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ECONOMIC BENEFITS OF CENTRALIZED AND DISTRIBUTED STORAGE UNDER REDISTRIBUTION TOU DEMAND TARIFF

Junxiong Zhao[1], Menglian Zheng[1,2,*], and Yi Ding[3]

1 Institute of Thermal Science and Power Systems, School of Energy Engineering, Zhejiang University, Hangzhou 310027, China

2 State Key Laboratory of Clean Energy Utilization, Zhejiang University, Hangzhou 310027, China

3 School of Electrical Engineering, Zhejiang University, Hangzhou 310027, China

ABSTRACT

A practical redistribution time-of-use (TOU) demand tariff which allows an aggregator to purchase electricity from grid and redistribute electricity to participants is adopted, a TOU upper demand limit storage control strategy is proposed and applied to a case study of a group of average U.S. households with centralized and distributed storage devices to provide demand response. The impact of the scale of group to provide centralized-storage-based demand response on the economic benefits is also studied. Results show that the proposed control strategy is economically viable and the smallest aggregation scale to obtain the lowest household-average total annual cost is found. The adopted tariff, proposed storage dispatch strategy and the result of this study can be applied to the design of a newly-built storage device sharing among multiple households to provide community-level demand response.

Keywords: vanadium redox flow battery, redistribution tariff, dispatch strategy, community-level

NONMENCLATURE

Abbreviations	
PC	Power Capacity
EC	Energy Capacity
SoC	State of Charge
DL	Demand Limit
TOU	Time of Use
HH	Household
TAC	Total Annual Cost
AnnLev	Annually Levelized
Symbols	
P	Power
η	Efficiency of Energy Conversion
t	Time
I	The ith Household
J	The jth Month

1. INTRODUCTION

The rapid technological improvements along with the significant cost reductions in electricity storage devices have driven the expansion of electricity storage in a variety of energy system applications [1] [2] [3] [4] . Among various applications, electric energy storage-based demand response, usually in the residential sector, is expected to bring multiple benefits such as economic benefits, environmental benefits, and improvement of the reliability of the electric grids without the effects on the electricity consumption behaviors of users [5] . A number of previous studies have been focused on the development of the practical storage dispatch strategies of storage to enable demand response in the residential sector and evaluate the potential economic and environmental impacts under realistic tariffs.

For example, under the U.S. realistic TOU demand tariff that the electricity bills of customers depend largely on the maximum of power demand, Zheng et al. [5] proposed to use an upper demand limit to control the (dis)charging behavior of household-level storage and to constrain the net power drawn from gird to cut down the total annual cost (storage and electricity bill costs included). Edwin García et al. [6] adopted storage batteries to provide demand response service of minimizing the peak demand of a certain range during the day and extended the application of proposed system to electric vehicles. However, community-level demand response is not taken into consideration.

Kaveh Paridari et al. [7] and Jiyun Yao et al. focused [8] on community aggregated by multiple households with energy storage sharing and proposed a distributed algorithm and centralized control strategy respectively to minimize the aggregated electricity cost. Sibo Nan et al. [9] classified common household load into different categories and proposed optimal scheduling scheme for smart residential community with storage, PV and EVs. However, studies mentioned above have not considered the impact of the scale of community to provide storage-based demand response on economic benefits.

In addition, the tariff adopted in the case study can also have an effect on the design of dispatch strategy, to the our best knowledge, few study adopted the practical redistribution tariff such as SC8 II (Specification Classification 8) tariff provided by the Consolidated Edison Company of New York, under which aggregator can purchase electricity from the grid and redistribute the electricity to participants.

Based on the analysis above, main contributions of this paper include:

First, a practical redistribution tariff is adopted under which a case study for a community of households to provide storage-based demand response is practical and meaningful.

Second, a storage dispatch strategy taking the TOU characteristic of the adopted tariff into consideration is proposed to maximize the economic profits considering the storage levelized cost and electricity bills.

Last, the impact of the scale of community to provide storage-based demand response on economics of storage is studied and the smallest scale of community to gain the maximal economic benefits is found.

The rest of the paper is structured as follows: in Section 2, the adopted redistribution TOU demand tariff and the proposed storage dispatch strategy is introduced in detail and applied to a case study under two different storage configurations, i.e., the centralized and distributed storage. The economic feasibility evaluation model and solution to the optimization problem, GA optimization are also introduced. In Section 3, the results of this study including optimal results of storage design parameters and control parameters, the economic feasibility and the demand profile under two storage configuration, the impact of aggregation scale on economic benefits are discussed. In Section 4, main results and contributions of this study are summarized.

2. DATA AND METHODS

2.1. Redistribution TOU demand tariff and storage dispatch strategy

The redistribution TOU tariff adopted in the present study is the SC8 II (Specification Classification 8) tariff provided by the Consolidated Edison Company of New York [10] , which allows aggregator to purchase electricity from the grid and redistribute the electricity to participants and charges different rates (demand charge measured in dollar per maximum kW over the billing period and energy charge in dollar per electricity consumption) for different time periods of the day. The demand charge rates are 8.65 $/kW from 8 am to 6 pm, 19.32 $/kW form 8 am to 10 pm, and 18.49 $/kW for all other time. More details can be found in [10] .

Under this specific demand tariff, the electricity bills depend largely on the maximum demand over different time periods. Therefore, based on [5] , a TOU storage dispatch strategy is developed in which different upper demand limits are designed for different time periods (i.e., from 8 am to 6 pm; from 8 am to 10 pm; and all other time) to reduce the annual demand charge of the households. Considering the different demand patterns of electricity users in different seasons, upper demand limits are further set differently in different seasons, as illustrated in Table 1.

2.2. Storage device configurations

The TOU storage dispatch strategy proposed in Section 2.1 is applied to both distributed and centralized storage configurations. As illustrated in Fig. 1, 20 households which are simulated based on the stochastic demand model developed by Zheng et al. [4] , are equipped with the centralized and distributed vanadium redox flow batteries (VRFBs) respectively. The major difference rests in that the centralized storage capacity and the corresponding upper demand limit is determined by the group demand while each household's storage capacity and upper demand limit is determined by individual household. The (dis)charge power of storage is constrained by the upper demand limit, the power capacity of the storage, and also SoC of the storage which is set in the range of 0.1-1.0. The control strategy of both centralized and distributed storage can be formulated as follows:

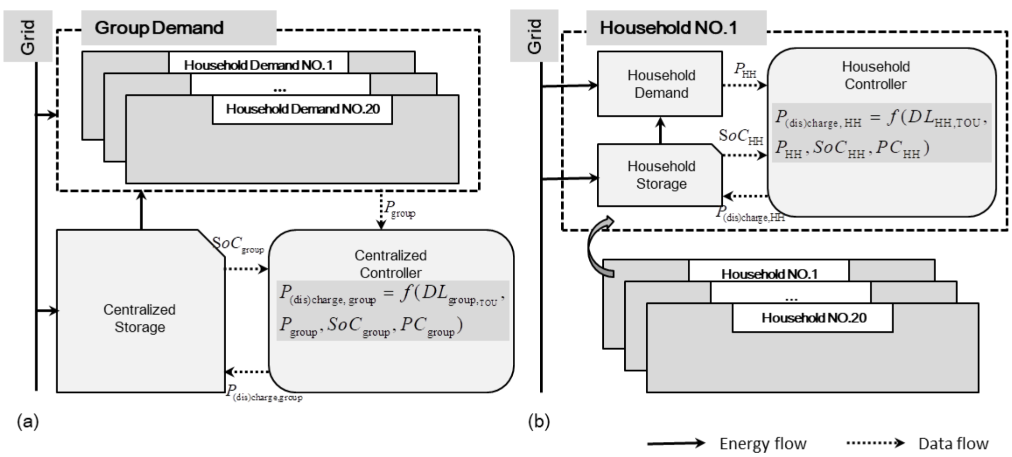


Fig. 1. Storage configurations: (a) Centralized storage and (b) distributed storage configurations

$$P_{\text{charge, group}}(t) = \min\left(DL_{\text{group, TOU}} - P_{\text{group}}(t), PC_{\text{group}}, \frac{60 \times \frac{EC_{\text{group}}}{\eta_{\text{grid-storage}}} \times (1 - SOC_{\text{group}}(t))}{\eta_{\text{grid-storage}}}\right)$$

$$P_{\text{charge, HH}, i}(t) = \min\left(DL_{\text{HH, TOU}, i} - P_{\text{HH}, i}(t), PC_{\text{HH}, i}, \frac{60 \times \frac{EC_{\text{HH}, i}}{\eta_{\text{grid-storage}}} \times (1 - SOC_{\text{HH}, i}(t))}{\eta_{\text{grid-storage}}}\right)$$

$$P_{\text{discharge, group}}(t) = -\min\left(P_{\text{group}}(t) - DL_{\text{group, TOU}}, PC_{\text{group}}, 60 \times \frac{EC_{\text{group}}}{\eta_{\text{grid-storage}}} \times (SOC_{\text{group}}(t) - SOC_{\min}) \times \eta_{\text{storage-appliance}}\right)$$

$$P_{\text{discharge, HH}, i}(t) = -\min\left(P_{\text{HH}, i}(t) - DL_{\text{HH, TOU}, i}, PC_{\text{HH}, i}, 60 \times \frac{EC_{\text{HH}, i}}{\eta_{\text{grid-storage}}} \times (SOC_{\text{HH}, i}(t) - SOC_{\min}) \times \eta_{\text{storage-appliance}}\right)$$

$$P_{\text{grid,group}}(t) = P_{\text{group}}(t) + P_{\text{(dis)charge,group}}(t)$$

$$P_{\text{grid,HH},i}(t) = P_{\text{HH},i}(t) + P_{\text{(dis)charge,HH},i}(t)$$

2.3. Economic feasibility evaluation model and GA optimization

In order to compare the economic profits produced by the centralized storage and distributed storage configurations under the storage dispatch strategy proposed in Section 2.1, an economic feasibility evaluation model based on [11] [12] is introduced. Considering that flow batteries have flexible power and energy capacity configurations and the cost is related both power and energy capacities, a new storage cost model based on [13] is used in the model. The total annual costs analyzed are defined as follows:

$$C_{\mathrm{TAC,centralized}} = C_{\mathrm{storage,AnnLev,group}} + C_{\mathrm{tariff,year,group}}$$

$$C_{\mathrm{TAC,distributed}} = \sum C_{\mathrm{storage,AnnLev},j} + C_{\mathrm{tariff,year},j}$$

As mentioned in Section 2.1, three upper demand limits are set for summer, winter, spring and autumn, respectively, and further, for each season, three upper demand limits are set for the time periods from 8 am to 6 pm, from 6 pm to 10 pm, and all other time, respectively. Parameters to be optimized are defined in details in Table 1. Recognizing that the solution space is a eleven-dimension continuous space (including 9 upper limit variables and 2 capacity parameters of storage), Genetic Algorithm, a heuristics solution method based on the evolutionary theory is used to solve the optimization problem [13] . 1000 generations are implemented to optimize the variables as the optimal solution for achieving the lowest C_{TAC}.

3. RESULTS

3.1. Optimal results of parameters

The optimal results of EC, PC and DL for 20 households with the centralized storage and one household with the distributed storage are shown in Table 1. As illustrated in Table 1, the upper demand limit in the time period from 22 p.m. to 8 a.m. of a day is the largest among three time periods of a day throughout the whole year. The reason is that the demand charge for time period from 8 a.m. to 22 p.m. (19.32 $ per kW), is higher than that for time period from 22 p.m. to 8 a.m. (18.49 $ per kW), therefore the upper demand limit for the latter is set higher than the former to migrate demand from high charged rate time period to low charged rate time period to reduce the tariff cost.

Table 1 Optimal result of parameters

Symbol	Description	Centralized Storage (20 households)	Distributed Storage (1 household)
PC	power capacity of storage(kW)	8.64	1.59
EC	energy capacity of storage(kWh)	348.84	65.83
$DL_{\mathrm{Spring\&Autumn,8\_6}}$	upper demand limit for 8a.m. to 6p.m. in spring and autumn(kW)	13.70	0.70
$DL_{\mathrm{Spring\&Autumn,6\_10}}$	upper demand limit for 6p.m. to 10p.m. in spring and autumn(kW)	13.70	0.70
$DL_{\mathrm{Spring\&Autumn,other}}$	upper demand limit for other time in spring and autumn(kW)	16.44	0.91
$DL_{\mathrm{Summer,8\_6}}$	upper demand limit for 8a.m. to 6p.m. in summer(kW)	45.87	2.10
$DL_{\mathrm{Summer,6\_10}}$	upper demand limit for 6p.m. to 10p.m. in summer(kW)	41.70	2.10
$DL_{\mathrm{Summer,other}}$	upper demand limit for other time in summer(kW)	45.87	2.73
$DL_{\mathrm{Winter,8\_6}}$	upper demand limit for 8a.m. to 6p.m. in winter(kW)	28.10	1.26
$DL_{\mathrm{Winter,6\_10}}$	upper demand limit for 6p.m. to 10p.m. in winter(kW)	28.10	1.26
$DL_{\mathrm{Winter,other}}$	upper demand limit for other time in winter（kW）	30.91	2.66

3.2. Analysis of economic feasibility

In Fig. 2. It is found that both distributed and centralized storage configurations are economically feasible by yielding 41.1% and 61.4%, respectively, lower C_{TAC} compared to that of 20 households without storage. The centralized storage yields more reduction in the electricity demand cost, which is 72.5% of that in the no-storage case and 13.9% of that in the distributed storage case. Moreover, the centralized storage also yields lower storage cost, which is 75.4% of that in the distributed storage case. The underlying rational explanation is that the centralized storage can enable energy sharing among households, possibly leading to more feasible energy utilization and more efficient storage capacity utilization.

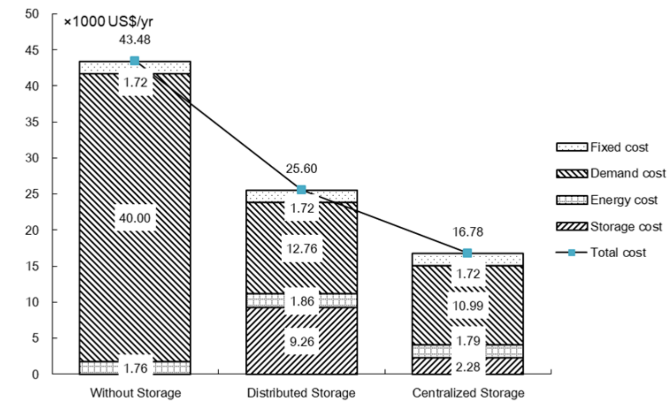
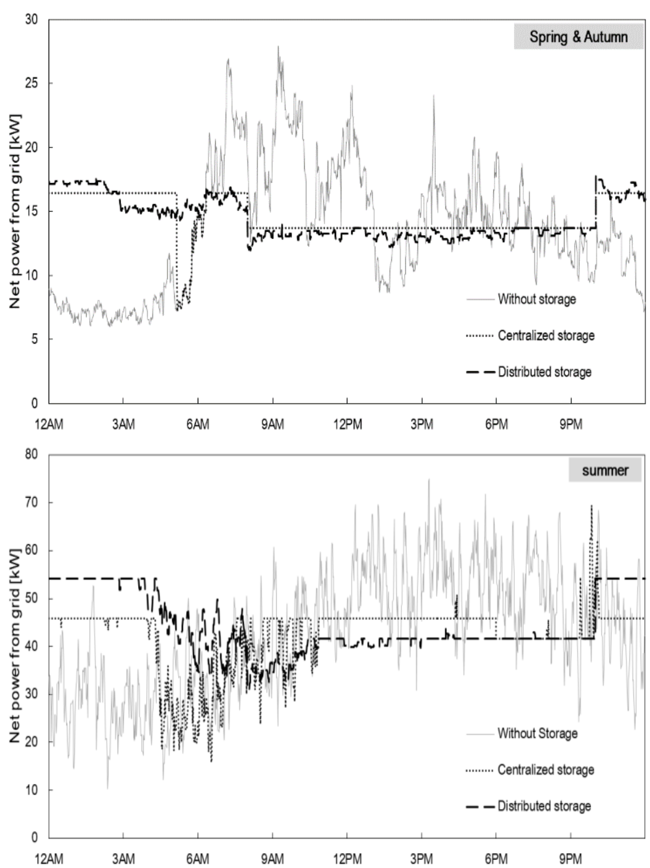


Fig 2 Total annual cost of 20 households without storage, with distributed and centralized storage.

3.3. Demand profiles with centralized and distributed storage



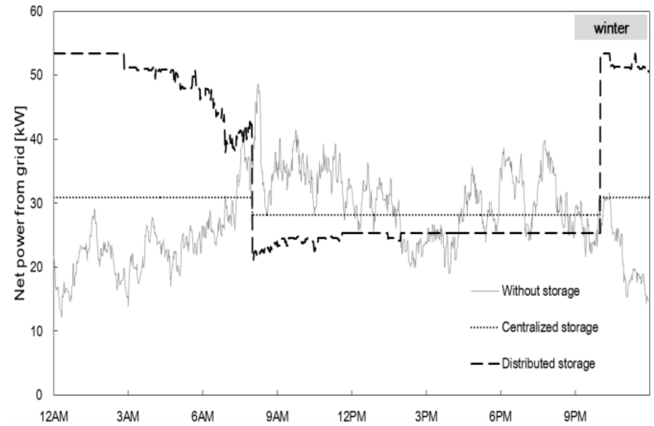


Fig 3 Net power from grid of 20 households without storage, with centralized and distributed storage

The demand profiles of the abovementioned 20 households without storage, with distributed storage, and with centralized storage in spring and autumn, summer, and winter are shown in Fig 3. It can be seen that without storage, the grid demand from 8 am to 22 pm when the demand charge is high is higher than other time periods, resulting in high demand costs. With the centralized and distributed storage, the grid demand is constrained by the upper demand limits for different time periods and the result is that demand is lower from 8 am to 22 pm when higher demand charge rates are applied, yielding reduced demand costs.

3.4. Aggregation scale for centralized storage

In this section, the impact of aggregation scale on the household-averaged C_{TAC} will be discussed. As illustrated in Fig. 4, as the aggregation scale grows from 20 to 1000 households, the household-averaged C_{TAC} decreases steeply first and then shows a moderate decreasing rate. The difference in the household-averaged C_{TAC} is less than 1 $ between 800 and 1000 households. In this regard, 800 households can be seen as the smallest aggregation scale to obtain the lowest household-average total annual cost. The result can be employed to direct the design of community-level storage to provide demand response.

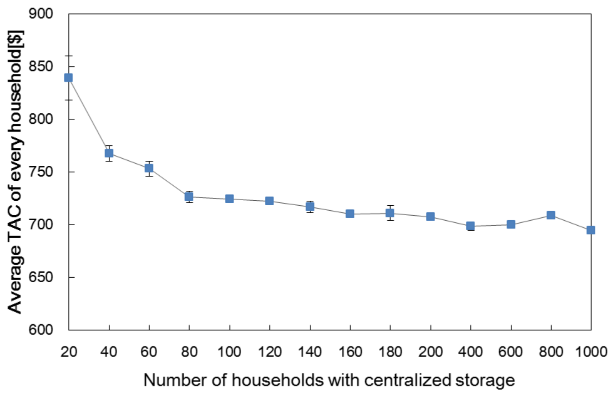


Fig 4 Impact number of households with centralized storage on household-averaged C_{TAC} (standard errors of the means due to stochastic simulations are within 1 \$)

4. CONCLUSION

In the present study, under a redistribution TOU demand tariff provided by Consolidated Edison Company of New York, a storage control strategy is proposed and applied to a case study of a group of 20 average U.S. households with centralized and distributed storage providing community-level demand response. The economic results verify the effectiveness of proposed storage control strategy. The impact of the scale of community to provide storage-based demand response on economics is also studied and the smallest scale of community to gain the maximal economic benefits is found. The adopted tariff, proposed storage dispatch strategy and the result of this study can be applied to the design of a newly-built storage device sharing among multiple households to provide community demand response.

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