Building electricity demand, renewable power generation and electricity mismatch

The annual aggregated electricity demand/supply of the studied single-family houses is in the range of 1640~11,600 $kW{\cdot}h$. Fig. 3 presents the hourly electricity demand, PV power production and energy mismatch of the 50 buildings of the community in a selected summer week. In the time slot with simultaneous positive energy mismatch and negative energy mismatch, the positive energy mismatch can compensate with the negative energy mismatch and thus creates potentials for energy sharing. Table 1 summarizes the techno-economic parameters used for performance evaluation.

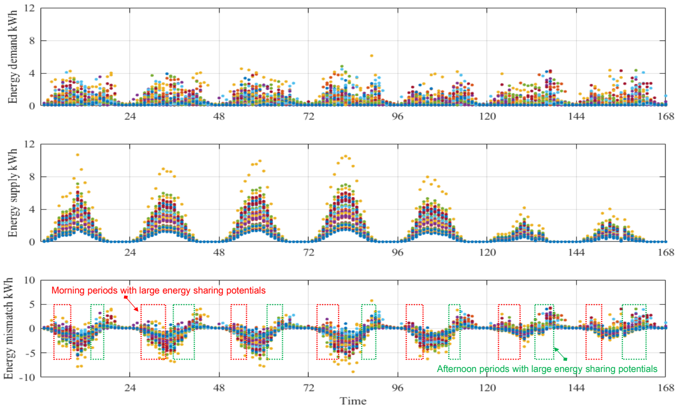

Figure 3 Hourly power demand, production and mismatch of the 50 buildings in a summer week

Table 1 Techno-economic parameters [4] [8]

Input name	value
Price of electricity bought from the grid [€]	0.16
Price of electricity sold to the grid [€]	0.05
Price of electricity bought from the building community [€]	0.1
Price of electricity sold to the building community [€]	0.1
Cost of the storage system including installation [*€/kW·h*]	250
Maximum charging/discharging rates of battery [*% Capacity*]	30%
User-required PV power self-consumption rate	60%
Battery roundtrip efficiency	92%
Battery storing efficiency	92%
Surplus sharing efficiency (due to power transmission loss)	92%
Storage sharing efficiency (due to power transmission loss)	92%

3.2 Performance comparison

Using the electricity demand and PV power production data as inputs, the three different design methods have been used to design the battery system in the building community. In Scenario 1, the capacity of distributed battery is sized to achieve a 60% self-consumption rate for each individual building with the minimized payback period. In Scenarios 2&3, the capacity of the shared battery is sized to achieve a 60% self-consumption rate for the whole building community with the minimized payback period.

Table 2 compares the design results and economic performances of the three methods. Under the individual design and operation scenario, the aggregated capacity of the distributed batteries was 322.1 *kW·h*. While the capacity of the shared battery in Scenario 2 and the aggregated capacity of the distributed batteries in Scenario 3 were both 204 *kW·h.* The aggregated battery capacities were the same in Scenarios 2&3, since the proposed design used the virtual 'shared' battery capacity (obtained from group design) as benchmark to instruct the sizing of distributed batteries. Meanwhile, since in Scenarios 2&3 the buildings can share their surplus PV power production with other buildings, the need of battery for storing the excessive PV power is reduced. The aggregated battery capacity was significantly reduced (i.e. 36.6% decrease) compared with Scenario 1. Correspondingly, the initial investment of battery was significantly reduced in Scenarios 2&3 (i.e. 36.6% decrease). The community-level annual cost saving of Scenario 1 was about 5.3% higher than the cost savings in Scenarios 2&3. This is because in Scenario 1 the aggregated battery capacity was much larger, which could help keep more surplus power inside the community and thus reduce the grid power imports.

Table 2 Comparison of the design results under different scenarios

	Individual design	Group design	Proposed design
Aggregated battery capacity (kW·h)	322	204	204
Battery investments (€)	80,525	51,000	51,000
Cost saving per year (€/Year)	4,129	3,912	3,917
Payback period (Year)	19.5	13.0	13.0

Fig. 4 presents the annual PV power self-consumption rates at the building-community-level under the three different designs without considering the energy loss (i.e. Fig. 4(a), the valued used in the constraint check) and with energy loss considered (i.e. Fig. 4(b)). As shown in Fig. 4(a), all the three designs meet the user-required threshold for self-consumption rate (i.e. 60%). The community-level self-consumption rate is 61% in Scenario 1, slightly higher than the threshold. This is because the individual design takes the single building's self-consumption rate as the design constraint. Fig. 4(b) displays the self-consumption rate considering the energy losses. When the energy loss is considered, the self-consumption rate in the Scenario 1 decreases to be close to Scenarios 2&3, due to the relatively larger energy loss in battery storage.

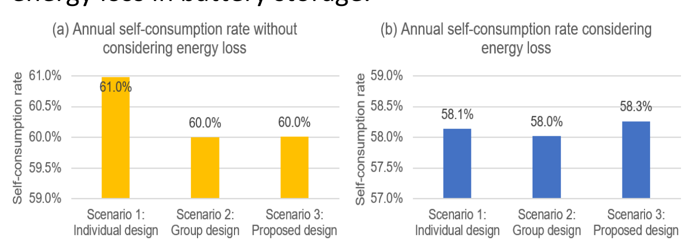

Figure 4 Self-consumption of the whole building community under different scenarios (a) not considering energy loss (b) considering energy loss

Fig. 5 compares the amount of energy losses in different processes under the three scenarios. In Scenario 1, the energy losses occur in the battery charging/discharging, battery storing, and the surplus sharing process. While in Scenarios 2&3, the energy losses also occur in the storage sharing process. In all the three scenarios, the energy loss in battery storage accounts for the largest percentage (i.e. 89.9%, 64.2% and 73.2%, respectively). In Scenario 1, the energy loss in battery storing is much larger than Scenarios 2&3 (about 50.1% increase). This is because the aggregated battery capacity is much larger, and thus more electricity can be stored in the battery. The energy loss due to surplus sharing in Scenario 1 is much smaller than Scenarios 2&3. This is because after the battery regulation of each single building's energy mismatch, the remaining energy mismatch of most buildings will approach zero, and thus reducing the potentials of surplus sharing. While in Scenarios 2&3, surplus sharing is implemented before the battery regulating, when there is large diversity between different buildings' energy mismatch, and thus there are more potentials of surplus sharing (and more losses due to surplus sharing as well). The energy loss due to storage sharing in Scenario 3 is smaller than the loss in Scenario 2 (about 2412 $kW{\cdot}h$ decrease). This is because in the distributed battery configuration, the buildings can use their own batteries as part of the electricity storage and thus reduce the need of storage sharing. Such reduced energy loss in storage sharing contributed to a slight increase in the community-level self-consumption rates (i.e. about 0.3%, see Fig. 4(b)).

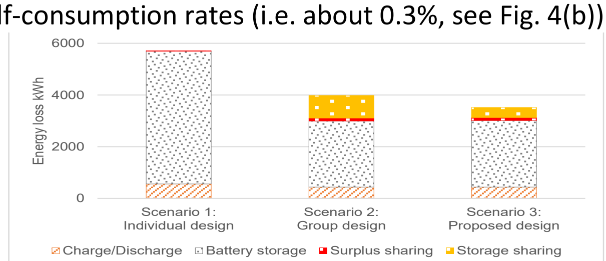

Figure 5 Energy losses of the whole building community in different scenarios

4. CONCLUSION

This study has proposed a hierarchical design optimization of distributed batteries in solar power shared building community. The developed design method has been compared with two existing design methods based on a virtual building community located in Sweden. At a user-required community-level self-consumption rate of 60%, the proposed design reduced the aggregated capacity of the distributed batteries in the community by 36.6% compared with individual design (i.e. Scenario 1). The payback period was reduced by 33.3% from 19.6 years in the individual design to 13 years in the proposed design. Compared with the group design of shared battery, the proposed design effectively reduced the amount of storage sharing, and thus the power loss due to the relatively long-distance low-voltage power transmission. The reduction in power loss reached over 55%.

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