A Distributed Electricity Trading System in Active Distribution Networks Based on Multi-Agent Coalition and Blockchain

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***Abstract*—The prevalence of distributed energy resources encourages the concept of an electricity "Prosumer (Producer and Consumer)". This paper proposes a distributed electricity trading system to facilitate the peer-to-peer electricity sharing among prosumers. The proposed system includes two layers. In the first layer, a multi-agent system is designed to support the prosumer network, and an agent coalition mechanism is proposed to enable the prosumers to form coalitions and negotiate electricity trading. In the second layer, a Blockchain based transaction settlement mechanism is proposed to enable the trusted and secure settlement of electricity trading transactions formed in the first layer. Simulations are conducted based on the java agent development environment to validate the proposed electricity trading process.**

***Index Terms*—Active distribution network, multi-agent coalition, prosumer, Blockchain, transactive grid, power market.**

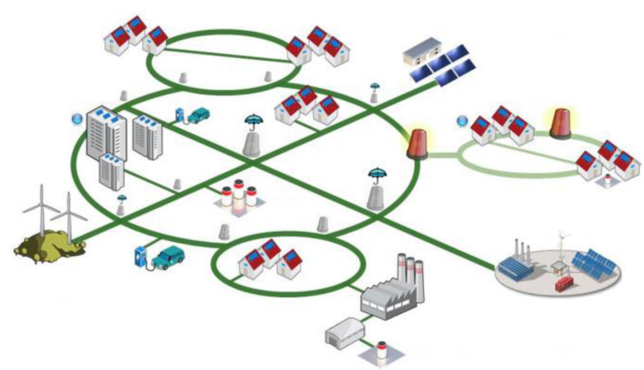

Fig. 1. Depiction of active distribution network (figure source: [5]).

I. Introduction

ENERGY shortage and climate change are increasingly drawing worldwide attentions. Driven by the global challenges of climate change, the concept of a "smart grid" was proposed in the early 21th Century, bringing profound reconstructions for modern power systems. As an important part of smart grid, the distribution network is also experiencing a significant transformation. In 2008, the concept of "Active Distribution Network (ADN)" was proposed by the International Council on Large Electric Systems (CIGRE) [1]. ADN is characterized by features such as high penetration of distributed renewable sources and energy storage systems, prevalence of electric vehicles (EVs), participation of flexible loads, and formation of microgrids/virtual power plants [2].

A. Need of Electricity Trading Mechanism in ADN

A noticeable entity in ADN is the energy Prosumer (producer and consumer)" [3], which refers to autonomous entity that manages a number of energy resources and is able to generate and consume energy simultaneously. An energy prosumer could be a commercial building, a house, a residential community, a microgrid, a load aggregator, etc., as depicted in Fig. 1 [4]. Unlike traditional energy consumers, prosumers can produce reverse power flows. Meanwhile, the intermittent nature of distributed renewable energy poses a number of challenges and complexities for prosumers to maintain real-time balance of local power generation and demand. On one hand, when there is not enough power to serve the demand, prosumers must purchase energy from the grid based on the electricity retail price; on the other hand, when there is surplus power, it would be injected into the grid with or without a certain feed-in-tariff scheme.

The increasing number of prosumers naturally implies the requirement of establishing an electricity trading mechanism for prosumers to trade electricity with each other. Although different countries adopt different structures, current wholesale power markets make it hard to serve the electricity trading on the distribution side because: (1) the wholesale power market sets up

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capacity barrier to entry. Capacities of prosumers in ADN are often too small to participate in the wholesale market; (2) the wholesale market is centralized, whereby the independent system operator (ISO) collects bids from participators, stack the bids, and determines the market clearance price and makes dispatches. This centralized structure is hard to scale for a huge number of prosumers; and (3) the centralized market structure is vulnerable to cyber-attacks. For example, in the authors' recent work [4], we demonstrate how a false data injection attack (FDIA) can falsify the state estimation results, and consequently mislead the ISO's decision making in the market. Due to the distributed nature and large number of prosumers in ADN, a distributed and scalable energy trading mechanism in the energy delivery side is considered desirable.

B. State-of-the-Art

When designing the distribution side electricity trading system, essentially there are two issues that need to be considered: (1) how to determine the electricity trading price and amount? and (2) once a trading contract is formed, how can it be settled in an effective and secure manner? Recently, distributed energy trading has become an active research direction, with a number of researches studying the energy trading system on the distribution side. For example, [6] gives an overview discussion on the energy market for residential buildings in a microgrid, and extracts seven fundamental components for microgrid markets.

Alternatively, other researches have focused on addressing the first issue, i.e., energy trading price determination. In early works [7], [8] studied the energy trading price negotiation problem between individual producers and consumers of a microgrid. In [8], a multi-agent system (MAS) was developed to support the real-time price negotiation between individual producer and consumer. In the microgrid market prototype described in [6], a pricing system is presented, which orders the price offers from sellers and buyers; this pricing system is similar with that in the wholesale market. In [7], multiple "group managers" are set up to collect the bids from producers and consumers and publish them on a "blackboard". The risks apparent in the centralized system, such as scalability and single point attack, also exist in the systems in [6] and [7]. [9] proposes an energy sharing model for peer-to-peer prosumers where the cost model for residential users and income model for the energy sharing provider respectively, provided the basis for the development of internal trading pricing models. Similar problems are also studied in [10] and [11], in which the Lyapunov optimization method and Stackelberg game approach are applied to determine the shared energy amount and internal energy trading price, respectively. [9]–[11] assume the prosumers are monogenous with all prosumers having the same energy resource configuration (solar panel and battery energy storage system) and following the same energy management policy. Based on this consideration, [9] and [11] aim to determine an internal trading price agreed by all prosumers. The homogeneity assumption is too strong to fit practical situations where different prosumers could be heterogeneous, i.e., have different kinds of energy resources and different autonomous energy management policies, and therefore offer different trading prices. [10] only determines the shared energy amount without considering the price signals. In reality, price signal would be the primary incentive for energy sharing. In addition, current research [6]–[11] does not consider the role of the existing electricity retail tariff in distributed energy trading. From our point of view, the future distribution side of energy trading will work in conjunction with the existing electricity retail market, rather than replacing it.

As for the second issue, i.e., secure settlement of energy trading transactions, recent advances in communication and information technology (ICT) provide a promising solution. Firstly, as proposed by Satoshi Nakamoto in 2008 [12], Blockchain (BC) has been successfully applied in the finance domain, i.e., the BitCoin [12], a digital payment system. Essentially, Blockchain is a distributed system where each peer acts as a node of the system and can participate in calculating the solution to a hash-based mathematical problem ensuring integrity of transactions. Each transaction record is then encapsulated as a block and added onto existing block chains. The recorded block contents are collectively referred to as the *ledger*. All information is then updated synchronously to the entire network so that each peer keeps a record of the same ledger. Through its consensus mechanism, integrity of the data recorded in the ledger can be ensured without a trusted third party.

The emergence of Blockchain and subsequent attention given to it has led to calls for it to be used within information infrastructure for energy trading. [13] gives a comprehensive discussion on using BC and asymmetric encryption. The most notable trial project integrating Blockchain into energy systems is the LO3 company's "Brooklyn Microgrid" project [5], [14], which uses Blockchain to implement peer-to-peer energy trading for ten residential units. In addition, the Share & Charge project [15] was launched to establish an open network for mobility companies to implement private electric vehicle charging pile sharing through BC; this network has been successfully applied in Germany and US.

C. Scope of this Paper

This paper proposes a distributed electricity trading system for prosumers in ADN. The proposed system addresses the aforementioned two issues respectively. The main contributions of this paper are as below.

1) This paper proposes a MAS based electricity trading architecture. Significantly distinguished from existing research [5]–[11], the proposed architecture treats prosumers as heterogeneous, autonomous entities. The trading architecture decouples the upper-level trading negation of prosumers from the lower-level autonomous energy management of individual prosumers. Such decomposed, layered design makes the system flexible and adaptable to the heterogeneous prosumer environment;
2) Based on the philosophy of multi-agent coalition technology, this paper proposes a set of multi-agent coalition formation and electricity trading negotiation protocols to enable prosumers to form coalitions and negotiate the electricity trading price and amount. The proposed protocols support the negotiation of prosumers in the group basis, which can harness the cooperation among prosumers.

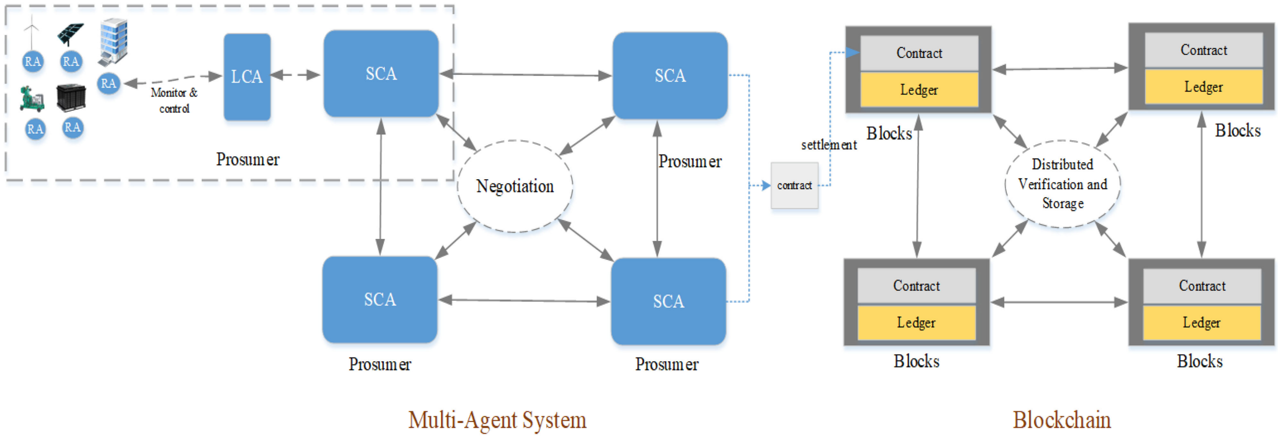

Fig. 2. Schematic of the distributed electricity trading system for ADN.

Distinguished from existing research [5], [6], [8], [9], [10], the energy trading negotiation mechanism proposed in this paper does not rely on any central controller, and is compatible with existing time-of-use electricity tariffs. It can be thus considered as an alternative solution with better scalability;

3) A BC based electricity transaction settlement system is proposed. Differing from existing BC based systems, the proposed system is based on a parallel double-chain combined with a high frequency verification mechanism. For each contract made in the negotiation system, it is verified, stored, and chained one by one as the first chain. Meanwhile, each ledger made after the distributed electricity trading negotiation system is verified, stored, and chained one by one as the second chain. A high frequency verification mechanism is designed to inspect any inconsistencies between the contract and ledger and to detect any malicious manipulation resulting from cyber attacks.

This paper is organized as follows. Section II gives an overview of the electricity trading system; Section III presents the proposed multi-agent coalition and trading negotiation mechanism; Section IV presents the proposed BC based transaction settlement system; Section V discusses a simulation with conclusions presented in Section VI.

II. Overview of the Electricity Trading System

In this section, we present the structure and overall workflow of the proposed electricity trading system. The schematic of the electricity trading system is illustrated in Fig. 2.

A. Overview of the Electricity Trading Negotiation System

The whole electricity trading negotiation system is essentially a MAS, with a layered model as shown in Fig. 3. Each prosumer is also modelled as a MAS, including multiple *resource agents* (RAs), one *local coordination agent* (LCA), and one *social coordination agent* (SCA). The prosumer's energy resources are located at the lowest layer, i.e., *physical resource layer*. Upon it is the *resource agent layer*, in which multiple RAs are located to perceive operational status of energy resources, and report the information to LCA, which is located at the *local coordination layer*.

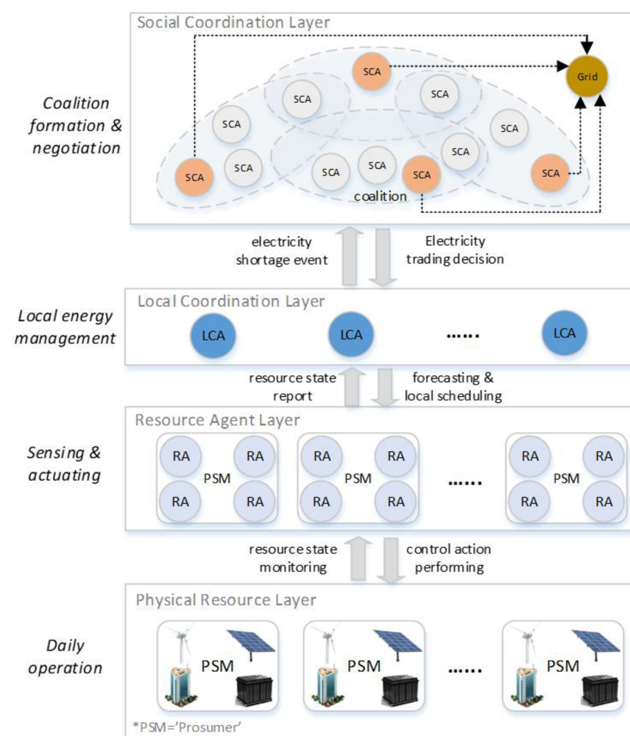

Fig. 3. Architecture of the MAS system for the prosumer.

Based on the energy resource information from RAs, the LCA performs autonomous energy management by solving a local scheduling model to determine optimal control actions of the internal energy resources (e.g., charging/discharging of batteries and plug-in electric vehicles, thermostat settings of air conditioning systems, etc.), with the aim to serve local power consumption. Based on the local scheduling result, the LCA sends control signals to RAs, and the latter applies actual control actions to the resources. The local scheduling can also be performed in a distributed manner as shown in our previous work [16]. In this way, the scheduling is performed in a distributed manner by RAs, and the role of the LCA is weakened from a centralized scheduler to be an intermediary that communicates with the RAs and SCA. If the scheduling result shows that the local consumption cannot be fully served by the local generation, an electricity shortage event is detected. Then, the prosumer has two options: a) purchase electricity from the grid with the retail price, or; b) negotiate electricity trading with other prosumers with a price lower than its retail price. In this paper, it is assumed that all prosumers are rational and thus always try option b) first. Therefore, the LCA will forward the electricity shortage information to the *social coordination agent* (SCA) located at the *social coordination layer*. After receiving the electricity shortage event, the SCA acts as a buyer and launches a request to claim the prosumer's electricity purchase intensions to other prosumers. SCAs of other prosumers then respond to the request, and form a coalition with the buyer by acting as sellers. SCAs in a same coalition then negotiate the electricity trading. If the buyer's energy shortage cannot be fully covered through the negotiation, the buyer (represented by the orange SCA circle in Fig. 3) will purchase energy from the grid according to the electricity retail price.

Once an electricity trading agreement is achieved, SCAs of sellers send the agreement information to their LCAs. Based on the traded energy amount, the LCA engages in autonomous energy management to schedule the local electricity output to meet the contract, before forwarding the control signals to RAs, which subsequently apply control actions to the resources.

It is worth noting that the designed MAS have the following features: (1) it naturally supports concurrent coalitions. That is, multiple buyers can launch multiple trading requests asynchronously; (2) a prosumer can be in different roles at different time points, i.e., act as either a seller or a buyer; (3) the proposed negotiation system is seamlessly compatible with the existing electricity retailing mechanism; and (4) a seller can join multiple coalitions to negotiate with multiple buyers simultaneously. Similarly, a buyer can negotiate with multiple sellers that join the coalition.

B. Overview of the Electricity Transaction Settlement System

The BC based electricity transaction settlement system essentially consists of a parallel double-chain. One chain is for the contract and the other chain is for the ledger. As depicted in Fig. 4, each block in the contract chain contains only one energy trading contract. The contract-blocks are chained sequentially according to the timestamps. The ledger chain is the final financial settlement which corresponds to each contract block. Secure hash algorithms (SHAs) are used to chain blocks in both chains.

Each pair of contract-block and ledger-block is equipped with a high frequency verifier that works uninterrupted once generated. The verifier periodically reads and calculates contents relating to the ledger block that it corresponds to with a relatively high frequency. The frequency is pre-set by a system designer but has a minimum threshold, i.e., the time interval between two scans should be larger than the sum of the time of reading the current contract and previous ledger, calculating new ledger, and checking the consistency between the previous and re-calculated ledgers. Any inconsistencies between the re-calculated ledger and existing one will cause an alarm sent to prosumers, indicating the suspicion of data manipulation by cyber-attackers.

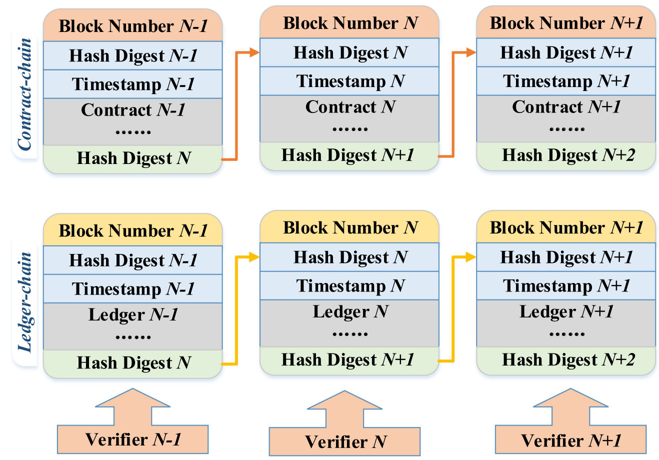

Fig. 4. Overview of the BC based transaction settlement.

C. Cyber Security Considerations

Cyber vulnerability of the proposed system could arise in two aspects: the Blockchain system and the MAS system. For the former, cyber attackers could try to tamper either the contract-chain or leger-chain to make financial profits. However, the Blockchain's consensus mechanism (discussed in Section IV) would make it extremely difficult for cyber attackers to launch a successful manipulation. For the latter, since LCA makes short-term forecasting based on the information from RAs, and RAs schedule local electricity output based on the control signals sent from the LCA, it would be possible for cyber attackers to make fake information on the communication channel between LCA and RAs to influence control decisions. Such vulnerabilities of sensors, actuators, and communication channels could exist in any network-based systems, and hardware-level cyber security enhancement is desired to ensure the communication security inside of a prosumer.

III. Multi-Agent Coalition System for Electricity Trading Negotiation

As an active research direction of MAS, multi-agent coalition technique has been widely studied [17], [18]. Multi-agent coalition refers to a way to cooperate agents to complete a task, where none of them can complete it independently. In recent years, multi-agent coalition has been successfully applied on power system problems, e.g., system fault restoration [19] and generation scheduling [20]. In this paper, we propose a multi-agent coalition mechanism to enable prosumers to negotiate the electricity trading. The overall negotiation workflow launched by a buyer is shown in Fig. 5.

As illustrated in Fig. 5, the negotiation workflow is based on a main loop, where the prosumer continuously monitors its on-site local energy resources and performs autonomous energy management. Once an energy shortage event is detected,

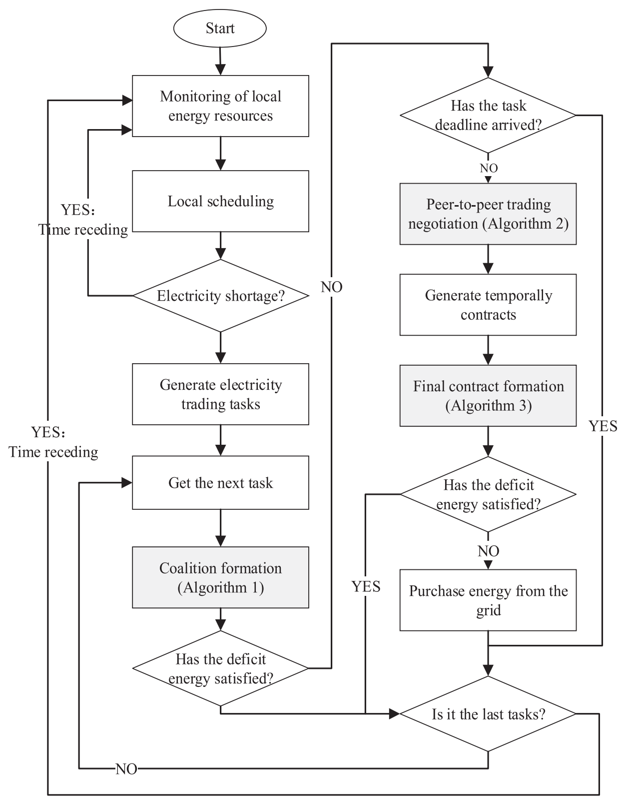

Fig. 5. Workflow of the electricity negotiation mechanism.

the prosumer acts as a buyer to launch electricity negotiation requests. The negotiation is backboned by three algorithm modules, which are detailed below.

A. Autonomous Energy Management of Prosumer

Denote the set of N networked prosumers as Φ, i.e., $|\Phi| = N$. For each prosumer i, RAs monitor the energy resources through sensors, and store data into local storage. Based on the historically recorded data, the LCA performs very short-term forecasting to predict the power generation and consumption over future T time intervals. The forecasting method itself is not the focus of this paper, while different available short-term forecasting techniques can be applied (see our previous work [21], [22]).

Based on the forecasting result, LCA solves a local scheduling model (Eq. (1)) to allocate power outputs of the on-site generation resources to serve the local load, while satisfying operational constraints (Eqs. (2)–(10)):

$$F = \min \sum_{t=1}^{T} \left(pr_{s,t}^{retail} P_{s,t}^{buy} \Delta t + \sum_{a\in\Pi_s^P} C_a^{prod}(P_{a,t}) + \sum_{b\in\Pi_s^C} C_b^{csm}(L_{b,t}) \right) \quad (1)$$

$$\sum_{a\in\Pi_s^P} P_{a,t} + P_{s,t}^{buy} \geq \sum_{b\in\Pi_s^C} L_{b,t} \; \forall s\in\Phi, t\in[1,...,T] \quad (2)$$

$$P_{s,t}^{buy} \leq P_s^{\max} \qquad \forall s\in\Phi, t\in[1,...,T] \quad (3)$$

$$P_{a,t} = g_{s,a}(\mathbf{s}_{s,a,t}) \quad \forall s\in\Phi, a\in\Pi_s^P, t\in[1,...,T] \quad (4)$$

$$L_{b,t} = f_{s,b}(\mathbf{s}_{s,b,t}) \quad \forall s\in\Phi, b\in\Pi_s^C, t\in[1,...,T] \quad (5)$$

$$\mathbf{s}_{s,a,t} \text{ s.t. } \Omega_{s,a,t}^{prod} \qquad \forall s\in\Phi, a\in\Pi_s^P, t\in[1,...,T] \quad (6)$$

$$\mathbf{s}_{s,b,t} \text{ s.t. } \Omega_{s,b,t}^{csm} \qquad \forall s\in\Phi, b\in\Pi_s^C, t\in[1,...,T] \quad (7)$$

Optional network constraints:

$$P_l = -v_i v_j (g_{ij}\cos\theta_{ij} + b_{ij}\sin\theta_{ij}) + g_{ij} v_i^2 \quad \forall s\in\Phi,\ (i,j)\to l, \forall l\in\Pi_s^L \quad (8)$$

$$Q_l = v_i v_j (b_{ij}\cos\theta_{ij} - g_{ij}\sin\theta_{ij}) + b_{ij} v_i^2 \quad \forall s\in\Phi,\ (i,j)\to l, \forall l\in\Pi_s^L \quad (9)$$

$$v_i^{\min} \leq v_i \leq v_i^{\max} \; \forall s\in\Phi,\ i\in\Pi_s^N \quad (10)$$

where $pr_{s,t}^{retail}$ is the electricity retail price of the retail plan signed by prosumer s at time t (\$/kWh); Δt is the duration of each time interval (hour); $P_{s,t}^{buy}$ is the power which prosumer s needs to buy from external suppliers at time t; $P_s^{\max}$ is the power capacity of the connection line that connects to prosumer s (kW); Π_s^P and Π_s^C are sets of producers and consumers of prosumer s; $P_{a,t}$ is the power output of the producer a at time t (kW); $L_{b,t}$ is the power consumption of consumer b at time t (kW); $\mathbf{s}_{s,a,t}$ and $\mathbf{s}_{s,b,t}$ are control actions on the producer a and consumer b of prosumer s at time t; $g_{s,a}(\cdot)$ and $f_{s,b}(\cdot)$ are functions to determine the power output of producer a and consumption of consumer b based on the control action vectors $\mathbf{s}_{s,a,t}$ and $\mathbf{s}_{s,b,t}$. $C_a^{prod}(\cdot)$ and $C_b^{csm}(\cdot)$ represent cost functions of producer a and consumer b, respectively; $\Omega_{s,a,t}^{prod}$ and $\Omega_{s,b,t}^{csm}$ are operational constraint sets of the producer a and consumer b of prosumer s at time t, respectively. Π_s^L and Π_s^N are sets of transmission lines and nodes of prosumer s, respectively; $(i,j)\to l$ means that i and j are the two ends of line l; v_i and v_j are voltage magnitude of the i-th and j-th node, respectively; $v_i^{\min}$ and $v_i^{\max}$ are minimum and maximum voltage limits; P_l and Q_l are real and reactive power flow on transmission line l. The network constraints (8)–(10) are optional, which would be applied to prosumers with networked energy resources, such as microgrids and virtual power plants. The decision variables of model (1) are $P_{s,t}^{buy}$, $\mathbf{s}_{s,a,t}$, and $\mathbf{s}_{s,b,t}$.

Note that the model (Eqs. (1)–(10)) provides a generalized form of the prosumer's autonomous energy management, while the concrete form depends on the implementation of the prosumer (i.e., energy resource types and models, controllable load models, constraint consideration, etc.). There are many internal energy management models available in the literature (e.g., [23], [24]), which can be applied.

By solving model (1), the LCA determines control schedules of local producers and consumers, and the amount of intended energy purchase, i.e., $P_{s,t}^{buy}\Delta t$. The rationale of model (1) is that the LCA uses $pr_{s,t}^{retail}$ to calculate $P_{s,t}^{buy}$, then if there exists $P_{s,t}^{buy} > 0\ \exists t = 1:T$, the LCA forwards the deficit energy $P_{s,t}^{buy}\Delta t$ to the SCA, and the latter will launch the coalition request to try to buy energy from other prosumers with a price lower than $pr_{s,t}^{retail}$. The coalition formation process is presented as below.

TABLE I
ALGORITHM 1: ALGORITHM OF AGENT COALITION FORMATION

begin:
(1) **for each** $\theta_k \in \Theta$, in sequential order
(2) initialize $Nbr(i)$;
(3) set $d=1$; /* initialize the coalition request propagation depth *d* */
(4) **while** $t < DL(\theta_k)$ /**t* is the real time*/
(5) **for** each j in $Nbr(i)$
(6) **if** $AE_j^{\theta_k} > 0$ /* $AE_j^{\theta_k}$ is the available energy of seller *j* for θ_k */
/*negotiage temporary contract $CON_{ij}^{\theta_k}$ */
(7) set $CON_{i,j}^{\theta_k}$ =**Negotiate** (i , j);
/*put $CON_{ij}^{\theta_k}$ into the temporary contract set $SCON_{i,\theta_k}^{tmp}$ */
(8) $SCON_{i,\theta_k}^{tmp} = SCON_{i,\theta_k}^{tmp} \circ CON_{ij}^{\theta_k}$;
(9) **end if**
(10) **end for**
(11) **if** $\exists l \in \Phi : \langle i,l \rangle \notin Nbr(i)$ and $d \le \tau$
(12) randomly select *k* as *Mediator* where $\langle i,k \rangle \in Nbr(i)$;
(13) $Nbr(i) = Nbr(i) \circ Nbr(k)$;
(14) **else**
(15) **break**;
(16) **end if**
(17) **end while**
(18) $SCON_{i,\theta_k}^{fn}$ =**FinalContractDetermination**(*i*, $SCON_{i,\theta_k}^{tmp}$);
/* $c{:}CP$ is the contracted trading energy amount*/
(19) **if** $\sum_{c \in SCON_{i,\theta_k}^{fn}} c{:}CP < E_{\theta_k}$
(20) set $CON_{i,\theta_k}^{grid} = E_{\theta_k} - \sum_{c \in SCON_{i,\theta_k}^{fn}} c{:}CP$;
(21) **end if**
(22) **end for**
end

TABLE II
ALGORITHM 2: NEGOTIATION PROTOCOL OF TWO MMAS

begin:
(1) for task θ_k , seller j generates an offer o to buyer i ;
(2) **if** i accepts o **then**
(3) generate *contract* $CON_{i,j}^{\theta_k}$ based on o;
(4) $SCON_{i,\theta_k}^{tmp} = SCON_{i,\theta_k}^{tmp} \circ CON_{ij}^{\theta_k}$;
(5) $SCON_{j,\theta_k}^{tmp} = SCON_{j,\theta_k}^{tmp} \circ CON_{ij}^{\theta_k}$;
(6) **return**;
(7) **else**
(8) i generates a counter-offer o' to j ;
(9) **if** j accepts o' **then**
(10) generate *contract* $CON_{i,j}^{\theta_k}$ based on o' ;
(11) $SCON_{i,\theta_k}^{tmp} = SCON_{i,\theta_k}^{tmp} \circ CON_{ij}^{\theta_k}$
(12) $SCON_{j,\theta_k}^{tmp} = SCON_{j,\theta_k}^{tmp} \circ CON_{ij}^{\theta_k}$
(13) **return**;
(14) **else**
(15) **return null;** /*no contract is formed*/
(16) **end if**
(17) **end if**
end

B. Multi-Agent Coalition Formation

The electricity purchase information sent from LCA is with the form of $\Theta = \{\theta_1, \ldots, \theta_m\}$, where item θ_k $(k = 1, \ldots, m)$ denotes a block of intended electricity purchase and m denotes the total number of blocks. θ_k includes 3 tuples: $[t_{\theta_k}^{start}, t_{\theta_k}^{end}, E_{\theta_k}]$, representing the start time, end time, and energy amount (kWh) of the electricity purchase, respectively.

By receiving Θ from LCA, the SCA starts a coalition request for each task in Θ. The whole agent coalition formation algorithm is shown in Table I. Firstly, the SCA of prosumer i (the buyer) initializes its neighbored SCA list (Line 2), denoted as $Nbr(i)$. Then, the buyer contacts SCAs in $Nbr(i)$ to negotiate electricity trading before the deadline $DL(\theta_k)$ (Lines 4–10). In this process, the buyer calculates its available energy $AE_j^{\theta_k}$ based on perceiving its connection line's power capacity, to ensure $AE_j^{\theta_k} \le P_j^{\max}$. The buyer also propagates the request to neighbors of a randomly selected SCA in $Nbr(i)$ if all following three conditions are satisfied (Lines 11–16): (1) the trading deadline is not reached; (2) if there is at least one SCA not in $Nbr(i)$; and (3) the request propagation depth is less than the pre-specified threshold τ. Here the control parameter τ controls the times the buyer can propagate the request through its connected SCAs. After the trading deadline arrives, the buyer determines the final contract set $SCON_{i,\theta_k}^{fn}$ from its temporary contract set (Line 18) and calculates the amount of electricity purchased from the grid (CON_{i,θ_k}^{grid}) (Lines 19–20).

In the rest of this section, the negotiation and final contract determination algorithms will be presented, respectively.

C. Electricity Trading Negotiation Protocol

By receiving the buyer's request, if the seller has available electricity during the period of task θ_k (i.e., $AE_j^{\theta_k} > 0$), it sends a reply to the seller and starts the electricity trading negotiation process. The proposed negotiation protocol of electricity trading is based on the alternating offers protocol [25], with the whole procedures shown in Table II. Firstly, the seller provides an offer to the buyer (Line 1). The energy selling price in the offer is based on the evaluation of the seller's generation cost and the number of existing temporary contracts the seller has:

$$pr_j^{sell,\theta_k} = gen(\theta_k) + \alpha_j \cdot \left| SCON_j^{tmp} \right| \tag{11}$$

where $gen(\theta_k)$ is the generation cost of serving the electricity demand of task θ_k. The value of $gen(\theta_k)$ is determined by the LCA of the seller through local scheduling. α_j is negotiation factor of the seller. The rationale of model (10) is that when generating an offer, the seller raises the selling price with the increase of the number of its existing temporary contracts.

By receiving the offer, the buyer has three options: accept the offer, reject the offer, or generate a counter-offer to the seller. The buyer firstly calculates its intended purchase price as:

$$pr_i^{buy,\theta_k} = pr_{i,t_{\theta_k}^{start}}^{retail} - \beta_i \cdot \left| SCON_i^{tmp} \right| \tag{12}$$

where β_i is the negotiation factor of prosumer i as a buyer; Model (8) shows that when the buyer has more temporary contracts in hand, its intended purchase price decreases.

Based on pr_i^{buy,θ_k} calculated by Eq. (12), the buyer makes a decision based on following rules:

$$\begin{cases} \text{accept offer if } pr_j^{sell,\theta_k} \leq pr_i^{buy,\theta_k} \\ \text{reject offer if } pr_j^{sell,\theta_k} \geq pr_{i,t_{\theta_k}^{start}}^{retail} \\ \text{generate counter - offer with } pr_i^{buy,\theta_k} \text{ if } pr_i^{buy,\theta_k} \\ \qquad\qquad < pr_j^{sell,\theta_k} < pr_{i,t_{\theta_k}^{start}}^{retail} \end{cases} \tag{13}$$

After receiving the counter offer, the seller decides to accept or reject the counter offer based on following conditions:

$$\begin{cases} \text{reject } o' \text{ if } \sum_{c\in SCON_{j,\theta_k}^{tmp}} c{:}CP > P_{\theta_k}\cdot\eta \text{ and} \\ \qquad \sum_{c\in SCON_{j,\theta_i}^{tmp}} c{:}pr / \left|SCON_{j,\theta_k}^{tmp}\right| > pr_i^{buy,\theta_k} \\ \text{accept } o' \qquad\qquad\qquad\qquad \text{otherwise} \end{cases} \tag{14}$$

where η is the decision making factor. The rationale of model (14) is if the total contracted energy amount of the temporary contracts owned by the seller is large enough ($\sum_{c\in SCON_{j,\theta_k}^{tmp}} c{:}CP > P_{\theta_k}\cdot\eta$) and the counteroffer price is smaller than the average price of temporary contracts, then the seller will reject the counteroffer; otherwise, the counteroffer will be accepted. One natural question is *why doesn't the seller accept all counteroffers, so that it has more "contract reservation"?* The answer is that if the seller does this, then in the final contract determination process, some temporary contracts with relatively lower prices might become final contracts, and some with higher prices would be cancelled, as discussed below.

D. Final Contract Determination

When the trading deadline arrives, the negotiation is finished. Final contracts will be selected from the temporary contract set. The final contract determination process is launched by the buyer, shown in Table III. Firstly, if the contract determination deadline ($DL'(\theta_k)$) does not arrive (Line 2), the buyer stacks its owned temporary contracts, and selects temporary contracts with the price from high to low. Once a contract is selected, the buyer sends a transaction request message to the seller (Line 9). When the seller receives the transaction request message, it firstly checks whether it has adequate energy capacity to accomplish this contract excluding existing final contracts. If so, then the seller sends a conformation message to the buyer, and the contract will be finally confirmed as a final contract (Lines 12–15); otherwise, the seller sends a cancel message to the buyer, the temporary contract will be cancelled, and the buyer proceeds to the next contract in its stacked contract list, until one of following three conditions is satisfied: (a) the sum of final contracted capacity reaches E_{θ_k} (Line 6); (b) all the temporary contracts have been processed; and (c) the final contract determination deadline arrives. When the final contract determination deadline arrives, all the remaining temporary contracts will be cancelled.

IV. BC Based Transaction Settlement Mechanism

In this section, the BC based electricity transaction settlement system is presented. All prosumers in the energy trading community compose a private distributed network, in which only registered prosumers can participate in the energy trading processes. Strict consensus that every prosumer must comply drives the automation of the network. Basically, the consensus in the proposed system contains three components: *contract-chain*, *ledger-chain*, and a high frequency verification module.

TABLE III
Algorithm 3: Final Contract Determination

begin:
(1) for task θ_k, buyer i sorts temporary contracts in $SCON_{i,\theta_k}^{tmp}$;
(2) **while** $t < DL'(\theta_k)$ /**t* is the real time*/
(3) **if** all temporary contracts in $SCON_{i,\theta_k}^{tmp}$ have been processed **then**
(4) **return;**
(5) **else**
(6) **if** $\sum_{c\in SCON_{i,\theta_k}^{fn}} c{:}CP \geq E_{\theta_k}$ **then**
(7) **return;**
(8) **else**
(9) get the next temporary contract c from $SCON_{i,\theta_k}^{tmp}$;
(10) i sends a transaction request message to j;
(11) i gets reply message from j;
(12) **if** j confirms the contract **then**
(13) $SCON_{i,\theta_k}^{fn} \leftarrow SCON_{i,\theta_k}^{fn} \cup c$;
(14) $SCON_{i,\theta_k}^{fn} \leftarrow SCON_{i,\theta_k}^{fn} \cup c$;
(15) **end if**
(16) **end if**
(17) **end while**
end

The separated storage of contract and ledger enhance the "width" of the chain from traditional single-chain to double-chain, which naturally increase the reliability of BC. Moreover, we propose to add a high frequency verification mechanism by eliminating the concept of proof of work. Our approach can significantly reduce the computational burden of the conventional BC, in which the nodes are required to solve puzzle problems [7]. More importantly, the proposed high frequency verification mechanism can detect malicious tampering from cyber-attackers and report it to the prosumer.

A. Contract Chain

Each prosumer acts as node of the BC system, identified by a unique digital address. Each prosumer is also assigned a pair of information keys with one as a public key and the other as a private key. A final contract formed in the MAS based negotiation system includes following information: (a) addresses of the buyer and seller; (b) amount of traded energy; (c) monetary payment; (d) start and end time of the energy provision; and (e) digital signatures of both the buyer and seller. The contract is verified by the system with following procedures:

(1) The buyer broadcasts the final contract to all other prosumers (nodes); (2) once received, other nodes decrypt the contract to confirm whether the contract is agreed by both the buyer and the seller; (3) the verification result is reviewed by the voting of all nodes, in which each node has precisely one chance to vote. Only when majority of nodes agree, the contract is considered as valid and written in a new *contract block*; (4) each prosumer then generates a hash digest by using SHAs to chain the new

contract block to the existing chain. SHAs are irreversible algorithms to concentrate all information of the *contract-block* into the fixed dimensions of a message digest so as to link two blocks together [7].

The threshold of the majority rule should be in the range of (50%, 100%]. The higher the threshold value, the stricter the verification is. The concrete setting of the threshold value should depend on practical deployment considerations.

B. Ledger Chain

Once a new contract block is chained onto the contract chain, each node calculates the ledger to update the balance after the execution of the new contract. A randomly selected node is responsible for broadcasting its calculated ledger to all other prosumers so as to let all nodes make a contradistinction between their calculated ledgers and the received one. The ledger is also reviewed by the voting mechanism. Only when majority of the prosumers agree, the new ledger is considered as valid and written in a new *ledger block*. Similar to the contract chain, the new ledger block is chained onto the ledger chain by using SHAs.

C. High Frequency Verification Mechanism

When a ledger block is chained onto the existing ledger chain, a high frequency verifier, which is located on each node, is triggered immediately to work uninterruptedly for the new generated *contract-block* (denoted as X_n) and *ledger-block* (denoted as Y_n) pair. Each verifier constantly reads the content of the block pair and the content of the previous ledger-block (represents as Y_{n-1}). The updated ledger (represented as $\widehat{Y}_n$) is then calculated as $\widehat{Y}_n = f(X_n, Y_{n-1})$, where $f(\cdot)$ represents the calculation of balance, which is always based on the current contract and the previous ledger. In normal situations, the calculated ledger should be consistent with the recorded one. Otherwise, it indicates cyber-attack activity that has manipulated either the contract or ledger. Once an inconsistency is detected between Y_n and $\widehat{Y}_n$, an alarm will be sent immediately to the prosumer to notify of the abnormal event.

The effectiveness of the high frequency verification mechanism is as follows: Firstly, any attempt at trying to manipulate contents in the contract chain and the ledger chain individually will be immediately detected. This is because once there is any modification in either X_n or Y_n, the calculated $\widehat{Y}_n$ would be deviate from Y_n and the alarm is thereafter triggered. Secondly, the high frequency verification mechanism is capable of detecting the manipulations on both contract chain and the ledger-chain. Since blocks are sequentially chained using SHAs and the verifier works on each pair of contract block and ledger block with a high frequency scan rate, all blocks after the target pair of contract block and ledger block are then fractured and show inconsistent signals. The only way for cyber attackers to succeed is to control the majority of prosumers and re-write all pairs of contract block and ledger block from the targeted pair to the very recent pair within the time interval between two high frequency scans. However, for each pair of contract block and ledger block, content filling cannot happen at the same time because ledgers are always generated after contracts; yet alone the difficulty of taking control of majority prosumers. Therefore, the proposed high frequency verification mechanism can be considered as a sensitive cyber attacker detector.

V. Simulation Studies

A. Simulation Setup

To validate the proposed electricity trading mechanism, we simulate a P2P environment with a various number of prosumers. The load curve of the prosumers are generated based on the Australian “Smart Grid, Smart City” dataset [26], in which the electricity consumption data of more than 300 Australian residential users in the state of New South Wales are recorded. Rooftop photovoltaic and/or distributed wind power sources are simulated for each prosumer, where the capacity of each one is randomly generated in the range of [3 kW, 10 kW]. Then, one-day wind speed and solar radiation profiles used in [27] and [23] are scaled and applied. For each prosumer, the on-site battery energy storage system (BESS) is simulated with the power capacity randomly generated in the range of [2 kW, 10 kW], and the energy capacity of the BESS is randomly set as the value in the range of [8 hours, 24 hours] based on the power capacity. The local scheduling model used by the LCA is based on [23], shown in the Appendix. This scheduling model is solved by the Matlab Optimization toolbox and used in this paper to model individual prosumers to test the proposed multi-agent coalition formation and negotiation protocols, whilst acknowledging that many more sophisticated local scheduling models are available in the literature (e.g., [24], [29]).

24-hour horizon is simulated, with the duration of each time interval set to be 30 minutes; the negotiation deadline ($DL(\theta_k)$) and final contract determination deadline are set as two minutes and one minute before the actual starting time of the task, respectively. The values of negotiation factors α_j, β_i, τ, η are set to be 0.02, 0.03, 2, and 1.5 for all prosumers. The MAS is implemented in the Java Agent Development Environment (JADE) [28] and executed on a DELL workstation with 128G memory and 2 Intel Xeon processors.

B. Simulation Results

Firstly, we investigated the electricity trading performance of the system with different numbers of prosumers, i.e., varied from 50–300, with the step of 50. For convenience, the prosumers are named as P1, ..., P300. Fig. 6 shows the numbers of tasks and correspondingly reached final contracts in the system, together with the average computation time to accomplish the negotiation of a task. Fig. 6 also shows that with the increase of the prosumer number, more electricity trading tasks are generated, correspondingly more electricity trading contracts are reached. The number of tasks is increases in an approximately linear relationship, which is mainly because in this simulation we set 50 prosumers as base configurations, and other prosumers are simply replicated with some variations. When there are 300 prosumers, totally 1,721 tasks are generated over the 24 hours, and finally 4,211 contracts are formed. Meanwhile, the average negotiation time increases with the increase of the prosumer

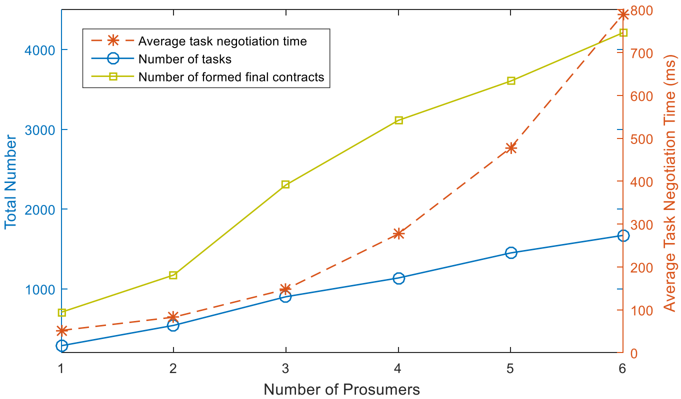

Fig. 6. Variations of total numbers of task and final contracts, and average task negotiation time.

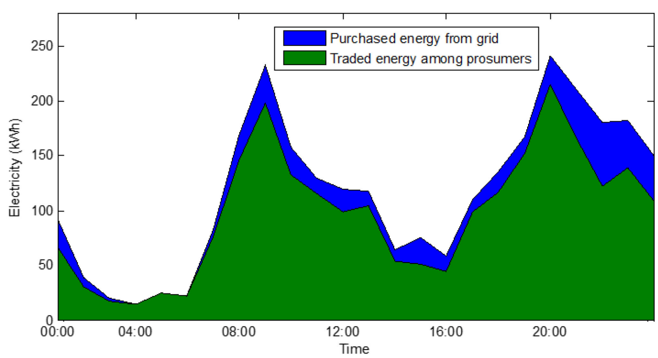

Fig. 7. Variations of total numbers of task and final contracts, and average task negotiation time.

number. This is because when there are more prosumers in the system, for a certain task, more prosumers would have the opportunity to participate in the coalition and perform negotiations with the buyer. Fig. 6 shows that when the communication network traffic is not considered, the average negotiation time is less than one second (about 700 ms) when there are 300 prosumers, which proves the efficiency of the proposed system. In practical applications, the negotiation time would depend on the real-time network traffic conditions.

Fig. 7 shows the total traded electricity among 300 prosumers and the electricity purchased by these prosumers from the grid. It can be seen that most of the deficit electricity detected by the prosumer are satisfied by trading electricity with other prosumers. Only for a small proportion of electricity, the trading negotiation is failed to reach agreement, and the prosumers have to purchase it from the grid at the retail price.

Next, as an example, we investigate a specific and representative agent coalition process. The timeline of the coalition formation process is shown in Fig. 8. At time 15:10 pm, The LCA of Prosumer P17 detects a 2.5 kW electricity shortage event in the period of 15:20–15:30 pm, then the SCA sends the trading request to its 3 neighbors. One neighbor (P19) which has surplus energy at [15:20 pm, 15:30 pm] responds to the request, and negotiates trading with P17. They negotiate to trade 0.27 kWh energy with the payment of 1.2 cents. Then, P17 further propagates the request to the neighbors of its 3 neighbors. Totally 8 prosumers respond to the request, and 6 temporary

TABLE IV
1-Day Operation Results of a Randomly Selected Prosumer P17

NoC_S	Sold Energy to Prosumers	NoC_B	Bought Energy from Prosumers	Bought Energy from Grid
28	7.03kWh	22	4.77kWh	0.85kWh

Note: 'NoC_S' means 'number of contracts signed as the seller'; 'NoC_B' means 'number of contracts signed as the buyer'.

TABLE V
Electricity Trading Summarization of the Prosumer Network

	No. of final contracts	Totally traded energy	Totally purchased energy from grid	Totally saved cost
50 prosumers	708	282.7 kWh	47.5 kWh	$42.6
100 prosumers	1,153	546.4 kWh	121.3 kWh	$79.5
200 prosumers	3,113	1315.5 kWh	281.9 kWh	$221.3
300 prosumers	4,211	2032.4 kWh	437.7 kWh	$378.2

contracts are formed. Finally, P17 signs two final contracts with P19 and P23. Compared to purchase all deficit energy from the grid, P17 can save 0.8 cents on this task. Table IV reports summarized one-day operation results of P17. Over the 24 hours, P17 totally signs 71 contracts with other prosumers acting either as a buyer or a seller. It sells 11.03 kWh electricity to other prosumers, buys 6.67 kWh electricity from external prosumers, and buys 0.87 kWh electricity from the grid. Fig. 9 illustrates the 24-hour internal energy resource scheduling performed by the LCA of P17, where the red line represents the normal load curve of the prosumer, and the stacked areas form the shifted load curve produced by the LCA, which are served by different energy sources.

Table V reports summarized 24-hour energy trading results of the whole prosumer network with different scales. In Table V, the column "totally saved cost" means the totally saved electricity purchase cost of all prosumers by buying the electricity from the prosumer network instead of from the grid. The results indicate that the developed energy trading framework can largely promote the energy sharing between prosumers, and can be considered as an alternative solution to foster the energy market in the energy delivery side.

Lastly, sensitivity studies are conducted for the four system parameters α_j, β_i, τ, and η. For each parameter, we vary its value while having other parameters fixed. The energy trading of the 100-prosumer network is investigated. The sensitivity study results are reported in Tables VI, VII, VIII, and IX, respectively.

The results (Table VI) show that with the increase of the seller's negotiation factor α_j, the number of formed final contracts decreases, and the total amounts of traded energy among prosumers also decreases. Correspondingly, the amount of purchased energy from the grid increases. These trends are because the larger of α_j means the seller asks for a higher price, which will increase the probability for the seller to reject the offer. As for the buyer's negotiation factor β_i, the results (Table VII) show that under the condition that all prosumers use a same β_i, its

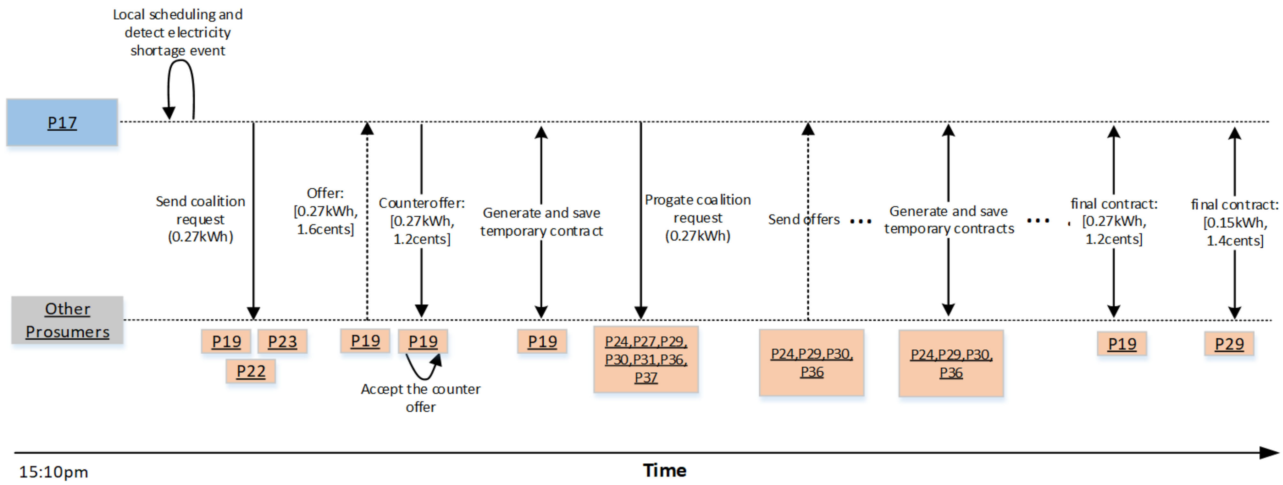

Fig. 8. Timeline of a typical coalition formation process.

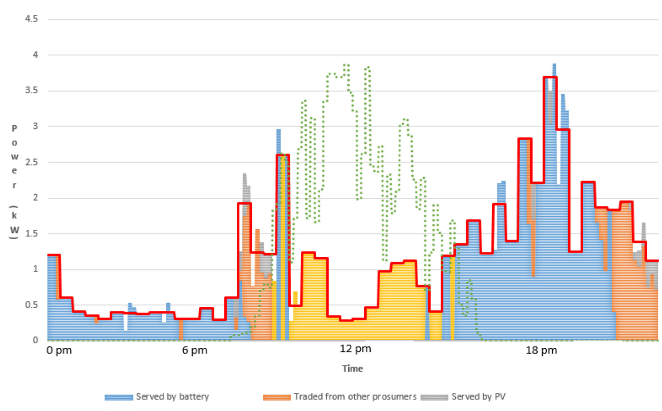

Fig. 9. 24-hour local scheduling results of prosumer P17.

TABLE VI
SENSITIVITY STUDY OF NEGOTIATION FACTOR α_j

α_j	No. of final contracts	Totally traded energy	Totally purchased energy from grid
0.01	1,189	557.3kWh	110.4kWh
0.02	1,153	546.4kWh	121.3kWh
0.03	1,104	513.3kWh	154.4kWh
0.05	862	420.1kWh	247.6kWh
0.08	302	145.7kWh	522.0kWh
0.1	289	141.4kWh	526.3kWh

Note: β_i, τ, and η are fixed as 0.03, 2, and 1.5.

TABLE VII
SENSITIVITY STUDY OF NEGOTIATION FACTOR β_i

β_i	No. of final contracts	Totally traded energy	Totally purchased energy from grid	Average trading price
0.01	1,174	549.2kWh	118.5kWh	0.17$/kWh
0.02	1,155	545.9kWh	121.8kWh	0.13$/kWh
0.03	1,153	546.4kWh	121.3kWh	0.12$/kWh
0.05	1,135	545.0kWh	122.7kWh	0.09$/kWh
0.08	1,120	541.4kWh	126.3kWh	0.04$/kWh
0.1	1,113	537.2kWh	130.5kWh	0.03$/kWh

Note: α_j, τ, and η are fixed as 0.02, 2, and 1.5.

TABLE VIII
SENSITIVITY STUDY OF COALITION PROPAGATION FACTOR τ

τ	No. of final contracts	Totally traded energy	Totally purchased energy from grid
1	379	302.2kWh	365.5kWh
2	1,153	546.4kWh	121.3kWh
3	1,335	601.1kWh	66.6kWh

Note: α_j, β_i, and τ are fixed as 0.02, 0.03, and 1.5.

TABLE IX
SENSITIVITY STUDY OF DECISION MAKING FACTOR η

η	No. of final contracts	Totally traded energy	Totally purchased energy from grid
1	833	525.3kWh	142.4kWh
1.5	1,153	546.4kWh	121.3kWh
2	1,537	561.0kWh	106.7kWh
3	1,537	561.0kWh	106.7kWh
4	1,537	561.0kWh	106.7kWh

Note: α_j, β_i, and τ are fixed as 0.02, 0.03, and 2.

TABLE X
ELECTRICITY TARIFF USED IN THE PROSUMER SIMULATION

Time-of-Use tariff scheme 1	
Period	Rate ($/kWh)
Peak: 2-8 PM	0.36
Shoulder: 7AM-2PM, 8-10PM	0.14
Off-Peak: 10PM-7AM	0.08
Time-of-Use tariff scheme 2	
Period	Rate ($/kWh)
Peak: 2-7 PM	0.43
Sub-Peak: 12AM-2PM; 7PM-8:30PM	0.31
Shoulder: 7AM-12AM, 8:30-11PM	0.1108
Off-Peak: 11PM-7AM	0.0614

different values have little influences on the totally P2P traded energy amounts. However, it significantly affects the averaged trading prices. The larger of β_i, the lower of the averaged trading price.

Table VIII shows that with the larger value of the coalition propagation factor τ, more contracts are formed and more P2P traded energy is achieved. This is understandable because the large value of τ allows a prosumer to negotiate more with other prosumers. Lastly, Table IX shows that when the decision making factor of the seller (η) varies from 1 to 2, more contracts are formed and more energy are traded among prosumers. This is because the larger η generally means less counteroffers can be formed. However, when η is larger than 2, adjusting its value will not affect the P2P energy trading process. This is because when η is larger than 2, thecounteroffer rejection condition Eq. (9) is rarely triggered, leading to all counteroffers being accepted as temporary contracts.

VI. Conclusion and Practical Considerations

In this paper, a distributed electricity trading system is proposed for electricity prosumers within a distribution network that includes two layers. In the upper layer, a multi-agent system-based trading negotiation mechanism is proposed to enable prosumers to negotiate the electricity trading contract; in the lower layer, a Blockchain based contract settlement system is proposed to implement the secure settlement of the contracts. Simulation results show that the proposed electricity trading mechanism can efficiently promote energy sharing among the prosumers and overall enhance the energy efficiency of the distribution network.

Market mechanism design for distribution side is an emerging research topic in recent year. Compared with existing research on distributed energy trading (e.g., [6], [9]–[11]), the proposed system decouples the upper-level trading negotiation process among prosumers from the autonomous, local energy management of individual prosumers. This structure is flexible and can therefore adapt to prosumers with different types and heterogeneous energy resources. Essentially, the system described in this paper can be directly applied to prosumers connected to a same feeder of a radiate distribution network (for example, residential units of multiple buildings in a same area), where power flow issues of the whole distribution network can be neglected. To apply the proposed system on a larger territory, a certain regulation and supervision mechanism needs to be established, where a third party (e.g., the utility or distribution system operator) would check and approve the trading contracts formed in the proposed system to ensure the power flows and node voltages of the distribution system are in secure ranges, in prior to the settlement of the contracts.

Appendix

The local scheduling of each prosumer is modelled to minimize the prosumer's energy management cost:

$$F = \min \sum_{t=1}^{T} \Big(pr_{s,t}^{retail} \Delta t P_t^{buy} + c\_bess(P_t^{bess}) + cost\_il(P_t^{shed}) \Big) \tag{15}$$

where $c\_bess(P_t^{bess})$ is the operational cost of BESS; $cost\_il$ (P_t^{shed}) is the cost of shedding the interruptible load; P_t^{bess} is the power output of the BESS at time t; P_t^{shed} is the shed power of the interruptible loads at time t (kW). It is considered that the maximum amount of the interruptible load at time t is $P_t^{shed} \leq \lambda \cdot P_t^{load}$, where P_t^{load} is the load of the prosumer at t and λ is a coefficient in the range of (0,1). In this paper, $c\_bess(P_t^{bess})$ and $cost\_il(P_t^{shed})$ are considered to be with following forms:

$$c\_bess(P_t^{bess}) = \beta P_t^{bess} \Delta t + \beta E_t^{bess} \eta_l \Delta t \tag{16}$$

$$cost\_il(P_t^{shed}) = c_{il} P_t^{shed} \Delta t \tag{17}$$

where β is the cost coefficient of the BESS lifetime depression; η_l is the leakage loss of the BESS (%); c_{il} is the load shedding cost coefficient (\$/kWh); E_t^{bess} is the energy stored in the BESS at time t (kWh). Energy changing of BESS is calculated as:

$$E_{t+1}^{bess} = E_t^{bess} + \Delta t P_t^{bess} - |P_t^{bess}| \eta_c \Delta t - E_t^{bess} \cdot \eta_l \cdot \Delta t \tag{18}$$

where E_{BESS}^t is the energy stored in the BESS at time t. The SOC of BESS at time t is then calculated as follows,

$$SOC_t = E_t^{bess} \big/ E^{bess,rate} \tag{19}$$

where $E^{bess,rate}$ is the rated energy capacity of the BESS (KWh); η_c is the BESS charging/discharging efficiency (%). Model (11) is subjected to following operational constraints:

a) BESS power limits constraint

$$P^{bess,dsc} \leq P_t^{bess} \leq P^{bess,chr} \tag{20}$$

where $P^{bess,dsc}$ and $P^{bess,chr}$ represent the rated discharging and charging power of the BESS.

a) Interruptible load capacity constraint

$$P_t^{il} \leq \lambda \cdot P_t^{load} \; 0 \leq \lambda \leq 1 \tag{21}$$

b) Load balance constraint

$$P_t^{res} + P_t^{bess} = P_t^{load} - P_t^{il} + P_t^{buy} \tag{22}$$

where P_t^{res} is the prosumer's renewable energy output at time t (kW).

In the simulation described in this paper, the parameter setting is as below. For each prosumer, λ is randomly generated within [0, 0.3]; β is randomly generated within [0.02, 0.06]; c_{il} is randomly generated in the range of [0.03, 0.08]. For all prosumers, η_c is set to be 0.9 for both charging and discharging. Meanwhile, for each prosumer, its used electricity retail tariff is randomly assigned as one of three time-of-use tariff schemes shown in Table V, which are modified from the time-of-use tariff published by EnergyAustralia [30]. Other settings are referred to Section V-A.

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