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Blockchain-based smart contract for energy demand management

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Abstract

This paper studies the design and management of distributed energy systems incorporating residential, commercial and industrial users. A hierarchical framework is first proposed for the energy demand side management through peer-to-peer exchange of information and energy in the real-time market. Smart contracts guaranteed by blockchain technologies are implemented to create a seamless and efficient trading system. The benefits of distributed energy management are presented such as economic savings, reduction of peak load and increased market efficiency facilitated by blockchain.

Keywords: distributed energy systems; smart contract; game theory; blockchain; micro-grid

1. Introduction

Current energy systems are facing a revolutionary transformation from both supply and demand sides [1]. Distributed energy resources (DERs) such as solar photovoltaic (PV) arrays and small-scale energy storage systems are becoming a substantial source of power. Meanwhile, technology evolution on the demand side will lead to the adoption of a significant number of electrical vehicles (EVs) and fuel cell (FC) vehicles, electrification of the heating sector, smart controllable loads, and the proliferation of using flexibility in load management schemes such as demand response (DR). These substantial changes require more flexible and resilient energy distribution networks and trading systems [2]. However, the existing transportation and energy systems are incapable of handling these flexibilities readily without deploying proactive design and operation strategies in a holistic system manner [3].

Blockchain is an emerging and fast developing technology that has gone through three stages generally. The first stage is the well-known Bitcoin cryptocurrency as first proposed in 2008 [4]. The Bitcoin system combines several technologies organically, including distributed systems, cryptography, consensus algorithms, chain data structure,

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which leads to the first world-wide digital currency system that has been verified over around ten years, using the block chain as a ledger to store and manage transaction history. The second stage is that Ethereum introduced smart contract into the blockchain [5]. The smart contract is a computer program installed on the blockchain as a system participant that can collect, store and send values and information, for example to trigger when certain conditions have been met. Smart contracts extend the blockchain technology to wider commercial applications. The generalized smart contract platform provides the framework of implementing all possible application scenarios based on blockchain technology with solid foundation of trust. Therefore, the third stage is regarded as the application of blockchain in specific scenarios [6]. Researchers and practitioners have tried to adopt blockchain to benefit their conventional fields, such as supply chain, finance, and more broadly internet of things [7].

Among all blockchain applications, the Peer-to-Peer (P2P) electric power trading stands out to be a suitable application, considering the following reasons:

1) The P2P trading and record of consensus can be achieved with blockchain.

Blockchain is a distributed system naturally designed for peer-to-peer interactions. In a P2P trading system, every participant is able to define their own behaviors and interact with others. Compared with the traditional grid, all the centralized actions, such as power transmission, pricing and settlement are now customized. Meanwhile, all end-users' activities can be recorded trustworthily, without the need for a third party.

2) Blockchain helps to reduce the threshold of participation in the electricity market for local retailers.

The grid infrastructure requires a huge amount of capital investment, as well as extensive operating and maintenance cost, keeping a high barrier for small-scale companies to participate. Blockchain technology enables fund-raising from investors and even end users. All participants will have partial ownership and benefit from grid infrastructures that are represented by the tokens in this system, which are their certification of right and can be traded as well. Moreover, blockchain will also reduce the cost of daily operation by using a decentralized system instead of a third-party intermediary. Therefore, end users can play an active role in energy sales, pricing and settlement in the electrical power trading, triggering more vitality in such markets.

3) Smart contract is a suitable platform for many new technologies to be implemented in P2P power trading system.

New paradigms such as demand response, auction mechanisms and scheduled power consumption, require the underlying framework to support synchronous circulation of information and value with automated actions taken on behalf of the energy user. Smart contract bears abundant capabilities to meet these requirements by offering programmable user behaviors, transparent and credible transaction records etc.

Motivated by all the potential advantages, active work is needed to develop feasible systematic protocols for blockchain enabled energy systems. This paper will first discuss the distributed energy systems management in Section 2, followed by case study and blockchain based smart contract implementation in Section 3.

2. Systems diagram and energy management models

In this section we first briefly introduce the overall methodology for the optimization of distributed energy supply and demand matching as illustrated in Figure 1. A game theory based model for demand side management under different supply constraints is presented as the foundation for implementing blockchain enabled smart contracts.

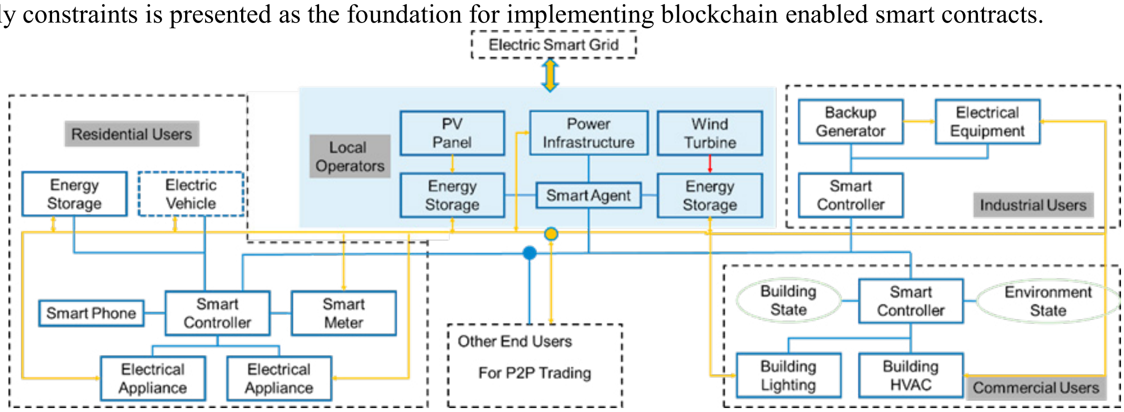


Fig. 1. Blockchain based cyber-physical system to enable interaction between different actors in a micro-grid.

In an integrated energy micro-grid, assuming the overall system comprises *n* consumers belonging to residential *r*, commercial *c* and industrial *i* sectors. Each user has two broad types of loads as schedulable and non-schedulable. Moreover, the residential users also own storage components *b* (which are connected to the grid).The industrial users own on-site energy generators *G* using renewable or diesel as resources. The hourly load profiles of a wide variety of consumers are defined by Eq. (1)-(3):

Residential

$$l_r^t = \sum_{a=1}^{A_r} xr_{r,a}^t + \sum_{b=1}^{r} sr_{r,b}^t \tag{1}$$

Commercial

$$l_c^t = \sum_{offa=1}^{Oa_c} x_{c,offa}^t \tag{2}$$

Industrial

$$l_i^t = \sum_{eqp=1}^{E_i} xi_{i,eqp}^t - \sum_{g=1}^{G} gtr_{i,g}^t \tag{3}$$

Where $xr_{r,a}^t$ denotes the hourly energy consumption for electrical device *a* of residential user *r* and $sr_{n,b}^t$ denotes the hourly discharge or charge of energy for storage component *b* of residential user *r* at time step *t*. $xc_{c,offa}^t$ denotes the hourly energy consumption for device *offa* of commercial user *c*. $xi_{i,eqp}^t$ denotes the hourly energy consumption for task/equipment *eqp* of industrial user i and $gtr_{i,g}^t$ represents the energy generated by industrial generator. The total hourly load profile of the entire system is given by Eq. (4):

$$L_t = \sum_{r=1}^{R} l_r^t + \sum_{c=1}^{C} l_c^t + \sum_{i=1}^{I} l_i^t \tag{4}$$

Peak to average ratio (PAR) defines the unevenness in the load profile which can be found by using the peak and average load profiles of the system where:

$$L_{avg} = \frac{1}{H}\sum_{t=1}^{H} L_t,\ \ L_{peak} = \max L_t \text{ for t} = \{1, \ldots, \text{H}\},\ \ PAR = L\_peak/L\_avg \tag{5}$$

PAR reduction is a primary objective in most energy demand-side management models to reduce stress on the grid and maximise utility from infrastructure investments. The price of energy is an increasing function of the load system load $P_t(L_1^t) < P_t(L_2^t)\ given\ L_1^t < L_2^t$ **.** The price function is assumed to be strictly convex and is given by:

$$P_t(L_t) = f * L_t^2 \tag{6}$$

where f is a constant. The cost functions for the different categories of consumers are then as follows:

Residential Commercial Industrial

$$C_{r,t}(L_t) = P_t(L_t) \qquad C_{c,t}(L_t) = P_t(L_t) \qquad C_{i,t}(L_t) = P_t(L_t) + Gen_{i,t}(l_i^t) \tag{7}$$

The generator costs $Gen_{i,t}(l_i^t)$ depend on the amount of electricity produced which is linked to the amount of raw materials (fuels) consumed. It is taken to be linearly related to the amount of generated power l_i^t, plus the start-up and shut-down costs of the generator represented by c by Eq. (8):

$$Gen_{i,t}(l_i^t) = y * l_i^t + c \tag{8}$$

Every user in the system aims to minimize their costs by lowering their load which in turn minimizes the peak load and system cost. However, the devices owned by the consumers follow certain constraints as discussed below. The detailed mathematical models are developed for systematic optimization, but not shown here (part of modelling can be referred to [8]). The operation of the household appliances is time-shiftable. Each appliance will have a time interval for scheduling as specified by the consumer along with its daily energy consumption level. While the residential and industrial users will follow the exact defined energy consumption, the commercial users can have lower consumption than specified. This is due to the fact that the flexibility for commercial users is derived by changing power levels of lighting and HVAC systems as power-flexible devices.

All the residential appliances will have standby power and maximum power limit in the energy systems model. Thus, the energy profile will have to meet these limits during operational hours. Meanwhile, the storage components have different states representing the state of charge. The energy supplied by the storage component in a time slot t depends on its state of charge, efficiency and the initial energy state. Also, the total energy at any given time cannot exceed the maximum energy capacity. Moreover, the total daily energy usage for the storage component can be used to define its state of charge by the end of the day. The user can set the value for the state of charge at the end of day.

For the commercial sector, demand response utilities request commercial users to shed a specific amount of power and the time required to shed it; the commercial users then, based on multiple parameters, decide how much power can be shed while keeping constraints in mind, and respond accordingly. The demand response for commercial sector is dependent on the comfort level of people in the buildings. The schedulable appliances for the commercial sector considered in this model are assumed to be power flexible. This power flexibility margin is defined by the occupancy level and weather forecast which are linked back to the comfort level of the people. Historical data is analysed to determine occupancy levels. Based on the hourly occupancy level, values will be assigned to $Occup_{t,c}$ which represent maximum allowable the level of power reduction that does not result in discomfort. Furthermore, W_t will represent the tolerable power reduction linked to the weather. The weather data based on forecast will have two levels: sunny or not sunny. For this model, occupancy data is defined with three levels, i.e. Full (100% occupied), Mid (40-70% occupancy), and Low (40% or less occupancy). Each commercial user will define the maximum allowable power flexibility linked to the two stated parameters of occupancy and weather conditions. So, the power limits of schedulable appliances will be set by these parameters as given by Eq. (9):

$$Nc_{c,a,t} * P_{c,offa} * Occup_{t,c} * W_t \leq xc_{c,\text{offa}}^t \leq Nc_{c,a,t} * P_{c,offa} \quad (9)$$

At higher occupancy level the ability to shed power will be lower. For sunny weathers users can make use of natural light thereby allowing some flexibility to dim the lights and hence lower the power consumption. The actual reduction in power will be linked to the system condition, if the system load is already low no change will be made, however, at peak conditions the power consumption of the devices will be reduced within the stated limits. This reduction is captured by the load factor function:

$$load\_factor(t) = 1 - e^{-d*L_{avg}/load(t)} \quad (10)$$

Where *d* is a constant. The system conditions will act as a signal to shed power, similar to the signal sent by utilities in the real-time scenario.

The industrial users will have fixed power margins for the schedulable tasks. The amount of energy produced by industrial generators cannot exceed the total load at any hour as Eq. (11) for economic efficiency but this constraint can be relaxed if more active P2P trading is enabled.

$$\sum_{eqp=1}^{E_n} xi_{i,eqp}^t \geq g_i^t \quad (11)$$

where the total power produced can also not exceed the power rating of the generator.

At the system level, a game theory model is proposed, which is defined by all involved players, their strategies and the corresponding payoffs. In this model, the consumers act as players and thus $\boldsymbol{n}$ defines the set of players going from 1, 2…, *N*. The strategies are the energy scheduling vectors that the players desire to optimize in order to increase their payoffs, i.e. reduce their costs. As each player is concerned about their own payoffs, the aggregated load can be broken into load of the n^{th} consumer and load of all other consumers in the system. Thus the payoffs for consumer *n* can be defined as Eq. (12) as the objective function to be minimized as well:

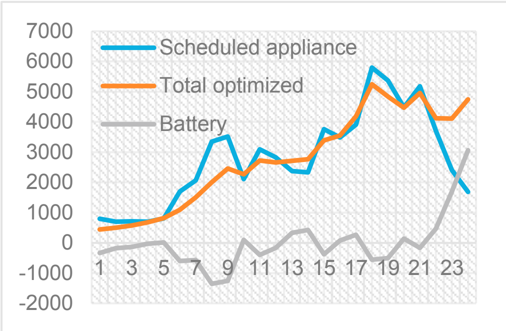
$$C = \sum_{t=1}^{H}\{g * k * (l_n^t + L_m^t)^2 + \sum_{a=1}^{A_n} w_{n,a} * (l_n^t - l\_sch_{n,a}^t)^2\} \quad (12)$$

At the start of the day, the utility company will gather the schedules from all consumers and based on that it will forward the aggregated load for each hour to consumers. Having this information beforehand, the gaming algorithm will be run at each consumer's end to optimize their energy scheduling profiles. If they make changes to the schedule, they will submit any variations to the utility. Thus, utility will keep forwarding the updated aggregated load to all consumers until no further changes are made and an optimum solution is reached for all.

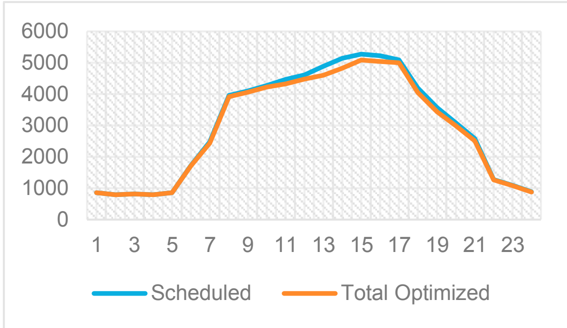
3. Case study and smart contract implementation

To illustrate the approach the model is applied to a case study with an integrated micro-grid incorporating residential, commercial and industrial users, with demand data adopted from real energy consumptions in these sectors

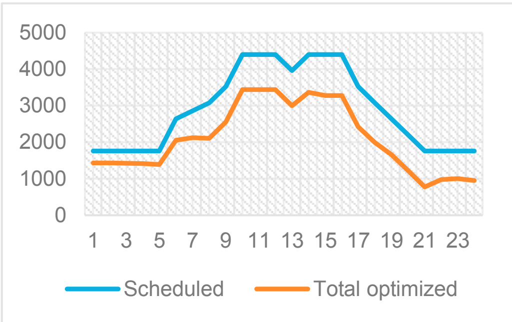
[9]. The detailed results of optimized power profiles over a day are illustrated in Fig.2 as the foundation for further implementation of smart contracts.



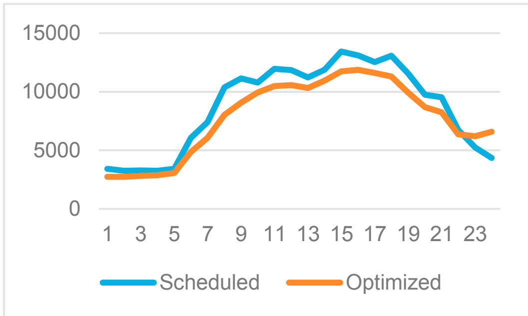
(a) Residential sector



(b) Commercial sector



(c) Industrial sector



(d) Overall system

Fig. 2. Blockchain based cyber-physical system (power consumption in kW over 24 hours of a day).

The focused energy system is evaluated by the PAR values. It is analysed that the total peak load has reduced from 13,433 kW to 11,873 kW. While the average load is 8,695 kW after demand management compared with the original value of 7,795 kW. As a result, the PAR decreases from 1.545 to 1.523.

Finally, we implement the inherent system to guarantee effective transactions through smart contracts and blockchain through a single, secured transaction. When there is excessive amount of power from the prosumers, blockchain-based smart contracts allow selling that energy in an automated fashion or user controlled scheme to other participants in the micro-grid. The left column in Fig. 3 shows the transaction from a chemical plant to a shopping mall when the industrial user has extra generation. And the right part of the figure demonstrates details of this transaction and block generated. Blocks are connected by encrypted hashes, protecting content from being changed and allowing the history to be audited. In summary, block chain is implemented through data encryption, timestamps, intelligent contract and other technical means. As a distributed ledger maintained by many nodes in the system, a blockchain creates an unchangeable record of time-stamped transactions. The ledger is visible to all users and is continually updated for current transactions. The P2P transactions are therefore guaranteed in the absence of third-party trusted endorsement. This way, the multi-actor energy trading and optimization shown in Fig 1 could be implemented with the financial transactions facilitated by the blockchain technology.

Fig. 3. Procedures and the states of blockchain-based transactions

4. Conclusions and future work

As a summary, we have shown promising results in distributed energy systems management for more efficient power trading and demand management schemes. However, P2P power trading is still in development compared with the traditional power trading mode. Blockchain is also an immature technology, not only in the technical basis for better performance and features, but also in the commercial model to get adapted to existing industries. There are three main aspects for the blockchain approach described in this paper to be improved: the technical infrastructure, applications and governance. First, some technical issues are still unsolved for P2P power trading to be applied in large scale. For example, transaction throughput may not support high frequency power trading and suffer scalability problems. Other technical challenges include, but are not limited to, cryptography for user privacy protection, tradeoff between consensus efficiency and system security, blockchain-supported power equipment, user adoption and so on. Secondly, decentralized application for P2P power trading on blockchain is under developed. Many works such as on chain power metering, smart contract controlled electrical equipment and decentralized power exchange remain to be improved. Last, governance is the approach to regulate the development of infrastructure and motivate the application ecosystem. The way to attract more users to participate in, to balance the interests among traditional grid, retailer, end user, developer and investor, to motivate contributors and punish perpetrators, to handle unexpected situations are all in the context of governance and need to be well designed and comprehensively verified in future work.

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