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# Thermally controllable demand response with multiple load aggregators

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ABSTRACT

Demand response (DR), as an effective way to improve operational efficiency of distribution networks, also imposes challenges on the mechanism design of ancillary services. Thermally controllable load (TCL), e.g. heating, ventilating, air-conditioner, has increased significantly in recent decades, which can be leveraged as a flexible resource owing to its well responsive capability towards the market incentives. Nevertheless, the spatially distributed TCLs are hardly coordinated through traditional DR schemes directly implemented by distribution network operators (DNOs). In this paper, a hierarchical market model is newly proposed to address this issue, where multiple load aggregators (LAs) perform as profit-pursing intermediaries by offering aggregated service to bridge interaction between DNOs and end-users. This model is devised with two levels. At the top level, aggregators' benefits are determined by Shapley value method, which is in proportion to their contributions to cost minimization in utility operation. At the bottom level, end-users decide the temporally responsive amount by reaching a trade-off between the monetary revenue and resultant discomfort. Case studies illustrate that the proposed model provides an easy access to multiple aggregators to coordinate the widely distributed TCLs, which exhibits a high potential of practical application for system operators.

## 1. Introduction

The advanced technology transformation of distribution networks enables efficient operation interaction ability of all entities in the context of electricity market. However, the increasing involvement of the demand side, especially for widely distributed responsive users, poses challenges, as well as brings opportunities for the market participants [1].

In the future smart grid, the energy consumption pattern of end-users, serving as flexible energy resource, can be responsive to incentives to share an active role in system-level operation [2–4]. In Refs. [5,6], a simple price elastic matrix is employed to capture the demand response features of the end-users. However, a more elaborate demand response model should be incorporated into the DR implementation process, since the future technical framework is required to carry out DR programs in an efficient way to mitigate end-users' discomfort and integrate human feedback into the DR schemes [7]. Thermally controllable load (TCL), e.g. heating, ventilating, air-conditioners (HVACs) shows untapped potential to offer DR services due to its huge thermal capacity and easy controllability [8,9]. However, distribution network operator (DNO) usually lacks the know-how to integrate such spatial-distributed controllable resources for DR programs at a large scale.

Fortunately, the presence of load aggregators (LAs) acting as intermediators to represent corresponding end-users in interacting with DNO, saves large communication and management work for DNO. Currently, LAs generally pay a monthly fee to the end-users to gain direct control of their appliances, e.g. HVACs [12]. But the emergence of pervasive mobile communication capabilities and smart grid technologies enables a much tighter information feedback loop among market entities. Traditional works [10,11] implementing DR programs in day-ahead market and real-time market with a fixed pre-defined incentive mode fail to adapt to the actual operation status in the distribution network. Incentive-based demand response proposed in [13,14], provides a promising method to induce the demand flexibility of end-users on a voluntary basis. However, a more efficient participation mechanism of responsive load in DR programs ought to be developed by leveraging pricing and load information exchange schemes.

For DNO, due to the high transmission energy loss of the distribution network caused by relatively high resistance to inductance ratio of low voltage, a DR program can be a practical solution to network energy loss [15,16]. In Ref. [15], a residential DR program implemented in the power distribution network, aiming to improve the system performance from an economic perspective, has been well studied. In Ref. [16], a market-based mechanism is proposed to alleviate distribution

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**Nomenclature**

*Parameter*

| | |
|---|---|
| $b_{ij}$ | Series susceptance in the $\pi$ -model of line *ij* |
| $P^G$ | Real power produced by the generator |
| $b_{shij}$ | Shunt susceptance in the $\pi$ -model of line *ij* |
| $P^D$ | Initial real power load demand |
| $g_{ij}$ | Series conductance in the $\pi$ -model of line *ij* |
| $P^m$ | HVAC rated power |
| m | Number of lines |
| $Q^G$ | reactive power produced by the generator |
| n | Number of nodes |
| $Q^D$ | Initial reactive power load demand |
| D | Set of Las |
| $Q^I$ | Reactive power injection |
| Z | Set of end-users |
| $R$ | Thermal resistance |
| $C(i)$ | Set of nodes connected to node $i$ by a line |
| $C$ | Thermal capacitance |
| $\theta$ | Voltage angle |
| $C^{RT}$ | Real-time electricity price |
| $U$ | Voltage magnitude |
| $C_{min}/C_{max}$ | The upper/lower bound of incentive value |
| $I$ | Current magnitude |
| $T^{set}$ | Temperature set-points |
| $T$ | Temperature |
| $T^{db}$ | Temperature dead-band |
| $\rho$ | Cost coefficient of the switching action of reconfiguration process |
| $T^{OA}$ | Ambient temperature |

*Variables*

| | |
|---|---|
| $P^{cur}$ | Desired power curtailment by DNO |
| $C^{LA}$ | Incentive price for LA to curtail power per unit |
| $P^{cur}_{max}$ | Maximum power curtailment for LA |
| $\lambda$ | Compensation price for end-user to curtail power per unit |
| $P^{LA}$ | Actual power reduction by LA |
| $P^I$ | Real power injection |
| $P^0$ | Preferred energy consumption of end-user |
| $\Delta T$ | Temperature deviation from the set-points of end-user |
| $\Delta P$ | Power deviation from the preferred energy consumption pattern of end-user |
| $\sigma_l$ | Variable set to 1 if the line is connected and to 0 if the line is disconnected |

*Subscript*

| | |
|---|---|
| $i$ | Node i |
| $d$ | Load aggregator $d$ |
| $ij$ | Form node $i$ to node j |
| $z$ | End-user $z$ |
| $l$ | Line $l$ |
| $t$ | Time slot $t$ |

network congestion condition through a DR program. Network reconfiguration, as a positive method in reducing the network loss [17], can be well coordinated with DR programs. However, this point is rarely investigated in the existing literatures. Additionally, LAs take different proportions of contribution on reducing the operation cost of the system due to their location diversity and market participation level [18]. Therefore, an unbiased allocation of incentive prices conducted by DNO for LAs joint in a DR program is necessitated.

In this paper, a market-based DR mechanism in combination of network reconfiguration is devised for scheduling sub-hourly energy consumption of TCLs, which is suited for the provision of peak-shaving services. The proposed bi-level model aiming at a win-win operation framework of the distribution network, enables efficient interaction of DNO, LAs, and end-users. The main contributions of this paper are:

- A bi-level DR model is proposed, where spatially distributed thermal loads are well coordinated to participate in a DR market. Specially, the reconfigurability of distribution network is considered and scheduled with the DR program so as to enhance the applicability of the whole DR scheme in the distribution network.
- Apart from traditional pricing model in a DR market, a fairness function is modeled to assist DNOs in ensuring that the DR compensation provided for LAs are fairly allocated according to their contributions on minimizing system operation cost.
- TCLs are self-scheduled in response to the DR program without compromising comfort expectation. To achieve this, the responsive capability of TCLs is interactively evaluated before the implementation of the DR program, which ensures the acceptable thermal envelops for all end-users.
- Diverse interests of different entities are well captured and defined in the proposed model. The formulated bi-level optimization problem can be effectively solved in an iterative manner with satisfactory solutions. The hierarchic negotiation process ensures a competitive market environment for all participants.

The rest of the paper is organized as follows. In Section 2, we give details of problem formulation. Section 3 introduces the overall bi-level market model for all market entities considering the DR program. Simulation results are reported in Section 4, which demonstrate the effectiveness of the proposed method. Section 5 concludes this paper.

## 2. Problem formulation

The components of the proposed market scheme contains the DNO, a set of LAs $\mathbf{D} = \{LA_1, LA_2, \cdots, LA_D\}$ and a set of end-users $\{1,2,\ldots,Z\} \in LA_d$, where the end-users sign an aggregation contract with corresponding LA $_d$ (as illustrated in Fig. 1). $t = \{1,2, \cdots, T_N\}$ is denoted as the sequential time slots.

The hierarchical DR model provides a good platform for the dynamic interaction of all market participants. Prior to the activation of demand response, DNO broadcasts an incentive price signal/desired load curtailment for each interval of the event according to the predicted operation condition of the system for the future time interval. LAs respond by bidding a parameter for each time interval which provides a compact description of their responsive function at the incentive price. The interaction between end-users and LAs is analogous

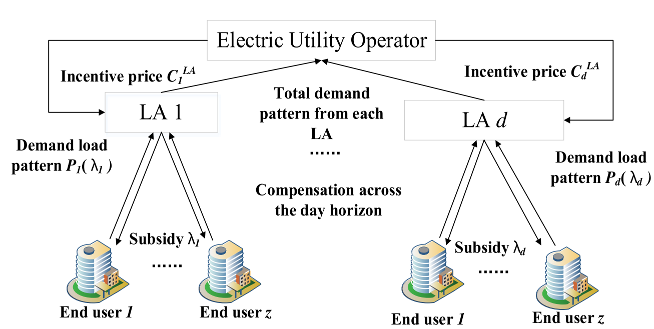


**Fig. 1.** The hierarchical structure of the proposed market model.

to that of LAs and DNO. The whole negotiation process iterates until price converge and all entities reach an agreement.

### 2.1. DNO: operation cost minimization

Operation cost is the major concern of the distribution network operator. Since network reconfiguration and a DR program both share as active roles in the operation cost minimization of distribution network, DNO has to handle the tradeoff between the reconfiguration and load curtailment. Frequent switching actions will lead to irreversible degradation of switching devices. In general, minimization of the operation cost concerns the DR compensation cost, the network energy loss and the switching action cost. Thus, the decision model for the utility operator can be written as follows.

$$\min_{P_{d,t}^{cur},C_{d,t}^{LA},\sigma_{l,t}} \sum_{t\in T_N} \left( \sum_{d=1}^{A} P_{d,t}^{cur} C_{d,t}^{LA} + \sum_{i=1}^{n} P_{i,t}^{I} C_{d,t}^{RT} + \rho \sum_{l=1}^{m} |\sigma_{l,t} - \sigma_{l,t-1}| \right) \tag{1}$$

Subject to

Net power injection constraints:

$$\begin{cases} P_i^I = \sum_{j\in C(i)} \sigma_{ij}[g_{ij}U_i^2 - U_iU_j(g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij})] \\ = P_i^G - P_i^D + P_i^{cur}, \\ Q_i^I = \sum_{j\in C(i)} \sigma_{ij}[-(b_{ij} + b_{shij}/2)U_i^2 + U_iU_j(b_{ij}\cos\theta_{ij} - g_{ij}\sin\theta_{ij})] \\ = Q_i^G - Q_i^D, \\ I_l^2 = \sigma_l[A_{ij}U_i^2 + B_{ij}U_j^2 - U_iU_j(C_{ij}\cos\theta_{ij} - D_{ij}\sin\theta_{ij})] \end{cases} \tag{2}$$

where

$$\begin{cases} A_{ij} = g_{ij}^2 + (b_{ij} + b_{shij}/2)^2 \\ B_{ij} = g_{ij}^2 + b_{ij}^2 \\ C_{ij} = g_{ij}^2 + b_{ij}(b_{ij} + b_{shij}/2) \\ D_{ij} = g_{ij}b_{shij}/2 \end{cases} \tag{3}$$

2) Operation security constraints

$$U_i^{\min} \le U_i \le U_i^{\max},\ I_l^{\min} \le I_l \le I_l^{\max} \tag{4}$$

3) Network radiality constraints

$$\sigma_{ij} + \sigma_{ji} = \sigma_l,\ l \in m \tag{5}$$

$$\sum\nolimits_{j\in C(i)} \sigma_{ij} = 1, i \in n \tag{6}$$

$$\sigma_{ij} \in \{0, 1\},\ \sum\nolimits_{l=1}^{m} \sigma_l = n 0 \le \sigma_l \le 1 \tag{7}$$

4) Incentive price constraints

$$C_{\min,t} \le C_{d,t}^{LA} \le C_{\max,t},\ d \in \mathbf{D} \tag{8}$$

The constraints include net real and reactive power injection Eq. (2), node voltage magnitude and line ampacity limits (4), radiality constraints (5)–(7) and price constraint (8). Note that the network loss is equal to the value of the total real generation minus total real demand, which is the same as the summation of net real power injections at all nodes of the system [19]. The distribution network corresponds to a spanning tree connected to the main substation, by introducing two binary variables $\sigma_{ij}$ and $\sigma_{ji}$ corresponding to each line $l$, so as to sufficiently guarantee network radiality. Equation (6) ensures that every node except the root (substation node) has exactly one parent. The current switch status of the line $l$ can be given by the variable $\sigma_{l,t}$, Any change in the switch status of a line would result in $|\sigma_{l,t} - \sigma_{l,t-1}| = 1$. In this case, we reformulate the problem in terms of its continuous variables as a convex second-order cone program to obtain a convex relaxation which recovers the exact solution at optimality [19].

### 2.2. LAs: profit maximization

#### 2.2.1. The object of LAs

Individually distributed end-users enroll in a DR scheme provided by LAs. Assuming that only one LA is allowed to provide the DR program at each node of the system. DNO intends load curtailment $P_d^{cur}$ from LA $d$, but the bidding decision $P_d^{LA}$ of LA $d$ is optimized to realize the maximum economic benefit within its dispatch feasibility of loads $P_{max,d}^{cur}$, which is determined by received incentive price and the associated aggregation cost function $f(\cdot)$, i.e., the cost of power reduction from end-users, and thus, the objective of LA $d$ can be expressed as the following optimization problem.

$$\max_{P_{d,t}^{LA},} \sum_{t\in T_N} (P_{d,t}^{LA} C_{d,t}^{LA} - f(P_{d,t}^{LA})) \tag{9}$$

subject to

$$\begin{cases} P_{d,t}^{LA} \le P_{\max,d,t}^{cur} d \in \mathbf{D} \\ P_{d,t}^{LA} \le P_{d,t}^{cur} \end{cases} \tag{10}$$

#### 2.2.2. Fairness quantification for multiple LAs

LAs regulate their total load demand in response to the received incentive price from DNO, but they contribute different proportions on system operation cost minimization as they enroll in the DR program. The Shapley Value method [20] is employed to measure the contributions of LAs in a mathematical way, so as to realize allocation fairness among the LAs. The system operation cost without the DR program derived from Eq. (1) can be calculated as

$$V_t = \sum_{i=1}^{n} P_{i,t}^{I} C_{d,t}^{RT} + \rho \sum_{l=1}^{m} |\sigma_{l,t} - \sigma_{l,t-1}| \tag{11}$$

And the system operation cost with the participation of LA $d$ can be expressed as

$$V_t = \sum_{i=1}^{n} P_{i,t}^{I} C_{d,t}^{RT} + \rho \sum_{l=1}^{m} |\sigma_{l,t} - \sigma_{l,t-1}| + P_{d,t}^{LA} C_{d,t}^{LA} \tag{12}$$

The incentive price $C_{d,t}^{LA}$ obtained by LA $d$ should correspond to its impact $\phi_t^d$ playing on the operation cost as LA $d$ participate in the DR program. Thus, the fairness function can be defined as (13), where $C_{d,t}^{LA}$ is proportional to the impact $\phi_t^d$ of LA $d$ compared with the impact $\phi_t^g$ of LA $g$ and its corresponding incentive price $C_{g,t}^{LA}$.

$$C_{d,t}^{LA} = \frac{\phi_t^d}{\phi_t^g} \cdot C_{g,t}^{LA} \tag{13}$$

Note $\phi_t^d$ can be calculated from two scenarios, one case is that LA $d$ participates in the DR program, while in another case LA $d$ is not part of the DR program.

$$\phi_t^d = \sum_{S\in A} \frac{(S-1)!(A-S)!}{A!} [V_{S\cup\{d\},t} - V_{S,t}] \tag{14}$$

where $S$ denotes the number of LAs in the virtual subset. $V_{S,t}$ and $V_{S\cup\{d\},t}$ are the operation cost of subset $S$ with LA $d$ and without LA $d$ at time slot $t$, respectively.

### 2.3. End-user: profit maximization

#### 2.3.1. TCL Model: HVAC system

The energy consumption of TCL can be appropriately scheduled while keeping the indoor temperature to vary within pre-specified zone. Assuming a LA would can negotiate with end-users on the subsidy price to incent them to optimally schedule their individual HVAC unit. The dynamics of thermal loads are affected by ambient temperatures and internal sets, which can be described and further discretized as [21]:

$$T_{z,t+1} = T_{z,t} \cdot e^{-\frac{\Delta t}{R_z C_z}} + (R_z P^m \beta_{z,t} + T_t^{OA}) \cdot (1 - e^{-\frac{\Delta t}{R_z C_z}}) \tag{15}$$

Here, $\Delta t$ is the time step. The state of the HVAC unit is captured by the binary signal $\beta_t$. $\beta_t = 1$ denotes the HVAC unit in the ON-state at time $t$ and $\beta_t = 0$ means that the unit is in the OFF-state [22]. To simplify the model, the approximate model is used for the overall analytical work. Here, end-user $z$ accepts any continuous power input $P_z \in [0, P^m]$ and therefore the dynamics can be descript as below.

$$T_{z,t+1} = T_{z,t} \cdot e^{-\frac{\Delta t}{R_z C_z}} + (R_z P_{z,t} + T_t^{OA}) \cdot (1 - e^{-\frac{\Delta t}{R_z C_z}}) \tag{16}$$

We denote that the nominal power required to keep HVAC owner $z$ at its set-point at time $t$ is $P_{z,t}^0$, and the accepting power deviation $\Delta P_{z,t}$ around its nominal power consumption that should meet end-users' specified comfort bounds as described below

$$\begin{cases} P_z^0 + \Delta P_z \le P^m \\ |T_z - T_z^{set}| \le T_z^{db} \end{cases} \tag{17}$$

### 2.3.2. End-user demand reduction function

Here, TCLs act as supplier of energy regulation and end-users are assumed to be rational market participant. For each end-users $z \in \mathrm{LA}_d$, the determination of demand reduction $\Delta P_z$ involves a tradeoff between the received subsidy price $\lambda_d$ and the discomfort caused by temperature deviation as below.

$$\max_{\Delta P_{z,t}} \sum_{t \in T_N} \lambda_{d,t} \Delta P_{z,t} - \sum_{t \in T} \pi_z(\Delta T_{z,t}) \tag{18}$$

Subject to

$$\sum_{z \in A_d} \Delta P_{z,t} = P_{d,t}^{LA} \tag{19}$$

The disutility function $\pi_z(\cdot)$ describes the comfort level of each end-user in a financially quantified way [23], which penalizes deviations from the set temperature. The level of discomfort for each period can be descript as

$$\pi_z(\Delta T_{z,t}) = |T_z - T_z^{set}|^\delta / D_z \tag{20}$$

where $D_z$ represents the willingness of end-user $z$ to participate in DR services. The set parameters of the disutility function $D_z > 0$, $\delta = 2$ guarantee the disutility function $\pi_z(\cdot)$ a convex function. Using Eq. (16), the disutility functions can be expressed in terms of $\Delta P_z : \tilde{\pi}_z(\Delta P_z) = \pi_z(\Delta T_z(\Delta P_z))$. Fig. 2 describes the decision behaviors of end-users towards the increasing subsidy price. Smaller the $D$ value is, more reluctantly end-users deviate from their preference temperature, as illustrated in Fig. 2(b). Fig. 2(a) illustrates that higher subsidy price incents end-users to reduce more energy demand, as long as the indoor temperatures are maintained at the specific ranges.

### 2.3.3. The negotiation process between end-users and LA

The LA motivates end-users to voluntarily manage their demand by providing them with subsidy during the day in an economic manner. The demand reduction function of end-user $z \in LA_d$ is given by $\Delta P_z(\lambda_d) = (\pi_z')^{-1}(\lambda_d)$ through the end-user problem (18). Then, each end-user bids its demand reduction function to its signed LA $d$ so that LA $d$ has the complete knowledge of the pair of the information, the subsidy price and the associated demand reduction quantity, i.e., $P_d^{LA}(\lambda_d) = \sum_{z \in LA_d} \Delta P_z(\lambda_d)$. Therefore, the associated cost function of the LA $d$ can be described as the function of $\lambda_d$ during the period $T_N$, i.e., $f(P_d^{LA}) = \sum_{t \in T_N} \lambda_{d,t} \sum_{z \in LA_d} \Delta P_{z,t}$, which is equal to the total subsidy payment LA $d$ offering to end-users. Given incentive price $C_d^{LA}$, the LA $d$ can solve the optimization problem of (9) with respect to $\lambda_d$ (instead of $P_d^{LA}$) and the optimal $P_d^{LA}$ of LA $d$ is given by $P_d^{LA} = P_d^{LA}(\lambda_d)$

$$\lambda_d = \arg\max_{\lambda_d} C_d^{LA} P_d^{LA} - \lambda_d \sum_{z \in A_d} \Delta P_z(\lambda_d) \tag{21}$$

## 3. The market model for utility-aggregator-user interaction

In this section, a bi-level DR market structures is proposed, where LAs serve as DR intermediates. At the upper level, the economy of the operation process is continuously updated and quantified to assist DNO in managing DR resources in consideration of network reconfiguration, which involves the lower-level optimization problems. At the lower level, LA negotiates with end-users to modulate the aggregate energy consumption such that the actually aggregated load in the service area closely follows the accepted demand bids at the upper level. The objectives of the co-optimization problem can be formulated as Eqs. (1), (9) and (18), subject to (3)–(8), (10) and (17), illustrated in Fig. 3.

To solve the optimization problem, an exhaustive method is employed: increasing the incentive price by a fixed increment $\Delta C_d^{LA}$ iteratively until the maximum value is reached or the bids are accepted. Several main steps are involved as follows.

1) DNO firstly initializes the incentive information for LAs. The expected power reduction $P_d^{cur}$ of DNO at node $i$ is calculated by Eq. (1), and the initial Shapley-determined incentive prices are determined by Eq. (13).
2) Each LA participating in the DR program negotiates with its signed end-users, submitting its optimal demand reduction offer $P_d^{LA}$ to DNO for sake of profit maximization in Eq. (9). The responsive capacity of demand is evaluated before each LA responds to DNO.
3) The fair allocation of incentive prices for LAs can be determined by Eq. (13) according to the submitted demand reduction amount of $P^{LA}$.
4) DNO re-estimates the operation condition. if submitted reduction amount of LAs reaches the desired reduction amount or the incentive price reaches the maximum incentive price, DNO proceeds to step 7, vice versa DNO proceeds to step 6.
5) Increase the incentive price by a fixed increment $\Delta C_d^{LA}$ and iterate from step 2–6.
6) DNO calculates the operation cost and decides whether to execute

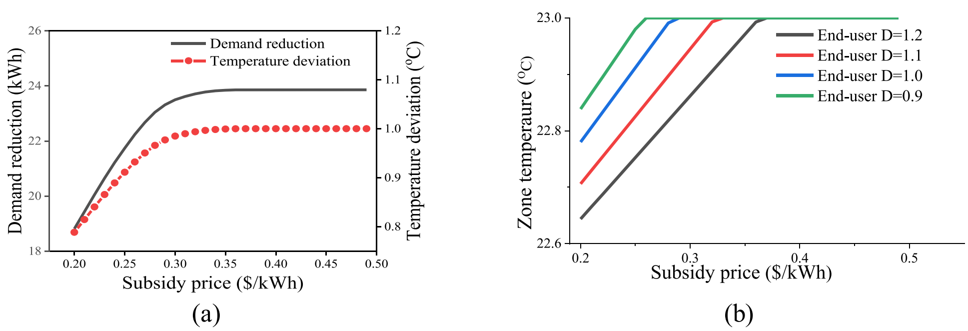


**Fig. 2.** End-users' reaction towards subsidy prices: (a) the relationship between demand reduction/temperature deviation and subsidy price; (b) the relationship between end-users' willingness and subsidy price.

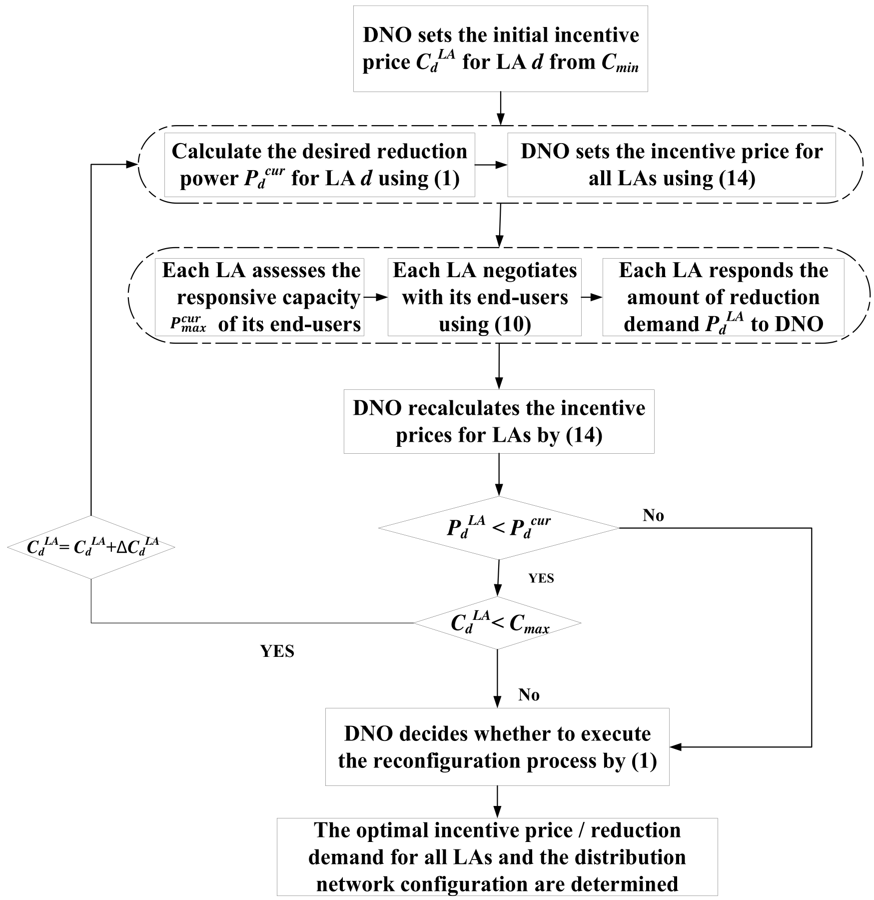


**Fig. 3.** Flowchart of the proposed method.

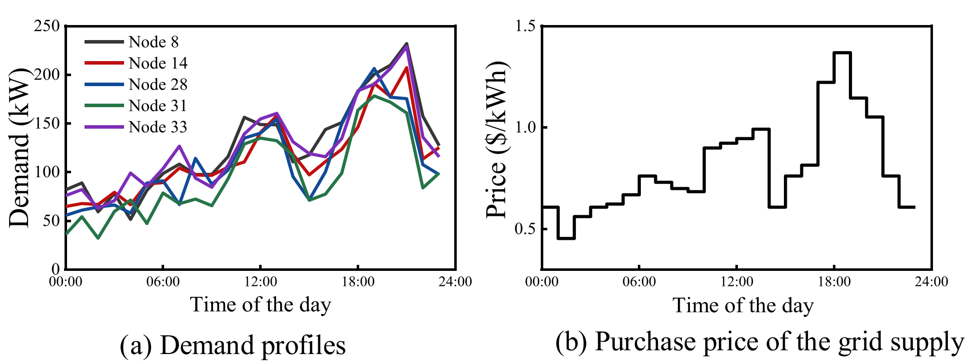


**Fig. 4.** Demand profiles and real-time electricity price.

**Table 1**
Typical parameter values for a residential TCL unit.

| Parameter | Description | Value | Unit |
|---|---|---|---|
| $C_0$ | Thermal capacitance | 7 | kJ/°C |
| $R_0$ | Thermal resistance | 47 | °C/kW |
| $P_m$ | Rated electrical power | 5 | kW |
| $T^{set}$ | Temperature setpoint | 22 | °C |
| $T^{db}$ | Temperature dead band | 1.0 | °C |
| $D$ | End-users' preference to participant in the DR program | 1 | ~ |

the process of the network reconfiguration or not. And finally, the optimal incentive prices for LAs and the corresponding load pattern of LAs coordinated with network configuration that minimize the system operation cost can be obtained.

Additionally, the proposed bi-level DR schedule model is flexible and scalable, which can be further extended to other operation scenarios of distribution networks with the support of load-curtail DR programs to satisfy the system operation goals, e.g., decreasing peak demand ratio, reducing carbon emission, improving system frequency stability, given small adjustment of DNO's objective.

## 4. Case study

### 4.1. Parameter setting

The proposed method is validated based on the modified IEEE 33-bus benchmark system. The distribution network employed here is set to be equipped with 30 sectional switches and 7 tie switches, which are responsible for the reconfiguration process. Five LAs are in charge of DR business for five nodes, i.e., node 8, 14, 28, 31, and 33, respectively,

**Table 2**
Comparison of the operation cost among three cases of the entire day.

| | Total demand of 5 nodes (MWh) | Total demand of the system (MWh) | Net energy Loss of the 5 nodes (MWh) | Net energy Loss of the system (MWh) | Money loss ($) |
|---|---|---|---|---|---|
| Base case | 13.754 | 107.365 | 1.430 | 14.078 | 11924 |
| Base case (with reconfiguration) | 13.754 | 107.365 | 1.405 | 13.985 | 11900 |
| DR case (with reconfiguration) | 12.748 | 106.359 | 1.351 | 13.585 | 11766 |

**Table 3**
Reconfiguration result across the day.

| | Open lines | Times of switch action |
|---|---|---|
| Base case (with reconfiguration) | 17–18, 8–21, 9–15, 3–23, 12–22 | 5 |
| DR case (with reconfiguration) | 18–33, 8–21, 9–15, 12–22, 3–23 | 1 |

and the load profiles of each LA and purchasing price of grid supply for DNO investigated in [24] are presented in Fig. 4. The time interval $t$ is set to be one hour, and the total amount of the time period $T_N$ is a whole day. We consider each LA contracts with a population of 50 diverse TCL owners, of which the nominal model parameters are listed in Table 1. And the TCL parameters are drawn from a uniform distribution with 10 % heterogeneity around their nominal values [22], i.e., $R_z \tilde{} U(0.95R_0,\ 1.05R_0)$. The assumed ambient temperature was illustrated in [21], and the initial temperatures of end-users are randomized around users' desired set-points.

### 4.2. Base case and DR case

A system operating without the DR program and network reconfiguration is chosen as the base case. As expected, the peak of demand curve is temporally coincidental with the peak of price curve (around 9:00 PM), often accompanied by the maximum energy loss of the system. Therefore, DNO will suffer great economic loss from the network energy loss. DNO calculates the optimal amount of the demand reduction each hour to guarantee the economics of the distribution network. Table 2 represents the great benefit that DR case has brought for DNO and Table 3 shows the reconfiguration results. By reducing the demand during peak periods, the network energy loss has been successfully reduced by 5.94 % from 14.078 MW h to 13.584 MW h across the day, which brings 1.38 % reduction of the net money loss (covering the DR program cost). In addition, the necessary times to operate the switch equipment have decreased from 5 to 1. Moreover, though the DR program has cost some money in the form of incentive rewards offering to LAs, it has benefited DNO from two aspects. On the one hand, the proposed market model compensates DNO by reducing network energy loss and minimizing switching actions. On the other hand, the peak shaving DR programs guarantee the secure operation of the distribution network and defer the cost in capacity expansion of the equipment.

Fig. 5 corresponds the iteration process of the load demand pattern across a day. We set the incentive price $C^{LA}$ for LAs changing from 0.25 $/kWh with an incremental amount $\Delta C^{LA}$ 0.01 $/kWh per step. The iteration process of the desired load pattern of DNO is depicted in the Fig. 5, as well as the initial load pattern of the base case where no compensation is provided to LAs. The incentive price of the first iteration is relatively low, that inspires DNO to execute the DR program to minimize its net energy loss. However, LAs are not willing to accept the bids due to the low incentive value. The incentive price continually increases, which plays a negative role on DNO, i.e., the high incentive price lowers the requirement for curtailing load. The accepted bids are reached through the iteration as illustrated in Fig. 5(b). Note that DNO chooses not to conduct any DR program during the first few hours of the day, due to the cheap electricity price in the early morning. Thus, the implementation of the DR program is not cost-effective for DNO.

### 4.3. Benefits of the proposed DR model

As discussed previously, DNO suffers economic challenge at peak period, which leads to the implementation of the DR program. The incentive prices should satisfy Eq. (13) to achieve fairness. Thus, the incentive value for all LAs can be calculated once $C_1^{LA}$ is determined. Notes that the incentive price for different time slot is diverse, but here we set the uniformly initial incentive price for the 24 h for simplicity to study the general trend of the iterating process of the proposed model.

Fig. 6 provides the relationship between the incentive price $C_1^{LA}$ and other relative indexes during the day. The increment of incentive prices intensifies the reluctance of DNO on executing DR as shown in Fig. 6(a). The decreased amount in demand curtailment saves the incentive payment of the DR in Fig. 6(b) though, results in increment of the network energy loss and operation money loss, illustrated in Fig. 6(c) and (d), which is not cost-effective for DNO. DNO and LAs agree to the incentive price 0.38$/kWh. Moreover, the DR benefits for all entities are quantified, namely the net benefits of LAs given by (9) in Fig. 6(f), and the net benefit derived by end-users given by (18) in Fig. 6(e). Here, we analyze the comfort deviation and the rewarded money of end-users respectively to better clarify the relationship among all factors. As the bids are accepted, the increment of the incentive price only leads to benefit loss of all entities, as depicted in Fig. 6 (e) and (f). Note that the operator would not implement any DR program on the condition that the DR program results in economic disadvantage. The

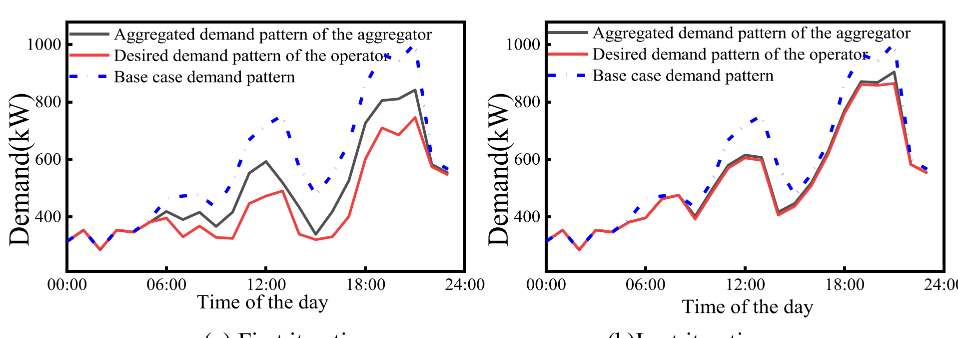


**Fig. 5.** Iteration process of aggregate demand pattern.

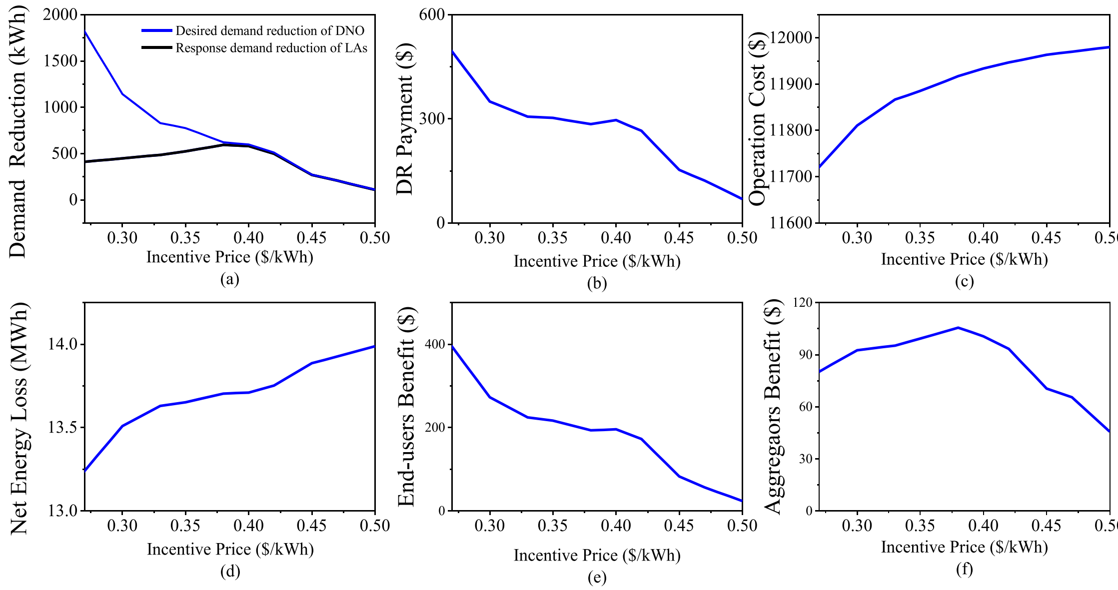


**Fig. 6.** The relationship between incentive price and six relating factors.

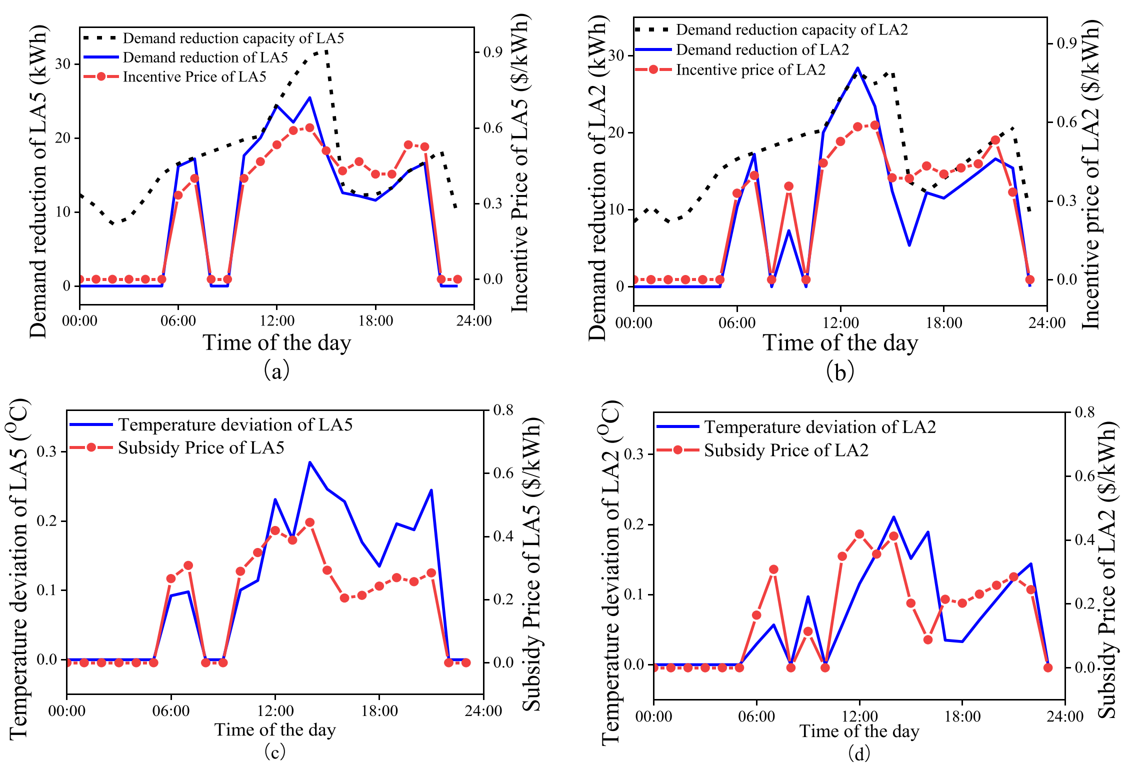


**Fig. 7.** The accepted bids of the LA 5 and LA 2.

operator plays a dominated role obtaining greater profit than LAs and end-users from this respect. The additional market gain provided by DNO is shared unevenly between LAs and end-users.

Fig. 7 depicts the ultimate bids of the LA 5 and LA 2 across the day. Thanks to the increment of the incentive price accompanied by the growth of the subsidy price, end-users are more willing to deviate from their preferable temperatures. The dealing subsidy prices offered to end-user behaves approximately in proportion to the incentive prices provided for LAs. The peak of demand reduction curve appears during the noon instead of the night, due to the power reduction capacity of end-users as illustrated in Fig. 7(a) and (b). It costs TCLs more energy to maintain the indoor temperature at noon due to the high ambient temperature, which provides more flexible capacity for LAs to conduct the DR program. Moreover, the DR program has caused certain degree of temperature deviation, which requires more energy of TCLs to regulate zone temperatures. That offers potentially adjustable space for LAs, as long as temperatures are kept within the acceptable thermal envelops of end-users. Fig. 7(a) and (b) also compare the ultimate bids between LA 5 and LA 2, which are different in DR execution time and accepted incentive values on account of the local diversity and participation level. Moreover, Total 31 kinds of virtual sets of 5 LAs can be designed to simulate the operation process with the participating of differential virtual sets. Therefore, the contribution of each LA can be calculated by DNO using Eq. (13) to achieve fair allocation of incentive

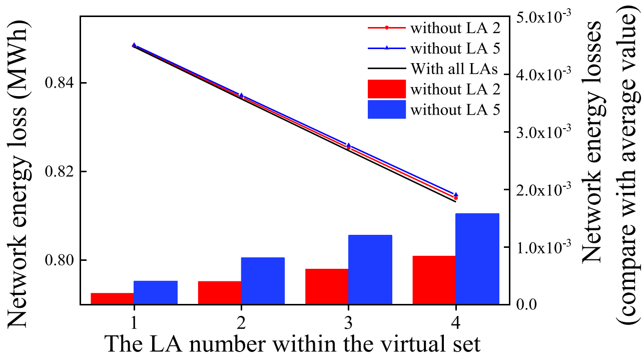


**Fig. 8.** The network energy loss with different LA participation sets.

**Table 4**
Benefit of the DR case across the day.

| | LA 1 | LA 2 | LA 3 | LA 4 | LA 5 |
|---|---|---|---|---|---|
| Incentive price ($/kWh) | 0.385 | 0.453 | 0.391 | 0.432 | 0.467 |
| Compensation price ($/kWh) | 0.262 | 0.313 | 0.267 | 0.321 | 0.312 |
| Demand reduction (kWh) | 134.56 | 217.58 | 154.21 | 198.01 | 246.79 |
| Aggregator benefit ($) | 17.134 | 32.492 | 20.178 | 23.388 | 38.691 |
| End-users benefit ($) | 37.327 | 69.125 | 43.117 | 64.483 | 78.436 |
| Comfort deviation (°C) | 0.0568 | 0.0649 | 0.0853 | 0.0982 | 0.1042 |

price.

Fig. 8 represents the simulation results of network energy loss with the participation of different virtual sets at time slot 12. The increasing number of LAs within virtual sets, i.e., more participants in the DR program, leads to decreased network energy loss. However, different LAs contribute differential proportions on the operation cost minimization. The energy loss of virtual sets without LA 5 is significantly higher than that of sets without LA 2 compared with the average loss of the fixed sets, which means the participation of LA 5 is more efficient and deserves higher incentive price than LA2.

Table 4 shows the detailed parameters of the DR case i.e., the accepted bids of all entities, where the incentive price and the subsidy price are the average value across the day. The comfort deviation value is the average temperature deviation from preferred comfort level of end-users signed with each LA across the day.

### 4.4. DR cases comparison

Moreover, an auction-based DR model has been established to compare with our proposed DR model in the context of the same parameters of the grid, LAs and end-users. In this case, the procedure of negotiation process between DNO and LAs is substituted by an auction process without the fairness function. DNO defines its demand curve at

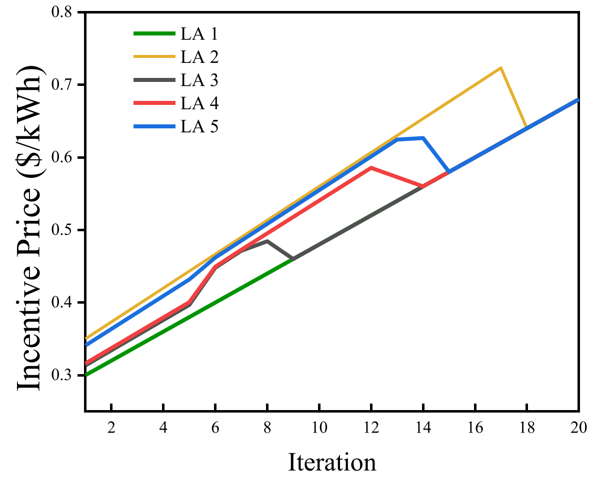


**Fig. 10.** The incentive prices for all LAs offered by DNO through the iteration.

first, i.e., the uniform price offered to LAs and the intended curtailed demand at each node of distribution network. Each LA offers its bids according to its own objective function. The bid of a LA is a supply-price curve indicating its supplying variation with DNOs' incentive prices. Thus, the market equilibrium results from intersection between the supply curve of LAs and demand curve of DNO. The operation process can be expressed as below:

1) DNO initializes the uniform price $C_d^{LA}$ for LA d.
2) DNO calculates its demand curve $f_d(P_d^{cur}, C_d^{LA})$ at node $d$ of the distribution networks by Eq. (1);
3) Each LA participating in the DR program negotiates with its signed end-users, submitting its optimal supply curve $g_d(P_d^{LA}, C_d^{LA})$ to DNO for sake of profit maximization by Eq. (9). The responsive capacity of demand is evaluated before each LA responding to DNO.
4) The DR market clears, and the results are calculated.

Fig. 9 illustrates the demand curve of DNO and supply curves of LA 2 and LA 5 at time plot 14 in the auction-based DR case, respectively, where the increasing incentive prices will decrease the willing of DNO to conduct the DR program while increasing the willing of LAs to reduce more demand. The simulation shows that DNO and LA 2 reach an agreement at incentive price 0.415 $/kWh with 27.05 kW h reduced demand, while DNO and LA 5 agree to the incentive price 0.425 $/kWh with 29.32 kW h load being curtailed. Moreover, the network energy loss is 0.835 MW h with the 680.3 $ operation fee in this auction-based DR case.

However, in our proposed DR scheme, the incentive price offering to each LA changes with the LA corresponding contribution on the system, with compensation re-allocation process by the proposed

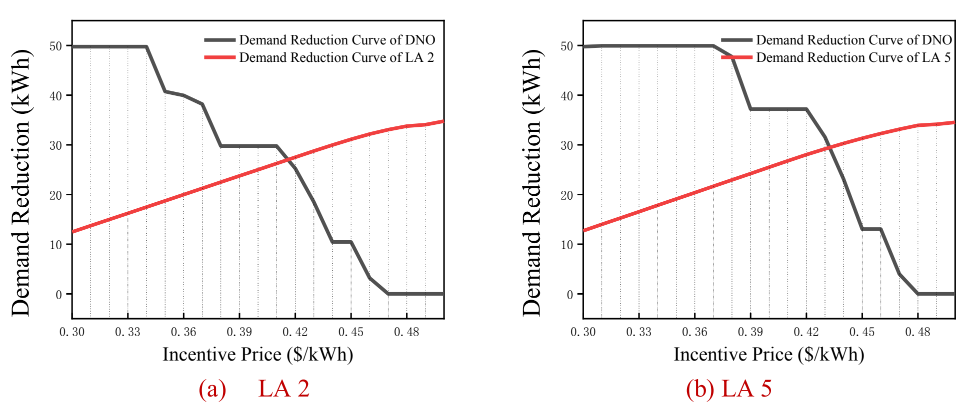


**Fig. 9.** The intended demand reduction curve of DNO and bidding curve of LA 2 (a) and LA5 (b) in auction-based DR model.

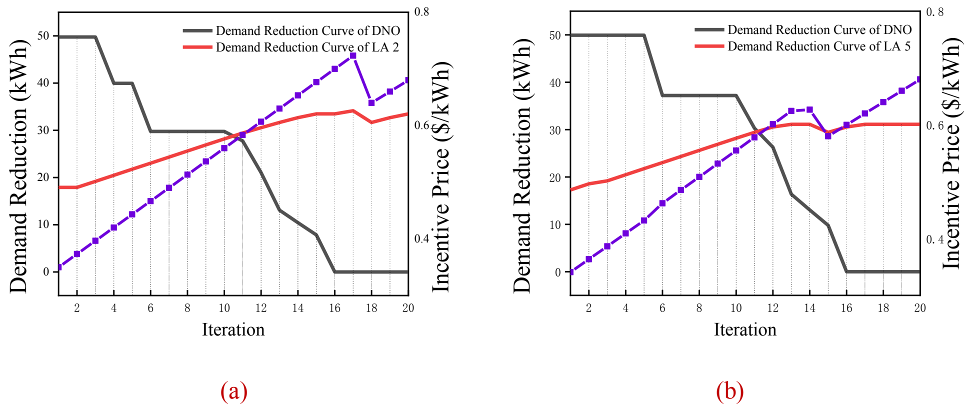


**Fig. 11.** The demand reduction curve of DNO and curve of LA 2 (a) and LA5 (b) through the iteration in the proposed DR model.

fairness function (13). Fig. 10 illustrates the iteration process and Fig. 11 show the evolution trend of the demand curve of DNO and supply curves of LA 2 and LA 5 at time plot 14 in our proposed DR case. The offered incentive prices for all LAs show an increasing trend through iterations though, the increasing amount for each LA is slightly different from others due to their contribution diversity. Fig. 11 shows LA 2 accepts the incentive price 0.582 $/kWh with 28.4 kW h demand reduction, while LA 5 and DNO agree to the incentive price 0.601$/kWh with 30.6 kW h curtailed demand. Additionally, the network energy loss of the system is 0.825 MW h with 680.2 $ operation fee.

The simulation result shows that both the auction-based DR model and our proposed DR model are able to reach the market equilibrium, where the DNO and LAs comes to the final consensus on curtailed demand and the incentive prices. The network energy loss in our DR case is less than the auction-based DR case with nearly the same operation fee, which can further prove the effectiveness of the proposed DR model. Moreover, compared with the traditional auction-based DR model, our proposed DR scheme shows the following advantages: (1) the negotiation process provides adjustment opportunities for DNO to change its initial operation strategy according the real-time operation status of the system, which can be highly affected by the bidding decisions of market participants at the node level; (2) The efficiency-based fair allocation of DR compensation process guarantees that the DR prices can reflect the real value of the implementation of the DR program at each node of distribution network.

## 5. Conclusion

In this paper, an efficient bi-level DR scheme is proposed, in which the widely distributed TCLs are organized by multiple LAs to take incentive response to meet DNO's peak shaving demand. The presented model appropriately captures the diverse objectives of the involved market entities and defines the roles and decision behaviors of all participants. From DNO aspect, the model provides an incentive tool to reduce operation cost and alleviate heavy-load situation. Moreover, the presented scheme enables the relatively fair benefits allocation for LAs according to their essential contributions on the economic improvement of distribution network operation. In addition, the negotiation-based DR framework is able to encourage LAs to leverage the demand flexibility of distributed TCLs in an interactive way. The theoretical analysis and case study demonstrated that the proposed DR machine has led to significant benefits by providing all the involved entities the optimizable space for reasonable profit feedback. However, the impacts derived from response uncertainty of end-users and possible malfunction of communication system are not considered here, which will be further investigated in the future work.

## Conflict of Interest

None.

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