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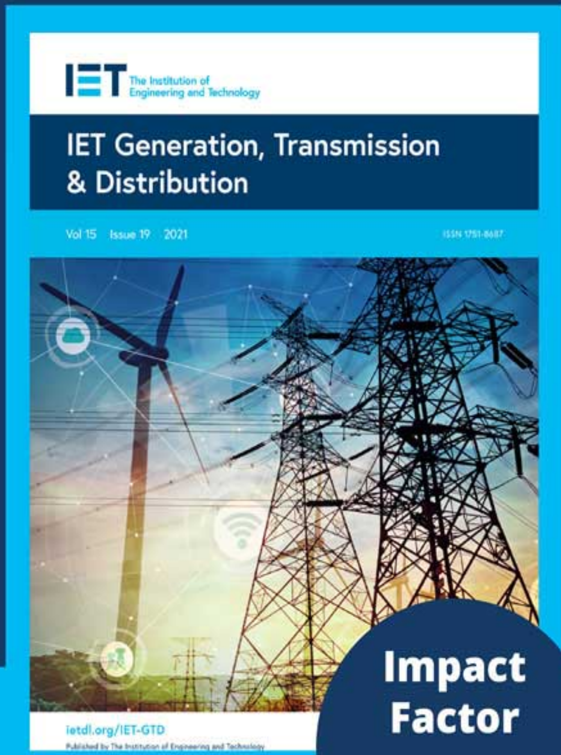

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Research Article

Two-stage optimal demand response with battery energy storage systems

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Abstract: This study proposes a two-stage co-optimisation framework for the planning and energy management of a customer with battery energy storage systems (BESSs) and demand response (DR) programs. The proposed method can assist a customer to make the most beneficial plans to join DR programs and install BESS in the planning stage, and optimally schedule the loads, DG outputs and BESS according to the planning decisions made in the first stage. The novel method considers multiple DR programs, various customer types and demand scenarios, and the integration of BESS. Case studies on a small commercial building and a large commercial/industrial campus demonstrate the effectiveness of the proposed method and the impacts of BESS and DGs on customer behaviours. The proposed method can provide guidance to a customer to make the most beneficial decisions in an electricity market with multiple DR programs.

Nomenclature

$a_{h,y,w}$	capacity factor of generator
$d_{y,w}$	discomfort index
D	days in a year (e.g. 365)
$G^{\max}$	maximum output of generator
i	index for DR programs: 1 – peak-time rebate (PTR); 2 – time-of use (TOU); and 3 – critical peak pricing (CPP)
IC^s	investment cost of batteries
$l^{c}_{h,y,w}$	curtailed load
$L^{0}_{h,y,w}$	load consumption without DR programs
M^s	maximum charging/discharging of one battery unit
OC^{g}	operation cost of generators
p^{curt}	curtailment payment
$p^{t}_{h,y,w}$	carbon tax price
P^{0}_{y}	electricity price without DR programs
P^{r}	reliability cost
$\Delta\mathrm{PTOU}_{h,y,w}$	price change due to TOU
$r_{y,w}$	reliability index
$s_{h,y,w}$	state of charge of batteries
W_w	probability of scenario w
W^{d}	weight for discomfort
y	index for year
z^s	number of batteries to be installed
$\alpha^{s}_{h,w}$	load shifting ratio
γ	aging factor of batteries
η^{l}	battery leakage
$C^{l}_{y,w}$	total cost
D^s	charging/discharging duration
$g_{h,y,w}$	output of generators
h	index for hour of the day
IC^{g}	investment cost of generators
$l_{h,y,w}$	net load consumption
$l^{s}_{h,y,w}$	shifted load
$L^{\max}_{y,w}$	max. load consumption without demand response programs
N^s	minimum charging/discharging of one battery unit
$p_{h,y,w}$	net electricity price
p^{ocs}	operation cost of batteries
$\mathrm{PTR}_{h,y,w}$	peak-time rebate
P^{d}	discomfort cost
$\Delta\mathrm{PCPP}_{h,y,w}$	price change due to CPP
$q^{sc}_{h,y,w}/q^{sd}_{h,y,w}$	charging/discharging power
$R^{\mathrm{PTR}}_{y,w}$	total PTR
$S^{dr}_{i,w}$	sign-on bonus of program
W^{c}	weight for cost
W^{r}	weight for reliability
z^{g}	number of generators to be installed
$\alpha^{c}_{h,w}$	load curtailment ratio
β_y	discount factor
η^{c}/η^{d}	charging/discharging efficiency
w	index for scenario

1 Introduction

Energy storage systems (ESSs), demand response (DR) and distributed generation (DG) play an important role in peak shaving, demand levelling and load consumption reduction in a modernised distribution system. As an essential element of a smart grid, ESSs can store energy in off-peak periods and provide power support to the system during peak hours. The operation of ESSs can be combined with DR to increase the economic benefits and reliability of a smart distribution grid [1].

DR is becoming an important part of smart grids and electricity markets for the economical and operational considerations. DR offers a variety of financial and operational benefits such as bill savings of participants, improved system operation, and better market performance [2]. In practice, a utility company usually offers various DR programs for its customers. It is a challenging problem for a customer to select appropriate DR programs to participate in. ESSs can provide local capacity to improve demand–supply balance, so they can be a powerful instrument to facilitate the implementation of DR programs. There are many energy storage technologies, such as batteries, pumped hydroelectric energy storage, flywheels, capacitors and so on. This paper considers batteries as the energy storage technology, i.e. the battery ESSs (BESSs). Although the integration of BESS can improve the operation, reliability, and economic benefits, it also adds complexity to the planning and energy management of a customer with DR programs.

Many studies have been performed on the optimal energy management with DR programs in the existing literature. The study in [1] proposed an energy management system to facilitate power trading among multiple microgrids by using the energy availability from demand response, DGs and distributed ESSs. The study in [3] proposed a centralised demand response algorithm to regulate frequency in a microgrid. The study in [4] introduced three models to characterise the behaviours and load shifting capabilities of domestic appliances, so as to facilitate the implementation of demand response programs. The study in [5] proposed a demand shifting and peak shaving measures to improve the generation–load balance for a power system with a high integration level of wind. The study in [6] proposed a direct load control scheme for large-scale residential demand response based on a consensus algorithm. The objective was to achieve the optimal aggregated demand consumptions in a decentralised way. The above mentioned literature assumes that a consumer is already participating in a certain DR program. There are also papers that consider the selection of multiple DR programs. The study in [7] provided mathematical models of price–demand elasticity of various DR programs to help DR regulators select favourite programs. The study in [8] developed an economical model based on price elasticity of multiple DR programs. An analytical hierarchy process was used to select the most effective DR program. However, the methods proposed in [7, 8] are based on a predefined demand–price elasticity. In practice, the price elasticity of a customer may vary a lot from one DR program to another. Moreover, the models in [7, 8] require that all possible combinations of DR alternatives be analysed thoroughly before making an optimal decision to join certain DR programs. Therefore, the above-mentioned methods cannot be easily applied to assist customers to make optimal plans to join DR programs.

A list of literatures has studied the coordinated energy management with ESSs and DR. The study in [9] reviewed the state-of-the-art of present applications of thermal storage for demand response. The study in [10] proposed an agent-based energy management system with demand response and distributed ESSs to minimise the supply–demand gap in multiple microgrids. A virtual market with demand side management, DGs and energy storage were designed to allow neighbouring microgrids to trade with each other. The study in [11] investigated scenarios of a household with photovoltaic systems, batteries, and demand side management in the electricity market of Texas. The battery capacity and total revenue of the household were optimised with real-time market prices. The study in [12] proposed a framework to maximise the payoff of a DR aggregator in a wholesale market based on a mixed-integer linear program. ESSs, DGs, and DR programs were used to reduce the load consumption. The study in [13] discussed the demand side management for large-scale data centres based on the stochastic optimisation approach. By optimally shifting the cloud service tasks among data centres, the financial benefits can be improved. The study in [14, 15] investigated the demand side management with electrical vehicle batteries to improve load profiles. The study in [16] proposed an operation strategy of ESSs to facilitate demand response by allowing energy storage devices to be controlled jointly by end customers and network operators. The sizing and placement of ESSs will impact the system operation. The study in [17] proposed a discrete Fourier transform-based method for coordinated sizing of ESSs and diesel generators in a microgrid considering generation–demand imbalance. The study in [18] proposed a second-order cone programming approach to optimally allocate ESSs in a distribution system for energy balance and grid support.

Utilities usually offer many alternatives of DR programs for customers to select. For example, Pacific Gas and Electric (PG&E) provides time-of-use (TOU), peak-time rebate (PTR), and critical time pricing (CPP) [19]. The existing literature only considers one DR program and cannot assist customers to select the programs to participate. ESSs play an important role in demand side management. The joint optimisation of energy storage integration and DR participations has not been covered in the above literature. Moreover, if a customer installs ESSs and joins multiple DR programs, the corresponding energy management problem becomes more challenging.

In this paper, we propose a two-stage model for the planning and operation of a customer with BESS and demand response. Multi-stage optimisation has been widely applied to solve energy management problems in the literature. Asimakopoulou *et al.* [20] studied the energy management of networked MGs by using a bi-level programming. Wang *et al.* [21] proposed a two-stage stochastic model for the coordinated energy management of networked microgrids. Jiang *et al.* [22] proposed a double-layer energy management system for a microgrid with a schedule layer to obtain an economic operation plan based on forecasted data, and a dispatch layer to control the DG outputs based on real-time data. Jabr *et al.* [23] studied two-stage robust optimisation for multi-period optimal power flow with storage and renewable energy. The objectives of our proposed model are to minimise the investment and operation costs and maximise the profits and customer satisfaction. The first stage (planning stage) conducts the co-optimisation of the integration of BESS and the selection of DR programs. Multiple DR alternatives ranging from price-based programs to incentive-based ones are considered simultaneously. The second stage (operation stage) performs scheduling of BESS and load dispatch according to the decisions made in the first stage. Different demand scenarios such as summer/winter weekdays, summer/winter weekends, and event days are considered in the model. Compared to existing work on the planning and operation with DR programs and BESS, the proposed method has the following main contributions: (i) it co-optimises the planning (i.e. to select beneficial DR programs to join) and energy management with demand response, (ii) it considers multiple DR programs simultaneously, and (iii) it takes into account DGs, BESS and a variety of demand scenarios.

The reminder of the paper is organised as follows. Section 2 proposes the two-stage co-optimisation framework for the planning and energy management of a customer. Section 3 introduces the detailed mathematical model. In Section 4, numerical results are provided. Section 5 concludes the paper with major findings.

2 Two-stage framework for planning and energy management

In a practical market, utilities provide multiple options of demand response programs to customers, so as to reduce or shift the peak-time demand, and improve the system operation and reliability. On the other hand, customers have various demand profiles. The integration of customer-owned DGs and BESS brings further challenges. As shown in Fig. 1, we propose a novel method to assist various types of end-use customers to make the most beneficial plan to participate in DR programs, and to integrate customer-owned DGs and BESS. Meanwhile, the developed method can also help customers schedule the charging/discharging of BESS and perform load management accordingly.

Multiple objectives are considered in the decision-making process, which include costs, reliability, and discomfort. The costs include electricity purchases and investments of BESS and DGs. The reliability is defined as the curtailment index of loads. The discomfort is defined as the index of shifted load consumption. In the first stage, multiple types of DR programs are considered, i.e. PTR, TOU, and CPP programs in this paper. At the same time, the integration of consumer-owned DGs and BESS is also taken into account. The decisions in the first stage include the optimal combination of DR programs and the number of BESS that need to be integrated to coordinate with the DR operation. An important characteristic of the decision-making process is that it allows the concurrent opt-in/out of multiple DR programs.

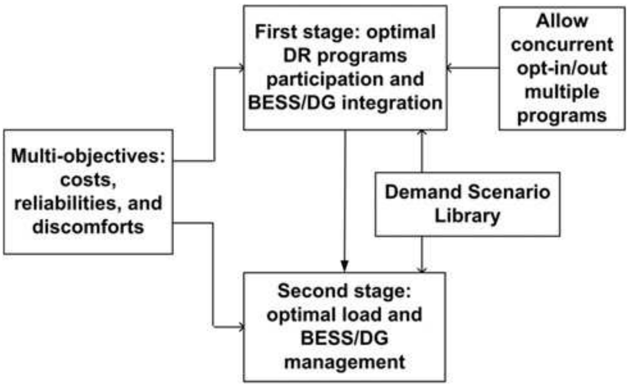

Fig. 1 *Two-stage framework for planning and energy management of a customer with DR and BESS*

In the second stage, dispatches of loads, BESS and DGs are performed based on the decisions made in the first stage. In particular, this stage makes hourly decisions on load shifting, charging/discharging of BESS, and the output of DGs. Five demand scenarios are taken into account in the proposed framework, i.e. summer weekdays, summer weekends, winter weekdays, winter weekends, and event days.

It can be seen that the proposed model can assist various types of end-use customers to make the most beneficial plan to participate in demand response programs, and to integrate customer-owned BESS/DGs in the planning stage, while performing energy management accordingly in the operation stage. The proposed procedure accounts for: (i) multiple DR programs; (ii) cost of supplying loads from external grid and/or local capacities together with the cost of BESS investment/maintenance; and (iii) load shifting and load curtailment; and (iv) multiple demand scenarios.

3 Mathematical formulation

This section provides the optimisation formulation of the proposed two-stage planning and operation framework. The objective is to minimise the costs and maximise the profits of a customer

$$\min\left(W^{\mathrm{c}}\left(\mathrm{IC}^{s}z^{s}+\mathrm{IC}^{\mathrm{g}}z^{\mathrm{g}}-\sum_{i,y}S_{i,y}^{dr}\right)\right)+D\sum_{y,w}W_{w}(W^{\mathrm{c}}C_{y,w}^{l}+W^{\mathrm{r}}P^{\mathrm{r}}r_{y,w}+W^{\mathrm{d}}P^{\mathrm{d}}d_{y,w}) \quad (1)$$

subject to

$$C_{y,w}^{l}=\beta_{y}\left(\sum_{h}(\mathrm{OC}^{\mathrm{g}}g_{h,y,w}+(p_{h,y,w}+p_{h,y,w}^{\mathrm{t}})l_{h,y,w}+p^{\mathrm{curt}}l_{h,y,w}^{\mathrm{c}}+p^{\mathrm{ocs}}(q_{h,y,w}^{\mathrm{sd}}+q_{h,y,w}^{\mathrm{sc}}))-R_{y,w}^{\mathrm{PTR}}\right),\quad \forall y,w \quad (2)$$

$$l_{h,y,w}=L_{h,y,w}^{0}-g_{h,y,w}-l_{h,y,w}^{s}-l_{h,y,w}^{\mathrm{c}}-Q_{h,y,w}^{\mathrm{sd}}+Q_{h,y,w}^{\mathrm{sc}},\quad \forall h,y,w \quad (3)$$

$$l_{h,y,w}\le L_{h,y,w}^{\max},\quad \forall h,y,w, \quad (4)$$

$$\sum_{h}l_{h,y,w}^{s}=0,\quad \forall y,w \quad (5)$$

$$l_{h,y,w}^{s}\le\alpha_{h,w}^{s}\left(\sum_{i}z_{i,y}\right)L_{h,y,w}^{0},\quad \forall h,y,w, \quad (6)$$

$$l_{h,y,w}^{\mathrm{c}}\le\alpha_{h,w}^{\mathrm{c}}(z_{1,y}+z_{3,y})L_{y,w}^{\max},\quad \forall h,y,w, \quad (7)$$

$$p_{h,y,w}=P_{y}^{0}+z_{2,y}\Delta\mathrm{PTOU}_{h,y,w}+z_{3,y}\Delta\mathrm{PCPP}_{h,y,w}-z_{2,y}z_{3,y}\Delta\mathrm{PTOU}_{h',y,w},\quad \forall h'\in[14,18],h,y,w, \quad (8)$$

$$R_{y,w}^{\mathrm{PTR}}=z_{1,y}\sum_{h\in[14,18]}(L_{h,y,w}^{0}-l_{h,y,w})\mathrm{PTR}_{h,y,w},\quad \forall y,w, \quad (9)$$

$$s_{h,y,w}=\eta^{\mathrm{l}}s_{h-1,y,w}-(\eta^{\mathrm{d}})^{-1}q_{h,y,w}^{\mathrm{sd}}+\eta^{\mathrm{c}}q_{h,y,w}^{\mathrm{sc}},\quad \forall h,y,w, \quad (10)$$

$$s_{1,y,w}=s_{24,y,w}=\gamma^{y-1}D^{s}z^{s}M^{s},\quad \forall y,w, \quad (11)$$

$$q_{h,y,w}^{\mathrm{sd}}\le\gamma^{y-1}z^{s}M^{s},\quad \forall h,y,w, \quad (12)$$

$$q_{h,y,w}^{\mathrm{sc}}\le\gamma^{y-1}z^{s}M^{s},\quad \forall h,y,w, \quad (13)$$

$$D^{s}z^{s}N^{s}\le s_{h,y,w}\le\gamma^{y-1}D^{s}z^{s}M^{s},\quad \forall h,y,w, \quad (14)$$

$$d_{y,w}=\sum_{h}\left|l_{h,y,w}^{s}\right|,\quad \forall y,w, \quad (15)$$

$$r_{y,w}=\sum_{h}l_{h,y,w}^{\mathrm{c}},\quad \forall y,w, \quad (16)$$

$$g_{h,y,w}\le z^{\mathrm{g}}a_{h,y,w}G^{\max},\quad \forall h,y,w, \quad (17)$$

$$z^{s}\in\text{integer},\quad z\in\text{binary}, \quad (18)$$

$$C^{1},r,d,l,g,l^{\mathrm{c}},q^{\mathrm{sd}},q^{\mathrm{sc}},s\ge 0 \quad (19)$$

In the above formulation, the objective function (1) minimises the total costs during the planning horizon. The costs include the investment and operation costs of ESSs and distributed generators, the reliability cost, and the discomfort cost. The sign-on bonus is considered as a negative cost. It is assumed that there are 365 days in one year. Constraint (2) represents the operation costs, the first item is the operation cost of distributed generators, the second item is the cost of load consumption, the third item is the cost of load curtailment, the fourth item represents the operation cost of ESSs, and the last item is the total PTR. Constraint (3) represents the net load consumption. The first item represents the original load consumption of the customer, the second item represents the generation of distributed generators, the third item represents the shifted load, the fourth item represents the curtailed load, and the last two items represent the charging and discharging of ESSs. Five representative scenarios are considered, winter weekdays, winter weekends, summer weekdays, summer weekends, and critical days (only applicable under certain demand response programs). Constraint (4) indicates that the net load consumption with demand response programs should be no larger than the load consumption without demand response programs. In constraint (5), the net shifted load in a day should be zero, since all shifted load consumption can be supplied eventually. Constraint (6) represents the maximum allowable load shift, which should be a certain portion of the original load consumption. Constraint (7) represents the maximum allowable load curtailment. Constraint (8) represents the net electricity price with demand response programs. The first item represents the electricity price without any demand response programs. The second item represents the price adjustment of TOU program. The third item represents the price adjustment of CPP program. If a consumer participates in both TOU and CPP, there exists a duplicate charge during peak hours (i.e. 14:00–18:00), which is deducted by the last item. Constraint (9) represents the PTR. Peak time is defined as 2–6 pm in this paper. The operator can change the settings according to practical scenarios. Equations (10)–(13) represent the operation constraints of ESSs. Constraint (10) calculates the state of charge (SOC) of the ESSs for each time period. According to the operation requirement of ESSs, the SOC at the end of the day should be equal to the SOC at the beginning of the day, which is indicated

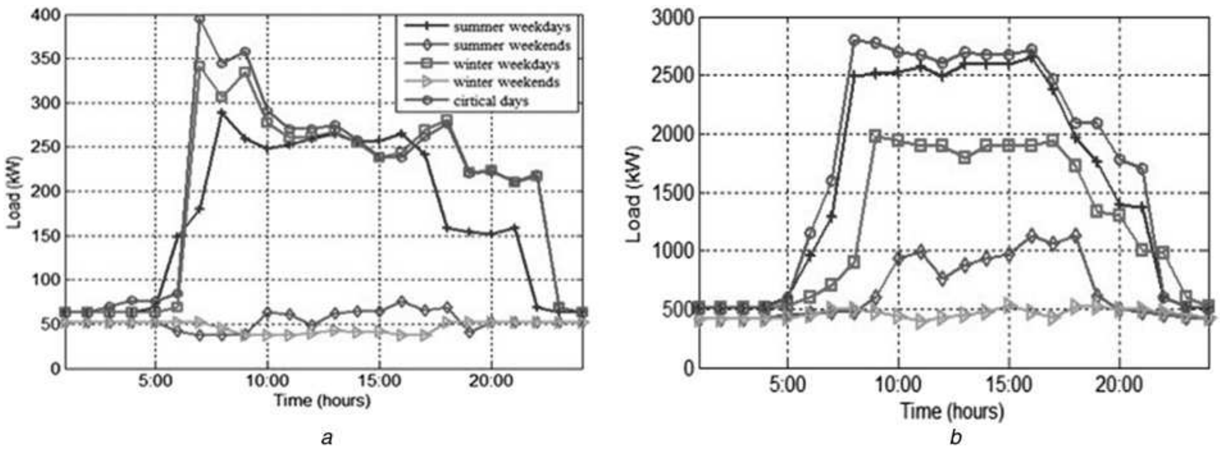

Fig. 2 *Five load scenarios for*

a Small commercial/industrial buildings
b Large commercial/industrial campuses

by constraint (11). Constraints (12) and (13) represent the maximum discharging and charging constraints of ESSs, respectively. Constraint (14) represents the range of SOC. Constraint (15) defines the discomfort index as the total shifted load consumption during a day. In constraint (16), the reliability index is defined as the total curtailed loads. Constraint (17) represents the maximum allowable outputs of generators.

The first-stage decision variables are z_s, z_g, and $z_{i,y}$; and the second-stage decision variables are $g_{h,y,w}$, $q^{sd}_{h,y,w}$, $q^{sc}_{h,y,w}$, $l_{h,y,w}$, $l^{s}_{h,y,w}$, and $l^{c}_{h,y,w}$. Therefore, the first stage of the formulation assists customers in selecting the most beneficial demand response programs (i.e. TOU, CPP, and PTR). The first stage also makes decisions on the integration of customer-owned BESS and DGs. The second stage performs the load management and generation scheduling according to the decisions made in the first stage. The proposed formulation is a mixed integer non-linear program which is solved by BOMIN solver in GAMS [24, 25].

4 Numerical results

The proposed framework has been tested with two types of customers: small commercial/industrial buildings and large commercial/industrial campuses. Five demand scenarios are considered in the case study: (i) summer weekdays, (ii) summer weekends, (iii) winter weekdays, (iv) winter weekends, and (iv) critical days (event days). In general, hot summer weekdays and cold winter weekdays with severe events are considered as critical days. The probabilities of the five demand scenarios are set to be $W_1 = 0.3425$, $W_2 = 0.1370$, $W_3 = 0.3425$, $W_4 = 0.1370$, and $W_5 = 0.041$.Fig. 2 shows the load consumption of five scenarios for small commercial/industrial buildings and for large commercial/industrial campuses.

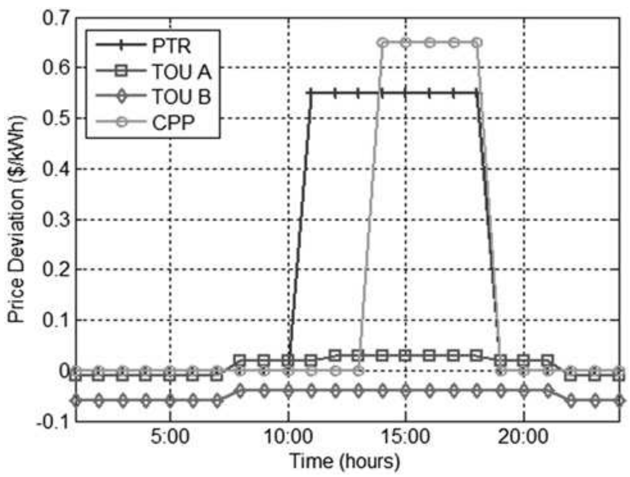

Fig. 3 *Price deviations of demand response programs*

The base electricity price P^0_1 is set to be 0.20 \$/kWh, the price deviations of demand response programs are shown in Fig. 3 [26]. TOUA represents the price deviations for summer/winter weekdays and TOUB represents the price deviations for summer/winter weekends.

As shown in (8), the electricity price for a certain time slot is the aggregation of the base price and the corresponding price deviations. It is assumed that the base electricity price increases linearly by \$0.02 per year. The annual discount rate is 0.9. The planning horizon is set to be 5 years. $G^{\max}$ is set to be 80 kW for small commercial/industrial buildings, and 600 kW for large commercial/industrial campuses. OC^{g} is set to be \$0.1/kWh with the annual increase of \$0.02. Sign-on bonus is applied to the CPP program, and is set to be \$0.5/kW of the maximum load consumption. $\alpha^{s}_{h,w}$ is set to be 0.05 and $\alpha^{c}_{h,w}$ is set to be 0.05. For the ESSs, η^{l} is set to be 0.95, η^{c} is set to be 0.90, η^{d} is set to be 0.90, γ is set to be 0.9, P^{ocs} is set to be 0.50 \$/kWh, D^{s} is set to be 4 h, and M^{s} is set to be 3 kW. We assume the weights of costs, reliability index, and discomfort index are 0.45, 0.45, and 0.1, respectively. It should be noted that all of the simulation settings are for illustration, operators can change the settings according to the operation and available information of a system. All the experiments are implemented using GAMS 22.5 at Intel Quad Core 2.40 GHz with 8 GB memory. The solution time of the formulation defined in (1)–(19) is within 1 min in the studied two cases, i.e. smaller commercial/industrial building, and large commercial/industrial campuses.

4.1 *Simulation results for small commercial/industrial buildings*

Simulations are run for a small commercial/industrial building with load profiles shown in Fig. 2. Table 1 summarises the first-stage results during the planning horizon.

Table 1 First-stage results for a small commercial/industrial building

Year 1	Year 2	Year 3	Year 4	Year 5	Number of BESS
T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	47

T: time-of-use, P: peak-time rebate, C: critical peak pricing

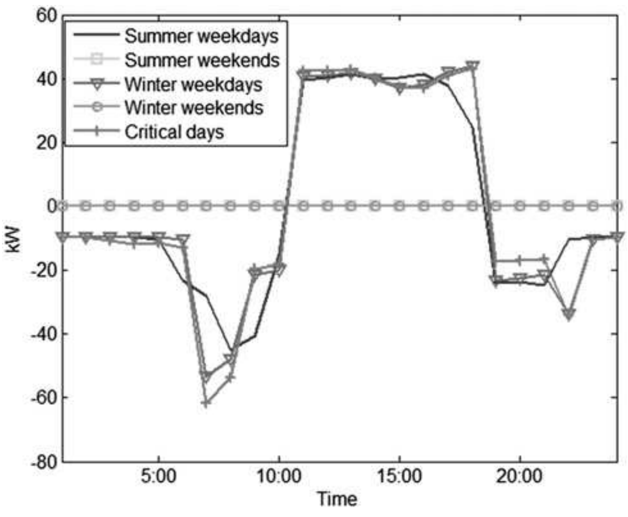

Fig. 4 *Load shifting results of a small commercial/industrial building in the first year*

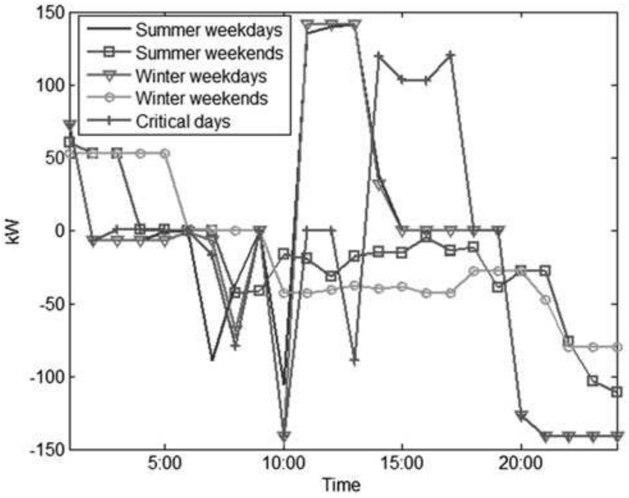

Fig. 5 *Aggregated charging/discharging of BESS of a small commercial/industrial building in the first year*

According to the results, the building installs one DG and 47 battery units, and participates all three DR programs in the five years. Fig. 4 shows the load shifting results in five demand scenarios in the first year. A positive value represents the load is shifted from the corresponding time, and a negative value represents that the load is shifted to the time period. It can be seen that the total shifted load consumption during 24 h is zero as constrained by (5). There is no shifted load in scenarios 2 and 3 since they represent weekend load demand which is usually low. Load consumption during 11:00 am to 6:00 pm in summer/winter weekdays and event days has been shifted to off-peak hours.

Fig. 5 shows the aggregated charging/discharging operation of all installed battery units in the first year. A positive value represents batteries are operating at the discharging state, and a negative value indicates that batteries are operating at the charging state. It can be seen that the operations of batteries in different demand scenarios are different with each other. In general, the charging/discharging power in summer/winter weekends is relatively small; the charging/discharging power in summer/winter weekdays and event days is larger. Meanwhile, batteries operate in the discharging state for a longer time in event days. Since grid electricity price in critical periods is very high, the building tends to support its load using batteries and DGs.

Fig. 6 shows the net imported power from the grid in the first year in four demand scenarios, i.e. summer weekdays, summer weekends, winter weekdays, and critical days. To show the impacts of BESS on customer behaviours, we compare the net imported power with and without BESS for the four scenarios. It can be seen that the imported power in cases without BESS is smaller than those with BESS since there is no battery unit that needs to be charged. However, for a building without BESS, its imported power during peak time (2:00–6:00 pm) becomes larger in summer/winter weekdays (Figs. 6*a* and *c*) and critical days (Fig. 6*d*). This is because the demand can only be supplied by the grid and DG. In Fig. 6*d*, the building with BESS can be self-supplied in peak hours in critical days to avoid buying electricity from grids at a much higher price. In Fig. 6*b*, the net imported power of the building without BESS is close to zero because the load in weekends is small and can be supplied by the DG. The building with BESS needs to import relatively cheap electricity from the grid to charge the BESS in the night.

Table 2 shows the sensitivity analysis of DG sizes to demonstrate their impacts on planning and operation results. When DG sizes are small (i.e. <80 kW), the building decides not to participate critical

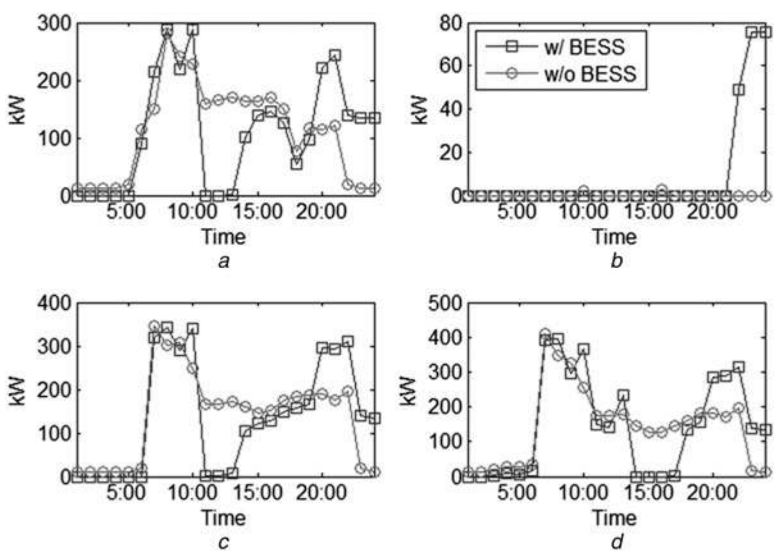

Fig. 6 *Power imported from the grid of a small commercial/industrial building in the first year*

a Summer weekdays
b Summer weekends
c Winter weekdays
d Critical days

Table 2 Sensitivity analysis of DG sizes for a small commercial/industrial building

DG size, kW	Year 1	Year 2	Year 3	Year 4	Year 5	Objectives, $	Number of BESS
0	T, P	T, P	T, P	T, P	T, P	527,369	6
20	T, P	T, P	T, P	T, P	T, P	398,162	18
40	T, P	T, P	T, P	T, P	T, P	282,833	27
60	T, P, C	T, P, C	T, P	T, P	T, P	188,940	42
80	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	96,588	47
100	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	8883	63
120	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	−74,924	55
140	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	−15,418	50
160	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	−229,837	41
180	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	−301,989	35

T: time-of-use, P: peak-time rebate, C: critical peak pricing, objectives are defined in (1)

Table 3 Sensitivity analysis of DR program designs for a small commercial/industrial building

Year	TOU ratio	CPP/PTR ratio	DR programs	Objectives, $	Number of BESS
1	0.5	0.25	T, P	382,442	0
2	1.0	0.50	T, P	290,101	0
3	1.5	0.75	T, P	191,313	2
4	2.0	1.00	T, P, C	63,359	75
5	2.5	1.25	T, P, C	−115,550	87

T: time-of-use, P: peak-time rebate, C: critical peak pricing, objectives are defined in (1)

time pricing program because the self-generation and storage capacities are not enough to support its load during peak times on critical days. The number of installed BESS increases with the DG size since DG generation can be used to charge BESS when the electricity price is high. After the DG size exceeds 100 kW, the building installs less BESS because more load consumption can be supported by the DG. The total operation cost is also impacted by DG sizes. As the DG size increases, the operation cost decreases since the DG generation can be used to support more load consumption and BESS charging during peak hours.

Table 3 shows the sensitivity analysis for electricity prices. The base prices can be shown in Fig. 3. In the price sensitivity analysis, the applied TOU and CPP/PTR price is their base price times the corresponding ratios. When electricity prices are low, the costs of installing BESS cannot be justified by the potential benefits. Therefore, no BESS or only a few BESS are installed. The operation of certain DR programs such as CPP requires a large number of BESS to reduce the peak-time load. When electricity prices are high, the building decides to install more BESS and participate in CPP to receive the rebates.

4.2 Simulation results for large commercial/industrial campuses

In this case, we run simulations a large commercial/industrial campus with load profiles shown in Fig. 2*b*. Table 4 summarises the first-stage results during the planning horizon.

According to the results, the building installs one DG and 468 battery units, and participates all three DR programs in the five years. Fig. 7 shows the load shifting results in five demand scenarios in the first year. Similar to the load shifting results in the small commercial/industrial building, load consumption is mostly

Table 4 First-stage results for a large commercial/industrial campus

Year 1	Year 2	Year 3	Year 4	Year 5	Number of BESS
T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	468

T: time-of-use, P: peak-time rebate, C: critical peak pricing

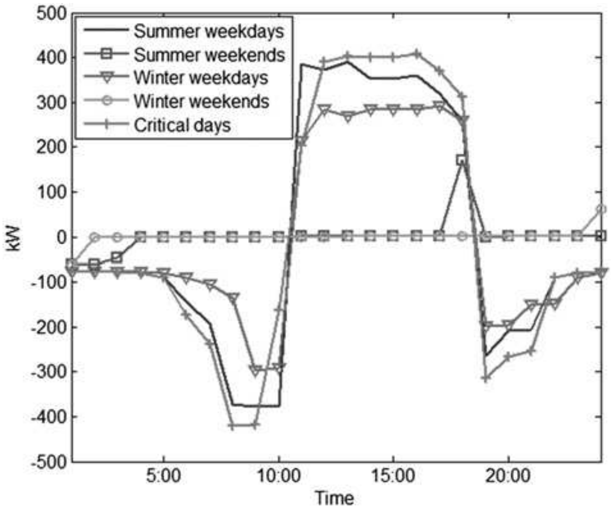

Fig. 7 *Load shifting of a large commercial/industrial campus in the first year*

shifted during peak hours in summer/winter weekdays and event days.

Fig. 8 shows the aggregated charging/discharging operation of all installed battery units in the first year. It can be seen that battery units operate in the discharging mode to support demand during peak periods in summer/winter weekdays, summer weekends, and event days. The charging/discharging power in winter weekends is still small due to the relatively flat and small demand. In all five

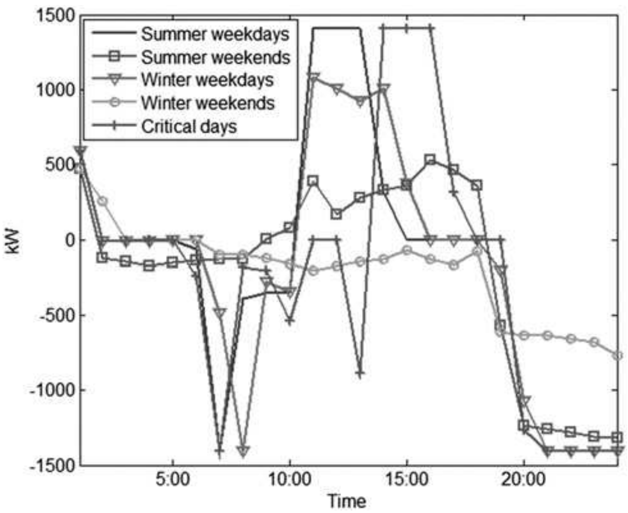

Fig. 8 *Aggregated charging/discharging of BESS of a large commercial/industrial campus in the first year*

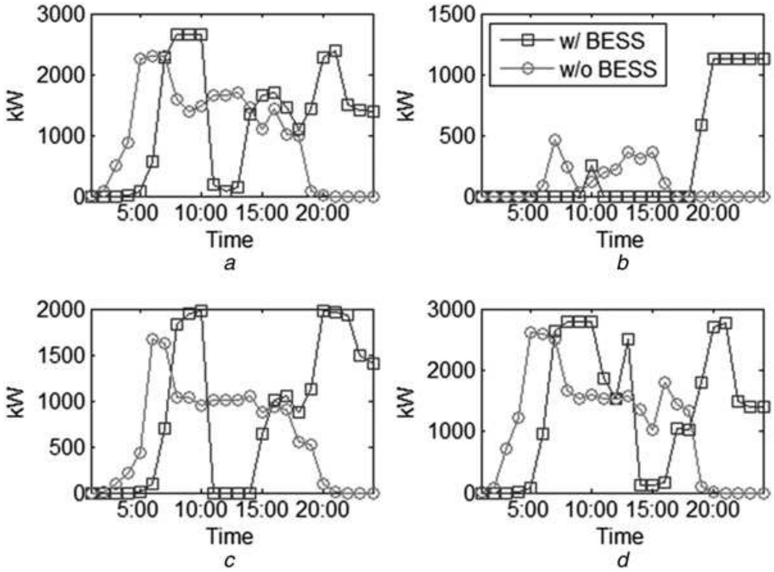

Fig. 9 *Power imported from the grid of a large commercial/industrial campus in the first year*

a Summer weekdays
b Summer weekends
c Winter weekdays
d Critical days

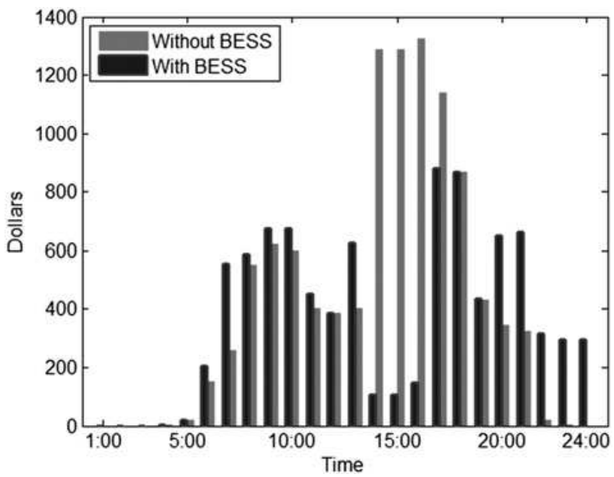

Fig. 10 *Hourly payment to the utility in a critical day*

scenarios, battery units are operated in the charging state from 8:00 pm to midnight to take advantage of the relatively cheap electricity.

Fig. 9 shows the net imported power from the grid in the first year. In the night, the campus with BESS imports relatively cheap electricity from the grid to charge the BESS. It can be seen from Figs. 9*a–d* that the campus with BESS can be self-supplied during peak hours. In contrast, the campus without BESS needs to buy more electricity at a higher price in the peak periods. The total operation costs of the customer with and without BESS over a period of 5 years are \$693,517 and \$940,560, respectively. Therefore, the operation costs can be reduced by optimally integrating BESS.

Fig. 10 shows the hourly payment to the utility of the large campus in a critical day. During peak hours (2:00–6:00 pm), the consumer pays much less if BESS is installed. The total daily payment with and without BESS are \$8913 and \$10,404, respectively.

Table 5 shows the sensitivity analysis of DG sizes on the planning and operation results. When DG sizes are small (i.e. <600 kW), the campus decides not to participate critical time pricing program because the self-generation and storage capacities are not enough to support its load during peak times on critical days. The number of installed BESS increases with the DG size since DG generation can be used to charge BESS when the electricity price is high. After the DG size exceeds 1000 kW, the campus installs less BESS because more load consumption can be supported by the DG.

Table 6 shows the sensitivity analysis for electricity prices. The base prices can be shown in Fig. 3. In the sensitivity analysis, the applied TOU and CPP/PTR price is their base price times the corresponding ratios. Similar to the results of a small building, no BESS is installed when electricity prices are low since the costs of installing BESS cannot be justified by the potential benefits. The

Table 5 Sensitivity analysis of DG sizes for a large commercial/industrial campus

DG size, kW	Year 1	Year 2	Year 3	Year 4	Year 5	Objectives, \$	Number of BESS
0	T, P	T, P	T, P	T, P	T, P	4,425,850	61
200	T, P	T, P	T, P	T, P	T, P	3,107,834	179
400	T, P	T, P	T, P	T, P	T, P	1,985,705	246
600	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	693,517	468
800	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	31,988	475
1000	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	–803,318	481
1200	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	–1,560,459	428
1400	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	–2,311,725	421
1600	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	–3,054,885	337
1800	T, P, C	T, P, C	T, P, C	T, P, C	T, P, C	–3,714,225	282

T: time-of-use, P: peak-time rebate, C: critical peak pricing, objectives are defined in (1)

Table 6 Sensitivity analysis of DR program designs for a large commercial/industrial campus

Year	TOU ratio	CPP/PTR ratio	DR programs	Objectives, $	Number of BESS
year 1	0.5	0.25	T, P	3,181,170	0
year 2	1.0	0.50	T, P	2,507,998	0
year 3	1.5	0.75	T, P, C	1,763,372	84
year 4	2.0	1.00	T, P, C	929,166	488
year 5	2.5	1.25	T, P, C	62,856	612

T: time-of-use, P: peak-time rebate, C: critical peak pricing, objectives are defined in (1)

operation of CPP requires a large number of BESS to reduce the peak-time load. When electricity prices are high, the campus decides to install more BESS and participate in CPP to receive the rebates.

5 Conclusions

In this paper, a two-stage framework for the planning and energy management of a customer with ESSs and demand response programs is proposed. The first stage is to assist the customer to select the most beneficial programs to participate and install an appropriate number of battery units. The second stage is to perform energy management according to the decisions made in the first stage, which includes dispatches of loads, DGs and BESS. The proposed method can be applied to residential, commercial and industrial customers with various demand scenarios. For illustration, we consider two types of customers (small commercial/industrial buildings and large commercial/industrial campuses) and five demand scenarios (summer/winter weekdays, summer/winter weekends, and critical days) in the case study. TOU, critical time pricing and PTR are considered as options of demand response programs. The numerical results demonstrate the effectiveness of the proposed method. It has been shown that the integration of battery units has great impacts on the energy management with DR programs. Customers can receive more profits by installing an appropriate amount of BESS while joining DR programs.

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