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Transactive Demand–Response Framework for High Renewable Penetrated Multi-Energy Prosumer Aggregators in the Context of a Smart Grid

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Featured Application: A transactive demand-response framework is useful for a high renewable penetrated microgrid and smart grid.

Abstract: Demand–response (DR) can provide the economic flexibility required to adapt a high proportion of renewable energy in the context of a smart grid. This paper proposes a transactive DR framework to enable the multi-time-scale proactive participation of demand-side flexible multi-energy resources. In this framework, the distribution system operator distributes the real-time DR request and the high renewable penetrated multi-energy prosumer aggregators provide the ancillary services based on their adjustable potential. To facilitate such multi-time-scale prosumer–operator interactions, a flexibility potential evaluation method is developed for the quantification and pricing of prosumer flexibility. The positive and negative flexibility potential of the demand-side prosumer aggregators are defined as deviations from the optimal pre-dispatch operation, which are further quantified using the aspects of flexible time and power. Based on the introduction of a flexibility pricing mechanism to identify the economically optimal ancillary service requirements, each prosumer aggregator performs an optimal real-time DR scheduling. Case studies over several DR schemes are performed to confirm the effectiveness and superiority of the proposed method on the economy and flexibility of the system.

Keywords: smart grid; economic optimization; demand–response; microgrid; renewable energy

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1. Introduction

1.1. Motivation

As the global climate problems become more and more serious, countries worldwide have begun to implement "dual-carbon" policies in order to accelerate development towards a clean and low-carbon smart grid [1,2]. Renewable energy sources, especially solar and wind energy, are characterized by randomness, intermittency, and volatility. It is impractical to accurately capture their power generation, which poses difficulty in the supply–demand balance of the whole smart grid. Demand–response (DR) could provide a certain degree of supply–demand flexibility via shifting or shedding the electricity consumption of demand-side flexible resources [3]. Some countries, such as Australia, Korea, China, and the United States, have been increasingly conducting experimentation around DR policy frameworks, which technically facilitate the participation of demand-side resources in the provision of flexibility to the smart grid. This paper focuses on the DR potential across the different flexible resources in order to better understand the interactions between the demand side and the distribution system operator, but also to figure out which factors could contribute to this potential.

1.2. Background and Literature Review

Traditional consumers have been gradually transforming towards prosumers for both consuming and producing energy. With the deployment of advanced metering and smart management technologies, different demand-side flexible resources can contribute significantly to DR implementation. Since most prosumers are small in size and cannot directly participate in flexibility or electricity markets, a prosumer aggregator is required to facilitate such transactive interactions. The most common DR framework for prosumer aggregators can be categorized into price-maker or price-taker [4]. The former one indicates that prosumer aggregators perform flexible DR to determine the market clearing price and quantities. In [5], a two-stage stochastic optimal bidding strategy is proposed for prosumer aggregators to participate in the tertiary reserve market under the pay-as-bid remuneration scheme. In [6], an optimal bidding strategy of prosumer aggregators is proposed based on their bottom-up responsiveness. The latter one indicates that prosumer aggregators act as retailers in order to economically optimize the DR based on retail tariffs. Generally, time-varying retail tariffs are adopted, such as time-of-use pricing (TOU) [7] and real-time pricing (RTP) [8]. They are all used to encourage the participation of prosumer aggregators in distribution system flexibility or electricity services.

Based on the operational time scales of prosumer aggregators, DR can be divided into two types. The first one is off-line DR. Heating ventilation air conditioning (HVAC) is a commonly used load, which is controllable and flexible resource that participates in day-ahead DR [9]. In [10], a resistance capacity model is adopted to simulate the thermal dynamics of a HVAC-based area, and its operational potential is evaluated based on substantial amounts of smart meter data. In [11], an interrelated indoor thermal response and HVAC are coordinated to day-ahead electricity prices. Other demand-side flexible resources, including electric vehicles (EVs), also can participate in the DR. EV users and an EV aggregator are investigated in [12] based on their stochastic reality needs. The existing off-line DR schemes [9–12] of prosumer aggregators assume the perfect forecasting of uncertain factors, including renewable generations, ambient temperature, and EV charging needs, which pose difficulties in practical applications.

The other one is the on-line DR of prosumer aggregators. HVAC can quickly respond to the price signal or renewable energy fluctuations, which can serve as flexible resources in real-time operation. In [13], a resistance-capacity model for HVAC is reviewed and a transactive building–aggregator–grid framework is developed via a robust model predictive control (MPC) algorithm. In [14], a unified appliance model is proposed to aggregate diverse types of flexible resources, and a dynamic energy management framework is developed based on MPC. By augmenting it using a rule-based method, real-time electrical and multi-energy DR are investigated in [15,16]. In [17], a robust multi-time-scale model is proposed for price-based and incentive-based multi-energy DR. In [18], the real-time multi-energy DR of aggregators are optimized via a hierarchical distributed structure. Nevertheless, the existing on-line DR schemes [13–18] of prosumer aggregators assume that all flexible resources are equipotent and equally willing to participate in the DR program, which is impractical. The transactive DR framework for the multi-time-scale proactive participation of multi-energy prosumer aggregators with 100% renewables has not been involved yet.

The concept of flexibility has, in general, been introduced to understand the function mechanism of and improvements made in DR. During the practical implementation of DR, a reasonable and accurate evaluation of the flexibility potential can provide a certain number of dispatch references for prosumer aggregators [1,19]. According to the nature of the evaluation methods, the DR flexibility potential evaluation can be divided into qualitative and quantitative evaluation. The qualitative evaluation of the DR flexibility potential can only reflect its general behavior and not provide accurate values [20], which is rarely applied practically. The quantitative evaluation of the DR flexibility potential uses the available statistical data to obtain the adjustable capacity of different flexible resources, which would be aggregated to respond to the system operator. The indicators and definitions of the DR flexibility potential are reviewed in [21,22]. In [23], the electricity flexibility potential of HVAC and a storage tank is quantified via their physical operational mechanism. The electricity flexibility potential of price-based and incentive-based DR programs are calculated in [24], based on their technical flexibility characteristics. In [25], the flexibility potential of various flexible generation resources is evaluated based on their operational mechanism, which are further priced to participate in local flexibility markets. In [26], the DR flexibility potential within the multi-energy system is evaluated from five dimensions and graded into four levels. A generic simulation-based method is adopted in [27] in order to quantify the DR flexibility potential of zero-energy buildings. However, the existing DR flexibility potential studies [19–27] are simply from the aspects of the inherent operational mechanism or its external characteristics, which ignores the fluctuations in the real-time surrounding supply–demand environment. The DR potential of diverse flexible multi-energy resources cannot fully be utilized practically.

1.3. Contribution and Paper Organization

In the context of a smart gird, this paper proposed a transactive DR framework for high renewable penetrated multi-energy prosumer aggregators based on a flexibility potential evaluation. Table 1 summarizes the differences in the typical works. The contributions are summarized as follows:

Table 1. Differences in the proposed approach.

References	100% Renewable	Multi-Energy	Time Scale	Flexibility Potential Evaluation	
				Quantification	Pricing
[5,6]	✓	✓	Day-ahead	×	×
[4,9]	✓	×	Day-ahead	×	×
[10,13]	No renewable	×	Day-ahead	×	×
[11]	No renewable	×	Day-ahead	×	×
[12]	×	×	Day-ahead	×	×
[7,8,14]	✓	×	Real-time	×	×
[15,19]	×	×	Real-time	×	×
[16]	✓	✓	Multi-time-scale	×	×
[17]	×	✓	Multi-time-scale	×	×
[20,23]	No renewable	×	Real-time	Quantitative	×
[22]	No renewable	×	Real-time	Quantitative	×
[24]	No renewable	×	Day-ahead	Quantitative	×
[25,26]	×	✓	Day-ahead	Quantitative	✓
[27]	✓	×	Day-ahead	Quantitative	×
Proposed	✓	✓	Multi-time-scale	Quantitative	✓

(1) While some previous literature [14–16] assumes that all flexible resources are equipotent and equally willing to participate in the DR program, some previous literature [5,6] has tended towards one-time market clearing. These frameworks cannot practically exploit the inherent flexibility of prosumer aggregators. Instead of relying on highly susceptible unperfect forecasting in off-line DR schemes [9–12], a transactive DR framework is proposed to enable the multi-time-scale proactive participation of demand-side flexible multi-energy resources. Under such a framework, diverse flexible multi-energy resources are aggregated as prosumer aggregators to participate in the multi-time-scale transactive interactions, thereby cost-effectively providing additional auxiliary services and accommodating the high penetration of renewable energy.

(2) While previous literature [22,26] has developed various indicators to evaluate the DR flexibility potential based on the operational mechanism or external characteristic, a flexibility potential quantification method is developed to evaluate the positive and negative flexibility of prosumer aggregators from the aspects of flexible time and power. Such a quantification evaluation of the DR flexibility potential can not only improve the

utilization rate of various generation devices, but also promote the accommodation of renewable energy.

(3) Instead of using the incentives [5,6] and constant time-of-use/real-time prices [7,8], a flexibility potential pricing mechanism is introduced to comprehensively consider the overall supply–demand level and prosumer–operator interactions. The economically optimal guaranteed flexibility that the prosumer aggregators must provide is obtained to achieve a break-even cost for the ancillary service, showing better practicability.

The remainder of this paper is structured as follows: Section 2 presents the proposed transactive DR framework using the flexibility potential evaluation method (including flexibility potential quantification and pricing). The detailed implementation process is then presented in Section 3. The case study and conclusions are presented in Sections 4 and 5.

2. Problem Formulation

2.1. Transactive DR Framework

Figure 1 is the proposed transactive DR framework for high renewable penetrated multi-energy prosumer aggregators, which includes the distribution system operator, ancillary service center, and prosumer aggregators. With the integration of energy storage and renewable energy sources, more and more passive consumers are transforming into prosumers and changing towards aggregated systems for proactive DR participation. In addition to demand-side power flexible and time flexible loads, a prosumer aggregator includes various flexible energy production, conversion, and storage equipment. In a prosumer aggregator, 100% of the renewable energy is firstly converted via wind turbine (WT), photovoltaic thermal (PVT), and geothermal generators into different energy carriers; these are conditioned via various energy conversion and storage equipment, including combined heat and power (CHP) and power to gas (P2G), in order to embrace the needs of users [16]. As proactive end-users, prosumer aggregators act as price-takers to buy or sell electricity from or to the distribution system operator [4].

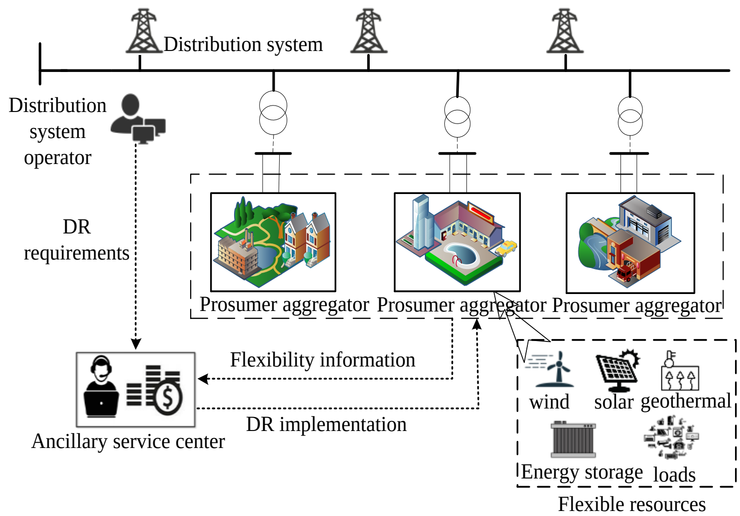


Figure 1. Transactive DR framework in the context of a smart gird.

In the distribution system, all flexible multi-energy resources within prosumer aggregators can participate in the regulation of energy supply and demand. DR can make full use of the adjustable potential of flexibility resources in order to improve the economy of the distribution network. In this framework, the DR program is integrated with a flexibility potential quantification, which allows one to calculate the maximum possible deviation of every flexible resource from the cost-optimal operation. Once the resource flexibility is quantified and sent to the ancillary service center, it is then priced to calculate the profitability of the prosumer aggregators in an ancillary service. After interacting with the distribution system operator, the DR program of prosumer aggregators can be optimally and flexibly coordinated.

2.2. Flexibility Potential Quantification

Here, the flexibility potential quantification for the flexible multi-energy resources within the prosumer aggregators is presented. Flexibility is, in general, defined as the shifting of supply–demand behavior in response to price signal or incentives [25]. For any flexible multi-energy resources, the allowable schedule is the resource flexibility, which represents the boundaries of the possible variations from the optimal operation without violating its physical constraints. For example, a battery under normal operation follows an optimal operation plan, and the maximum deviation at any timestep is constrained by its state-of-charge (SOC) limits. Based on the above definition, positive flexibility is defined as a prosumer service that results in a net addition of energy to the grid. Conversely, negative flexibility is a prosumer service that results in a net removal of energy from the grid. The flexibility potential quantification would obtain the available positive and negative flexibility in terms of power, energy and time.

The flexibility potential for all flexible resource can be expressed using constraint (1).

$$e_{t,n,flex} = P_{t,n,flex} \cdot \lambda_{t,n,flex} \cdot \Delta t \tag{1}$$

Battery energy storage (BES) has a high level of flexibility, which can provide both positive and negative flexibility. The negative flexibility of BES is additional energy charged from outside. The maximum amount of available flexibility is subject to the SOC levels of the BES. constraint (2) shows the available maximum negative flexible energy $ebes_{t,n,max\text{-}}$ from a BES, which is the difference between the current and maximum SOC. The negative flexible power might not always be the maximum charging. For instance, if the BES is scheduled to discharge, the negative flexible power will be the maximum charge and the scheduled discharge, as shown in constraint (3).

$$ebes_{t,n,\max-} = (SOC_{e,n,\max} - SOC_{e,t,n}) \cdot E_{bes} \tag{2}$$

$$Pbes_{t,n,flex-} = E_{e,ch,n,\max} + E_{e,dis,t,n} - E_{e,ch,t,n} \tag{3}$$

The maximum flexible energy in constraint (2) can be offered continuously only if the flexible power is equal or greater in the next few timesteps. The possible time is subject to constraint (4), which is until this constant power curtailment is feasible. Here, $N(f(n))$ is used to obtain the number of timesteps subjected to the $f(n)$. Constraint (5) finds the number of continuous timesteps that are subjected to both the limitation of the maximum flexible energy and the operation of constant flexible power.

$$\lambda_{k,bes-} = N\Big(Pbes_{k,n,flex-} \geq Pbes_{t,n,flex-}\Big)\mathrm{k} \in [t+1, \ldots T] \tag{4}$$

$$\lambda bes_{t,n,flex-} = \min\left\{\frac{ebes_{t,n,\max-}}{Pbes_{t,n,flex-} \cdot \Delta t}, \lambda_{k,bes-}\right\} \tag{5}$$

The positive flexible power can be calculated by the maximum discharge and BES charging, as shown in (7). Similar to (2) and (5), the maximum positive flexible energy and the minimum number of steps subjected to continuous power operation and SOC limits are established in (6) and (9).

$$ebes_{t,n,\max+} = (SOC_{e,t,n} - SOC_{e,n,\min}) \cdot E_{bes} \tag{6}$$

$$Pbes_{t,n,flex+} = E_{e,dis,n,\max} - E_{e,dis,t,n} + E_{e,ch,t,n} \tag{7}$$

$$\lambda_{k,bes+} = N\Big(Pbes_{k,n,flex+} \geq Pbes_{t,n,flex+}\Big)\mathrm{k} \in [t+1, \ldots T] \tag{8}$$

$$\lambda bes_{t,n,flex+} = \min\left\{ \frac{ebes_{t,n,\max+}}{Pbes_{t,n,flex+} \cdot \Delta t}, \lambda_{k,bes+} \right\} \tag{9}$$

Similarly, gas storage tanks can also provide both positive and negative flexibility services, which are constrained by SOC, the scheduled charge and discharge. Constraint (10) represents the available maximum negative flexible energy $egas_{t,n,\max-}$ from a gas storage tank, which is the difference between the current and maximum SOC. The flexible output of gas storage tanks and the minimum number of steps subjected to continuous power operation and SOC limits are established in (11)–(13).

$$egas_{t,n,\max-} = \left(SOC_{g,n,\max} - SOC_{g,t,n}\right) \cdot E_{gas} \tag{10}$$

$$Pgas_{t,n,flex-} = \left(E_{g,ch,n,\max} + E_{g,dis,t,n} - E_{g,ch,t,n}\right) \cdot Q_{gas} \tag{11}$$

$$\lambda_{k,gas-} = N\left(Pgas_{k,n,flex-} \geq Pgas_{t,n,flex-}\right) \mathrm{k} \in [t+1, \ldots T] \tag{12}$$

$$\lambda gas_{t,n,flex-} = \min\left\{ \frac{egas_{t,n,\max-}}{Pgas_{t,n,flex-} \cdot \Delta t}, \lambda_{k,gas-} \right\} \tag{13}$$

The positive flexibility is characterized by flexible gas storage, which is related to planned charging and discharging, as shown in (14)–(17).

$$egas_{t,n,\max+} = \left(SOC_{g,t,n} - SOC_{g,n,\min}\right) \cdot E_{gas} \tag{14}$$

$$Pgas_{t,n,flex+} = \left(E_{g,dis,n,\max} - E_{g,dis,t,n} + E_{g,ch,t,n}\right) \cdot Q_{gas} \tag{15}$$

$$\lambda_{k,gas+} = N\left(Pgas_{k,n,flex+} \geq Pgas_{t,n,flex+}\right) \mathrm{k} \in [t+1, \ldots T] \tag{16}$$

$$\lambda gas_{t,n,flex+} = \min\left\{ \frac{egas_{t,n,\max+}}{Pgas_{t,n,flex+} \cdot \Delta t}, \lambda_{k,gas+} \right\} \tag{17}$$

The flexibility calculation of heat storage tanks is similar to the BES. The negative flexibility service is offered by the maximum charging power and the scheduled discharge, as shown in (18)–(21).

$$eheat_{t,n,\max-} = (SOC_{h,n,\max} - SOC_{h,t,n}) \cdot E_{heat} \tag{18}$$

$$Pheat_{t,n,flex-} = E_{h,ch,n,\max} + E_{h,dis,t,n} - E_{h,ch,t,n} \tag{19}$$

$$\lambda_{k,heat-} = N\left(Pheat_{k,n,flex-} \geq Pheat_{t,n,flex-}\right) \mathrm{k} \in [t+1, \ldots T] \tag{20}$$

$$\lambda heat_{t,n,flex-} = \min\left\{ \frac{eheat_{t,n,\max-}}{Pheat_{t,n,flex-} \cdot \Delta t}, \lambda_{k,heat-} \right\} \tag{21}$$

Similarly, the positive flexibility of heat storage tanks is described by (22)–(25).

$$eheat_{t,n,\max+} = (SOC_{h,t,n} - SOC_{h,n,\min}) \cdot E_{heat} \tag{22}$$

$$Pheat_{t,n,flex+} = E_{g,dis,n,\max} - E_{g,dis,t,n} + E_{g,ch,t,n} \tag{23}$$

$$\lambda_{k,heat+} = N\left(Pheat_{k,n,flex+} \geq Pheat_{t,n,flex+}\right) \mathrm{k} \in [t+1, \ldots T] \tag{24}$$

$$\lambda heat_{t,n,flex+} = \min\left\{ \frac{eheat_{t,n,\max+}}{Pheat_{t,n,flex+} \cdot \Delta t}, \lambda_{k,heat+} \right\} \tag{25}$$

The negative flexible power of CHP is provided only when it is forced to turn from OFF to ON. The negative flexible power is defined as its operating power, as shown in constraint (26).

$$PCHP_{t,n,flex-} = P_{CHP,t,n} \tag{26}$$

The flexible time of CHP is limited by the ON/OFF state and SOC of the heat storage system. Hence, the flexible time is defined as the minimum value of the above two constraints, as shown in (27)–(29).

$$\lambda_{k1,CHP-} = N(k \cdot a_{CHP,t,n} - t \geq 0)\mathrm{k} \in [t+1, \ldots T] \tag{27}$$

$$\lambda_{k2,CHP-} = \frac{SOC_{h,t,n} \cdot E_{heat}}{P_{CHP,t,n} \cdot \Delta t} \tag{28}$$

$$\lambda CHP_{t,n,flex-} = \min\{\lambda_{k1,CHP-}, \lambda_{k2,CHP-}\} \tag{29}$$

The positive flexible power of CHP is provided only when it is operating, which is defined as its installed capacity. This is represented in constraint (30).

$$PCHP_{t,n,flex+} = P_{CHP,n,\max} \tag{30}$$

The ON/OFF state and SOC are also the limits of the positive flexible time, as shown in (31)–(33). Constraint (31) expresses the time until the next switching state and $1 - a_{CHP,t,n}$ finds the available time in the optimal operation.

$$\lambda_{k1,CHP+} = N(k \cdot (1 - a_{CHP,t,n}) - t \geq 0)\mathrm{k} \in [t+1, \ldots T] \tag{31}$$

$$\lambda_{k2,CHP+} = \frac{(SOC_{h,n,\max} - SOC_{h,t,n}) \cdot E_{heat} \cdot \eta_{eCHP}}{(P_{CHP,n,\max} - P_{CHP,t,n}) \cdot \Delta t \cdot \eta_{hCHP}} \tag{32}$$

$$\lambda CHP_{t,n,flex+} = \min\{\lambda_{k1,CHP+}, \lambda_{k2,CHP+}\} \tag{33}$$

The negative flexibility of P2G is provided when it is forced to OFF. The maximum negative flexible power of the P2G is expressed by the optimal schedule in (34).

$$PP2G_{t,n,flex-} = P_{P2G,t,n} \tag{34}$$

The negative flexible time of P2G is similar to CHP, as shown in (31)–(33). The P2G supply is forced to OFF and the flexible time is limited via the present SOC of the gas storge tanks. Constraint (35) expresses the available time required to supply the demand.

$$\lambda P2G_{t,n,flex-} = \min\left\{N(k \cdot a_{P2G,t,n} - t \geq 0), \frac{SOC_{g,t,n} \cdot E_{gas}}{P_{P2G,t,n} \cdot \Delta t}\right\} \mathrm{k} \in [t+1, \ldots T] \tag{35}$$

The positive flexible power of P2G is provided only when it is forced to turn on. The positive flexible power is defined as its installed capacity, as shown in (36). The positive flexible time of P2G is similar to CHP, which is calculated using (37).

$$PP2G_{t,n,flex+} = P_{P2G,n,\max} \tag{36}$$

$$\lambda P2G_{t,n,flex+} = \min\left\{N(k \cdot (1 - a_{P2G,t,n}) - t \geq 0), \frac{(SOC_{g,n,\max} - SOC_{g,t,n}) \cdot E_{gas} \cdot Q_{gas}}{(P_{P2G,n,\max} - P_{P2G,t,n}) \cdot \Delta t \cdot \eta_{gas}}\right\} \mathrm{k} \in [t+1, \ldots T] \tag{37}$$

2.3. Flexibility Potential Pricing Mechanism

Three typical pricing mechanisms are generally used to encourage the DR of prosumer aggregators in the distribution system. While TOU pricing is generally obtained from markets, incentives can be calculated via market clearing or set as constant parameters.

RTP, which is set as a time-varying parameter, is another pricing mechanism used to facilitate DR experimentation. Previous studies have shown that the above price-based DR and incentive-based DR are popular in peak shaving, since the man-made pricing mechanisms can directly execute the regulation measure of system operators. However, these pricing mechanisms have no considerations for the overall supply–demand level and prosumer–operator interactions. Even though the end-users can benefit from the pricing mechanisms financially, the overall system load profile cannot be flattened. Ideally, it would be possible or technically possible to repeatedly simulate each flexible resource in order to calculate the exact flexibility price. However, this is a machine-intensive process and cannot be put into use practically.

To facilitate the prosumer–operator interactions, a flexibility potential pricing mechanism is alternatively developed. Once positive and negative flexibility are quantified in Section 2.1 from the aspects of time and power, these can be aggregated to form the overall flexibility potential of prosumer aggregators. While previous mechanisms use the man-made constant/time-varying parameters to price the resource flexibility, the flexibility potential pricing mechanisms intend to reflect the high degree of scarcity and the real-time supply–demand within the distribution system. Depending on the real-time supply–demand, the more resource flexibility there is, the more reward it will obtain. Basically, the flexibility potential prices are positively correlated with the flexibility $e_{n,flex}$ of each aggregator. Inspired by the pricing function [16], an increasing and strictly convex quadratic function is adopted in order to calculate the flexibility potential pricing $pr_{n,flex}$:

$$e_{n,flex} = \sum_{t\in\{1,\ldots T\}} \sum_{j} P_{j,t,n,flex} \cdot \lambda_{j,t,n,flex} \tag{38}$$

$$pr_{n,flex} = a \cdot {e_{n,flex}}^2 + b \cdot e_{n,flex} + c \tag{39}$$

3. Transactive DR Based on Flexibility Potential Evaluation

3.1. Functional Process of Transactive DR Framework

The functional overview of the proposed transactive DR framework is represented in Figure 2, and characterized as a five-step process:

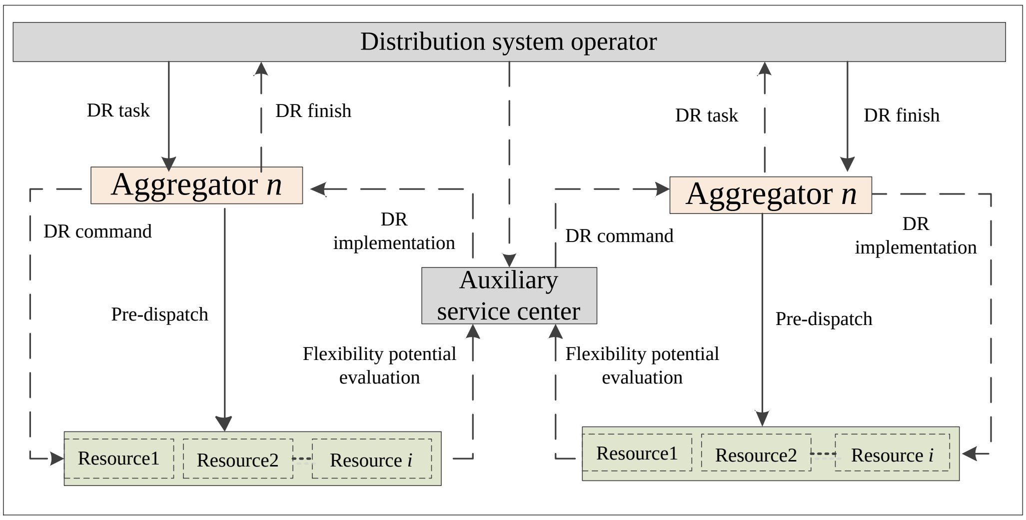


Figure 2. Functional process of the transactive DR framework.

(1) A pre-dispatch would be performed for each prosumer aggregator with the forecasted multi-energy supply–demand. All flexible and inflexible multi-energy resources are economically optimized.

(2) A flexibility potential quantification method is developed in order to compute the maximum possible deviation of every flexible resource from the cost-optimal pre-dispatch

at any given time. Once the positive and negative flexibility are quantified from the aspects of time and power, these can be aggregated to form the overall flexibility potential of prosumer aggregators.

(3) A pricing mechanism is developed to price the flexibility potential of prosumer aggregators and account for their profitability in an ancillary service.

(4) Once receiving the real-time DR task from the distribution system operator, cost-optimal scheduling is performed to obtain the scheduling plan for each prosumer aggregator.

(5) After receiving the scheduling plan, each prosumer aggregator performs real-time DR to re-schedule the flexible and inflexible multi-energy resources, while meeting its own supply and demand balance.

3.2. Pre-Dispatch Optimization

In order to effectively evaluate the flexible multi-energy resources of each aggregator, day-ahead pre-dispatch is performed according to the predictive wind–solar and load demand. Prosumer aggregators act as price-takers in order to buy or sell electricity from or to the distribution system operator, while optimizing its own flexible multi-energy resources.

(1) Objective function: The objective function of the prosumer aggregator is the minimization of the system's operational costs, including the power procurement cost $PC_{t,n}$ and the battery degradation cost $BC_{t,n}$.

$$\min \mathrm{F}_n = \sum_{t \in \{1,\cdots T\}} (PC_{t,n} + BC_{t,n}) \tag{40}$$

$$PC_{t,n} = (\mu_{\mathrm{buy,t}} E_{buy,t,n} - \mu_{\mathrm{sell}} E_{sell,t,n})\Delta t \tag{41}$$

$$BC_{t,n} = (E_{\mathrm{ch},t,n} + E_{\mathrm{dis},t,n})\mu_{BES} \cdot \Delta t \tag{42}$$

(2) Power-flexible loads: The power of load $P_{pf,t}$ can be shifted within the installed capacity in constraint (43), and is expected to ensure the lowest working value EP_0 in (44).

$$P_{pf,\min} \le P_{pf,t} \le P_{pf,\max} \tag{43}$$

$$\sum_{t \in \{1,\cdots,T\}} P_{pf,t}.\Delta t \ge E_{p0} \tag{44}$$

(3) Time-flexible loads: The operation time can be shifted with constant power P_{tf0} in constraint (45). Depending on the operating mode, they can be divided into two subtypes, including time-continuous and time-discontinuous loads. The work time of time-discontinuous loads could be arbitrarily adjusted within the predefined working time t_1, as enforced in constraint (46). The time-continuous loads must continuously work to satisfy the predefined working value t_2, as is shown in constraint (47).

$$P_{tf,t} = u_k \cdot P_{tf_0} \tag{45}$$

$$\sum_{t \in \{1,\cdots,T\}} u_t = t_1 \tag{46}$$

$$\sum_{r=t}^{t+t_2} u_r \ge t_2 \cdot (u_{t+1} - u_t) \tag{47}$$

where u_k, u_t, u_r are the ON/OFF state variable.

(4) Temperature-flexible loads: The operational temperature of these loads $T_{tf,t}$ can be adjusted within certain limits. The operational temperature is calculated and determined via the outside temperature, colling power and heating power, as shown in constraint (49):

$$T_{tf,t} = T_{tf,t-1} + \alpha_1(T_{out,t} - T_{tf,t-1}) - \alpha_2 \cdot H_{tfcool,t} + \alpha_2 \cdot H_{tfheat,t} \tag{48}$$

$$T_{\min} \leq T_{tf,t} \leq T_{\max} \tag{49}$$

(5) Switchable loads: This load can be switched into electrical mode or gas mode according to the energy price. Generally, this load would operate at a fixed power P_{s0} or gas G_{s0}, as expressed in (50) and (51). Constraint (52) shows the lowest working value E_{s0}.

$$P_{s,t} = P_{s_0} \cdot v_t \tag{50}$$

$$G_{s,t} = G_{s_0} \cdot (1 - v_t) \tag{51}$$

$$\sum_{t \in \{1, \cdots T\}} P_{s,t} + \alpha_3 \sum_{t \in \{1, \cdots T\}} G_{s,t} \geq E_{s0} \tag{52}$$

where v_t is a switchable state variable.

(6) Multi-energy station: The SOC of the battery, heat, and gas storage tanks are expressed in (53), and these ranges are limited in (54) and (55).

$$\begin{bmatrix} SOC_{e,t} \\ SOC_{h,t} \\ SOC_{g,t} \end{bmatrix} = \begin{bmatrix} SOC_{e,t-\Delta t} \\ (1-\eta_w)SOC_{h,t-\Delta t} \\ SOC_{g,t-\Delta t} \end{bmatrix} + \begin{bmatrix} (\eta_{ch} E_{e,ch,t-\Delta t} - E_{e,dis,t-\Delta t}/\eta_{dis})\Delta t / E_{bes} \\ (E_{h,ch,t-\Delta t} - E_{h,dis,t-\Delta t})\Delta t / E_{heat} \\ (E_{g,ch,t-\Delta t} - E_{g,dis,t-\Delta t})\Delta t / E_{gas} \end{bmatrix} \tag{53}$$

$$\begin{gathered} E_{i,ch,t} \leq E_{i,ch,\max} \\ E_{i,dis,t} \leq E_{i,dis,\max} \end{gathered} \tag{54}$$

$$\begin{gathered} SOC_{e,\min} \leq SOC_{e,t} \leq SOC_{e,\max} \\ SOC_{h,\min} \leq SOC_{h,t} \leq SOC_{h,\max} \\ SOC_{g,\min} \leq SOC_{g,t} \leq SOC_{g,\max} \end{gathered} \tag{55}$$

(7) Multi-energy flow constraints: the supply and demand of multiple energy carriers must be balanced. According to its connection and energy flow, it can be formulated as (56).

$$\begin{bmatrix} L_{e,t,n} + P_{pf,t,n} + P_{tf,t,n} + P_{s,t,n} \\ L_{h,t,n} + H_{tfcool,t,n} + H_{tfheat,t,n} \\ L_{g,t,n} + G_{s,t,n} \end{bmatrix} = \begin{bmatrix} P_{WT,t,n} + P_{PVT,t,n} + P_{geo,t,n} + P_{CHP,t,n} + E_{buy,t,n} - E_{sell,t,n} - P_{P2G,t,n} + E_{e,dis,t,n} - E_{e,ch,t,n} \\ P_{PVT,t,n} \cdot \eta_{hsolar} + P_{geo,t,n} \cdot \eta_{hgeo} + H_{CHP,t,n} + E_{h,dis,t,n} - E_{h,ch,t,n} \\ V_{gas,t,n} - G_{CHP,t,n} + E_{g,dis,t,n} - E_{g,ch,t,n} \end{bmatrix} \tag{56}$$

(8) Multi-energy conversion constraints: Constraints (57)–(59) are the operations of P2G and CHP with constant conversion efficiency. Constraints (60)–(62) enforce the limits of the multi-energy market and converters.

$$V_{gas,t,n} = P_{P2G,t,n} \cdot \eta_{gas} \cdot \Delta t / Q_{gas} \tag{57}$$

$$P_{CHP,n,t} = G_{CHP,n,t} \cdot Q_{gas} . \eta_{eCHP} / \Delta t \tag{58}$$

$$H_{CHP,t,n} = G_{CHP,t,n} \cdot Q_{gas} . \eta_{hCHP} / \Delta t \tag{59}$$

$$\begin{gathered} E_{buy,t,n} \leq E_{buy,\max} \\ E_{sell,\mathrm{t,n}} \leq E_{sell,\max} \end{gathered} \tag{60}$$

$$0 \leq P_{P2G,t,n} \leq P_{P2G,\max} \tag{61}$$

$$0 \leq P_{CHP,t,n} \leq P_{CHP,\max} \tag{62}$$

3.3. Real-Time Demand–Response

After receiving the DR task from the distribution system operator, the scheduling plan of each aggregator is optimized in order to satisfy real-time positive and negative response demands. Considering the lowest economic cost of DR services, the prosumer aggregators at each node of the distribution system need to meet the power flow constraints.

Here, a linearized branch flow model is adopted to describe the power flow of each prosumer aggregator.

$$P_{mn} + p_{n,g} = \sum_{k \in \pi(n)} P_{nk} + p_{n,d} \tag{63}$$

$$Q_{mn} + q_{n,g} = \sum_{k \in \pi(n)} Q_{nk} + q_{n,d} \tag{64}$$

$$U_n = U_m - \frac{r_{mn} P_{mn} + x_{mn} Q_{mn}}{U_0} \tag{65}$$

In addition, the power p_n provided by each aggregator should meet the range of evaluated flexibility:

$$\sum_j P_{j,n,flex-} \le p_n \le \sum_j P_{j,n,flex+} \tag{66}$$

The objective function of the scheduling plan is minimizing the total service cost:

$$\min S = \sum_{n \in \pi(n)} p_n \cdot pr_{n,flex} \tag{67}$$

After receiving the scheduling plan in (67), each aggregator performs real-time DR using a rolling horizon strategy. Each rolling decision solves the current time and the future time. The objective function of real-time scheduling is shown in (68):

$$\min \mathrm{F}_n = \sum_{t \in \{\xi, \cdots T\}} \Big((\mu_{\mathrm{buy,t}} E_{buy,t,n} - \mu_{\mathrm{sell}} E_{sell,t,n}) \Delta t + (E_{\mathrm{ch},t,n} + E_{\mathrm{dis},t,n}) \mu \cdot \Delta t \Big) - \sum_{n \in \pi(n)} p_n \cdot pr_{n,flex} \tag{68}$$

3.4. Solution Procedures

Figure 3 illustrates the flowchart of the proposed transactive DR framework. Once the pre-dispatch references are obtained from (40)–(62) and the flexibility potential evaluation is performed via (1)–(39), cost-optimal real-time DR can be implemented for prosumer aggregators. All the schemes are coded on the YALMIP toolbox of MATLAB 2020b and solved using the CPLEX V12.10.0 solver.

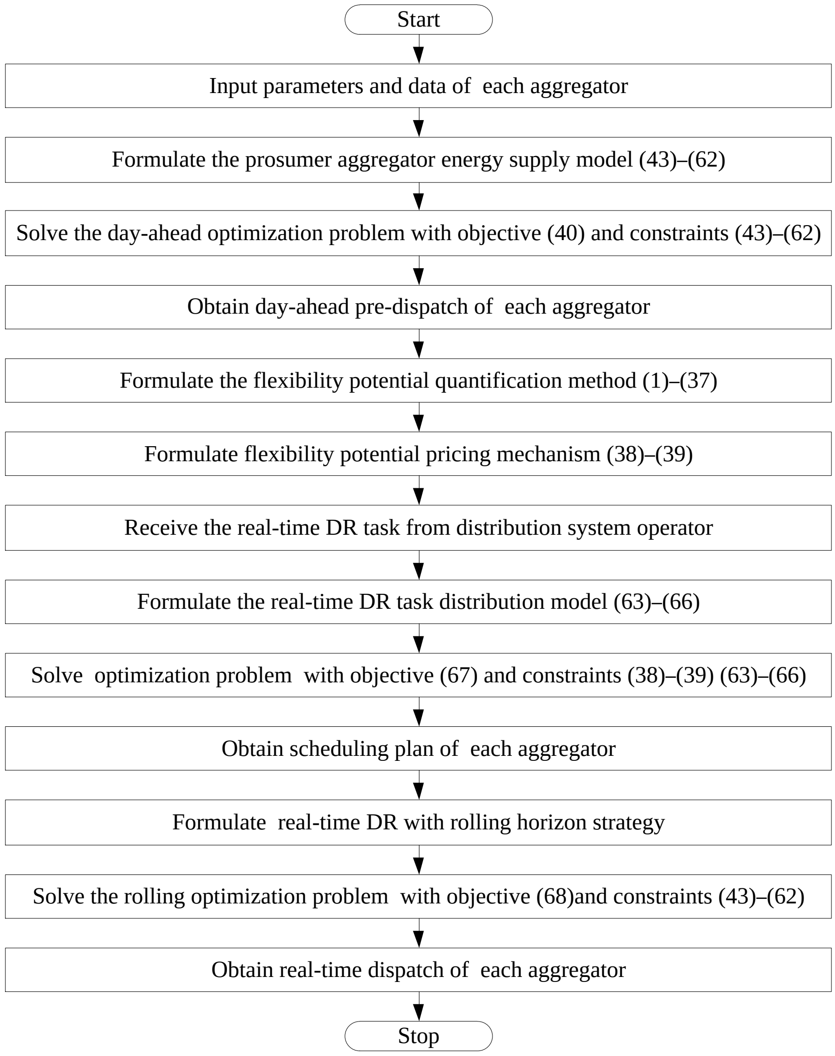


Figure 3. Flowchart of the proposed transactive DR framework.

4. Case Study

4.1. Case Comparions and Results

To verify the effectiveness of the proposed transactive DR framework for high renewable penetrated multi-energy prosumer aggregators, a case study was conducted on a distribution network with five nodes. The network included three aggregators located at nodes 2, 4, and 5, whose parameters were taken from the literature [28–31]. Node 1 released the DR demand. Comparative schemes were performed:

(1) Scheme 1 was the proposed transactive DR framework based on the flexibility potential evaluation in Sections 2 and 3;

(2) Scheme 2 was pre-dispatch without consideration of prosumer–operator interactions [16];

(3) Scheme 3 is the transactive DR framework without the flexibility potential evaluation.

Table 2 lists the system operating cost for the three prosumer aggregators of schemes 1–3. For every scheme, the operating cost of each prosumer aggregator is different based on their capacity for flexible resources. Compared with schemes 2 and 3, the proposed transactive DR framework based on the flexibility potential evaluation can cost-effectively explore resource flexibility in order to fulfil the DR requirements:

Table 2. Optimized results of schemes 1–3.

Scheme	Prosumer Aggregator	Operating Cost ($)
1	1	**61.78**
	2	**125.78**
	3	**40.84**
2	1	63.55
	2	126.12
	3	44.18
3	1	66.21
	2	128.31
	3	44.99

The best values in these tables are highlighted in bold.

Comparison with scheme 2 or previous literature without prosumer–operator interactions: prosumer–operator interactions when the distribution system is overloaded can reduce the requirements for building new energy plants. By coordinating various prosumer aggregators to manage and adjust the timing of flexible loads, the large daily fluctuations can be smoothed out. Since flexible multi-energy resources are fully utilized in scheme 1, the operating cost of scheme 1 is decreased by up to 7.6% compared with scheme 2.

Comparison with scheme 3 or previous literature without a flexibility potential evaluation: when facing the DR tasks from the grid, the flexible loads of prosumer aggregators could be programmed to turn ON/OFF to meet the consumer's desire for comfort and cost-savings. The flexibility potential evaluation in scheme 1 can offer choices and information in order to give consumers greater control over personal energy use. As for scheme 3, the prosumer aggregators have to equally respond to the DR tasks, and the operating cost even increases.

Figures 4–6 show the positive and negative flexibility of the energy storage system according to the proposed flexibility potential evaluation. The flexibility of BES is different from other prosumer aggregators because of different electricity storage capacities, while the positive flexibility of the gas tanks and heat tanks is the same during hour 2–20 and hour 13–16. Though energy storage system can technically provide both positive and negative flexibility, they tend to provide positive flexibility in the morning hours and negative flexibility in the night hours.

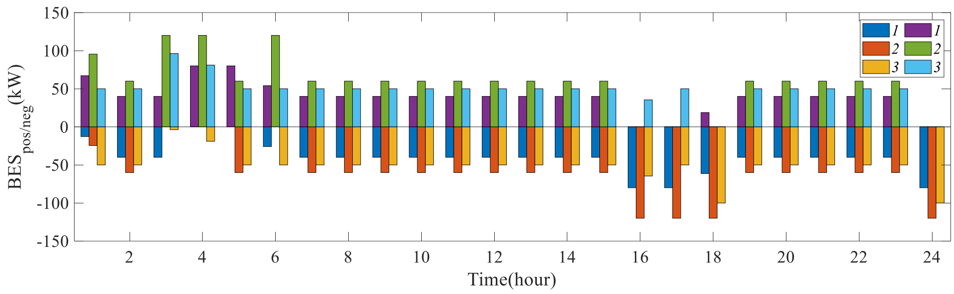


Figure 4. Positive and negative flexibility of BES.

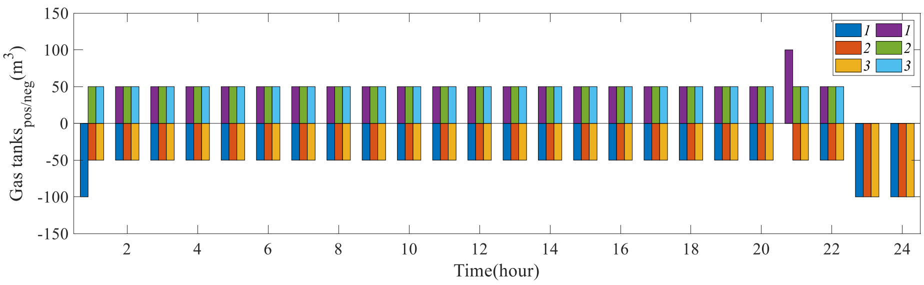


Figure 5. Positive and negative flexibility of gas tanks.

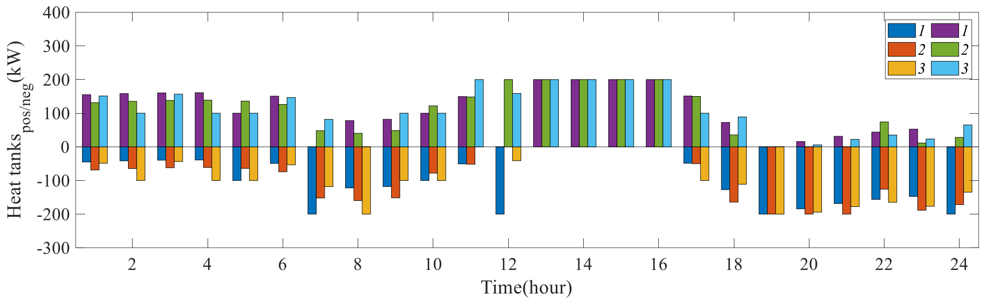


Figure 6. Positive and negative flexibility of heat tanks.

Figures 7 and 8 show the positive and negative flexibility of CHP and P2G according to the proposed flexibility potential evaluation. The positive and negative flexibility of CHP and P2G are different with the energy storage systems. While the CHP tends to offer positive flexibility, P2G tends to offer positive and negative flexibility based on its pre-dispatch optimal operation. It can also be found that the negative flexibility of CHP is at a low level, which is subject to the energy storage system and the forced OFF state in Figure 7. Conversely, the positive flexibility of CHP is given when CHP is limited by the ON state.

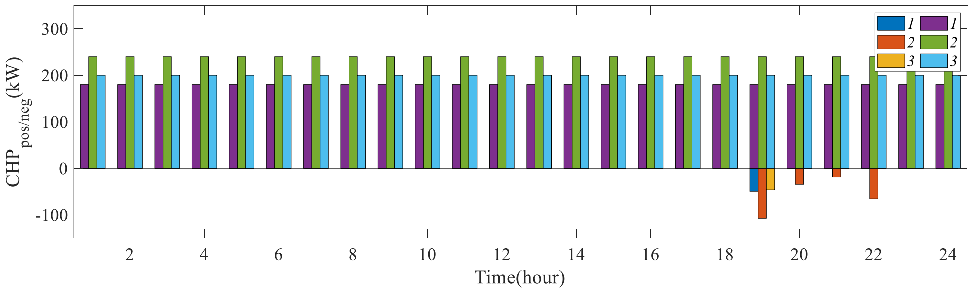


Figure 7. Positive and negative flexibility of CHP.

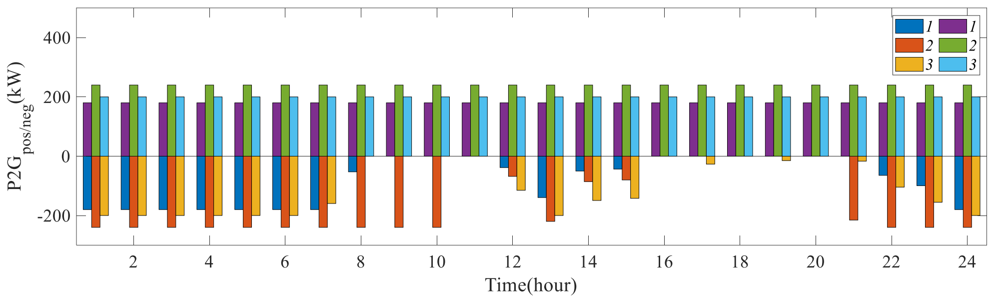


Figure 8. Positive and negative flexibility of P2G.

Figures 9–11 show the electrical, thermal, and gas DR results of the three prosumer aggregators. It can be seen that the proposed DR load can successfully accommodate the uncertainties of the RESs and loads. With the proposed flexibility potential evaluation to consider the flexibility difference of three aggregators as an important objective, the DR loads can provide more flexibility for each aggregator.

Figures 12–14 show the battery SOC, gas storage SOC, and P2G of schemes 1–3. It should be noted that the differences in the three schemes are not large since the real-time DR is based on the same pre-dispatch results. It can be seen that, since the DR assignment is issued at the 13th hour, the flexible device starts to operate at the current moment. The battery in prosumer aggregator 2 discharges when power is needed. Since the grid operator only distributes the power demand, the actions of the gas storage tanks are less than the battery. Because of the flexibility evaluation, the P2G of the aggregator with more flexibility tends to be scheduled in scheme 1. However, in scheme 3, the output of P2G is scheduled to be almost the same.

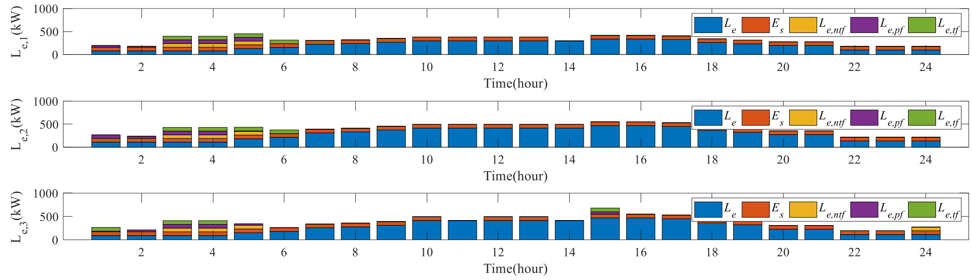


Figure 9. Electrical demand–response.

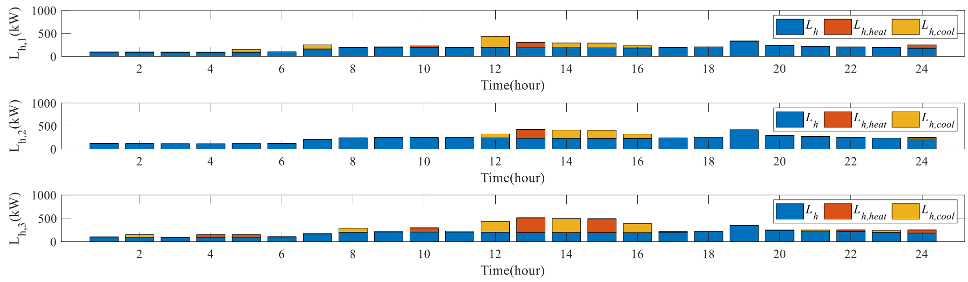


Figure 10. Thermal demand–response.

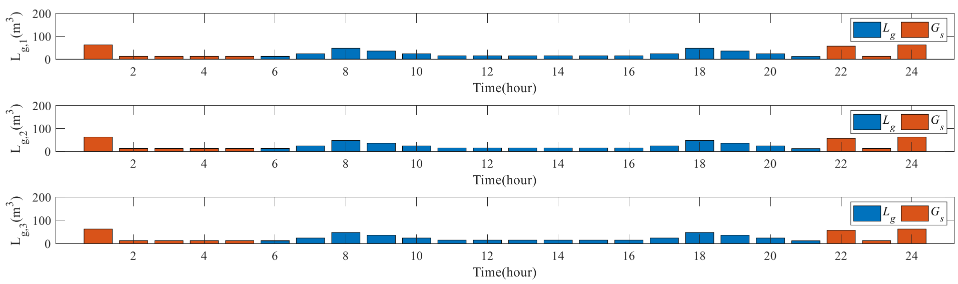
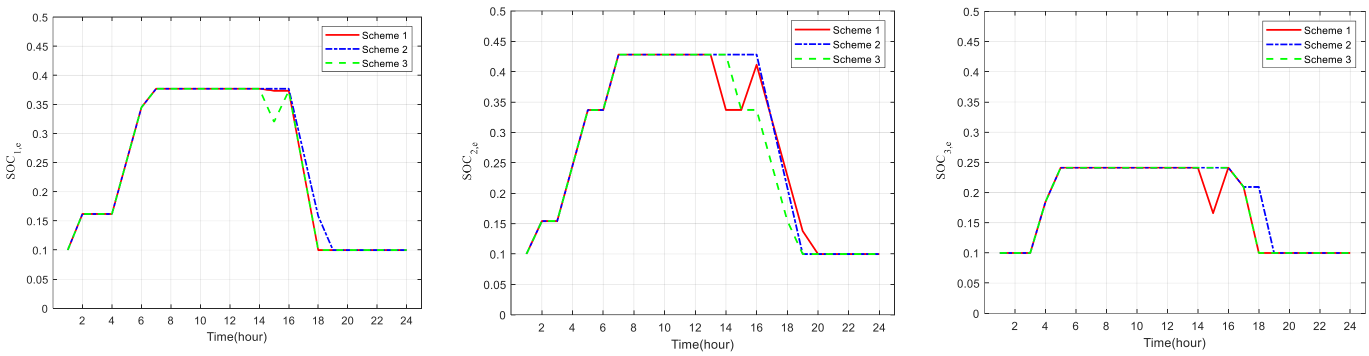
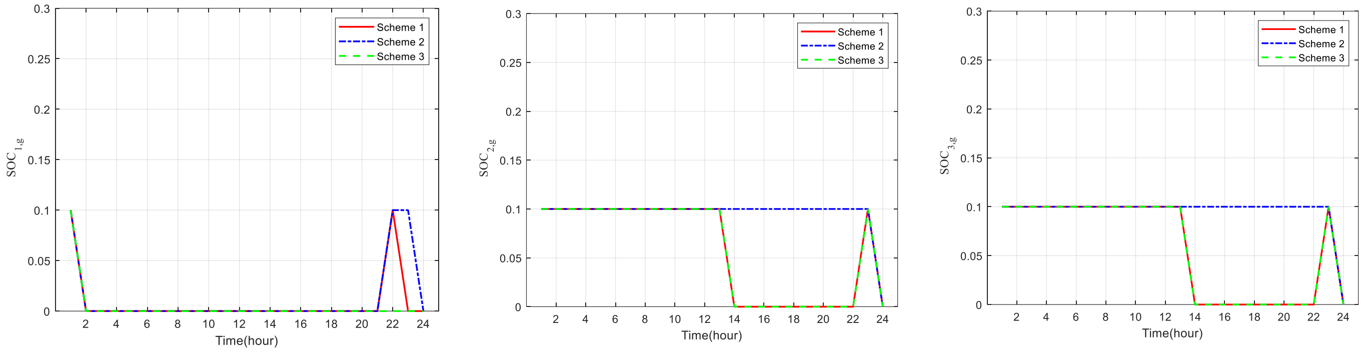


Figure 11. Gas demand–response.



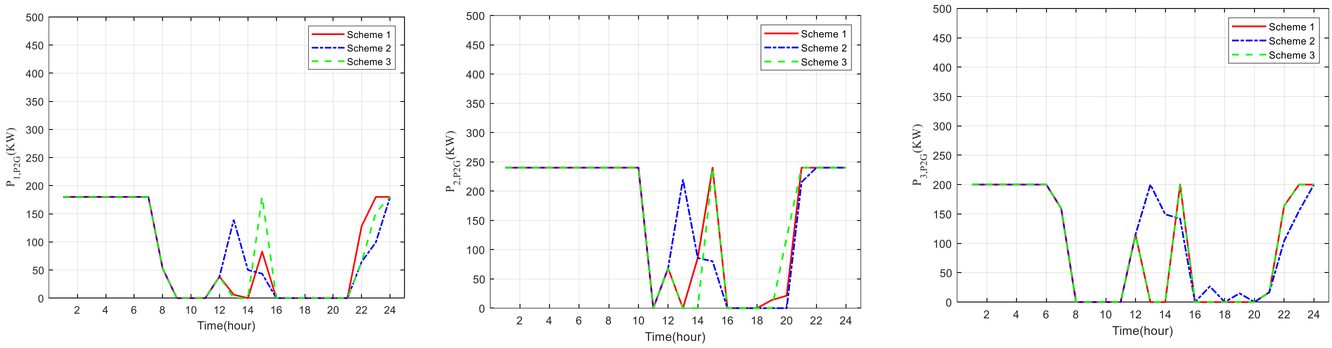
(**a**) prosumer aggregator 1 (**b**) prosumer aggregator 2 (**c**) prosumer aggregator 3

Figure 12. Daily battery charging/discharging.



(**a**) prosumer aggregator 1 (**b**) prosumer aggregator 2 (**c**) prosumer aggregator 3

Figure 13. Daily gas storage tanks.



(**a**) prosumer aggregator 1 (**b**) prosumer aggregator 2 (**c**) prosumer aggregator 3

Figure 14. Daily output of P2G.

4.2. Discussions on Practical Applications

With the expansion and diversification of prosumer aggregators, the challenges of practical DR are varied, numerous and continue to change. The rate at which the DR scale is changing is likely the greatest challenge to power grid companies struggling to gain a foothold or even to those leading the way. But a change in scale is paramount to actualization, for there are still many barriers to their practical application. A few of the challenges are listed below:

(1) Problem complexity: In real-world scenarios with a higher number of prosumer aggregators and diverse RESs, the complexity of the implementation of the transactive DR framework is proportionable. The DR with a flexibility potential evaluation alone requires considerable computational resources, in addition to the data acquisition and information transfer. Since each prosumer aggregator can be regarded as a relatively independent part, a distributed methodology with massively parallel processing is recommended.

(2) Cyber security: Since smart grid data acquisition infrastructures are vulnerable to cyber-attacks, DR digitalization may give rise to another considerable challenge in cyber-security. The attacker can manipulate meter readings/power consumption and launch false data injection attacks against DR implementation, having negative impacts on the normal operation. Resilience DR enhancement against cyber-attacks is recommended to maintain a reliable and secure energy system.

(3) Prosumer management: Unlike other regulation schemes, such as energy efficiency, which focuses on the energy generation or consumption, DR depends upon a change to normal human behavior. Practically, DR may suffer from initial or halfway rejection, which may pose a more considerable barrier to its implementation than a lack of policy. An empowered DR contract with prosumers is recommended so that rewards and punishments that will result in arbitrary action are delivered.

5. Conclusions

This paper proposes a transactive DR framework and a flexibility potential evaluation method to enable the multi-time-scale proactive participation of demand-side flexible multi-energy resources. According to the flexibility potential quantification and pricing of prosumer aggregators, an economically optimal ancillary service using prosumer aggregators can be implemented to respond to the DR tasks. Case studies have verified the following:

(1) The multi-time-scale transactive coordination of multiple multi-energy prosumer aggregators can enhance the flexibility of the system in real-time DR, thereby promoting the accommodation of renewable energy.

(2) The flexibility potential evaluation method can quantify prosumer flexibility, and the proposed scheme can reach a break-even DR contract for prosumer aggregators compared with other schemes. Since flexible multi-energy resources are fully utilized in scheme 1, the operating cost of the prosumer aggregator is reduced by at most 7.6%. Without a flexibility potential evaluation, the prosumer aggregators in schemes 3 have to follow the grid demand to respond to the DR tasks, and the operating cost even increases.

(3) The proposed transactive DR framework can outperform others in terms of economy and flexibility, which shows great development potential in community energy systems.

This paper has verified the effectiveness and superiority of the proposed transactive DR framework. Along with the dual carbon goal, multi-energy interconnection with other energy systems and proactive participation in the multi-energy market are possible, which should be discussed in further works.

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Nomenclature

Indices and sets	
t	Time index
n	Number of prosumer aggregators
Symbols	
a,b,c	The price coefficients
$E_{buy,t,n}$, $E_{sell,t,n}$	The amount of electricity bought and sold
$E_{i,ch,t,n}$	The charging output of i
$E_{i,dis,t,n}$	The discharging output of i
E_i	The capacity of i
$E_{i,ch,n,max}$	The maximum charging of i
$E_{i,dis,n,max}$	The maximum discharging of i
$e_{t,n,flex}$	Flexibility of flexible resource
$ebes_{t,n,max-}$	The maximum negative flexible energy for BES
$ebes_{t,n,max+}$	The maximum positive flexible energy for BES
$egas_{t,n,max-}$	The maximum negative flexible energy for gas storage tank
$egas_{t,n,max+}$	The maximum positive flexible energy for gas storage tank
$eheat_{t,n,max-}$	The maximum negative flexible energy for heat storage tank
$eheat_{t,n,max+}$	The maximum positive flexible energy for heat storage tank

Gs,t	The gas output of switchable load
$H_{tfcool,t,n}$, $H_{tfheat,t,n}$	The cooling power and heating power
$L_{i,t,n}$	Stationary load
Ps,t	The power of switchable load
$P_{CHP,n,max}$	The maximum power for CHP
$P_{P2G,n,max}$	The maximum power for P2G
$P_{t,n,flex}$	Flexible power
$P_{pf,t,max}$, $P_{pf,t,min}$	The maximum and minimum power of power flexible load
$Pbes_{t,n,flex-}$	The negative flexible power for BES
$Pbes_{t,n,flex+}$	The positive flexible power for BES
$Pgas_{t,n,flex-}$	The negative flexible power for gas tank
$Pgas_{t,n,flex+}$	The positive flexible power for gas tank
$Pheat_{t,n,flex-}$	The negative flexible power for gas tank
$Pheat_{t,n,flex+}$	The positive flexible power for gas tank
$PCHP_{t,n,flex-}$	The negative flexible power for CHP
$PCHP_{t,n,flex+}$	The positive flexible power for CHP
$PP2G_{t,n,flex-}$	The negative flexible power for P2G
$PP2G_{t,n,flex+}$	The positive flexible power for P2G
$P_{WT,t,n}$, $P_{PVT,t,n}$, P_{geo}	The output of wind, solar, geothermal
P_{mn}, Q_{mn}	The active and reactive power
$p_{n,g}/p_{n,d}$, $q_{n,g}/q_{n,d}$	The active and reactive generation/demand
$pr_{n,flex}$	The flexibility potential pricing of aggregator
Q_{gas}	The conversion coefficient of gas
r_{mn}, x_{mn}	The line resistance and reactance
$SOC_{i,t,n}$	The optimal SOC of i
$SOC_{i,n,max}$	The maximum SOC of i in aggregator n
$SOC_{i,n,min}$	The minimum SOC of i in aggregator n
$SOC_{i,min}$, $SOC_{i,max}$	The maximum and minimum SOC of i
$SOC_{i,t}$	The state of charge of i
T_{max}, T_{min}	The maximum and minimum temperature of flexible load
T_{out}	The outside temperature
U_n, U_0	The voltage magnitude at bus n, slack bus
$\mu_{buy,t}$, $\mu_{sell,t}$	Buying and selling electricity price
$\eta_{e,CHP}$	Electrical conversion efficiency of CHP
$\eta_{h,CHP}$	Heat conversion efficiency of CHP
μ_{BES}	Battery degradation coefficient
$a_{CHP,t,n}$	The ON/OFF state of CHP
$a_{P2G,t,n}$	The ON/OFF state of P2G
α_1, α_2	The coefficients of temperature
η_{ch}, η_{dis}	The charging and discharging efficiency of BES
η_w	The loss rate of heat storage tank
$\lambda_{t,n,flex}$	The number of flexible timestep
$\lambda bes_{t,n,flex-}$	The negative flexible timestep for BES
$\lambda bes_{t,n,flex+}$	The positive flexible timestep for BES
$\lambda gas_{t,n,flex-}$	The negative flexible timestep for gas storage tank
$\lambda gas_{t,n,flex+}$	The positive flexible timestep for gas storage tank
$\lambda haet_{t,n,flex-}$	The negative flexible timestep for heat storage tank
$\lambda heat_{t,n,flex+}$	The positive flexible timestep for heat storage tank
$\lambda CHP_{t,n,flex-}$	The negative flexible timestep for CHP
$\lambda CHP_{t,n,flex+}$	The positive flexible timestep for CHP
$\lambda P2G_{t,n,flex-}$	The negative flexible timestep for P2G
$\lambda P2G_{t,n,flex+}$	The positive flexible timestep for P2G

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