Blockchain-based Power Energy Trading Management

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Distributed peer-to-peer (P2P) power energy markets are emerging quickly. Due to central governance and lack of effective information aggregation mechanisms, energy trading cannot be efficiently scheduled and tracked. We devise a new distributed energy transaction system over *energy IIoT* based on predictive analytics, blockchain and smart contract technologies. We propose a solution for scheduling distributed energy sources based on the *Minimum Cut Maximum Flow* (MCMF) theory. Blockchain is used to record transactions and reach consensus. Payment clearing for the actual power consumption is executed via smart contracts. Experimental results on real data show that our solution is practical and achieves a lower total cost for power energy consumption.

CCS Concepts: • **Information systems** → **Data analytics**; • **Computing methodologies** → **Planning and scheduling**; • **Applied computing** → **Command and control**.

Additional Key Words and Phrases: distributed energy market, blockchain, smart contract, predictive analytics, minimum cut maximum flow

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1 INTRODUCTION

The scheduling and transaction management of distributed power energy resources in energy markets is a subject of great relevance in nowadays energy systems [18, 19]. The consumers want the power supply with lowest cost possible and the producers would like to sell all their energy with highest price possible, while the transporters mainly focus on power transportation efficiency and dissipation. Management of the consumption, production and transportation of power energy between these parties is of paramount importance for a city and the related energy market.

Many countries have been trying to facilitate the distribution of the markets for power energy production and consumption. Chinese government recently announced policies to encourage the

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distributed clean energy sources such as photovoltaic and wind power to connect to the State Grid for sell [21]. However, there are several challenges and problems in the energy-trading market as follows:

- Due to the tradition of central governance and the lack of effective aggregation mechanisms, the distributed clean energy sources cannot be efficiently connected to the State Grid and be efficiently used; this would result in the waste of energy.
- The consumers and producers cannot make the transactions directly, and it is difficult to track the prices for power buying and selling because of the centralized market.
- The price structure of the power energy market varies considerably for different time periods and different energy sources. A comprehensive strategy model is needed for the overall scheduling of the distributed energy resources.

In the city domain, clean energy produced by plots, such as residential houses and factories, is cheaper than the grid energy most of the time. Due to the challenges and problems mentioned above, there are not many competitions between different energy sources and peer-to-peer energy trading for plots. This paper aims to handle the prediction and scheduling on the distributed energy from various domains of a city, for minimizing the total energy consumption cost of the whole city domain given a predefined price policy of grid and clean power. We collect the data of power consumption, production and transportation from the sensors over the Internet-of-Things (IoT) networks, and record the data in blockchain ledgers [33]. The collected data are used for the prediction of power consumption and production capabilities. Smart contract is triggered periodically for the payment and the clearing of the power consumption bills.

The main contributions of this paper are summarized as follows:

- We study the aggregation of distributed energy transactions in a city domain sector to minimize the energy consumption cost. A distributed energy transaction system (DETS) is proposed based on predictive analytics, blockchain and smart contract technologies over energy Industrial Internet-of-Things (E-IIoT).
- Time-series data are collected and analyzed for the prediction of energy consumption and production. We propose a solution for scheduling of distributed power energy sources based on the Minimum Cut Maximum Flow theory. Blockchain is used to record these data and reach consensus of the transactions. Payments clearing for the actual power consumption is executed with smart contracts.
- Application results with real consumption data, show that our solution achieves a lower total cost for power energy consumption. Performance evaluation over smart contracts demonstrates that our system is practical.

The rest of the paper is organized as follows. Section 2 reviews briefly on related studies. Section 3 presents the proposed distributed energy transaction system, including the design of ledgers and blockchain operations. Section 4 formulates the problem and the assumptions of the distributed energy scheduling, and proposes our solution, which includes algorithms for scheduling, control, and smart-contract-based payment clearing. In Section 5, we implement an industrial application to validate our proposed system, and we present the analysis and discussions of the experimental results in a real-world application setting. Section 6 concludes the paper and presents our future work.

2 RELATED WORK

Renewable energy-aware pricing scheme was established to minimize the total electricity cost among all customers through cross entropy optimization, which can reach the theoretical lower bound of the community wide total electricity bill [15]. To obtain the energy availability and the minimum selling cost negotiated in market, an aggregator was provided to manage and integrate the distributed energy resources in energy systems and markets [24]. Game theory, with proper penalty and payoff depending on the behavior of the consumers, was presented to balance energy consumption in clustered wireless sensor networks [32]. This scheme has obtained the Nash equilibrium strategy of the clustering game through convex optimization. Specifically, each sensor node can achieve its own maximal payoff when it makes the decision according to this strategy.

There are some recent studies in the forecasting of energy consumption, Yu et al. [34] presented a clustering protocol for local electricity consumption forecast and optimization, providing an efficient approach for energy usage management solutions. With this protocol, they ensured that electricity consumption is balanced at the distribution system level. In [16], the authors developed a series of neural networks to design a decision support system for predicting, analyzing and monitoring the performance indicators in the field of renewable energy, which could forecasts the total active energy export and the total active power, when knowing the solar irradiation, the ambient temperature, the humidity, the wind direction and the wind speed.

Management of hybrid energy has attracted extensive attentions. Hill et al. [8] presented a technical overview of battery energy storage systems and integrated solar power to the electricity distribution system, and illustrated a variety of modes of operations for battery energy storage systems in grid-tied solar applications. It can obtain more effective grid management and create a dispatchable power product from as-available resources. In [28], the authors introduced a two-stage power control strategy to smooth the power output of a grid connected photovoltaic power plant. This scheme allows the customers to choose between photovoltaic power and grid power. A unified power management scheme was proposed for a grid interactive hybrid micro-grid with hybrid energy storage systems in [11]. The technique did not require forecasting of weather and measurement of load currents or powers, which reduced the complexity and the number of sensors. Decentralized and distributed power system integrated with photovoltaic power were presented in [30] for the reliability of hybrid power systems. Li et al. [13] studied the reliability issue of power grid w.r.t. the increasing demand on charging the Plug-in Electric Vehicles.

Peak shaving is an important strategy for distributed power energy scheduling and management. Different peak shaving methods [27] have been presented, including the integration of energy storage system, demand side management, and integration of electric vehicle to the grid. There has been a significant increase in penetration of customer-owned photovoltaic panels [8, 22, 28] for energy storage systems. The authors of [23] proposed a home energy management scheme for cost and peak load reduction for single household.

Blockchain technology has led to an increasing interest in wide span of technical communities, such as finance [5], supply chain [1], public service [25], healthcare [17] and IoT [7, 31]. It is considered as an implementation of a shared secure distributed ledger, where the participants can read from and write to, when specific constraints are met. Smart contracts [26] provide the ability to directly track and execute complex agreements between parties without human interaction, which resides on the blockchain, and as such its code can be inspected by every network participant. Blockchain technology is applied in power energy markets with IIoT because of its advantages of decentralization, anonymity and fairness [2, 12, 14, 20]. Our previous work [29] has indicated that permissioned blockchain is applicable to decentralized transaction systems. In this paper, we integrate the permissioned blockchain, namely Hyperledger Fabric [3], for data storage, energy transaction, pre-sell, and bill payments. Different entities in the energy market are extracted as blockchain peers participating in the deal.

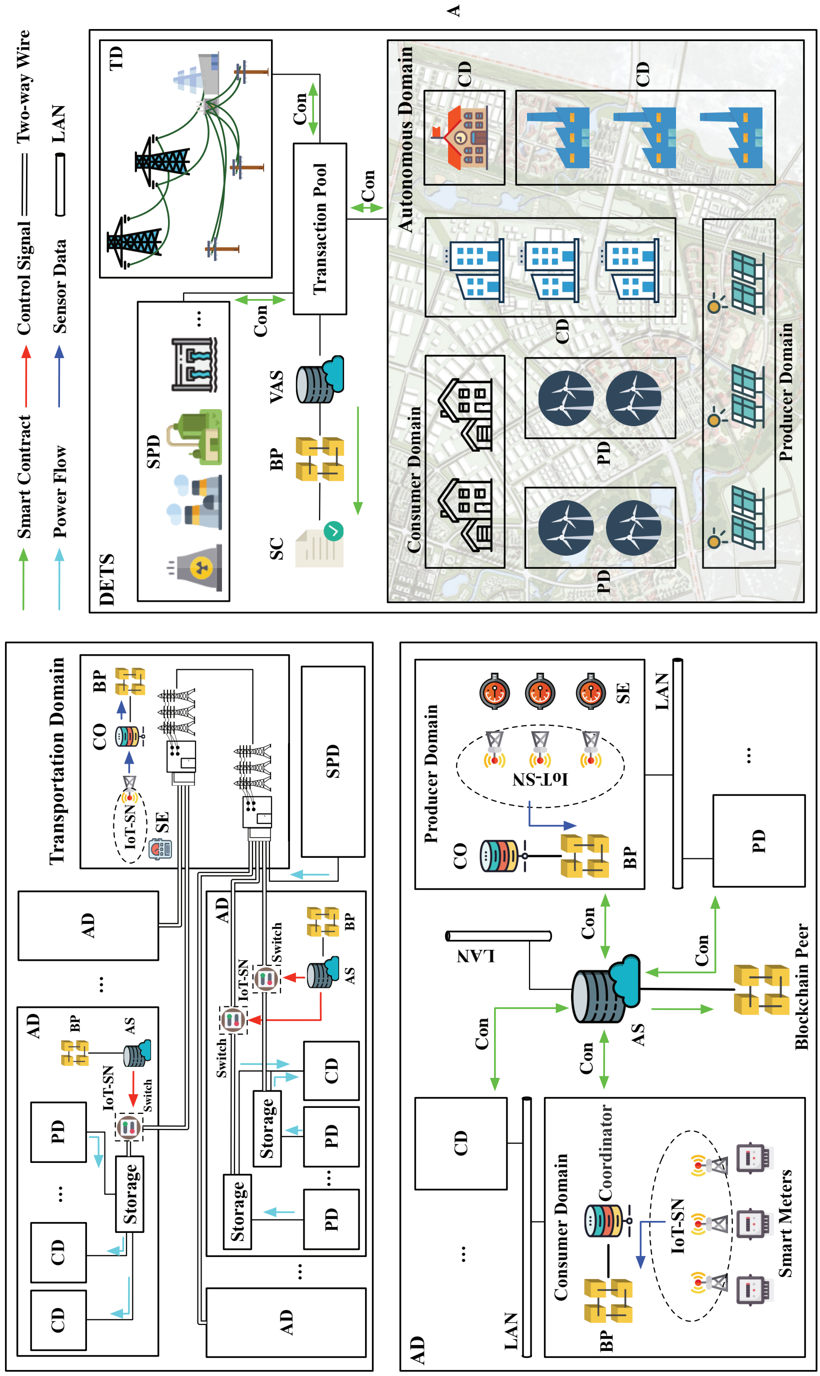

Fig. 1. Blockchain-based distributed power energy transaction management over E-IIoT. Part A is a sketch of DETS. Part B shows the detail logical frame of AD. Part C shows the relationship between ADs, TD and SPD.

3 BLOCKCHAIN BASED DISTRIBUTED ENERGY TRANSACTION SYSTEM

3.1 System Description

We aim to aggregate the transactions for a distributed power energy market. The system has been designed in a flexible and feasible way. Using the different domains and adjustable parameters, it can be readily adopted in power markets in the context of different countries. In Figure 1, red arrows indicate control signals using communication messages. Green arrows represent hyperledger synchronizations between the blockchain nodes. Light blue denotes the power flow. Navy blue arrows indicate the data collecting operations from sensors. Consider the following system and entities depicted in Figure 1:

- *Autonomous Domain (AD)*: In each AD there are several CDs and PDs, or just CDs without any PD, or just PDs without any CD. AD is the minimum unit to deal with energy transactions: buying, selling energy from other ADs or the SPD. In AD, consensus (Con) could be made for the electricity price for each CD and PD through smart contracts.
- *Consumer Domain (CD)*: CD is the basic unit that connects to the electricity storage of PDs in its AD. In each CD there are several users. A user is the atomic power consumption unit in CD, which could be a family or an enterprise with a smart meter to measure the power usage.
- *Producer Domain (PD)*: PD provides the self-produced energy, which could be for self use, or be sold to other ADs through the transaction pool, or be sold to the SPD. In each PD, there is an electricity storage and a switch controlled by the E-IIoT. If the volume and voltage of the storage is lower than a normal value, the switch will turn to the wire of buying electricity from the SPD. If the volume and voltage of the storage exceeds the maximum threshold, the switch will turn to the wire of selling electricity to SPD.
- *Special Producer Domain (SPD)*: SPD provides unlimited power energy from the State Grid, such as hydro power, nuclear power and coal power. SPD does not consider the limit of storage, but PD does. Therefore, PD needs cost computation and SPD cannot be a sub-domain of PD.
- *Transportation Domain (TD)*: The power energy is transported in TDs between ADs. When electricity is transported in TD between ADs, there exists power dissipation.

The above entities represent the blockchain peers in the DETS, who can share all the power transaction information. The detailed data of power consumption, production and transportation are recorded in blockchain. Smart contract is distributed between these peers for electricity presell and bill payment clearing. In CD, PD and TD, E-IIoT is introduced to collect the data of power consumption, power productivity and power dissipation rate with secondary equipment such as smart meter, watt meter and volt meter. For E-IIoT, Zigbee and Narrow Band IoT [4] technologies and sensors are deployed for data collection and control signal transmission. Autonomous server (AS) is responsible for local optimization of power energy consumption and distribution, and voted autonomous server (VAS) is used for global prediction and optimization. Coordinator (CO) is for forwarding the collected data from the sensor network.

The flows for data and control signals of all operations are depicted in Figure 1. There are four types of flows in DETS: power flow, sensor data flow, control signal flow and smart contract (SC) flow. Control signal is used for the power flow/sources switching inside ADs. Sensor data flow gathered from secondary equipment (SE) would be distributed to different blockchain peers (BP) for storage. SPD, ADs and TDs will get the consensus for power presell in the transaction pool and generate SC to BP, as shown in part A of Figure 1. PDs and CDs in a single AD will get the consensus through VS for the power scheduling and switch control signal, as shown in part C of Figure 1. The acronyms for entities mentioned above have been summarized as follows:

A Summary of Acronyms

AD	Autonomous Domain	CD	Consumer Domain
PD	Producer Domain	SPD	Special Producer Domain
TD	Transportation Domain		
AS	Autonomous Server	VAS	Voted Autonomous Server
CO	Coordinator	SC	Smart Contract
SE	Secondary Equipment	BP	Blockchain Peer

3.2 Ledgers Design and Operations in DETS

Five groups of data are collected from sensors in E-IIoT and appended to ledgers of the blockchain in every Δt: consumed electricity, consumed self-produced electricity, productive electricity, residual electricity in storage and power dissipation rate as shown in Table 1. For example, Ledger-CE-AD-CD-User represents the consumed electricity for each user of every CD from all ADs. For all entries there are indexes i, j and k to label specific user's $data$. Ledger-CE-AD-CD-User belongs to the same CD converge into Ledger-CE-AD-CD for this CD, and Ledger-CE-AD-CD belongs to the same AD converge into Ledger-CE-AD.

Table 1. Data recorded in ledgers of blockchain from sensors

Categories	**Ledgers** (ID:Ledger-)	**Entries**
Consumed Electricity	CE-AD-CD-User CE-AD-CD CE-AD	$(t, i, j, k, data)$: consumed electricity for user$_k$ in CD$_j$ of AD$_i$ $(t, i, j, data)$: consumed electricity for CD$_j$ of AD$_i$ $(t, i, data)$: consumed electricity for AD$_i$
Consumed Self-prod Electricity	CSE-AD-CD CSE-AD	$(t, i, j, data)$: consumed self-produced electricity for CD$_j$ of AD$_i$ $(t, i, data)$: consumed self-produced electricity for AD$_i$
Productive Electricity	PE-AD-PD PE-AD	$(t, i, j, data)$: self-produced electricity for PD$_j$ in AD$_i$ $(t, i, data)$: self-producted electricity for AD$_i$
Residual Electricity	RE-AD-PD RE-AD	$(t, i, j, data)$: redidual electricity for PD$_j$ in AD$_i$ $(t, i, data)$: redidual electricity for AD$_i$
Sold Electricity	SE-AD-PD SE-AD	$(t, i, j, data)$: sold electricity for PD$_j$ in AD$_i$ $(t, i, data)$: sold electricity for AD$_i$
Power Dissipation Rate	pdr	(t, m, r_m): power dissipation rate for TD$_m$

For DETS, the main operations can be summarized as sets $\mathcal{OP} = \{\mathcal{OP}_1, \mathcal{OP}_2, \mathcal{OP}_3, \mathcal{OP}_4, \mathcal{OP}_5\}$. Each operation has its time interval, as depicted in Figure 2. $\mathcal{OP}_1$ is repeated in Δt among the E-IIoT, then CO writes the data into blockchain peer. $\mathcal{OP}_2$, $\mathcal{OP}_3$, $\mathcal{OP}_4$ and $\mathcal{OP}_4$ are repeated in ΔT sequentially by AS/VAS and BP. For prediction, L past feedbacks are used iteratively.

4 FORMULATION AND IMPLEMENTATION FOR DETS

In this section, we present the problem definition and assumption about the distributed energy scheduling, to maximized the energy usage and minimized the consumption cost for the overall city sector.

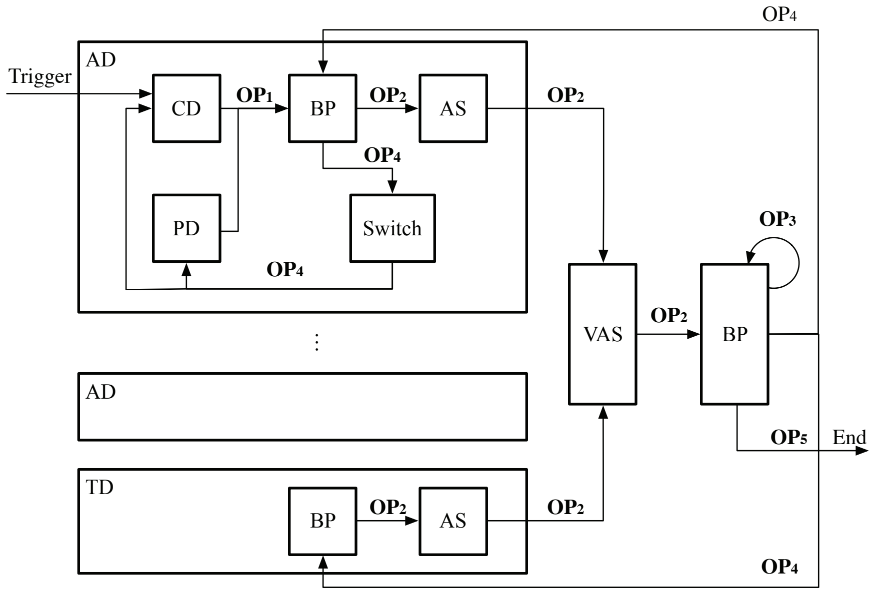

Fig. 2. The main operations for DETS in each time slot: $\mathcal{OP}_1$, collecting data from E-IIoT to block entries; $\mathcal{OP}_2$, reading data from BP, voting one AS as VAS and predicting for power scheduling of ADs in city sector; $\mathcal{OP}_3$, generating and installing of SC for power presell; $\mathcal{OP}_4$, reading control signal from BP and transmitting it over E-IIoT to specific power source for each AD according to prediction; $\mathcal{OP}_5$, generating and installing of SC for bill payment and clearing between different entities.

4.1 Problem Formulations

Based on the system framework for the management and scheduling of power energy market as given in Section 3, we assume that: 1) power supply from SPD is unlimited, while supply from PDs is limited; 2) the power price of SPD varies with time interval ΔT, and the power price of PD is fixed for PDs; 3) the power prices of SPD and PD at any moment are public to all ADs; 4) in the city sector, the total power energy consumption at $(t + \Delta T)$ is fixed:

$$E = E_b + E_s, \tag{1}$$

where $E_b,\ E_s$ can be summarized as the following equations respectively:

$$E_b = E_{b0} + E_{b1} = \sum_{i=1}^{N} be_i^{spd} + \sum_{i=1}^{N}\sum_{j=1}^{N} be_{ij}, \tag{2}$$

$$E_s = \sum_{i=1}^{N} ce_i^s. \tag{3}$$

Let function f_i denote the power consumption cost of each AD_i,

$$f_i = be_i^{spd} pr_{spd} + \sum_{j=1}^{N} be_{ij} pr_{pd} - \sum_{j=1}^{N} se_{ij}(pr_{pd} + pr_{ij}). \tag{4}$$

Variables and parameters

t	current time
Δt	time interval for data collection from sensor networks
ΔT	time interval for prediction and smart contract execution, $\Delta T = n\Delta t$
N	number of ADs in the city sector
K	number of ADs with PD
M	number of TDs between all ADs
L	number of samples for prediction
E	total power consumption of all ADs at $(t + \Delta T)$
E_b	total power consumption of all ADs bought from other ADs and SPD at $(t + \Delta T)$
E_s	total self-produced power consumption of all ADs at $(t + \Delta T)$
E_{b0}	total power consumption of all ADs bought from SPD at $(t + \Delta T)$
E_{b1}	total power consumption of all ADs bought from other ADs at $(t + \Delta T)$
ce_i	power consumption of AD_i at $(t + \Delta T)$
ce_i^s	power consumption of self-produced electricity for AD_i at $(t + \Delta T)$
be_{ij}	bought electricity from AD_j for AD_i at $(t + \Delta T)$
se_{ij}	sold electricity to AD_j for AD_i at $(t + \Delta T)$, $se_{ij} = be_{ji}$
pe_i	power production of AD_i at $(t + \Delta T)$
re_i	residual electricity of AD_i at $(t + \Delta T)$
re_i^{max}	maximum of redisual electricity for AD_i at $(t + \Delta T)$
be_i^{spd}	bought electricity from SPD for AD_i at $(t + \Delta T)$
pr_{ij}	minimum price for dissipation of power transportation between AD_i and AD_j of TDs
pr_{pd}	fixed power price for PD
pr_{spd}	power price for SPD at $(t + \Delta T)$
pdr	power dissipation rate

For the city sector, the aim is to minimize the total consumption cost function F for power energy. And the problem can be summarized as follows :

$$\min F = \min \sum_{i=1}^{N} f_i \tag{5a}$$

$$\text{s.t. } ce_i = be_i^{spd} + ce_i^s + \sum_{j=1}^{N} be_{ij}, \tag{5b}$$

$$\sum_{j=1}^{N} se_{ij} \leq (re_i + pe_i) - ce_i^s, \tag{5c}$$

$$ce_i^s + pe_i \leq re_i^{max}, \tag{5d}$$

$$be_{ij} = se_{ji}, \forall i, j \in [1, N]\,. \tag{5e}$$

According to (2), (4) and (5e), F can be derived as:

$$\begin{aligned} F &= \sum_{i=1}^{N} be_i^{spd} pr_{spd} + \sum_{i=1}^{N}\sum_{j=1}^{N} be_{ij} pr_{pd} \\ &- \sum_{i=1}^{N}\sum_{j=1}^{N} se_{ij}(pr_{pd} + pr_{ij}) \\ &= E_b pr_{spd} - \sum_{i=1}^{N}\sum_{j=1}^{N} se_{ij}(pr_{spd} + pr_{ij}). \end{aligned} \tag{6}$$

E_b and pr_{spd} are fixed at $(t + \Delta T)$ and according to (5c), equation (6) has a minimum value if and only if:

$$\sum_{i=1}^{N}\sum_{j=1}^{N} se_{ij} = \sum_{i=1}^{N} \Big[(re_i + pe_i) - ce_i^s\Big],$$

which means all the ADs should sell their residual electricity after self consumption as much as possible. Then, the problem can be rewritten as:

$$\min F = \max \sum_{i=1}^{N}\sum_{j=1}^{N} se_{ij}(pr_{spd} + pr_{ij}), \tag{7a}$$

$$\text{s.t.} \sum_{i=1}^{N}\sum_{j=1}^{N} se_{ij} \le \sum_{i=1}^{N} \Big[(re_i + pe_i) - ce_i^s\Big]. \tag{7b}$$

It can be seen from (7a) and (7b) that all ADs should try to sell out the residual power energy if any. This is a multi-source multi-sink *Minimum Cut Maximum Flow* (MCMF) problem [6]. The minimum cut means the dissipation of transportation power should be less, and maximum flow means the residual electricity should be sold and transported to other ADs as much as possible. The MCMF problem is based on a directed graph representation of the dynamic resource allocation problem. The directed graph is represented by $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$, with $\mathcal{V}$ corresponding to the set of vertices and $\mathcal{E}$ is the set of arcs.

4.2 Solutions

Let $\mathbb{C} = [ce_i]_{1\times N}$, $\mathbb{P} = [pe_i]_{1\times N}$, and $\mathbb{R} = [re_i]_{1\times N}$ denote the power consumption, power production and power residual of ADs, respectively at time $(t + \Delta T)$. Power residual $\mathbb{R}$ can be collected from the storage at any moment. For $\mathbb{C}$ and $\mathbb{P}$, there is some regularity in all industries for electricity consumption, and power producitivity depends on the seasonal variances of climate a lot. Therefore, the predictive analytics approach is introduced to address this problem. For the time series prediction issue, there are many algorithms with excellent performance. In this work we select the *Long Short Term Memory* (LSTM) [9] method to predict the electricity consumption and production at next ΔT. LSTM has been proven effective in sequence learning with temporal correlations, and it has been successfully applied in power load forecasting [10]. We need to handle the prediction and the actual scheduling of the power energy transaction, payments, and deal with the deviation between prediction and reality for next interval. In particular, to predict the data at $(t + \Delta T)$, the past L data will be used in training. For AD$_i$, $i \in [1, N]$, data are extracted from blockchain as series: $CE_i = \{ce_i^{t-(L-1)\Delta T}, ce_i^{t-(L-2)\Delta T}, ..., ce_i^t\}$, and $PE_i = \{pe_i^{t-(L-1)\Delta T}, pe_i^{t-(L-2)\Delta T}, ..., pe_i^t\}$, for training predictors $\mathcal{P}_i^{ce}, \mathcal{P}_i^{pe}$. Then, $\mathbb{C} = \{\mathcal{P}_i^{ce}(t + \Delta T), i \in [1, N]\}$, $\mathbb{P} = \{\mathcal{P}_i^{pe}(t + \Delta T), i \in [1, N]\}$.

Algorithm 1: Power Energy Scheduling

Input: ADs, $\mathbb{C}$, $\mathbb{P}$, $\mathbb{R}$
Output: $\mathbb{B}$, $\mathbb{S}$
Initialize: $\mathrm{AD}_p \leftarrow \emptyset$, $\mathrm{AD}_{np} \leftarrow \emptyset$, $\mathbb{S} \leftarrow \emptyset$, $\mathbb{B} \leftarrow \emptyset$
Divide ADs into AD_p and AD_{np}
for Each $\mathrm{AD}_k \in \mathrm{AD}_p$ **do**
  Separate CDs and PDs in AD_k into two parts: $\{\mathrm{PD}_k\}$, $\{\mathrm{AD}_k\}$
end for
Form graph $\mathcal{G}_a = \langle \mathcal{V}_a, \mathcal{E}_a \rangle$, with:
$\mathcal{V}_a = \{\mathrm{AD}_i | i \in [1, N]\} \cup \{\mathrm{PD}_i | i \in [1, K]\} \cup$
$\{\mathrm{SPD}\} \cup \{s, t\}$,
$\mathcal{E}_a = \{\mathrm{TD}_i | i \in [1, M]\} \cup \{ae\}$
Initialize the capacity and cost of each edge $\in \mathcal{E}_a$ according to $\mathbb{C}, \mathbb{P}, \mathbb{R}$
$\mathbb{B} = \mathrm{MCMF}_{ap}(\mathcal{G}_a)$
$\mathbb{S} = \left[be_{i,j}\right]^T_{N \times N}$
return $\mathbb{B}$, $\mathbb{S}$

From the description in Section 3, we divide ADs into two groups: AD_p and AD_{np}, where AD_p denotes the ADs with PDs and AD_{np} denotes the ADs without PDs. Then PDs, CDs in AD_p can be separated to two parts for new graph. SPD is also added to the graph for the solving of MCMF problem. Augmenting path is used to solve this issue [29], in which vertices source s, sink t and also the augmenting edges ae are augmented to original graph $\mathcal{G}$, generating a new graph $\mathcal{G}_a$. Hence, $\mathcal{G}_a = \langle \mathcal{V}_a, \mathcal{E}_a \rangle$ will have $\mathcal{V}_a = \{\mathrm{AD}_i | i \in [1, N]\} \cup \{\mathrm{PD}_i | i \in [1, K]\} \cup \{\mathrm{SPD}\} \cup \{s, t\}$ and $\mathcal{E}_a = \{\mathrm{TD}_i | i \in [1, M]\} \cup \{ae\}$. It can be inferred that $|\mathcal{V}_a| = (N + K + 3)$ and $|\mathcal{E}_a| = (M + N + K + 2)$. For the target of power scheduling from AD_p and SPD to AD_{np} or AD_p, we have to solve the shortest path for graph $\mathcal{G}_a$. After that, the standard augmenting path algorithm can be applied to $\mathcal{G}$ for MCMF, naming it MCMF_{ap}. Let $\mathbb{S} = \left[se_{i,j}\right]_{N \times N}$ denotes the scheduling energy between all ADs, where se_{ij} means power energy selling from AD_i to AD_j; and let $\mathbb{B} = \left[be_{i,j}\right]_{N \times N} = \left[se_{i,j}\right]^T_{N \times N}$. The power energy scheduling algorithm can be summarized as Algorithm 1.

Algorithm 2: Switch Signal Control over E-IIoT

Input: AD_i, $\mathbb{C}$, $\mathbb{R}$, $\mathbb{S}$
Output: Control signal for Switches in AD_i
for Each $\mathrm{PD}_j \in \mathrm{AD}_i$ **do**
  Switch (Condition):
    Case $ce_i > 0$ and $re_j >$ threshold:
      Turn Switch_j to selling wire, update se_i, ce_i
    Case $ce_i > 0$ and $re_j <$ threshold:
      Turn Switch_j to buying wire, update ce_i
    Case $ce_i == 0$ and $re_j >$ threshold:
      Turn Switch_j to selling wire, update se_i
    Case $ce_i == 0$ and $re_j <$ threshold:
      Break Switch_j
end for

When $\mathbb{S}$ is resolved, the related SM for power presell scheme between all ADs is generated and installed at every peer of the blockchain for consensus. Once the consensus is reached, it is triggered for execution, which would lead AS sending the control signals to switches for specific energy sources scheduling. Algorithm 2 depicts the detailed control algorithm of power switches in each AD.

Algorithm 3: Smart Contract for Power Energy Consumption and Transportation Payment

Input: $\mathbb{S}$, $\mathbb{C}^*$, pr_{spd}, pr_{pd}, Ledger-CE-AD, Ledger-CES-AD, Ledger-SE-AD, Ledger-pdr
Output: $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3, \mathcal{P}_4$

Initialize $\mathbf{v}_{ce}, \mathbf{v}_{ce^s}, \mathbf{v}_{se}$ from Ledgers
Initialize $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3, \mathcal{P}_4$ with 0
for $se_{ij} \in \mathbb{S}$ and $s_{ij} \neq 0$ **do**
  Initialize pdr with entries from Ledger-pdr: $\mathbf{r} = \left[r_1, r_2, ..., r_{M1}\right]$
  $rbe_j = \mathbf{v}_{ce}\left[j\right] - \mathbf{v}_{ce^s}\left[j\right]$
  $rse_{ij} = \mathbf{v}_{se}\left[i\right] \frac{se_{ij}}{\mathrm{sum}(\mathbf{v}_i)} \prod_{m=1}^{M1} \left(1 - r_m\right)$
  $rse_j = \sum_{k=1}^{n} rse_{kj}$
  if $rse_j < rbe_j$ **then**
    for $k \leftarrow 1$ *to* N **do**
      $\mathcal{P}_1\left[k, j\right] = rse_{kj} pr_{pd}$
    end for
    $\mathcal{P}_2\left[j\right] = (rbe_j - rse_j) pr_{spd}$
  else
    for $k \leftarrow 1$ *to* N **do**
      $\mathcal{P}_1\left[k, j\right] = \frac{rse_{kj}}{rse_j} rbe_j pr_{pd}$
    end for
    $\mathcal{P}_3\left[j\right] = \mathcal{P}_3\left[j\right] + \frac{rse_{ij}}{rse_j}(rse_j - rbe_j) pr_{pd}$
  end if
  $\mathcal{P}_4\left[j\right] = rbe_j r_{ij}$
end for
return $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3, \mathcal{P}_4$

After interval ΔT passed, all ADs, TDs and SPD should clear the bills for power energy consumption and transportation. $\mathbb{C}^* = \left[ce_i^s\right]_{1\times N}$ denotes the self-produced power energy that each AD uses. The selling electricity from AD_i to other ADs can be denoted as vector $\mathbf{v}_i = [se_{i1}, se_{i2}, ..., se_{iN}]$, meanwhile, the selling electricity to a given AD_j from other ADs can be denoted as vector $\mathbf{v}_j = \left[se_{1j}, se_{2j}, ..., se_{Nj}\right]^T$. Let $\mathrm{sum}(\mathbf{v}_i) = \sum_{k=1}^{N} se_{ik}$, and $\mathrm{sum}(\mathbf{v}_j) = \sum_{k=1}^{N} se_{kj}$. Vector $\mathbf{r} = [r_1, r_2, ..., r_M]$ indicates the power dissipation rate, pdr, in all M TDs, in which $r_i \in [0, 1]$. For all possible payment directions, there would be $\mathcal{P}1$: AD to AD, $\mathcal{P}2$: AD to SPD, $\mathcal{P}3$: SPD to AD and $\mathcal{P}4$: AD to TD. In our payment solution, sensor data are obtained from the blockchain for the bills clearing: Ledger-CE-AD for actual electricity consumption, Ledger-CES-AD for actual self-producted electricity consumption, Ledger-SE-AD for actual sold electricity and Ledger-pdr for actual power dissipation rate. From these data, each $\mathrm{AD}_j \in \mathrm{AD}_{np}$, the actual bought electricity rbe_j of AD_j, and the actual sold electricity rse_j from all $\mathrm{AD}_i \in \mathrm{AD}_p$ to AD_j can be derived. Then, the payment will be cleared by the offset of rbe_j and rse_j. The detailed SM for the payment clearing is summarized as Algorithm 3. After the SM is generated every $(t + \Delta T)$, it is installed to every peers of the blockchain in DETS for the triggering and executing between all entities.

5 INDUSTRIAL APPLICATION

In this section, we compare our proposed strategy *Presell Contract Strategy* with 2 mono-strategies, namely *Internal Usage only Strategy* and *Sell only Strategy*. We apply the 3 strategies to one city in Guangdong Province, which is covered by the China Southern Power Grid, then analyze the results with 3 scenarios, *peak*, *off-peak*, and *valley hour*, with real monthly data from May 20 to June 20, 2018. The data set has 6921 rows and 4 columns, including *domain*, *month*, *timestamp* and *power cost*. In addition, the experimental results for a single AD are analyzed for power usage.

5.1 Application Setup

Three scenarios: peak, off-peak and valley hour are selected as the next ΔT for application. Three strategies: Presell Contract Strategy (PCS) between all ADs based on predictive analytics and smart contract, Internal Usage only Strategy (IUS) – self-produced electricity only for internal usage for all ADs, and Sell only Strategy (SS) – self-produced electricity only for selling for all ADs.

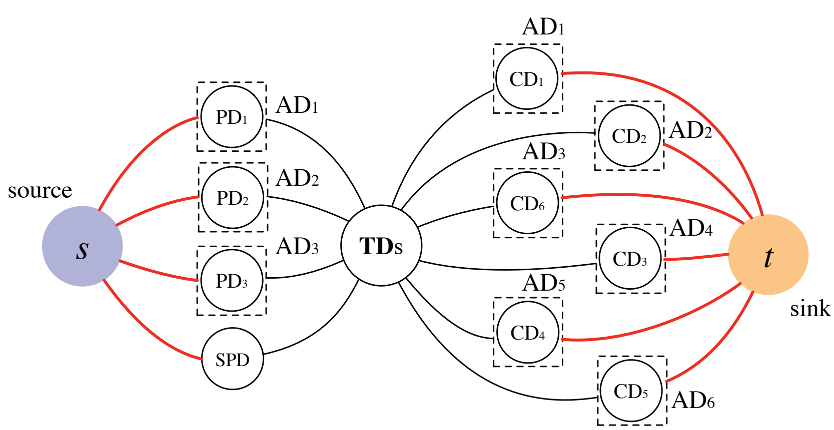

Fig. 3. The constructed graph $\mathcal{G}_a$ for application

The application has been carried out within 6 ADs: $AD_1(PD_1, CD_1)$, $AD_2(PD_2, CD_2)$, $AD_3(PD_3, CD_6)$, $AD_4(CD_3)$, $AD_5(CD_4)$, $AD_6(CD_5)$. Figure 3 shows the related graph, in which the PDs and CDs in same AD have been separated for Algorithm 1, while the cost between these PD and AD are 0. The source and sink vertices are added to the graph for augmenting path. Table 2 is the electricity price in different types of AD for the next ΔT in the three scenarios, in which we could see that the price of PD is fixed and that of SPD is varied in different scenarios. Table 3 gives all the power dissipation rates between PDs and CDs. The configurations of the smart meter, storage, switch controller for applications are 'sicamp201', 'ETNHF12-420wp-x' and 'LBT-LTS4P-N', respectively.

5.2 Application Process

The application works in the following steps: 1) The electricity production and consumption data: $\mathbb{P}$, $\mathbb{C}$ are predicted using LSTM; 2) The electricity scheduling scheme $\mathbb{S}$ between ADs is derived from Algorithm 1, and the internal control for power scheduling of each AD is derived from Algorithm 2; 3) Calculate the actual electricity consumption costs, in different scenarios of three strategies, given

Table 2. The electricity price of SPD and PD at different scenarios

–	pr_{spd}			pr_{pd}
Type	Industrial	Residential	Commercial	–
Peak	1.00390	0.97380	1.29260	0.45300
Off-peak	0.60840	0.59020	0.78340	0.45300
Valley	0.30420	0.25910	0.19590	0.45300

Table 3. The power dissipation rate between PDs and ADs

–	CD_1	CD_2	CD_3	CD_4	CD_5	CD_6
PD_1	0	.00605	.00297	.00762	.00131	.00511
PD_2	.00013	0	.00024	.00007	.00050	.00054
PD_3	.01736	.06231	.02562	.01653	.01074	0

the current electricity price and other captured data from E-IIoT such as pdr. The unit for electricity and price is kWh and CNY, respectively. Note that ΔT is set to 1 hour, and n is 10. For the choice of n, we have experimented with 5, 10, 20, and 50, and the impact on the results is neglectable. Thus, we fix the value of n at 10 for the whole application.

For augmenting path, the capacity of the arcs from the source is set as the electricity volume to sell for PDs or SPD, and the capacity of the arcs to sink is set to electricity to buy for CDs. Meanwhile, the cost of all augmenting path is 0. The capacity of TDs is unlimited for city sector, denoted as ∞, and the cost each TD_m is denoted as $pr_{pd}(1+r_m)$. For instances, from PD_3 to CD_3 the cost is 0 because they are in the same AD, and from PD_3 to CD_5 the cost is the $pr_{pd}(1+r_{35}) = .45300\times(1+.01074) = .45787$. For LSTM prediction, L is set to 8 for prediction sample and a $[8, 8, 1]$ network is constructed for training, where there are 6 hidden layers and each layer has 50 nodes. Learning efficiency is 0.001, the number of epochs is 500 and the ratio for training set is 0.8.

5.3 Application Results

5.3.1 Application between ADs. According to Algorithm 1, the power scheduling scheme between ADs in peak, off-peak and valley hour are derived as $\mathbb{S}_p$, $\mathbb{S}_{op}$ and $\mathbb{S}_v$:

$$\mathbb{S}_p = \begin{pmatrix} 0&0&0&0&0&0\\ 0&0&0&0&0&0\\ 0&0&0&0&0&52\\ 0&0&0&0&0&0\\ 0&0&0&0&0&0\\ 0&0&0&0&0&0 \end{pmatrix}, \ \mathbb{S}_{op} = \begin{pmatrix} 0&0&0&0&0&0\\ 0&0&0&3739&2739&198\\ 0&0&0&0&0&0\\ 0&0&0&0&0&0\\ 0&0&0&0&0&0\\ 0&0&0&0&0&0 \end{pmatrix},$$

$$\mathbb{S}_v = (\,0\,)_{6\times6}.$$

Figure 4 depicts the total consumption costs of all ADs in scenarios peak, off-peak and valley for strategies PCS, IUS and SS. It could be seen from the results that at peak and off-peak hour, the cost of strategy SS is higher than strategy PCS, especially current ΔT is off-peak hour and next ΔT is peak hour, when the electricity price goes up and ADs could store the extra electricity for sell in valley hour, then sell it in peak hour. For strategy IUS, because of internal usage of self-productive electricity, it will reduce the consumption cost. In peak hour, PD with PCS strategy cost is more than IUS and SS, because it supplies for another domain instead of itself. It will cost a little more in the local domain, but it reduces the total cost in all systems. However, the total cost is still higher than strategy PCS. Also, some ADs will waste the productivity when the storage are over capacity.

5.3.2 Application inside AD. Figure 5 depicts the internal electricity scheduling results of AD_2 during the whole ΔT ($\Delta T = 10\Delta t$). There are 6 variables in the scheduling: actual consumption

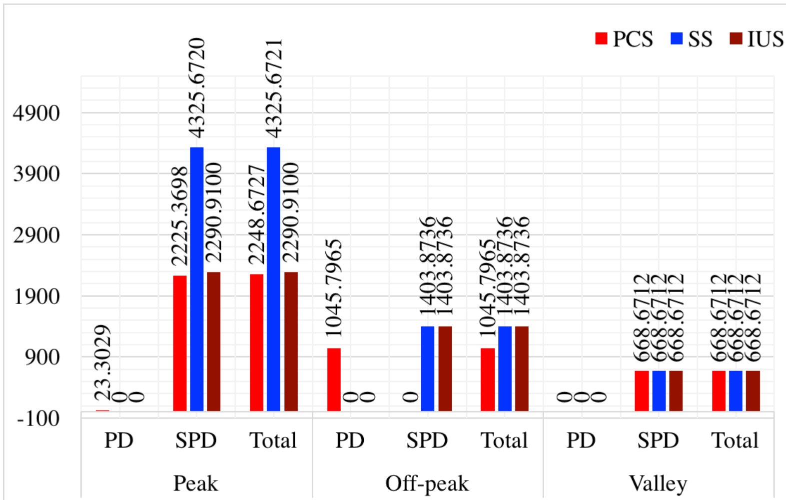

Fig. 4. The electricity consumption cost (unit: CNY *yuan*) of all ADs in three scenarios for different strategies

electricity ce, actual production of electricity pe, residual electricity re_1 before selling, selling electricity se_1 through PCS, selling electricity se_2 after PCS and residual electricity re_2 after all selling. From Algorithm 2, we know that if the selling of electricity for PCS is completed and the residual electricity reaches the threshold of power storage volume, the switch will be turned to TD for power selling for SPD. It can be derived from Figure 6 that for the first 6 Δt, the residual electricity can be sold out through PCS after self use. Especially at the 4th Δt, after the selling of electricity through PCS, there are still residual electricity from self production. Therefore the electricity is sold to SPD, otherwise this self produced volume would be wasted.

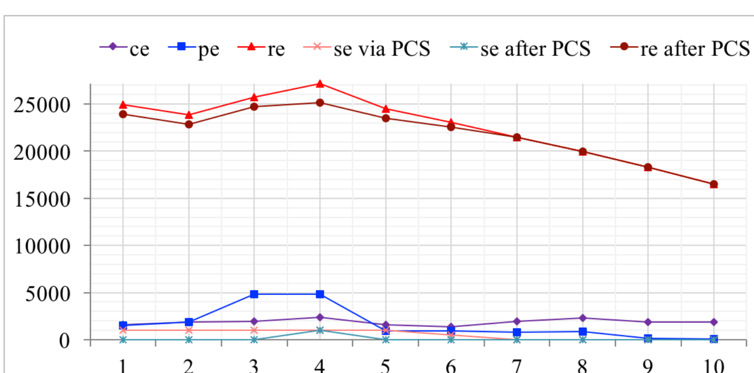

Fig. 5. The internal electricity scheduling (in kWh) of a single AD

5.3.3 Application of Blockchain and Smart Contract. A Redhat server has been used for the evaluation of Hyperledger Fabric, which provides 6 peers (nodes). Hyperledger Fabric SDK fabric-go-sdk and Beego have been integrated to invoke the API Invoke and Query. We have composed this blockchain cluster for payments clearing of smart contracts and connected these demo applications to a local bank. The number of concurrent transactions is set to 10. The TPS – transaction per second, has reached 670.237 during one performance testing. This transaction speed can meet the processing requirement of most of the medium and small banks in China, and also it can support the delay of transactions and inquires of the power industries. The results indicate that our scheme is extendable and applicable for fast energy trading, therefore enabling frequent electricity energy trading among different entities.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we have presented a distributed energy transaction system over E-IIoT. Ledgers have been designed for the storage of historical data collected from sensors. These data are extracted for LSTM prediction of power consumption and production. We have presented our solution based on the MCMF theory for the scheduling among different domains according to the prediction results. We have also designed smart contracts for payments clearing over Hyperledger Fabric. The experiments for real city monthly data have been performed in several scenarios and the results have demonstrated the feasibility of our solution.

We are further elaborating our system, such as considering the scheduling scheme in continuous ΔT, which will have a different optimal model. The impact of prediction accuracy over overall consumption cost is to be analyzed.

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