A Decentralized Peer-to-Peer Energy Trading Model in Integrated Electric-Thermal System

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Abstract

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1. Introduction

With the deep integration of the energy revolution and the digital technology, the traditional power system has gradually evolved into the heterogeneous energy systems with multiple energy generation, transmission, consumption, and trading gradually[1]. As a significant method in reducing carbon-emission, distributed energy resources (DERs) emerge with a large-scale and highly decentralized development trend. DERs are usually installed on the demand side, allowing traditional energy consumers to be prosumers participating in the energy trading. However, the distributed allocation among prosumers and the intermitteness of DERs complicate the scheduling strategies[2]. Besides, local flexibility market (LFM) development is in its infancy, and numerous challenges should be addressed, for example, the difficulty of private information sharing and more effective coordination model to minimize the costs et.[3]. Therefore, due to the limited self-regulation ability of grid and inadequate market mechanism, it is urgent to research how to promote the local accommodation of DERs.

Recently, Peer-to-peer (P2P) energy trading has been widely introduced for its flexibility and economic benefits [4]. Since a community microgrid consists of several prosumers in proximity with their own generation and demand, the P2P energy network can be modelled to optimize excess energy trading market locally [5]. Generally, it can be divided into two schemes: Pure P2P without agents [6], P2P with agent’s coordinating [7]. Although blockchain provides a trust market platform for pure P2P without reliance on third parties, the high cost of construction and maintenance make it difficult to be implemented widely. Considering the high frequency transactions with the main grid in pure P2P market, the energy trading agent (ETA) has become an emerging industry as a third-party intermediary, which can reduce the cloud computing burden of the centralized energy market. The ETA not only acts as the transaction matchmaker and demand response (DR) mechanism maker, but also actively participates in market transactions as a producer to obtain more profit and provide more sufficient local energy transactions coupling the horizontal and vertical [8]. The self-build photovoltaic (PV) and energy storage systems (ESS) of ETA are considered in [9], and the optimized trading strategy is proposed to maximize the profit of the ETA, which proves that the energy shifting ability of ETA can further improve the overall benefit.

Existing studies mainly focus on the model of electricity trading [10], while the potential of multi-energy systems participating in energy trading has not been explored sufficiently. The multi-energy trading system between commercial and residential buildings is proposed including the electrical, cooling, and heating power [11]. Work [12] establishes an integrated power trading framework, where the cooling power is not traded considering the long distance and considerable energy loss, and the decentralized thermal supply contributes to reduce heat losses utilizing local surplus thermal. The decentralized thermal network has also been implemented in a high school and childcare centre, and the possibility of heat prosumers feeding thermal networks is also verified in [13]. It is worth to be mentioned that the current network has not yet supported the reverse heat supply from prosumers to the central thermal grid [14]. In conclusion, the P2P electric-thermal energy trading market indicates a promising mode for the evolution of the local energy trading market.

Besides common thermal energy source like combined cooling heating and power (CCHP) and heat pump, the solar heat-pump hybrid thermal water system (SPTS) with storage tank is extensively applied in practice to obtain more revenue by optimizing its operation [15].
of heating network in P2P market is still an important issue to reduce the algorithm computation.

Source-load uncertainties are necessary factors to be considered in the optimization of energy trading. At present, stochastic optimization, robust optimization and chance-constraint programming have been proposed to solve it. Stochastic programming generates discrete various scenes based on probability density, then selects the typical scenes through scene reduction [18]. Heavy computational burden caused by a large number of detailed scenarios is inevitable
in stochastic optimization, and it is difficult to select the typical scenes with representativeness. Robust optimizations with uncertainty sets are applied to solve the optimal solution under the worst case, resulting in its over conservativeness [19]. The chance-constraint programming based on Gaussian hypothesis only requires that the probability of satisfying the critical constraint is higher than a certain level and allows low probability of constraint violation [20]. However, probability distribution of uncertain variables is usually described by a simple distribution (e.g., single Gaussian and single Beta), which may lead to larger errors and infeasible solutions. In most cases, the probability distribution of uncertain load and the output of PV cannot be represented by a single common probability distribution model with acceptable accuracy [21]. To overcome the challenge, Gaussian mixture model (GMM) is introduced in chance-constraints programming to accurately fit the arbitrary probability distribution based on the linear combination of multiple Gaussian distributions. The GMM combined with Bayesian information criterion is established to construct approximately probability distribution functions of PV and load profiles, which has been verified precise in [22]-[23].

To protect the privacy of prosumers and reduce the pressure of cloud computing, various distributed algorithms have been developed, to model each prosumer as a different interest subject. A stochastic leader–follower game based on prospect theory is proposed to achieve economical and efficient configuration in [24]. A relaxed consensus innovation (RCI) is designed to realize market-clearing in a fully decentralized manner [25]. Alternating direction method of multiplier (ADMM)-based algorithms are demonstrated with great potential to solve the P2P energy trading problem. Distributed ADMM (D-ADMM) is designed to accelerate the convergence of standard ADMM in [26]. Besides, the Nesterov-type ADMM (N-ADMM) based on predictor-corrector mechanism [8] and overrelaxed ADMM (O-ADMM) [27] are also proposed to accelerate. However, the integer variables of prosumers and ETA, such as the charging/discharging decisions of ESS and the buying/selling decisions of energy trading, make the problem non-convex, resulting in convergence failure that can not be solved by the existing acceleration mechanism [28].

To this end, there are still the following deficiencies: 1) lack of a proper framework for integrated electric-thermal energy trading considering the ETA and electric-thermal transferring energy loss; 2) decision errors caused by simple parameter distribution of uncertainties; 3) poor convergent performance of ADMM with a large number of binary variables. Motivated by these discussions, this paper designs an integrated electric-thermal energy trading model based on chance-constraints and improved N-ADMM. It aims to maximize the local energy utilization of DERs and the welfare of the system in the transactive market. The major contributions of this paper can be summarized as follows.

- Firstly, different from the most existing works merely focusing on the single electricity P2P energy transaction (e.g.,[8]-[10]), a P2P decentralized electric-thermal integrated energy trading model is proposed considering the ETA with electric/thermal DR and self-build energy system, which can achieve the sufficient regional energy trading while protecting the privacy. Moreover, although SPTS is widely equipped in demand side, it is usually studied in solar system (e.g.,[15]) and rarely studied in the energy management scheme. The SPTS with thermal storage/supplying tanks is introduced and modelled in energy management optimal based on law of conservation of energy for the first time. Particularly, considering that energy loss is always ignored in existing P2P energy transaction (e.g.,[11]), the Taylor expansion is applied to linearize heating loss model in P2P energy transaction and reduce computation complexity with the verified accuracy.

- Secondly, most previous studies on characterizing the uncertainty of load and PV assume that the factors obey a single probability distribution (e.g., Gaussian and Beta), while the statistical distributions of load and PV variation do not actually follow any common probability distribution function. To reduce the errors caused by imprecise distribution, the chance-constraints programming based on the GMM is proposed to describe and model the uncertainty of the net load in energy transaction accurately. And the model is transformed into a deterministic constraint through searching for the probability quantile value, which can be solved directly by a solver.

- Thirdly, the convergent oscillation caused by a large number of binary variables is hard to be solved in existing acceleration mechanism of ADMM algorithms (e.g.,[26]-[27]), an improved N-ADMM is proposed based on two-stage cycle iterations and the predictor-corrector mechanism. The first stage is to solve the optimal of continuous variables including the relaxed binary variables, then solve and fix the binary variables by minimizing the gap to the above optimal continuous variables. The second stage aims to solve other variables with the fixed binary variables. The improved N-ADMM can avoid the impact of binary variables on convergence, and the convergence is verified by simulation.

The rest of this paper is organized as follows: Section 2 introduces integrated electric-thermal energy trading structure in a P2P prosumer community. Section 3 describes the energy trading model. The solution algorithm is presented in Section 4. The simulation results and analysis are covered in Section 5 to demonstrate the effectiveness of the model. The conclusions are presented in Section 6.

2. Electric-thermal energy transaction structure

Commercial and residential buildings account for the significant portion of energy consumption[11]. The integrated electric-thermal energy trading structure in a P2P prosumer community is shown in Fig.1, in which different prosumers are connected by the utility grid and heating network. The prosumers refer to the commercial and residential buildings, which are assumed to be comprised of the rigid and flexible loads, ESS, SPTS, PV, and user energy management system (U-EMS). The ETA is considered as an independent commercial entity configured with PV and high-capacity ESS, participating in the P2P market for profit. Since the ETA generally only needs an office in the building to complete the transaction, the energy consumption of ETA itself is considered negligible [8]. Meanwhile, considering the high construction cost and low yield caused by heat loss, the heat storage system is not equipped for ETA.
As an intermediary, the ETA receives the prices from the main grid and heating supplies, then optimizes its own operations and implements electric/thermal DR prices to motivate prosumers to adjust their energy consumption to maximum the profit. The prosumers can appropriately optimize the energy consumption and energy purchasing/selling energy project (including purchase/sell energy prices and amounts) based on the prices from the ETA and other prosumers. Particularly, considering that the heating price models have not supported the reverse heat supply from the heat prosumers to the central network [14], the thermal selling to the central heating network is not considered.

The P2P trading behaviour can be implemented iteratively. In each iteration, the ETA can adjust the prices of electric/thermal energy to influence prosumers to change their energy project, the changed actual results will also influence other entities in the market to readjust their energy management optimizations similarly. The simultaneous interaction of two energy transactions may require a limited number of iterations until each market entity can no longer independently improve their own benefits by adjusting its decision variables.

In the above process, we assume the following points:

- Through the U-EMS, it is possible to share the trading information with others and obtain itself energy generation and consumption for prosumers.
- The information transmitted among the market entities is true and reliable, and the communication is stable.
- All prosumers fully trust the ETA without reservation.
- Each market entity is independent and rational.

### 3. Energy trading model description

Consider that an integrated energy community comprises of an ETA and a set of prosumers \( \mathcal{N} = \{1, 2, \ldots, N\} \) with index \( i \in \mathcal{N} \), where \( N = |\mathcal{N}| \) is the number of its elements, indicating the total number of prosumers in the system. Each prosumer participates into the energy trading market as an independent seller or buyer. Let \( \mathcal{T} = \{1, 2, \ldots, T\} \) represent a set of time steps with index \( t \in \mathcal{T} \). The time slot here is assumed to be one hour.

#### 3.1. Model of prosumers

In this paper, all prosumers are assumed to be equipped with rigid and flexible loads, ESS, SPTS and PV. The objective is to minimize the comprehensive cost of prosumer \( i \) as calculated in (1), and the subentry costs are as in (2)-(6).

\[
\text{min } C_i = \sum_{t=1}^{T} \Delta t \cdot \left( C^\text{DR} + C^\text{SF} - U^\text{ET} \right) \quad (1)
\]

\[
U^\text{ET} = \sum_{j \in \mathcal{N}} \left( \lambda_j^p \cdot P_{ij}^p + \lambda_j^h \cdot P_{ij}^h - \lambda_j^{s, p, j} \cdot Q_{ij}^p - \lambda_j^{s, h, j} \cdot Q_{ij}^h \right) \quad (2)
\]

\[
C^\text{DR} = c_{\text{up}} \cdot (P_{ij}^p + Q_{ij}^s) + c_{\text{down}} \cdot (P_{ij}^p + Q_{ij}^h)^2 + c_{\text{on}} \cdot (P_{ij}^b + P_{ij}^\text{bump}) + c_{\text{off}} \cdot (P_{ij}^b + P_{ij}^\text{bump}) \quad (3)
\]

Here, the profits of P2P energy trading (2) include the electric/thermal purchasing costs and selling profits with the ETA and other prosumers. (3) describes the costs of electric and thermal comfort loss with a second-order function, which are caused by adjusting the flexible loads to participate DR. (4) includes the maintenance costs of PV, SPTS and ESS, and the service fee to the ETA. (5) and (6) represent the total electric/thermal purchasing and selling amounts, respectively.

Each prosumer should meet the following conditions.

#### 1) DR Constraints

To meet the basic demand, the limitations on energy consumption are represented as shown in (7)-(8).

\[
\sum_{t \in \mathcal{T}} P_{ij}^p = \sum_{t \in \mathcal{T}} P_{ij}^\text{pre} + \sum_{t \in \mathcal{T}} Q_{ij}^p = \sum_{t \in \mathcal{T}} Q_{ij}^\text{pre} \quad (7)
\]

\[
P_{ij}^b \leq P_{ij}^\text{pre} \leq \bar{P}_{ij}^b, \quad \bar{Q}_{ij}^h \leq \bar{Q}_{ij}^h \leq Q_{ij}^p \quad (8)
\]

#### 2) ESS Constraints

Assuming the power fluctuation of the ESS in charge/discharge is negligible and the charge/discharge power is constant during a time slot, the dynamics of the ESS can be modelled as follows:

\[
E_{ij} = E_{ij, t-1} + \eta_i^b \cdot P_{ij}^b \cdot \Delta t - \eta_i^b \cdot \Delta t / \eta_i^\text{bump} \quad (9)
\]
\[ E_i \leq E_{f,j} \leq \bar{E}_i \]  
\[ 0 \leq P_{ij}^h \leq \bar{P}_{ij}^h, 0 \leq P_{ij}^{kh} \leq \bar{P}_{ij}^{kh} \]

To avoid simultaneous charging and discharging, the following constraint is required:
\[ P_{ij}^{bh} \cdot P_{ij}^{kh} = 0 \]

The nonlinear constraints are linearized by introducing 0-1 variables \( \delta \) based on the big M method:
\[
\begin{align*}
\delta_{ij} \leq P_{ij}^{bh} \leq \delta_{ij} \cdot M
\end{align*}
\]
\[
\begin{align*}
1 - \delta_{ij} \leq P_{ij}^{kh} \leq (1 - \delta_{ij}) \cdot M
\end{align*}
\]

Where the value of \( M \) is assumed to be a sufficiently large positive constant.

(3) Trading Balance Constraints

The power purchased by the prosumer \( i \) from the prosumer \( j \) is equal to the prosumer \( j \) to the prosumer \( i \) with the electrical and thermal power transferred. The loss caused by P2P trading, as shown in (14). It is worth noting that all the energy values in this paper are positive.

\[
P_{ij}^{bh} = P_{ij}^{bh} + \Delta P_{ij} \cdot \rho M_{ij} = Q_{ij}^{bh} + \Delta \theta_{ij,\theta} \]

(4) Solar Collector Constraint

The model of solar collector (SC) is described as follows [11]:
\[
\eta_{SC} = \varepsilon_i \left[ \frac{\varepsilon_i (SRI_i)}{SRI_j} + \frac{1 + \varepsilon_i (AM_i)}{AM_j} \right] + \varepsilon_i (T_j - T_i) + \eta_{EF} \]

\[
Q_{SC,max} = A_{SC} \times \eta_{SC} \times SRI_i
\]

\[
0 \leq Q_{SC} \leq Q_{SC,max}
\]

Where \( SRI_j \) indicates the solar radiation index (W/m²), \( AM_j \) is the air mass, \( T_a \) is the ambient temperature, \( A_{SC} \) is the area of SC panel (m²), \( \rho \) and \( \rho_a \) are the specific heat capacity (J/(kg·°C)) and density (kg/m³), \( c_1, c_2, c_3, c_4, c_5 \) are the generation coefficients of SC.

(5) SPTS Constraints

The SPTS provides a water-heating system for buildings, which consists of the sun-tracked solar collectors, the heat bump and two high-capacity insulated water tanks (thermal storage tank and thermal supplying tank), as shown in the Fig.2. Solar energy absorbed by collectors is transferred to the thermal energy in storage tank by circulating water through the collector tubes. Thermal demand is satisfied by supplying hot water from the supplying tank. When the temperature in the thermal supplying tank cannot reach the demand, it will be heated to the required temperature by the heat bump through the heat exchanger. Makeup water could be added to two tanks at different times and quantities. Assuming that two tanks are replenished automatically, its water storage capacity is constant.

Based on the law of conservation of energy, the thermodynamic model of tanks can be described as follows.

For the thermal storage tank, the energy is composed of the temperature change, energy loss, the energy from solar collector, make-up water, the energy to the supply tank and the energy for selling, its model is described as (18).

\[
Q_{TS}^{sc} = Q_{TS}^{MTS} + Q_{TS}^{SP} + Q_{TS}^{EH} + Q_{TS}^{loss}
\]

\[
Q_{TS}^{SP} = A_{TS} \cdot U_j \cdot (T_{TS}^j - T_{TS}^i)
\]

(19)

For the thermal supplying tank, the energy transfer includes the temperature change, the energy from storage tank, the energy loss, the supplying energy, make-up water, the energy converted from bump and the energy buying from others, its model is described as (20).

\[
Q_{TS}^{SP} + Q_{TS}^{EH} + Q_{TS}^{buy} = Q_{TS}^{MTS} + Q_{TS}^{SC} + Q_{TS}^{SP,loss}
\]

(20)

The temperature and energy transfer should meet the following constraints:

\[
T_{TS}^j \leq T_{TS}^j \leq T_{TS}^e, \quad T_{SP}^j \leq T_{SP}^j \leq T_{SP}^e
\]

(23)

\[
0 \leq Q_{TS}^{MTS} \leq Q_M, \quad 0 \leq Q_{TS}^{SP} \leq Q_M
\]

(24)

\[
0 \leq Q_{TS}^{SP} \leq Q_e, \quad 0 \leq Q_{TS}^{EH} \leq \bar{Q}_l
\]

(25)

(6) Thermal network loss

Thermal network transmits thermal through pipes and heat medium, which can be divided into hot water network and steam network according to different working medium. The hot water heating system under quantity regulation is taken as an example to establish a heating loss model, which is stable in hydraulic condition and more manageable. The external environment of pipe segment is considered stable.

Based on the principle of steady-state thermal transfer, the heating loss of per unit length of pipe can be modelled.

\[
\Delta h = \kappa \cdot (T_{TS}^j - T_{TS}^i)
\]

(26)

After the heating medium with initial temperature \( T_{TS}^j \) flowing through the pipe of length \( l \), the heating loss from prosumer \( i \) to prosumer \( j \) satisfies the following equation [29].

\[
Q_{ij,p}^h = Q_{ij,p}^h - \int_{0}^{l_j} \kappa \cdot (T_{TS}^j - T_{TS}^i) \cdot dx
\]

(27)

Derived from the above, the heating loss \( \Delta H_{ij,\theta} \) between prosumer \( i \) and \( j \) is calculated as follows:

\[
Q_{ij,\theta}^h = Q_{ij,\theta}^h - \int_{0}^{l_j} \kappa \cdot (T_{TS}^j - T_{TS}^i) \cdot dx
\]

(28)

\[
\Delta H_{ij,\theta} = Q_{ij,\theta}^h - Q_{ij,\theta}^h = Q_{ij,\theta}^h - \int_{0}^{l_j} \kappa \cdot (T_{TS}^j - T_{TS}^i) \cdot dx
\]

(29)

The last item of (29) is the first-order Taylor series at \( l_j = 0 \).

The above model decouples the available heat energy from the thermal flow in the network and transform the non-convex model into a mixed integer linear model, which can be solved directly by a solver.
The value of loss-coefficient $\varphi$ depends on the parameters and configuration of the network model.

(8) Energy Balance Constraint

The energy output and input of prosumers should be equal:

$$
P_{ij}^{pv} + P_{ij}^{sh} + P_{ij}^{buy} = P_{ij}^{EC} + P_{ij}^{gb} + P_{ij}^{bump} + P_{ij}^{sell}
$$

(31)

$$
Q_{ij}^{EC} + Q_{ij}^{sh} + Q_{ij}^{buy} = Q_{ij}^{EC} + Q_{ij}^{gb}
$$

(32)

At the time slot $t$, each prosumer cannot purchase or sell energy simultaneously, the purchase and sale of energy should meet the following constraints:

$$\begin{align*}
[P_{ij,1}^{gb}, P_{ij,2}^{gb}, \ldots, P_{ij,N}^{gb}] &\leq 0_{(N+4) \times (N+4)} \\
[Q_{ij,1}^{gb}, Q_{ij,2}^{gb}, \ldots, Q_{ij,N}^{gb}] &\leq 0_{(N+4) \times (N+4)}
\end{align*}
$$

(33)

(34)

In total, $[P_{ij}^{EC}, P_{ij}^{gb}, P_{ij}^{sh}, P_{ij}^{buy}, P_{ij}^{sell}, P_{ij}^{bump}]$ and $[Q_{ij}^{EC}, Q_{ij}^{gb}, Q_{ij}^{sh}, Q_{ij}^{sell}, Q_{ij}^{bump}]$ in the SPTS are the decision variables in the model of prosumers. The objective is to minimize (1) while satisfying the constraints as in (7)-(34).

3.2. Model of ETA

Besides as a coordinator, the ETA equipped with PV and ESS can trade with the main grid and prosumers to maximize its own profit and balance the regional energy. The utility maximum model can be expressed as follows:

$$
\max C_{ETA} = \sum_{j=1}^{N} \Delta t (U_{ET_{E,j}}^{SEA} + U_{G_{E,j}}^{SEA} - C_{SF_{E,j}})
$$

(35)

$$
U_{ET_{E,j}}^{SEA} = \sum_{i=1}^{N} (\lambda_{i,j}^{SEA}, \gamma_{i,j}^{SEA}, \lambda_{i,j}^{GB}, \gamma_{i,j}^{GB})
$$

(36)

$$
U_{G_{E,j}}^{SEA} = \gamma_{i,j}^{GB}, P_{ij}^{GB} - \gamma_{i,j}^{GB}, P_{ij}^{GB} - \gamma_{i,j}^{GB}, P_{ij}^{GB}
$$

(37)

$$
C_{SF_{E,j}} = c_{PV} * (P_{ij}^{PV} - c_{PV} * (P_{ij}^{PV} - c_{PV} * (P_{ij}^{PV} - c_{PV} * (P_{ij}^{PV}))
$$

(38)

Here, (36) represents the energy trading benefit with the prosumers, (37) represents the energy trading benefit with the main grid and thermal grid, (38) describes maintenance and service fee from other prosumers, determined by the total trading energy.

Accordingly, ETA should meet the following constraints.

(1) PV and ESS Constraints

PV and ESS constraints of ETA are similar to the constraints of prosumers, which are not repeated here.

(2) Trading Constraints

The restrictions with the main grid and thermal grid should be met as (39)-(40). Besides, the uniqueness should be considered, which means the ETA cannot simultaneously purchase or sell energy in the market, as in (41).

$$
0 \leq P_{ij}^{gb} \leq \overline{P}_{ij}^{gb}, 0 \leq P_{ij}^{sell} \leq \overline{P}_{ij}^{sell}
$$

(39)

$$
0 \leq Q_{ij}^{gb} \leq \overline{Q}_{ij}^{gb}
$$

(40)

$$
P_{ij}^{gb} * P_{ij}^{sell} = 0
$$

(41)

(3) Energy Balance Constraint

Energy generation/consumption in the region should satisfy the real-time balance in (42)-(43).

$$
\sum_{j=1}^{N} \overline{P}_{ij}^{EA, F} = P_{ij}^{gb} + P_{ij}^{sell} + \sum_{j=1}^{N} P_{ij}^{FC, F} + P_{ij}^{PV}
$$

(42)

$$
Q_{ij}^{gb} = \sum_{j=1}^{N} Q_{ij}^{gb, F}
$$

(43)

$$
\overline{P}_{ij}^{ea, f} = \sum_{j=1}^{N} Q_{ij}^{gb, f} + \sum_{j=1}^{N} \overline{P}_{ij}^{ea, F}
$$

(44)
Overall, the decision variables are \([P_{E}^{\text{th}_{i,j}}, P_{E}^{\text{th}_{i,j}}, P_{E}^{\text{th}_{i,j}}, P_{E}^{\text{th}_{i,j}}, P_{E}^{\text{th}_{i,j}}, Q_{E}^{\text{th}_{i,j}}, P_{E}^{\text{th}_{i,j}}, P_{E}^{\text{th}_{i,j}}, O_{E}^{\text{th}_{i,j}}, O_{E}^{\text{th}_{i,j}}, \ldots]\) and the objective is to maximize (35) while satisfying the constraints (39)-(43).

4. Solution algorithm

Due to the centralized optimization may breach the privacy of prosumers and ETA, this section adopts the distributed ADMM algorithm, in which each prosumer solves its sub-problem independently and exchanges merely boundary information with others. To ensure and accelerate the convergence, an improved N-ADMM is proposed based on two-stage cycle iterations and the predictor-corrector mechanism.

Since the purchasing/selling energy prices are crucial variables, the dynamic pricing mechanism in [9] is used to update the prices, including hierarchical pricing: 1) the electric/thermal energy prices based on supply demand ratio (SDR) and DR discount factors between prosumers; 2) the electric/thermal energy prices among prosumers is based on the market share of individuals resources in the energy market. It is worth mentioning that the pricing mechanism is solved independently in the improved N-ADMM algorithm.

4.1. Uncertainty factor

There are certain forecasting errors of PV’s output and load caused by weather, social events, etc., which is usually characterized by a normal distribution. However, statistical analysis has demonstrated that these uncertainty factors does not follow any specific probability distribution. As a result, the single-Gaussian is not suitable to describe the probability distribution of the uncertainties of PV’s output and load due to its large fitting error. To reduce the fitting errors, the GMM is introduced to describe the uncertainties of net electric load and its forecast error follows the GMM distribution as follows:

\[
\Pr(P_{\text{NET}}^{i,j}) = \sum_{s=1}^{S} \omega_{s} p(P_{\text{NET}}^{i,j} | \mu_{s}, \sigma_{s})
\]  

where \(\omega_{s}\) denotes the weight factor subjecting to \(\sum_{s=1}^{S} \omega_{s} = 1\), \(\mu_{s}\) denotes the mean of each distribution, \(\sigma_{s}\) denotes the standard deviation of each distribution. The values of above parameters can be calculated from historical data by employing expectation maximization (EM) algorithm and prediction strength of clustering method in [22],[23].

To balance the robustness and economy of the optimization results, chance-constrained programming is adopted to make the constraints with random variables hold at a certain confidence level. By giving the confidence level, the constraint on the power regulation interval can be described in the form of probability as follows:

\[
\Pr(P_{\text{NET}}^{i,j} \geq (P_{E}^{\text{EC}_{i,j}} + \mu_{i,j}) + P_{i,j}^{\text{th}} + P_{\text{jump}}^{i,j} - P_{i,j}^{\text{ch}} - P_{i,j}^{\text{buy}}) \geq \alpha
\]

where \(P_{\text{NET}}^{i,j}\) means the maximum power of regional tie-line power, \(\mu_{i,j}\) denotes the mean of forecasting error of the net electric load under GMM distribution. \(\alpha\) is confidence level, meaning the probability value satisfied by the constraint.

Transform the chance constraint (46) into an equivalent definite form (47) through searching for the probability quantile value, which can be solved directly without random variables.

\[
P_{\text{NET}}^{i,j} + P_{\text{PV}}^{i,j} \geq P_{\text{EC}}^{i,j} + P_{i,j}^{\text{th}} + P_{\text{jump}}^{i,j}
\]

\[
\Pr(P_{\text{NET}}^{i,j} \geq P_{\text{EC}}^{i,j} + P_{i,j}^{\text{th}} + P_{\text{jump}}^{i,j} + F^{-1}(\alpha) \cdot \sigma_{i,j}^{\text{NET}})
\]

where \(\sigma_{i,j}^{\text{NET}}\) means the standard deviation of forecasting error of the net electric load under GMM distribution. \(F^{-1}(\alpha)\) denotes the quantiles under the standard normal distribution function.

4.2. N-ADMM algorithm

N-ADMM introduces the predictor-corrector mechanism to improve convergence efficiency. The convergence rate can be \(O(1/k^{2})\), which is proved to be optimal, while the convergence rate of the standard ADMM algorithm is \(O(1/k)\) [30].

To simplify the formula, the section extends the number of \(\mathcal{N}\) to \(N+1\), \(i\) means the energy trading with ETA when \(n=N+1\). The energy trading problem can be formulated to minimize the opposite of the overall welfare as (48), which is a mixed integer linear programming model.

\[
\begin{align*}
\min & \quad C = \sum_{n=1}^{N} \sum_{i=1}^{N} C_{i} - C_{N+1} \\
\text{s.t.} & \quad A[x_{i}, x_{j}, \ldots, x_{N+1}] = B \\
& \quad x_{i} \in \chi_{i}
\end{align*}
\]

where \(A\) and \(B\) denote the coupled coefficient matrix and parameter matrix. \(\chi_{i}\) means the local domain of the coupled variable.

Introduce an auxiliary variable \(\hat{x}_{i}\), then the objective function can be constructed as an augmented Lagrange function based the standard ADMM as follows.

\[
x_{i} = \hat{x}_{i}
\]

\[
L(x_{i}, \hat{x}_{i}, \nu_{i}) = C + \sum_{n=1}^{N} \nu_{i} (x_{i} - \hat{x}_{i}) + \frac{\rho}{2} \sum_{n=1}^{N} (x_{i} - \hat{x}_{i})^{2}
\]

\[
L(x_{i}, \hat{x}_{i}, \nu_{i}) = C + \nu_{i} (x_{i} - \hat{x}_{i}) + \frac{\rho}{2} (x_{i} - \hat{x}_{i})^{2}
\]

\(\nu_{i}\) is Lagrange multiplier, non-zero \(\rho\) is a well-defined positive penalty parameter.

ADMM splits the optimization problem into two different sub-problems in per iteration \(k\) respectively.

\[
\hat{x}_{i}^{k+1} = \arg \min_{x_{i}} L(x_{i}, \hat{x}_{i}^{k}, \nu_{i}^{k})
\]

\[
\hat{
u}_{i}^{k+1} = \arg \min_{\nu_{i}} L(x_{i}^{k+1}, \hat{x}_{i}, \nu_{i}^{k})
\]

By introducing the predictor-corrector factor, the Lagrange multiplier \(\nu_{i}\) is updated by using following steps:

\[
\nu_{i} = \nu_{i}^{k} + \zeta(x_{i}^{k} - \hat{x}_{i}^{k})
\]
Share the electric/thermal DR prices \( \delta \), which are based on the optimal operation. This section proposes an improved N-ADMM algorithm.

### 4.3. Improved N-ADMM

The original problem contains a large number of 0-1 variables after linearizing the nonlinear constraints according to big-M method. Therefore, the convergence of standard ADMM is difficult to be guaranteed. This section proposes an improved N-ADMM by solving 0-1 variables in advance.

There are two stages in the circulation of N-ADMM. In the first stage, the objective is to solve the optimal of continuous variables with all 0-1 variables relaxed to continuous variables by using the N-ADMM in section 4.2. Then each prosumer solves the 0-1 variables by minimize the gap to the above optimal continuous variables, which can simplify the optimization process considerably in the case of the closest to the optimal. The second stage aims to solve other variables considering the transformed linear constraints with all 0-1 variables fixed as the optimal value obtained from the first stage.

The proposed improved N-ADMM algorithm is summarized in Fig 5, and specific calculation steps are as follows.

1. **Step 1: Initialization.**
2. **Step 2:** The ETA and prosumers solve for internal continuous variables with 0-1 variables relaxed to continuous variables.
3. **Step 3:** Update the decision variables and Lagrange multipliers according to (54)-(56).
4. **Step 4:** Determine convergence. If (57) meets, the first stage ends with optimal continuous variables. Otherwise, return to Step 3.
5. **Step 5:** Introduce 0-1 variables, and linearize the nonlinear constraints by the big-M. Then solve the 0-1 variables \( \delta_i \) with the smallest difference from the optimal corresponding continuous variables \( C_i \) and \( \hat{C}_i \) obtained in Step 4, the calculation is as follows.
   
   \[
   \delta_i = \arg \min \left\{ (C_i - \delta_i \cdot C_i) + (\hat{C}_i - (1 - \delta_i) \cdot \hat{C}_i) \right\}
   \]

6. **Step 6:** Fix the 0-1 variables obtained by Step 5, and ETA and each prosumer resolve the internal variables.
7. **Step 7:** Update the decision variables and Lagrange multipliers according to (54)-(56).
8. **Step 8:** Determine convergence. If (57) meets, the second cycle ends. Otherwise, return to Step 7.

### 5. Case study

This section presents the simulation results and analysis compared to various case studies, which demonstrate the effectiveness and advantages of the proposed energy trading model.

#### 5.1. Simulation Setup

The P2P energy trading community consists of the only ETA and five prosumers, including two residential buildings (RB), two commercial buildings (CB) and an office building (OB). The energy output and predicted consumption are derived from [11] and [24], which are based on the demonstration project of China Southern Grid. The simple distribution network without branches refers to the industrial park in China [6].

Based on the feed-in tariff of China, the prices \( \lambda^{\text{in}}_i \) is set to be 0.443, 0.728, and 1.095 (CNY/kWh) at different times, \( \lambda^{\text{out}}_i \) is set to be 0.370 (CNY/kWh), \( \lambda^{\text{in}}_i \) is set to be 0.49 (CNY/kWh) [9],[17]. The parameters of the solar collector model are derived form [11]. The detailed information on the SPTS can be found in [15][15]. The values of accelerated factors are adopted from [8]. Other important parameters and values are summarized in the Table 1.

The problem is solved by adopting commercial software CPLEX 12.9.0 through YALMIP in MATLAB on a 1.8 GHz, 8 GB Laptop.

### Table 1. Parameters of prosumers

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \eta^{\text{in}} ), ( \eta^{\text{out}} ), ( \eta^{\text{c}} )</td>
<td>90% [4]</td>
</tr>
<tr>
<td>( p^{\text{in}}_i ), ( p^{\text{out}}_i )</td>
<td>12 kW [4]</td>
</tr>
<tr>
<td>( E_{\text{d}} )</td>
<td>55 kWh [11]</td>
</tr>
<tr>
<td>( c_{\text{av}}, c_{\text{an}}, c_{\text{pr}}, c_{\text{as}}, c_{\text{sw}} )</td>
<td>0.1 [8]</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.6</td>
</tr>
</tbody>
</table>

![Fig. 5. Flowchart of the improved N-ADMM Algorithm](image-url)
5.2. Results of Convergence

To verify the effectiveness of the proposed algorithm, the solution process of the improved N-ADMM and the N-ADMM [8] are compared in Fig. 6. The deviation refers to the primal residual. Based on the termination criterion, the improved N-ADMM converges after two outer iterations including 25 inner iterations and 29 inner iterations separately. After completing the first stage of convergence (the 25th iteration), each prosumer solves the optimal binary variables through CPLEX and fixes them in the last solution individually. Then, N-ADMM is applied to resolve the optimization problem with fixed binary variables, and the second layer of loop iteration starts. For the N-ADMM using the same parameters, due to the incorporated binary variables, the primal residual keeps oscillating after 70 iterations, which denotes that this method cannot guarantee the convergence and inapplicable in practice.

5.3. Performance Comparison of GMM

To verify the performance of GMM, the Normal distribution and Beta distribution are fitted the probability density histograms of the net load prediction error (prosumer 1). After the net load prediction error is normalized, its distribution histogram and three-component GMM distribution are shown in the Fig.7. Obviously, the net load prediction error is not normal distribution, and the fitting distribution of the three-component GMM distribution is close to the historical data. Table 2 shows the Bayesian Information Criterion (BIC) for various distributions. A smaller value indicates a better fitting effect. It can also be obtained that the BIC of GMM is significantly smaller than that of the Normal distribution and Beta distribution, which indicates that it offers to provide a better fitting effect.

<table>
<thead>
<tr>
<th>Distributions</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMM</td>
<td>55.26</td>
</tr>
<tr>
<td>Normal</td>
<td>169.13</td>
</tr>
<tr>
<td>Beta</td>
<td>134.02</td>
</tr>
</tbody>
</table>

5.4. Results of optimally

Fig.8 and Fig.9 present the deviation between the predicted electric/thermal energy consumption and the optimized electric/thermal energy consumption under the electric/thermal DR of the ETA respectively. In the 10-18h, the PV and solar production are high, resulting the higher energy consumption, with a maximum increase of 19.8% (the upper limit of fluctuation is 20% at each slot). In other times, prosumers optimize energy reduction based on DR prices. Therefore, regional energy can be self-consumed as much as possible without being fed back to the grid. As the upper and lower limits of the fluctuation of the total energy consumption in a period are set, load rebound phenomenon may occur in several slots, as shown in 11h-12h of Fig.8. Overall, the flexible energy scheduling changed with the PV and solar production and the dynamic prices to get higher profits.

To demonstrate the advantages of the proposed energy trading model, following five various case studies are designed when all prosumers and the ETA own the same parameters. The results of prosumers’ costs and the ETA’s income are listed in Table 3.

Case 1: the proposed P2P electric-thermal trading market.

Case 2: the P2P electric trading market without both the ETA and thermal trading [25].


Case 4: the P2P electric trading market with the ETA, regardless of considering thermal trading [9].

Case 5: the P2P electric-thermal trading market with the ETA, in which the prosumers are not equipped with the bump.

Table 2. BIC for various distributions

<table>
<thead>
<tr>
<th>Distributions</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMM</td>
<td>55.26</td>
</tr>
<tr>
<td>Normal</td>
<td>169.13</td>
</tr>
<tr>
<td>Beta</td>
<td>134.02</td>
</tr>
</tbody>
</table>

Fig.8 the power consumption deviation under DR

Fig.9 the thermal consumption deviation under DR
In Case2 and Case3, since there is no DR mechanism of the ETA, prosumers’ response to regional load peaks and renewable energy output peaks is insufficient, resulting in obvious cost increasing reflected in the comparison between Case1 and Case3, and the comparison between Case2 and Case4. Besides, as the time-of-use prices of the grid is based on the SDR in province without considering the regional distributed characteristics, there may be conflicts with the SDR in a community, which will lead to the inadequate energy utilization. For example, in 10-12h, the supply of energy exceeds the demand in the community, and the DR mechanism based on the regional SDR of ETA guides prosumers to use and store more energy as shown in Fig.8. However, the demand exceeds the supply in the provincial region generally in the same slot, the grid may conduct prosumers to consume less energy and sell it at feed-in tariff lower than the P2P market price, though it may be microscale. It will not only decrease prosumers’ income, but also increase the risk of grid connection and the peak of load rebound.

Compared to Case4 without thermal energy trading, the prosumers’ cost in Case1 is significantly lower. The same result is also shown in the comparison between Case2 and Case3. Without thermal trading, prosumers can only buy high-priced thermal energy from the ETA and cannot sell it to obtain profits when the SPTS generate excess thermal. At the same time, due to the thermal dissipation effect, the thermal energy is difficult to be stored for a long time, which will cause the waste of thermal energy. Therefore, the cost differences are significantly, and the maximum cost reduction is 26.7% for prosumer5 in Case1 and Case4. The total cost of Case1 is 19.3% lower than that of Case 4, and the cost of Case 3 is 16.8% lower than that of Case 2.

Without the bump in Case5, electric and thermal cannot be switched. Although prosumers purchase less power, the purchase of thermal increases, and the energy trading also increases, which causes the increasing income of the ETA. As the price of thermal is higher than the power price during the trough period of power, the cost will be slightly higher than that of Case1.

This paper selects two P2P transaction performance evaluation indicators to verify the advantages: the electric/thermal energy balance index (EBI/EBIQ), and electric/thermal flatness index (PFI/PFIQ) proposed in [4], as shown in the Fig.10. EBI reflects the local energy balance of the P2P energy sharing region. The larger the value, the stronger the local energy balance is. PFI measures the peak power. The smaller the PFI, the smaller the power fluctuation is. It can be obviously observed that the PFI and PFIQ are lowest in Case1. And the electric/thermal DR mechanism of the ETA can stabilize the power fluctuations with a certain extent in Case1, Case4 and Case 5. Also, with the electric-thermal integrated energy trading, the EBI and EBIQ in Case 1, Case 3 and Case 5 are higher and increased by up to 61.8% compared with other cases, which means the local energy are self-consumed more sufficiently.

### Table 3. Prosumers’ Costs and ETA’s Income in Different Cases

<table>
<thead>
<tr>
<th></th>
<th>Prosumers1</th>
<th>Prosumers2</th>
<th>Prosumers3</th>
<th>Prosumers4</th>
<th>Prosumers5</th>
<th>ETA</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Prosumers’ Cost (CNY)</strong></td>
<td>1752.68</td>
<td>2191.92</td>
<td>2679.56</td>
<td>1232.80</td>
<td>1732.71</td>
<td>1193.45</td>
</tr>
<tr>
<td><strong>Prosumers’ Income (CNY)</strong></td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>725.75</td>
</tr>
<tr>
<td><strong>ETA’s Income (CNY)</strong></td>
<td></td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>1448.68</td>
</tr>
</tbody>
</table>

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![Fig.10 Evaluation Index in Different Cases](image)

![Fig.11 total power imported from the main grid](image)

![Fig.12 total power exported from the main grid](image)

![Fig.13 total thermal imported from the thermal grid](image)
energy system is proposed in this paper. Due to the wide application of the SPTS in demand side, the SPTS with two tanks is introduced and modeled based on the law of conservation of energy, which has been proved that it can further improve the local energy self-consumption. And the electric/thermal energy loss is also considered and linearized to reduce the solution complexity, and the accuracy has been verified. Then, the chance-constrained programing based on GMM is proposed to describe and solve the uncertainty of the load and PV. A distributed improved ADMM is proposed to maximize the revenue of ETA and minimize the costs of prosumers. The conclusions drawn from the simulation results are summarized as follows: 1) the electric-thermal energy trading market and STPS can enhance utilization of regional energy and achieve effective cost saving for prosumers. 2) the ETA with self-build system and electric/thermal DR mechanism can further achieve the sufficient regional energy trading and enhance the energy resource allocation ability, also suppress power fluctuations. 3) the improved N-ADMM can improve convergence efficiency and reduce convergent oscillation. In the future, more efforts are required to solve the model considering the carbon emission and voltage flow, and the communication delay in multi-energy trading market.

### Acknowledgment

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### References


### Table 4. Sensitivity of confidence

<table>
<thead>
<tr>
<th>Prosumers’ Cost and ETA’s Income (CNY)</th>
<th>( \alpha =0 )</th>
<th>( \alpha =0.5 )</th>
<th>( \alpha =0.6 )</th>
<th>( \alpha =0.7 )</th>
<th>( \alpha =0.8 )</th>
<th>( \alpha =0.9 )</th>
</tr>
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<tbody>
<tr>
<td>Prosumers1</td>
<td>1669.02</td>
<td>1747.40</td>
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<td>1765.45</td>
<td>1772.06</td>
<td>1820.51</td>
</tr>
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<td>Prosumers2</td>
<td>2118.88</td>
<td>2185.88</td>
<td>2191.92</td>
<td>2201.49</td>
<td>2291.49</td>
<td>2273.91</td>
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<td>2674.25</td>
<td>2679.56</td>
<td>2701.80</td>
<td>2704.22</td>
<td>2801.36</td>
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<td>Prosumers4</td>
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<td>1242.80</td>
<td>1268.63</td>
<td>1426.05</td>
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<td>1752.48</td>
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<tr>
<td>ETA</td>
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<td>1193.45</td>
<td>1193.47</td>
<td>1194.40</td>
<td>1194.95</td>
</tr>
</tbody>
</table>

### Fig. 14 Results of the No. Iterations and time cost

The power purchase and selling plan with the power grid are shown in Fig.11-Fig.12. The thermal purchasing plan is shown in Fig 13. The self-energy system of the ETA reduces external energy purchased and sold with the power grid and thermal company, which can be seen in the Fig.12-Fig.13. Besides, since this paper introduces the electric-thermal energy trading, the energy balance rate has been improved, and significant reduction of purchased thermal energy can be seen in Case1 and Case3 compared with other cases in Fig.13. Fig.12-Fig.13 highlight that the proposed model reduces the dependence on the utility grid and thermal company by sufficiently trading all available energy surplus within the local community.

### 5.5. Results of sensitivity and scalability

Considering the prediction errors and uncertainty factors, the selection of confidence level \( \alpha \) will have an impact on the results. The costs and incomes at different confidence levels are shown in Table 4. The system improves the system reliability at the cost of the total costs. When the \( \alpha \) increases, the total cost also increases in turn, which can reflect the impact of the randomness of photovoltaic and load on the results.

Larger-scale systems consisting of 5, 10, 15, 20, 25 and 30 prosumers are simulated to analyze the scalability performance of the proposed model. Fig.14 shows that the number of iterations and time cost increase with the increasing number of prosumers in the system. Considering that there are usually no more than 30 commercial and residential buildings in the area [24], and the maximum consumption time required is no more than 24h in day-ahead scheduling, the computation time and number of iterations are acceptable, and the proposed method is implementable.

### 6. Conclusion

A peer-to-peer distributed electric-thermal energy trading model considering the energy loss and ETA with self-build

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**Table 4. Sensitivity of confidence**

<table>
<thead>
<tr>
<th>Prosumers’ Cost and ETA’s Income (CNY)</th>
<th>( \alpha =0 )</th>
<th>( \alpha =0.5 )</th>
<th>( \alpha =0.6 )</th>
<th>( \alpha =0.7 )</th>
<th>( \alpha =0.8 )</th>
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<tr>
<td>Prosumers4</td>
<td>1204.32</td>
<td>1212.07</td>
<td>1232.80</td>
<td>1242.80</td>
<td>1268.63</td>
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<tr>
<td>ETA</td>
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<td>1194.95</td>
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for energy balance service provider (EBSP) considering market elasticity in community microgrid. Appl Energ. 2021 Dec 1; 303: 117596.


