Game-Theoretic Demand Side Management of Thermostatically Controlled Loads for Smoothing Tie-line Power of Microgrids

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***Abstract*—Thermostatically controlled loads (TCLs) are regarded as one of the promising resources for suppressing power fluctuations due to renewable energy (RENs). However, due to the great burdens of fully considering each users' characteristics, it is difficult to achieve unity of the individual optimal decisions and global optimum in demand-side management (DSM). This paper proposes a game-theoretic DSM that can optimize the global power consumption schedule by individual TCL user's optimization. By integrating the prediction of REN outputs into the pricing mechanism, the proposed DSM can guide the users to make their best power consumption schedules along with intermittent REN generations, thus to smooth the tie-line power of microgrids. In this paper, a novel pricing mechanism is firstly developed based on the concave N-person game theory, which is more adaptive and flexible compared with existing game-theoretic DSM. Then, an individual's power consumption optimization and its simplified model are developed considering the constraints of the TCL model and personal preferences. The simplified model can be easily solved and achieve a fast solution in the power consumption game. An implementation framework of the proposed DSM is further developed for practical application. Finally, numerical studies verify the effectiveness of the proposed models and methods.**

***Index Terms*—thermostatically controlled load; demand-side management; game theory; microgrid.**

I. Introduction

Renewable energies (RENs) can produce power in a low carbon fashion and are becoming one of the most important resources in microgrids (MGs) [1]. However, the power intermittence of RENs will lead to considerable power fluctuations to the MGs, and bring more challenges in system stability. Moreover, since most MGs are connected with the main grid, the unbalanced power within MGs may further threaten the secure operation of the main grid through tie-lines [2]. The tie-line refers to the feeder connection between the MG and the main grid. The tie-line power is the exchanged net power between the MG and the main grid, which is the gap of power demands and supplements in the MG. With the increase of RENs in MGs, it is important to suppress tie-line power fluctuations to reduce the impact on the main grid.

Generally, existing researches have mainly focused on energy storage systems to address the problem of RENs' fluctuations [3]. However, energy storage systems are relatively expensive till now and may entail adding costs in the form of a long period of planning and construction. With the development of information and [1]communication technologies, demand-side management (DSM) can be easily realized and is regarded as a significant alternative method for suppressing the power fluctuations brought about by RENs [4], [5]. Thermostatically controlled loads (TCLs), such as heating, ventilation, and air conditioning, are important regulation resources in DSM [6], [7]. TCLs can respond to control signals with only a slight impact on users' comfort [8], and meanwhile, they account for a significant proportion of power consumption, for example, constituting up to 30% in Spain [9] and 40% during summer peak load in China [10]. Consequently, modeling and utilization of TCL resources are attracting increasing attention from academia and industrials.

Previously, most studies have been dedicated to utilizing aggregated TCLs in a centralized control scheme like direct load control, due to its simple procedure and high efficiency [11]. Particularly, Lu et al. propose a state queueing model to analyze the response of aggregated TCLs [12]. On this basis, a centralized control scheme is built for continuous balancing services [13]. A single-input-single-output bilinear system is proposed in [14], to simulate the demand response of a group of homogeneous TCLs. The authors in [15] achieve optimal control actions based on a model predictive control scheme. Shi et al. further extend this application into system frequency regulation [16], [17]. Although the existing studies vary from models and applications, they are all carried out by a centralized utility (e.g., aggregator or system operator), and make decisions for each user based on identified individual parameters. However, due to the heterogeneity of a large number of users [18] as well as the increasing concern for personal privacy [19], it

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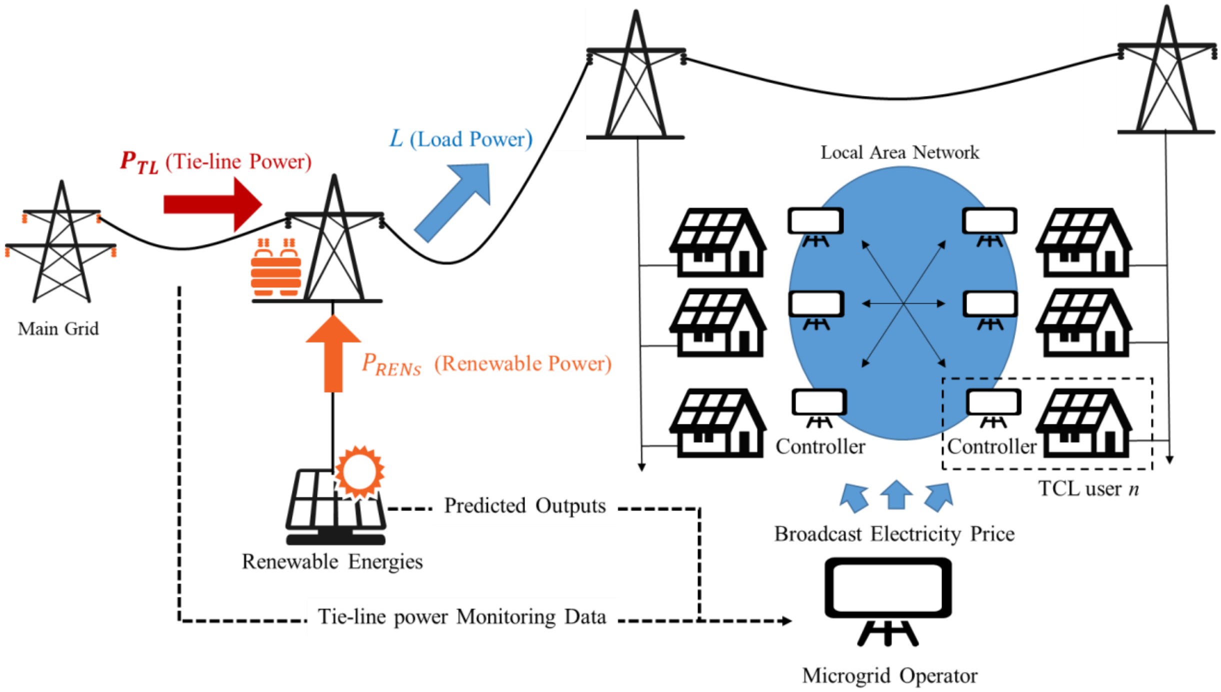

Fig. 1. The diagram of MG implementing game-theoretic DSM of TCLs

is difficult to access all the load parameters and make the best decisions for each user.

To achieve an individual's optimum and solve the problem of a great number of participants, some studies turned into a distributed control method [20-22]. Involved in DSM programs, users must reach an agreement with an aggregator or system operator to participate in the coordination mechanism. Through an individual's communications and interactions, the load aggregation can respond to demand response signals (e.g., real-time price) and provide ancillary services for the system [23]. However, since this coordination may lead to the sacrifice of individual interests [24], users often cannot achieve optimal energy management for themselves. Meanwhile, distributed control usually requires a complex communication mechanism to make sure every participant is running well, which adds difficulties during implementation.

Faced with the problems existing in both centralized and distributed schemes, this paper develops a novel game-theoretic DSM to achieve global optimal operation by scheduling the power consumption of users' TCLs to smooth the tie-line power between the MG and the main grid. The main contributions can be summarized as follows:

(1) A novel pricing mechanism is developed to achieve global optimal power consumption schedules based on an individual's autonomous response to pricing signals. The proposed pricing mechanism is more adaptive and flexible compared with existing game-theoretic schemes [25-28].

(2) An individual's power consumption model is built considering the constraints of the TCL model and personal preferences. The optimization model is innovatively simplified into the shortest path problem, which can rapidly determine the optimal power consumption schedule in the game.

(3) The implementation framework of the proposed DSM is further developed in detail, which provides a feasible scheme for practical application. The numerical studies prove the effectiveness of the proposed game-theoretic DSM.

The remaining contents are organized as follows. Section II introduces the considered MG and the pricing mechanism. Section III illustrates the power consumption optimization of TCL users. Section IV proposes the DSM framework. The effectiveness of the proposed models and methods are illustrated in Section V. Finally, Section VI concludes the paper.

II. Principle of Game-Theoretic DSM

This section will describe the problem. Then the existing game-theoretic pricing mechanism will be introduced and analyzed. Finally, the proposed game-theoretic DSM will be illustrated in comparison with the existing mechanisms.

A. *Problem description*

The proposed MG structure is developed based on a realistic program—Ecogrid EU on Bornholm [29], as shown in Figure 1. The MG is connected with the main grid through a tie-line, whose power P_{TL} (red) is determined by the difference between load L (blue) and renewable power output P_{RENs} (orange). The high REN penetration of the system will lead to considerable fluctuations of tie-line power P_{TL}. In this paper, the tie-line power P_{TL} is considered to be smoothed by the DSM of users, thus mitigating the impacts on the main grid.

Similar to the project in the Ecogrid EU program, the proposed DSM is implemented based on the electric price mechanism. A utility is considered as the organizer and implementer of the DSM program to manage demand-side resources. The utility can be a microgrid operator or an electricity retailer, acting as an agency to trade electricity in the wholesale market on behalf of small market participants within the MG (e.g., RENs, loads, diesel generators, and so on). The main objective of the utility is to minimize the total power consumption cost of all the users, whose optimization model is expressed as

$$\min\ C(L) = C(\sum_{k=1}^{K} P_k) \tag{1}$$

$$s.t.\ \boldsymbol{h}_k(P_k) \geq 0,\ k = 1,2,\ldots,K \tag{2}$$

where $C(L)$ is the total cost of users. $\boldsymbol{h}_k(\cdot)$ indicates an ensemble of multiple application demands of the k^{th} user, including shiftable demands (e.g., TCLs) and nonshiftable demands. It is difficult and even impractical to directly solve this problem because *i*) $\boldsymbol{h}_k(\cdot)$ usually involves a large number of constraints due to there are many users and applications within a user, and *ii*) privacy concerns make it difficult to obtain and collect the individual's application parameters to build constraints.

This paper is intended to design a pricing mechanism to form a game-theoretic DSM to achieve a global optimal power consumption scheme by an individual's rational response. To achieve this, it is assumed that all the users are equipped with a smart controller. The smart controller can communicate with the utility to receive price signals, and then act as an agent of a user to make the best power consumption schedules and control TCLs as established schedules. All smart controllers are also connected with others to exchange power consumption schedules in a local area network. Hence, the power consumption game (**Game 1**) among users is expressed as [25]

- Players: all the users participating in DSM.
- Strategies: power consumption schedules P_k that each user determines to maximize its payoff.
- Payoffs: negative energy cost $-B(P_k, P_{-k})$ for each user, where P_{-k} is the total power consumption except for the k^{th} user.

Hence, the decision making of each user can be also expressed as

$$\max\ -B(P_k, P_{-k}) \tag{3}$$

$$s.t.\ \boldsymbol{h}_k(P_k) \geq 0,\ k = 1, 2, ..., K \tag{4}$$

where $B_k(P_k, P_{-k})$ is the electricity cost of k^{th} the user. It should be noted that the total cost should be equal to the sum of all the individual costs, expressed as

$$C(\sum_{k=1}^{K} P_k) = \sum_{k=1}^{K} B(P_k, P_{-k}) \tag{5}$$

Hence, the core technique of the proposed DSM is to design an effective pricing mechanism (i.e., build a relationship between individual cost $B(P_k, P_{-k})$ and the total cost $C(L)$), which can map the intermittence of REN outputs while building a game environment among users.

B. Existing pricing mechanisms

Some literature has made attempts for designing a pricing mechanism for game-theoretic DSM, which is based on the theory of the N-person concave game [25]-[28]. The N-person concave game has two basic theorems [30]:

Theorem 1: If the individual cost function $B(P_k, P_{-k})$ is continuous and strictly convex concerning P_k, and the strategy sets $\boldsymbol{R} = \{P_k | \boldsymbol{h}_k(P_k) \geq 0\} (k = 1, 2, ..., K)$ are convex, closed, and bounded set, the Nash equilibrium point uniquely exists in **Game 1**.

Theorem 2: If the total cost function $C(\cdot)$ is continuous and convex, then the unique Nash equilibrium of **Game 1** is the global optimal schedule of the power consumption problem.

In the Nash Equilibrium point, all the users have achieved their best decisions, while the global also achieves the optimum according to *Theorem 2*. Hence, if the game in the proposed DSM satisfies the above two theorems, the unity of the individual and global optimum can be achieved in the Nash equilibrium. Assumed that the constraints of strategy sets $\boldsymbol{R}$ were convex, the conditions for the cost functions are listed as follows.

Condition 1: the individual cost function $B(P_k, P_{-k})$ should be strictly convex to P_k, and

Condition 2: the total cost function $C(\cdot)$ should be convex.

A general form of the existing game-theoretic pricing mechanisms contains two parts: total cost function and bill-split function, expressed as

$$B(P_k, P_{-k}) = S(P_k, P_{-k}) \cdot C(\sum_{k=1}^{K} P_k) \tag{6}$$

where $S(P_k, P_{-k})$ is the bill-split function for the users.

As for the total cost function, Ref. [25] adopts a quadratic cost function. Ref. [26] uses a logarithmic cost function to ensure effectiveness when the users can sell energy to the grid. Ref. [27] builds a quadratic real-time wholesale price from the Australian Electricity Market Operator. Ref [28] uses an artificial power function as the regular price function.

As for the bill-split function, Ref. [25]-[27] are based on the proportional cost-sharing, which divides the total cost among users according to power consumption. Ref. [28] calculates the individual cost by multiplying personal power consumption with the price. The schemes are summarized in Table 1.

Table 1. Summary of the existing game-theoretic pricing mechanism

Existing Literature	Total cost function	Bill-spilt function	Individual cost function
[25]	$C(L) = a \cdot L^2 + b \cdot L + c$ (quadratic)	$S(P_k, P_{-k}) = \frac{P_k}{P_k + P_{-k}} \approx \frac{E_k}{\sum E_k} = \Omega_k$ (constant)	$B(P_k, P_{-k}) = \Omega_k \cdot (a \cdot (P_k + P_{-k})^2 + b \cdot (P_k + P_{-k}) + c)$ (quadratic)
[26]	$C(L) = -a \cdot \log(1 - \frac{L}{b})$ (logarithmic)		$B(P_k, P_{-k}) = \Omega_k \cdot (-a \cdot \log(1 - \frac{P_k + P_{-k}}{b}))$ (logarithmic)
[27]	$C(L) = a \cdot L^2 + b \cdot L + c$ (quadratic)		$B(P_k, P_{-k}) = \Omega_k \cdot (a \cdot (P_k + P_{-k})^2 + b \cdot (P_k + P_{-k}) + c)$ (quadratic)
[28]	$C(L) = a \cdot L^{b+1}$ (power)	$S(P_k, P_{-k}) = \frac{P_k}{L} = \frac{P_k}{P_k + P_{-k}}$ (proportional)	$B(P_k, P_{-k}) = a \cdot P_k \cdot (P_k + P_{-k})^b$ (power)

Although the existing pricing mechanism is proved to be effective in some cases, there are still some drawbacks that limit the further implementations of the game-theoretic DSM.

a) The game-theoretic pricing mechanism cannot deal with the price-based cost functions, which, however, are more general in the electric market. The existing methods are only suitable for strictly convex cost functions (e.g., quadratic function). If a linear total cost function (i.e., price-based mechanisms, such as fixed price and TOU price) is applied, the individual cost function

$B(P_k, P_{-k})$ may not be strictly convex based on the constant or proportional bill-spilt function in the existing literature. In these cases, the DSM either has no Nash equilibrium point or has difficulties in reach the Nash Equilibrium point. Hence, the current pricing mechanism needs to be more general for the linear cost function.

b) The existing bill-split function may introduce unpredictable errors into the DSM. Most of the existing literature uses energy consumption E_k to calculate the proportion of a user's consumption. Hence this value should be determined before the game and be constant during the user's decision-making process. However, it is not easy to predict accurately although users are intended to be truthful in a game [25]. If someone is failed in predicting energy consumption accurately, it will result in an error in finding the optimal point, which will reduce the efficiency and limit the practicability of the game-theoretic DSM.

C. Proposed pricing mechanism

The proposed game-theoretic DSM takes advantage of a novel bill-split function. Here we first build the total cost function as a linear price-based form. The total cost paid to utility is expressed as

$$C(L) = \kappa \cdot (C_{Gen} \cdot P_{Gen} + C_{RENs} \cdot P_{RENs} + C_{TL} \cdot P_{TL}) \tag{7}$$

where $\kappa > 1$ is the utility earning rate, which is to ensure reasonable profits for the utility to provide services for end-users. The expression within the brackets is the utility cost to buy energy from local generations(P_{Gen}), the REN resource owner (P_{RENs}), and the main grid (tie-line power P_{TL}). Assuming that there are no other power resources within the MG and ignoring the loss during power distribution, the total load L should be equal to the whole power generation, expressed as

$$L = P_{TL} + P_{RENs} + P_{Gen} \tag{8}$$

C_{Gen} indicates the price of power outputs of local generators, such as diesel gensets owned by users. C_{RENs} is the price of RENs within MG, which is directly paid to the REN owners. C_{TL} is the electricity price paid for power exchanging through the tie-line.

In this paper, utilities are authorized to buy the generator and RENs resources at a constant price (i.e., C_{Gen} , and C_{RENs}). C_{TL} This is the dynamic price that MG trades energy with the main grid. C_{TL} is divided into two cases based on bi-direction of the tie-line power

$$C_{TL} = \begin{cases} C_{selling}, P_{TL} < 0 \\ C_{buyung}, P_{TL} > 0 \end{cases} \tag{9}$$

where $C_{selling}$ is the price that MG sells power to the main grid, while C_{buyung} is the price that MG buys energy from the main grid. In general, the price of renewable energies is less than the cost of local generators, expressed as $C_{RENs} < C_{Gen}$. The price of the grid C_{TL} is varying due to the power system state and whole-sale market bidding results. To minimize the electricity cost, the utility should adjust the electricity exchanges with the main grid and local generators to satisfy the users' demand. For example, if the main grid lacks generation or needs upward regulation, the main grid will tend to get power from MG with a price $C_{selling}$. At this moment, the $C_{selling}$ is higher than the local generation price C_{Gen} , while the price relationship is expressed as

$$C_{buying} > C_{selling} > C_{Gen} > C_{RENs} \tag{10}$$

Then the utility tends to buy more energy from the local generators rather than from the grid. Moreover, if there is extra energy within MG after meeting the power demand of users, MG will tend to sell energy to the grid through the tie line. In this case, tie-line power is inversed, expressed as $P_{TL} < 0$.

On the other hand, the bill-split function $S(P_k, P_{-k})$ is the function that distributes the energy cost to individual users. In particular, to ensure the pricing mechanism fair and reasonable, the bill-split function should satisfy the following requirements:

- $S(P_k, P_{-k})$ should be a continuous and strictly increasing function with P_k , while other's decision P_{-k} keeps unchanged. It is a straightforward principle that the more electricity users used, the more cost is needed to bill.
- $S(P_k, P_{-k})$ is nonnegative while the sum of all users' bill-split function should be 1, expressed as

$$\sum_{k=1}^{K} S(P_k, P_{-k}) = 1,\ 0 \le S(P_k, P_{-k}) \le 1 \tag{11}$$

where K is the total number of users.

- $S(P_k, P_{-k})$ should be built to ensure $B(P_k, P_{-k})$ it is a strictly convex function. Since users would like to minimize their split bill, if the split bills are convex, the revenue function for game participants are concave. In this way, it can form a concave N-person game for achieving Nash equilibrium, as an illustration in section II.

Here we use the bill-split function to ensure the individual cost function convexity. The split bill function shows as

$$S(P_k, P_{-k}) = \frac{(P_k)^m}{(P_k)^m + \sum_{l \in K \setminus k} (P_l)^m} \tag{12}$$

where m is a constant, following $m > 0$. It can be proved that Eq. (12) can satisfy the first two requirements. To find the conditions that meet the third requirement, this study is based on the assumption that $S(P_k, P_{-k})$ is convex. We use $S(P_k, P_{-k})$ because analyzing the convexity of the $S(P_k, P_{-k})$ is much simpler than $B(P_k, P_{-k})$. Moreover, the following will show that the condition of $S(P_k, P_{-k})$ is not difficult to be satisfied in practice.

To satisfy the third condition of $B(P_k, P_{-k})$ being strictly convex, we should derive the conditions of convexity of $S(P_k, P_{-k})$, which is achieved by its second derivative being larger than 0, obtaining

$$(m-1) \sum_{l \in K \setminus k} (P_l)^m - (m+1) \cdot (P_k)^m \ge 0 \tag{13}$$

If inequality (13) holds, (12) is a convex function. Therefore, we could discuss the relationship between m and P_k to check the convexity of the individual split bills. It is easy to judge that inequality cannot hold if $m \le 1$. But if $m > 1$, there is

$$\frac{(P_k)^m}{(P_k)^m + \sum_{l \in K \setminus k} (P_l)^m} = \frac{(P_k)^m}{\sum (P_l)^m} \le \frac{m-1}{2m} \tag{14}$$

That means when the maximum proportion of individual power consumption to the m is less than $(m-1)/2m$, the split bill is strictly convex. For example, when $m = 2$, the largest consumption of a user should not exceed 1/4 of the total power consumption of all the users. If Inequality (14) holds, then $S(P_k, P_{-k})$ is convex. The event that $S(P_k, P_{-k})$ is convex is a sufficient but not necessary condition for the event that $B(P_k)$ is strictly convex, whose proof is given in the Appendix. Although it is a stricter condition for the convexity of $B(P_k)$, it is not difficult to be satisfied in practice, because there are usually tens of users with similar loads involved in a DSM. If there are a large number of users, Inequality (14) can work in a smaller value of m. Therefore, a feasible value

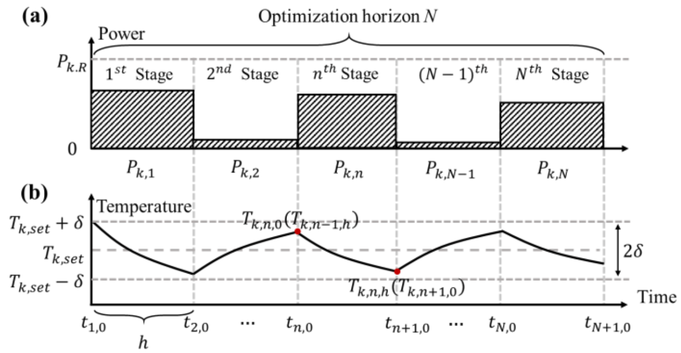

Fig. 2. Energy consumption optimization diagram in different stages: (a) Power consumption diagram. (b) Indoor temperature changing diagram.

of *m* can be easily selected based on Eq. (14) to guarantee the strict convexity of the $B(P_k, P_{-k})$.

Meanwhile, by adjusting the value of *m*, we could change the split bills to the users. For instants, if $m = 2$, when a user consumes twice electricity as another user, then he will be charged 4 times. In this way, the utility could make an appropriate *m* based on the difference of the users' power demand, thus adjusting the bill-split proportion according to the actual situation.

In conclusion, the split bill for users is shown as

$$B(P_k, P_{-k}) = \kappa \cdot \frac{(P_k)^m}{(P_k)^m + \sum_{l \in K \setminus k} (P_l)^m} \cdot C(P_k + \sum_{l \in K \setminus k} P_l) \tag{15}$$

As for a user, the only variable it could change is the power P_k. Users would like to minimize their bill in the power consumption game the DSM forms. Because the split bill $B(P_k, P_{-k})$ is positive, increasing, and strictly convex, it forms a concave N-person game and can guarantee that the Nash Equilibrium of the individual schedules is also the global optimal power consumption schedules. The details for the individual power consumption optimization model will be further illustrated in the following section.

III. Individual Model for DSM

In this section, the individual model is proposed to make the best power consumption schedules for the users. Firstly, the equivalent thermal parameter (ETP) model is adopted to describe TCL electric-thermal characters. Then, each individual's optimization is proposed, considering self-constraints as well as others' schedules. Finally, the optimization is simplified and the solution to the proposed optimization problem is introduced.

A. ETP model

This paper adopts the ETP model to describe the thermal dynamic of TCL [31]. The indoor temperature $T(t)$ can be represented as a function of time, which is expressed as

$$C_T \cdot \frac{dT}{dt} = H \cdot (T_{ext}(t) - T(t)) + Q(t) \tag{16}$$

where *H* is the equivalent thermal conductance between the indoor and the ambient air; $T_{ext}(t)$ and C_T are the ambient temperature and thermal mass of the room, respectively. $Q(t)$ is the heat energy increment provided by TCL, expressed by

$$Q(t) = K_E \cdot P(t) \tag{17}$$

where K_E is a coefficient for energy conversion from electricity to heating/cooling capacities, i.e., the coefficient of performance (COP) for heating or the energy efficiency ratio (EER) for cooling. K_E is assigned to be positive in the heating mode and negative in the cooling mode. Moreover, $P(t)$ is the real-time power of the TCL, calculated by $P(t) = s(t) \cdot P_r(t)$. In this expression, $s(t)$ indicates the TCL real-time state, where $s(t) = 1$ means running at rated power and $s(t) = 0$ means shut down. $P_r(t)$ is the rated power of the TCL. In practice, the states of fixed frequency air conditioners only contain rated power and shut down, while inverter air conditioners are allowed to run at states within the interval of $s(t) \in [0,1]$.

For the convenience of numerical simulation, the thermal model of the room can be described in discrete time

$$T(t) = T(t-\tau) + \frac{\tau \cdot (K_E \cdot P(t) + H \cdot (T_{ext} - T(t-\tau)))}{C_T} \tag{18}$$

where τ is the time step of the discrete model.

B. Optimal schedule of energy consumption

This subsection will build an individual's power consumption model as an optimization problem. The price signals in the proposed DSM will be released in advance. Consequently, the user could optimize their power consumption schedule based on the pre-issued electric price, whose advanced time is the optimization horizon *N* in Fig. 2 (a). Then the optimization horizon is further elaborated into *N* stages. Each stage contains *h* minutes. The time scale *h* can be also adjusted based on practical conditions and the characters of the participating DR resources. As for TCLs, it is assumed that *h* = 5 min in our studies. Therefore, the ensemble of the energy consumption schedules can be written as $\mathbf{S}_k = [P_{k,1}, P_{k,2} ... P_{k,3} ... P_{k,N-1}, P_{k,N}]$, where the power consumption values of the k^{th} TCL in the n^{th} stage is expressed as $P_{k,n}$. It should be noted that the power consumption within a stage is set to unchanged, but it can differ from different stages. The power consumption optimization is to determine the power consumption at different stages.

Fig. 2 (b) shows the indoor temperature changing diagram in different stages of different energy consumptions. The set temperature $T_{k,set}$ with a comfort band $\pm\delta$ represents the users' comfort ranges. Within the n^{th} stage, the initial temperature $T_{k,n,0}$ at the initial time $t_{n,0}$ is changed to the final temperature $T_{k,n,h}$ at the final time $t_{n,h}$ because of the effect of consumed power $P_{k,n}$. It should be noted that, among contiguous stages, the final temperature serves as the initial temperature of the next stage, expressed as $T_{k,n,h} = T_{k,n+1,0}$.

In this way, the optimization of the TCL agent is to schedule the power consumption of different stages to minimize their energy costs within the comfort temperature range.

(1) Objective function

Section II has derived the expression of individual split bills in a single stage. Here to build the power consumption optimization, it should be summed up to multi-stage bills, shown as

$$\min \ h \cdot \sum_{n=1}^{N} B_n(P_{k,n}) \tag{19}$$

where $B_n(\cdot)$ is the pricing function of the n^{th} stage for the k^{th} user. *h* is the time scale of single-stage, i.e., 5 min in this study. In particular, $P_{k,n}$ is the TCL's power consumption of the k^{th} user. Apart from controllable TCLs, users also have fixed power demand.

(2) Constraints

The proposed power consumption optimization is subject to the following constraints:

$$\text{s.t. } \max(\underline{P_{k,n}},0) < P_{k,n} < \min(\overline{P_{k,n}}, P_{k,R}) \tag{20}$$

$$\overline{P_{k,n}}(T_{k,n,0}) = \frac{H}{K_E}\frac{e^{-H/C\cdot h}}{1-e^{-H/C\cdot h}}T_{k,n,0} - \frac{H}{K_E}\cdot(\frac{T_{k,set}-\delta_k}{1-e^{-H/C\cdot h}} - T_n^{ext}) \tag{21}$$

$$\underline{P_{k,n}}(T_{k,n,0}) = \frac{H}{K_E}\frac{e^{-H/C\cdot h}}{1-e^{-H/C\cdot h}}T_{k,n,0} - \frac{H}{K_E}\cdot(\frac{T_{k,set}+\delta_k}{1-e^{-H/C\cdot h}} - T_n^{ext}) \tag{22}$$

$$T_{k,n+1,0} = G(T_{k,n,0}, P_{k,n}) \tag{23}$$

$$G(T_{k,n,0}, P_{k,n}) = e^{-H/C\cdot h}\cdot T_{k,n,0} + (1-e^{-H/C\cdot h})\cdot(T_{ext} - \frac{K_E}{H}\cdot P_{k,n}) \tag{24}$$

Inequality constraint (20) limits the power consumption $P_{k,n}$ within the user's comfort constraints. Electric appliances are neither allowed to exceed the rated power, nor fall below zero. Therefore, the inherent electric power constraints are set to range from 0 to the rated power $P_{k,R}$. As for the comfort constraints, $\underline{P_{k,n}}$ and $\overline{P_{k,n}}$ are the minimum and maximum limitations caused by users' comfort band, respectively. This means that, if TCL power satisfies these constraints, the temperature will be in the comfort band during this stage. In this process of comfort band determination, the main factor influencing the comfort power range is the initial temperature $T_{n,0}^{k}$ in the n^{th} stage. Therefore, $\underline{P_{k,n}}$ and $\overline{P_{k,n}}$ can be derived from Eq. (16) (ETP model), expressed as Eq. (21) and Eq. (22). T_n^{ext} is the ambient temperature in the n^{th} stage. $T_{k,set}$ and δ_k are set temperature and comfort band, representing k^{th} user's temperature preference, where $T_{k,set}+\delta_k$ and $T_{k,set}-\delta_k$ are the upper and lower bound of the comfort temperature range, respectively.

Eq. (23) is the state transition function, where the initial temperature $T_{k,n+1,0}$ of the next stage can be derived as a function of the initial temperature $T_{k,n,0}$ and power consumption $P_{k,n}$ of the current stage, which is expressed as Eq. (24).

(3) Solving method of the optimization model

The objective of the individual power consumption model is a convex but non-linear function, while the constraints (13-18) are linear. There are some effective and efficient algorithms (e.g., interior point methods [32]) and existing commercial tools (e.g., Matlab) to solve the proposed convex but non-linear optimization model. However, most of the methods are needed several times iterations and the speeds are also dependent on the starting point choice. The time to reach the optimal point is important for the game-theoretic method implementation. Hence, the numerical solution methods may not meet the requirements of the solving time. Meanwhile, considering the computing power of the smart controller installed in the user's house, the precise solution algorithm may also be inapplicable for implementation. Therefore, this paper develops a dynamic programming method [33] based on a practical simplified TCL model is proposed to obtain decisions efficiently. The effectiveness is further validated in case studies.

The proposed method takes advantages of the following two practical simplifications:

a) Limitations of the measurement accuracy of the temperature sensor of TCLs; For example, air conditioning only could measure temperature in a 0.5 ℃ step.

b) Power adjustment of TCLs. It is assumed that all the TCLs in this paper are inverter air conditioners, whose power can be changed smoothly [11].

Therefore, the problem can be transformed into the shortest path problem, as shown in Fig. 3. The users start from the initial temperature (start point), and then they should decide the optimal power consumption schedule (red edges shown in the figure) to the endpoint. Therefore, the nodes and weights of edges indicate the indoor temperature and energy cost, respectively.

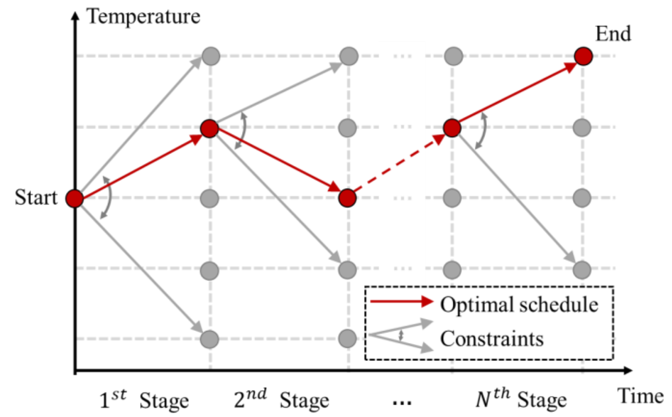

Fig. 3. The shortest path problem for the power consumption optimization.

The shortest path problem can be solved by DP. The Bellman equation of the DP algorithm in backward induction is given as

$$V_n(T_{k,n,0}) = \min_{\max(\underline{P_{k,n}},0)<P_{k,n}<\min(\overline{P_{k,n}},P_{k,R})} \left\{B_n(P_{k,n}) + V_{n+1}(T_{k,n+1,0})\right\} \tag{25}$$

where $V_n(\cdot)$ is the total cost function from the start of the n^{th} stage to the end of the N^{th} stage, which also can be expressed as the start of the fictitious $(N+1)^{th}$ stage satisfying $V_{N+1}(T_{k,N+1,0})=0$. In this manner, the proposed complex optimization problem can be broken down into simpler sub-problems expressed as Eq. (25) recursively. To solve this problem, the process shall begin at the start of the stage, and then solve the linear sub-problems of Eq. (25) to get the minimum cost value and power consumption of the N^{th} stage. And so on, solving the sub-problems of each stage until calculating optimal $V_1(\cdot)$, and the trajectory of power consumption choices is the optimal power consumption strategy.

IV. Game-Theoretic DSM

This section will first illustrate the power consumption game among TCL users, and then give the details of the DSM algorithm and implementation scheme.

A. Power consumption game

In the proposed DSM game, the smart controller is authorized by the user to make decisions for them. The smart controllers are assumed rational and only interested in reducing their energy costs. They will be driven to a better power consumption schedule for minimum energy cost if possible. Meanwhile, they are also willing to share some information if it could reduce their cost. All the decisions of the power consumption schedule are made by the smart controllers at a fast speed, which are agents for a user's response in the game. Define that $\mathbf{S}_k = [P_{k,1}, P_{k,2}...P_{k,n}...P_{k,N-1}, P_{k,N}]$ is the power consumption the k^{th} user, the game can be expressed as

- Players: All the users K.
- Strategies: Every user $k \in K$ decides their power consumption schedule of TCL to minimize their energy cost.
- Payoffs: $F(\mathbf{S}_k, \mathbf{S}_{-k})$ for the user $k \in K$, where

$$\min\ F(\mathbf{S}_k, \mathbf{S}_{-k}) = -h\cdot\sum_{n=1}^{N} B_n(P_{k,n}) \tag{26}$$

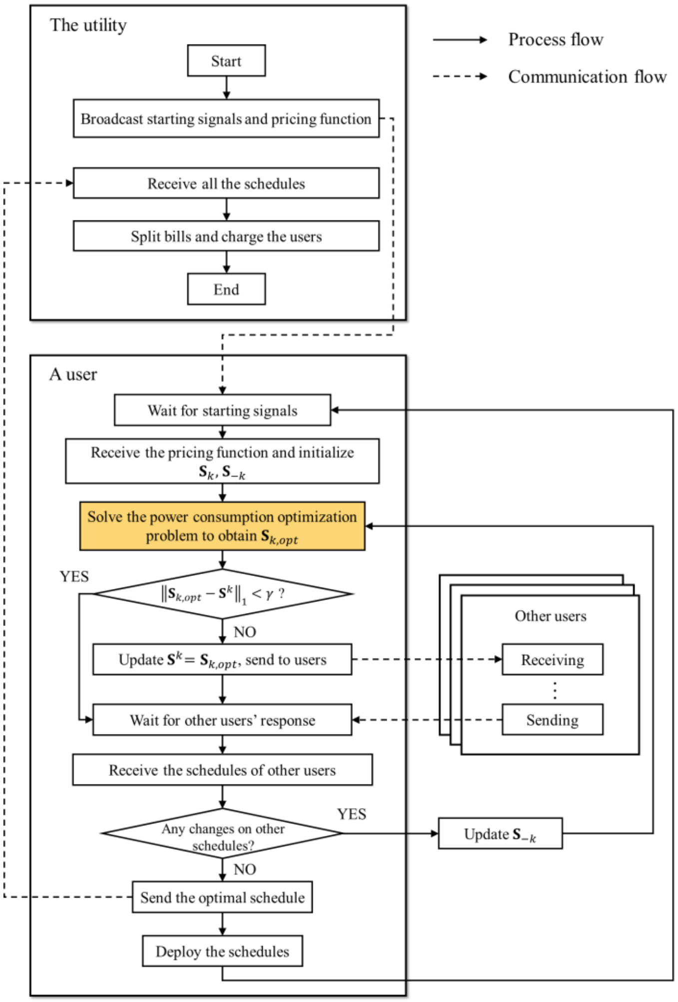

Fig. 4. The implementation framework of game-theoretic DSM.

where $\mathbf{S}_{-k}$ denotes the vector of the sum of power consumption schedules of all the users except the k^{th} TCL is expressed as:

$$\mathbf{S}_{-k} = [P_{-k,1}, P_{-k,2}, ..., P_{-k,n}] \tag{27}$$

B. DSM framework

(1) Single optimization procedure

In this subsection, an asynchronous decision-making algorithm is applied to achieve the optimal point. At first, users will be numbered in a certain order. The order will not influence the Nash equilibrium point [25], and therefore, the order can be random. And then, the smart controllers are allowed to perform their power consumption optimization one after another in order. It is only in their respective turn that the authorized smart controllers are allowed to reschedule energy consumption. Once a controller makes its decision, it is designed to share it on the local area network. Therefore, every user knows others' power consumption schedules.

Fig. 4 shows the details for a user participating in the game-theoretic DSM through sequential decision making, which can be described by the following steps.

Step 1: Utility: broadcast the starting signals and the dynamic pricing functions to all the smart controllers.

a) **User:** wait until receiving the starting signal with the dynamic pricing functions, and then initialize the power consumption schedules $\mathbf{S}_{-k}$ and $\mathbf{S}_k$ of TCLs.

b) **User:** solve the power consumption optimization using DP, then gain the optimal schedule in the current step $\mathbf{S}_{k,opt}$.

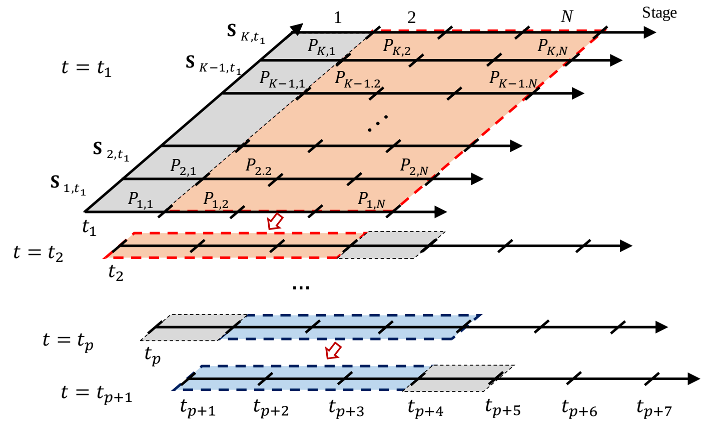

Fig. 5. The diagram of the application scheme of game-theoretic DSM.

c) **User:** judge whether there is a change between $\mathbf{S}_{k,opt}$ and $\mathbf{S}_k$, expressed as 1-norm of the difference between the two power consumption schedule vectors.

$$\left\|\mathbf{S}_{k,opt} - \mathbf{S}_k\right\|_1 > \gamma \tag{28}$$

where γ is a given tolerant value. If inequality (28) holds, continue. Otherwise, jump to Step e.

d) **User:** update $\mathbf{S}_k = \mathbf{S}_{k,opt}$, and send the consumption schedule to other smart controllers.

e) **User:** wait for its turn while continuing to receive the other power consumption schedules.

f) **User:** in its action round, judge whether there are any changes in others' consumption schedules compared with the last round. If yes, update the $\mathbf{S}_{-k}$ and jump to Step b. If no, continue.

g) **User:** send the current power consumption schedule to the MG operator.

Step 2: Utility: receive schedules and send deploying signals.

Step 3: Utility: account for the total energy cost and charge users for the split bills.

(2) Multi-step procedure

To reduce the impact of uncertainty of RENs prediction, a multistep scheme of the proposed DSM is developed using the rolling optimization strategy [34], as shown in Fig. 5.

If all the agents agree on the schedule $\mathbf{S}_k = [P_{k,1}, P_{k,2}...P_{k,n}...P_{k,N-1}, P_{k,N}]$ before $t = t_1$, the schedule will be implemented in the following time stage (i.e., from t_1 to t_2). Before the time reaches t_2, a new round of optimization of $t = t_2$ will begin. Hence, only the schedules from t_1 to t_2 will be implemented, while the other schedules from t_2 to t_N will not be implemented. In this paper, the unimplemented schedules will be passed to the next time (i.e., $t = t_2$) as the starting point of the iteration process (see the orange area in Fig. 5). Following the same process, the users at $t = t_p$ utilize optimization solutions of $t = t_{p+1}$ as their starting point, (see the blue area in Fig. 5). In this manner, the game-theoretic DSM can speed up the convergence time and reduce the impact of prediction uncertainty, which will be validated in Section V.

V. CASE STUDIES

A test system is built based on a practical pilot project at JS province in China to illustrate the effectiveness of the proposed game-theoretic DSM [18]. It contains hundreds of business users and residential users. In the following case studies, we use a case

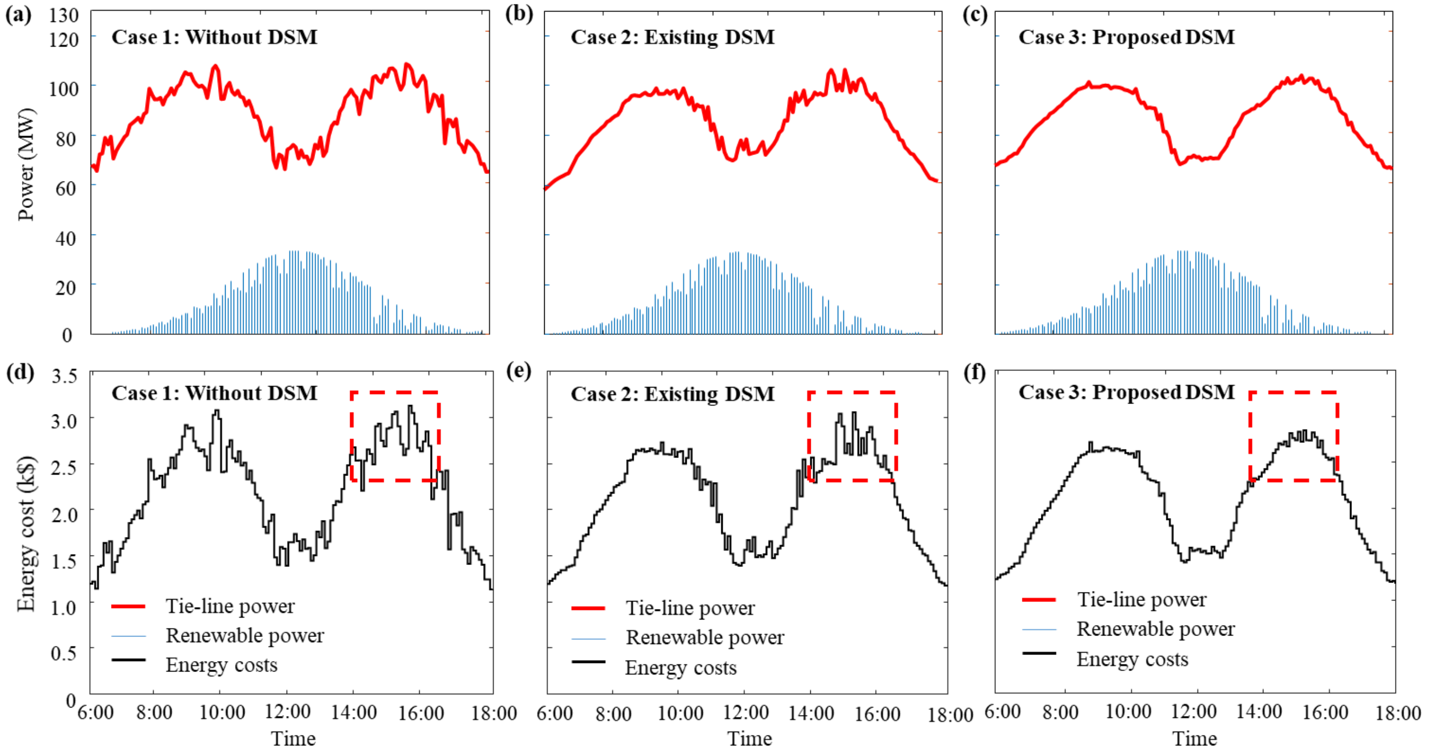

Fig. 6. Results of power smoothing and cost: (a), (b) and (c) are the tie-line power and the renewable power curves under Case 1, 2 and 3, respectively; (d), (e) and (f) are the energy costs under Case 1, 2 and 3, respectively;

study containing 50 business users to validate the effectiveness of the proposed DSM. The power smoothing performance, DP algorithm effectiveness, multi-step procedure, the impacts of value *m*, and the advanced time of price are studied and illustrated by numerical cases. Finally, we further address the advantages of the proposed method by comparing different practical price mechanisms using a case study including 118 large industrial users.

A. Smoothing power of the tie line

This section selects 50 business users with a daily average load from 1.58MW to 3.67MW. Three cases are set as follows:

Case 1: Practical case without DSM;

Case 2: with existing DSM;

Case 3: with the proposed game-theoretic DSM.

Fig. 6 (a)-(c) shows the aggregated power of the above three cases. As for Case 2, the DSM participators respond to price to minimize their own energy cost without considering other's responses. In the figure, the tie-line power P_{TL} is marked with a red line, while the blue bars are the PV output values. The results show that the tie-line power of Case 1 is the most volatile among the three cases. The tie-line power in Case 2 is much better than that in Case 1, due to the DSM. Compared with Case 1 and Case 2, the tie-line power in Case 3 is the smoothest, which indicates that the game-theoretic DSM is effective for smoothing power among the participating users. It also proves that the proposed DSM method in this paper is better than the existing DSM to smooth the tie-line power.

Fig. 7 shows the smoothing performances of the three cases quantitatively. The index of the smoothing performances is evaluated by the smoothing function (SF) [35], [36]

$$*P_{level} = \int_0^t \left| \frac{dP_{TL}(\tau)}{d\tau} \right| d\tau \tag{29}$$

where P_{TL} is the power from the grid at the time of *t*. If the considered system is discrete, Eq. (29) can be derived into

$$*P_{level} = \sum\nolimits_{j=1}^{n} \left| P_{TL,j+1} - P_{TL,j} \right| \tag{30}$$

where $P_{TL,i}$ is the deployed power consumption during the n^{th} time interval. Hence, if power volatility is lower, the value of the SF $*P_{level}$ should be smaller. In Fig. 7, the SF value of Case 1 is higher than that in the other two cases all the time. Before 9:00, the SF value in Case 2 and Case 3 share a similar curve. After that, Case 3 keeps lower values. During the simulation time from 6:00 to 18:00, the value of the SF in Case 3 decreases by almost 60% compared with that in Case 1. Therefore, the proposed method can achieve significant power-smoothing effectiveness to increase the operational efficiency of the main grid.

Fig. 6 (d)-(f) shows comparisons of the energy cost of different cases. Similar to the trend of the power in Fig. 6(a)-(c), the energy cost in Case 1 is the most volatile among the three cases, and Case 3 is the smoothest one. In particular, both Case 1 and Case 2 reach peaks when PV output drops. This phenomenon will increase the cost especially considering that most electricity generation can be approximated as a convex pricing function in reality (quadratic cost function in the case studies). Therefore, the proposed method can save energy costs by smoothing the power curve. The average costs are decreased from 7318$ in Case 1 and 6829$ in Case 2 to 6814$ in Case 3.

B. Effectiveness of DP in solving the optimization model

The DP method is proposed to improve the efficiency of solving the individual optimization model. This section will study the accuracy and efficiency of the DP method by comparing it with the non-linear programming results. Here non-linear programming results are solved by the interior-point method using the commercial tool, e.g., Matlab. Due to the individual optimization model is built as a convex problem, the result solved from the interior-point

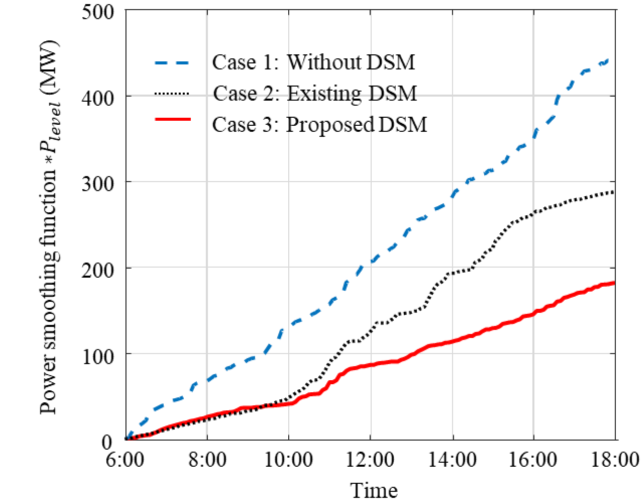

Fig. 7. Power smoothing function of different cases.

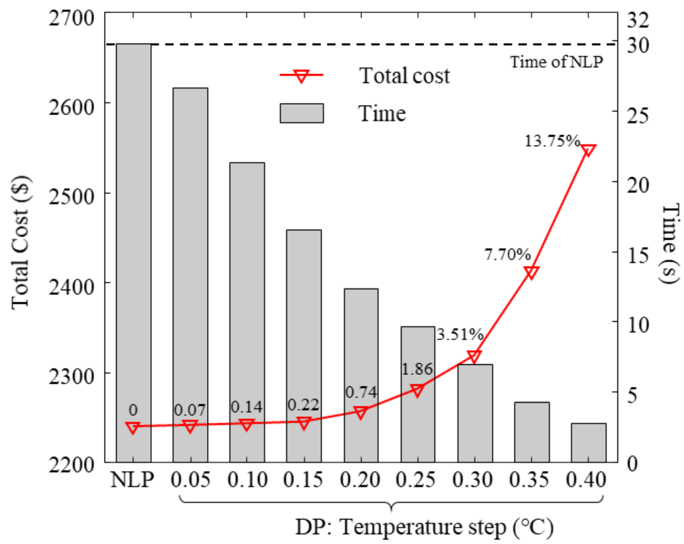

Fig. 8. Comparison of solving time of DP (dynamic programming) and NLP (non-linear programming)

method [32] is an optimal solution and can be regarded as an accurate result.

Fig. 8 shows the total energy cost and the simulation time of 50 business users in a converged state (Nash equilibrium). The x-axis distinguishes the NLP method and the DP method. Particularly, DP methods are set with different temperature steps. The temperature step indicates the number of states of the DP method. The smaller the step is, the more the state will be, which will increase the solving time. For example, if the temperature step is 0.40℃, there are 6 states (i.e., 24.0℃, 24.4℃, 24.8℃, 25.2℃, 25.6℃, 26.0℃) among the comfortable temperature range from 24℃ to 26℃. In practice, the temperature step can be determined by the minimum measurement of the temperature sensor. The temperature step chosen in the simulation is chosen from 0.05℃ to 0.40℃, which are accurate enough in practical buildings for users. As shown in Fig. 8, the grey bars indicate the simulation time to reach the optimal point. With the increase of the temperature steps, the solving time will decrease.

The red solid curve in Fig. 8 is the energy cost of the users. Meanwhile, the errors compared with the NLP result are marked in percentage on the red solid curve. It can be seen that with the decrease of temperature step, the total cost of the users will be closer to the NLP results. When the temperature step is less than 0.15 ℃, the accuracy is relatively high (around 0.22% error). Hence, there is a trade-off between cost accuracy and solving time. Considering the minimum measurement for the air-conditioning

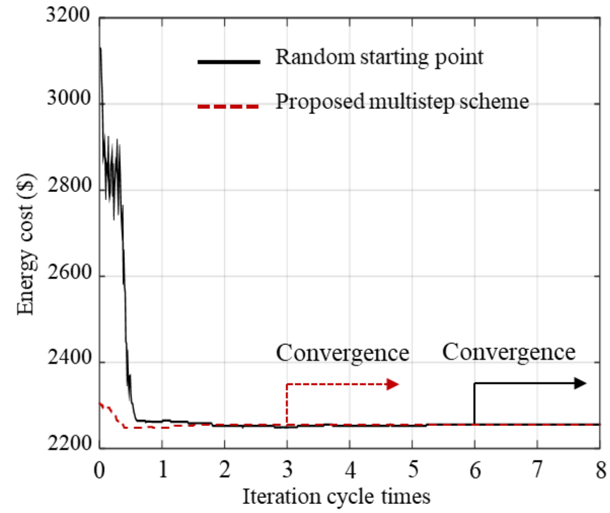

Fig. 9. Convergence performances of the game theoretic DSM

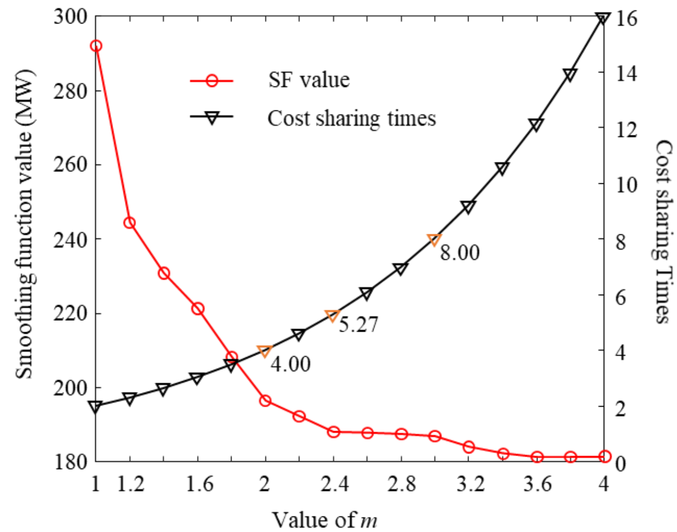

Fig. 10. Impacts of value of m

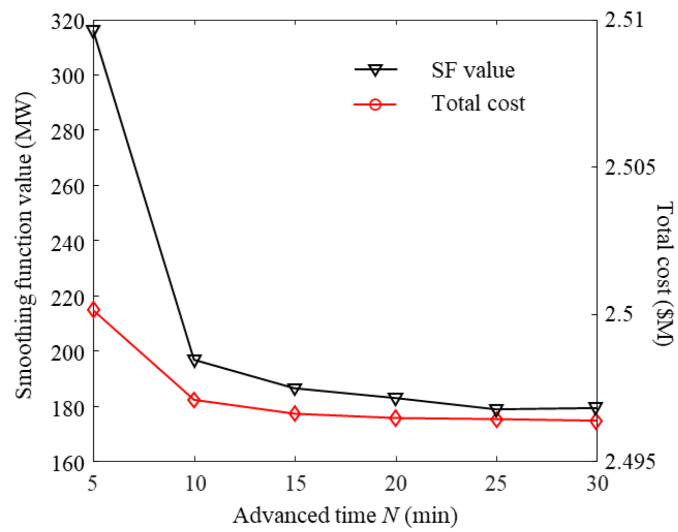

Fig. 11. Impacts of advance time of price

temperature sensor, it is suggested to choose 0.1℃ or 0.2℃ for temperature steps. In this manner, the solving time can get improved, while the energy cost is negligible.

C. Effectiveness of the multi-step procedure

The multi-step procedure utilizes rolling optimization to improve the convergence efficiency to reach the Nash equilibrium. This section will validate the effectiveness of the proposed multi-step procedure by comparing the proposed results with random initialization. Fig. 9 shows the energy cost convergence of the proposed DSM framework. The black solid curve indicates the convergence process using a random initialization, while the red dotted curve is based on a proposed multistep scheme using the previous optimization solution as the starting point. To eliminate the impacts of individual optimization solving time, the *x*-axis is the iteration cycle rather than the simulation time. An iteration cycle means each of the participating users makes a decision sequentially in the determined order. There are 50 users in this test system, and consequently, all 50 users will optimize their power consumption once in one cycle.

As Fig. 9 shows, the random starting point scheme starts from a higher total cost compared with the proposed multi-step scheme. This is because the proposed multi-step procedure uses the optimal power schedule as the start point of the next optimization. Since the renewable power prediction will not deviate from the actual value a lot in actual power systems, the previous result is very close to the current optimal point. Hence the proposed multi-step scheme is lower than the random starting point and closer to the optimal point. With the cycle proceeding, the two cases reach close to the final converged cost at around 0.5 cycle. It should be noted that although the total cost is closed to the optimal value, it is not the optimal state. Because not all the consumers have made his/her decision at this time (the 0.5 cycle means half of the users have not made power consumption decisions). In other words, even though the total energy cost is close to the optimal result, some individuals still are going to change his/her power consumption scheme in their turn. When these users make their decisions, the total cost will be changed. The power schedule will be determined and the optimal point will get reached, only when all the users have no motivation to change their power schedule. As for the convergence iteration, the random starting point scheme takes 6 iterations, while the multi-step scheme only takes 3 iterations to reach the same total cost ($ 2258). This proves that the proposed multi-step procedure can reduce the convergence time for the game-theoretic DSM.

D. Impacts of value m

The proposed game-theoretic DSM takes advantage of existing methods because it can adjust the bill sharing rate by changing the value of *m*. Fig. 10 shows the impacts of *m* on the SF values. The red line indicates the SF value under the different values of *m*. With the increase of *m*, the power smoothing values are reduced. However, when *m* is larger than 2.0, the power SF value will reduce slightly.

The black line in Fig. 10 shows the cost-sharing rate among users. With the increase of *m*, the cost-sharing rate increases with the multiple of 2^m. That is to say, if *m*=2.0, 2.4, or 3.0, the users should pay 2.00, 5.27, and 8.00 times than others, respectively. Hence, a too high value of *m* may lead to unreasonable electricity prices among users. In this study, the value of *m* is designed as 2.0. In practice, an appropriate value of *m* should be carefully chosen for the power smoothing performance as well as the reasonability of electricity price.

E. Impacts of advanced released time of the price

In the proposed DSM, individuals are designed to optimize power consumption schedules based on future *N*-min price information. This advanced released time of price *N* will also influence the performance of the proposed DSM. Fig. 11 shows the results of SF value and total energy cost under the different values of *N*. With the *N* increasing, both the SF value and total cost are decreasing. Particularly, the SF value underwent an obvious decrease from 316 MW to 179 MW. As for the total cost, the total cost decreases from about 2.499 $M to 2.497 $M. Hence, the results show that increasing the value of *N* can not only smooth the tie-line power but also help users to save money on energy. But it should be noted that a higher *N* can also add calculation burden for individuals and may increase the time to reach the optimal point. Hence, since both performances do not show much decrease after 15 min, N=15 min can be regarded as an appropriate value in this paper. In practice, an appropriate *N* should be determined by MG utility based on the DSM performances of power smoothing, cost-saving, and solving time. Moreover, practical conditions of the MG, such as electric market policy and REN prediction, also should be considered before being implemented by the utility.

F. Practical case study

This section selects 118 large industrial users with a daily average load from 4.90MW to 20.60MW. Two different pricing mechanisms are considered and tested in this case study, which are fixed price (0.071 $/kWh, the average electricity rate in American [37]) and the artificial cost function similar to Ref. [25], respectively. To ensure that the user's cost is almost equal under different price mechanisms, the parameters of the artificial cost function are assumed as a=0.00001819 while $b=c=0$. These two pricing mechanisms are implemented in the above different cases, the cases without DSM, existing game-theoretic methods, and the proposed methods.

Results of the smoothing function (SF) value and total cost and are shown in Table 2. Generally, both game-theoretic DSM schemes (i.e., Case 2 and Case 3) have smaller SF values and smaller total cost values compared with that in Case 1, no matter which pricing mechanism is adopted. The proposed game-theoretic DSM (Case 3) shows a smaller SF value and smaller total cost compared with the existing method (Case 2), which illustrates the effectiveness of the proposed methods. Meanwhile, comparing with the SF value and total cost value under different pricing mechanisms, it is obvious that both SF value and total cost are better under artificial quadratic cost function than the cases with fixed price. It proves that the price function has a great impact on the game-theoretic performances. And the artificial cost function also has the potential to be designed for better performance.

Table 2. Comparison of the proposed methods and existing methods

Cases		Fixed price [37] (Linear function)		Artificial cost function [25] (Quadratic function)	
		SF (MW)	Cost ($M)	SF (MW)	Cost ($M)
1	Practical loads	6009.5	25.61	6009.5	25.61
2	Existing DSM	4267.4	23.26	3935.2	22.29
3	Proposed	3539.5	23.03	2468.6	22.16

	DSM				

VI. Conclusions

This paper proposes a game-theoretic DSM to smooth the tie-line power for MGs based on a power consumption game among TCLs. A novel pricing mechanism is developed based on the conditions of forming a concave N-person game, which is more adaptive and flexible compared with existing game-theoretic DSM schemes. An individual's power consumption optimization and its simplified model are built and solved by dynamic programming, which achieves fast response and high accuracy in the power consumption game. The implementation framework of the proposed DSM is developed to guarantee the benefits of both individuals and groups. The numerical studies based on practical data validate the effectiveness of the proposed method in achieving better performance in power smoothing and cost-saving. By choosing appropriate parameters and carefully designing an artificial cost function, the proposed game-theoretic DSM is expected to make the best of the potentials of demand response in an MG, and further contribute to a user-friendly demand response program.

Appendix

Proof:

Sufficiency: *If $S(P_k)$ is convex, then $B(P_k)$ is strictly convex.*

The second derivative of $B(P_k)$ can be expressed as

$$\frac{\partial^2 B}{\partial {P_k}^2} = \frac{\partial^2 S}{\partial {P_k}^2}\cdot C + \frac{\partial S\cdot \partial C}{\partial {P_k}^2} + \frac{\partial^2 C}{\partial {P_k}^2}\cdot S \tag{31}$$

As defined in Section II-B and C, $S(P_k)$ and $C(P_k)$ are positive, increasing, and convex function. Hence,

$$S(P_k), C(P_k) > 0 \tag{32}$$

$$\frac{\partial S(P_k)}{\partial P_k}, \frac{\partial C(P_k)}{\partial P_k} \geq 0 \tag{33}$$

$$\frac{\partial^2 S(P_k)}{\partial {P_k}^2}, \frac{\partial^2 C(P_k)}{\partial {P_k}^2} \geq 0 \tag{34}$$

Hence, $\frac{\partial^2 B(P_k)}{\partial {P_k}^2} > 0$, $B(P_k)$ is strictly convex.

Necessity: *If $B(P_k)$ is strictly convex, then $S(P_k)$ is convex.*

Considering the case of the $S(P_k)$ satisfying

$$-\frac{\dfrac{\partial S\cdot\partial C}{\partial {P_k}^2} + \dfrac{\partial^2 C}{\partial {P_k}^2}\cdot S}{C} < \frac{\partial^2 S}{\partial {P_k}^2} < 0 \tag{35}$$

In this case, it satisfies $\frac{\partial^2 B(P_k)}{\partial {P_k}^2} > 0$, while $\frac{\partial^2 S(P_k)}{\partial {P_k}^2} < 0$.

Hence, if $B(P_k)$ is strictly convex, $S(P_k)$ is not necessary to be convex.

In conclusion, the event that $S(P_k)$ is convex is a sufficient but not a necessary condition for the event that $B(P_k)$ is strictly convex. ■

Acknowledgements

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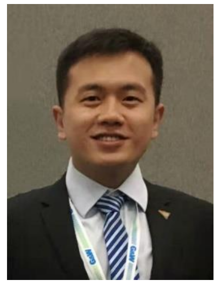

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