Small-scale Microgrid Energy Market Based on PILT-DAO

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***Abstract*—The energy market of DERs in Microgrids (MGs) is still under devolvement due to low security and transparency at present. Therefore, a small-scale microgrid energy market is proposed in this study based on Decentralized Autonomous Organization of Parallel, Integrity, Longevity, and Transparency (PILT-DAO) based on the features of the blockchain. A buyer or seller at the microgrid level can complete the transaction matching in the PILT-DAO market.**

In order to implement this energy trading platform, the first step is to simulate a modified distributed IEEE 13 node test feeders system. The next step is to develop a price mechanism based on a consensus + innovation distributed algorithm to calculate the Distribution Locational Marginal Price (DLMP). In the meantime, smart meters record the Power Flow (PF) data of each DG as one node of the whole simulated distribution power system and send them to blockchain including distributed price and power generation data. The third step is to constitute a decentralized autonomous market by programming smart contracts in Ethereum DAO, running in an artificial system parallelly. A case study of a small-scale microgrid energy market based on PILT-DAO is illustrated followed by the conclusion.

***Index Terms*—DC Optimal Power Flow (DCOPF), Distribution Locational Marginal Price (DLMP), Distributed Algorithm**

I. Introduction

In 1927, the Pennsylvania-New Jersey Interconnects became the first U.S. power pool, transiting to a fully independent transmission organization in 1997 with the opening of its first bid-based energy market. Federal Energy Regulatory Commission (FERC) approved the Pennsylvania, New Jersey, Maryland (PJM) pool as the first Independent System Operator (ISO) that year. And, two decades ago from now, a lot of studies show that electric utility companies quickly realized that they could interconnect with another one to decrease costs and enhance reliability and security such as Western Wind and Solar Integration Study and Eastern Renewable Generation Integration Study [1], [2]. Thus, they began to share generation resources in "power pools". As a result, the utility can transfer power to another in either wholesale or retail transactions.

Over time, electricity is widely regarded as a commodity. As a commodity, electricity is bought and sold as power (measured in KiloWatts or MegaWatts) and energy (measured in KiloWatt-hours) with various attributes being traded in electricity markets. The importance of transparency in wholesale electricity markets was underscored by the Energy Policy Act of 2005 (P.L. 109-58), which aimed to facilitate price transparency in interstate markets for the sale and transmission of electric energy, and to prohibit energy market manipulation. However, under FERC regulatory jurisdiction, each Regional Transmission Organization (RTO) has developed its own regulations or rules on markets. These regulations and rules make operational issues and regional differences more and more difficult [3].

Throughout the history of electricity markets in the United States, the centralized electricity markets of renewable energy sources are recently playing an important role in energy generation markets. However, in existing centralized microgrid energy markets, buyers or consumers can only indirectly trade with generation suppliers through the retailers or utility companies. Obviously, direct trading between consumers and generation suppliers will both improve their own benefits without retailers as an inter-mediator or third party. Furthermore, the transaction management methods of centralized electricity markets are still facing the following major problems: [4]–[8]

- Centralized electricity markets face information security problem such as losing data and users' privacy;
- It is difficult to ensure integrity, longevity, and transparency of transaction information between two parties with 100 percent trust.

Therefore, we need an efficient way to create a motivation for improving the benefits of renewable energy for both sides. A new energy market is proposed to design with new technologies for solving those problems. Meanwhile, the concept of blockchain was introduced by Satoshi Nakamoto in his paper entitled "Bitcoin: A Peer-to-Peer Electronic Cash System" in 2009 for solving double-spending problem without a third central party such as retailer or utility company in microgrid energy markets, using the technologies of asymmetric encryption, digital signature, and consensus mechanism. In addition, Decentralized Autonomous Organization(DAO) was introduced by Vitalik Buterin who is a co-founder of the most popular public blockchain platform Ethereum into blockchains. The definition was explained as "it is an entity that lives on the internet and exists autonomously, but also heavily relies on hiring individuals to perform certain tasks that the automaton itself cannot do" [9]. Therefore, DAO aims to be a platform of integrity, longevity, and transparency (ILT) where each person can manage their own identity, data, and the

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asset on a blockchain. A controversial crowdfunding project named "The DAO" was initiated in May 2016 which provides a new decentralized business model by programming a set of contracts on Ethereum public blockchain. However, it was hacked in June 2016. Obviously, the business model has a grand challenge to be a successful decentralized autonomous organization without any testing operations at the same time in another "parallel chain". Therefore, we consider applying another useful theory, parallel system methodology, in establishing this ILT-DAO business model. Specifically, PILT-DAO is based on parallel system methodology and the ACP approaches, i.e., modeling with "artificial systems" (A), analyzing with "computational experiments" (C), and controlling through "parallel execution" (P) [10], [11].

According to above problems of existing grid transaction market and the advantages of PILT-DAO, this paper proposes a future energy market based on PILT-DAO, which is illustrated in Figure 1 "architecture of small-scale microgrid energy market," to solve those problems – low security and low transparency. Therefore, this architecture is designed with three layers including entities modeling layer, pricing mechanism layer, and PILT-DAO market layer to replace previous three layers such as distributed energy resource layer, distribution system operator (DSO) layer and regional transmission organization (RTO) layer.

The remaining part of this paper is structured as follows. Section 2 presents DLMP formulation with consensus + innovation approach to achieve distributed multi-agent coordination in a Microgrid and calculate the DLMPs of a test power system for this energy market. Section 3 demonstrates a study case to program smart contracts into PILT-DAO communicating with distributed DLMPs and power generation data under normal and congested cases. Section 4 concludes this paper and discusses future works.

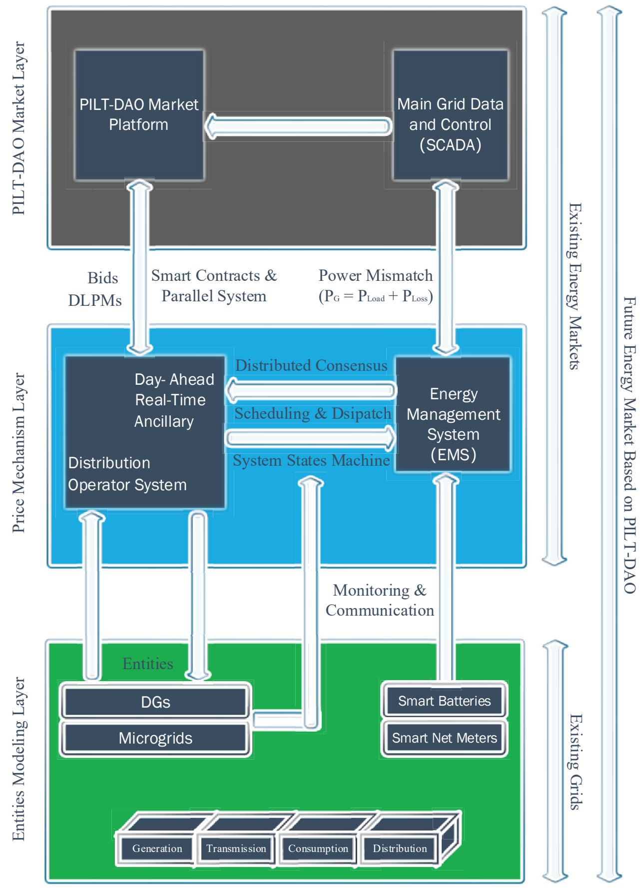

Fig. 1. Architecture of small-scale microgrid energy market

II. DLMP Formulation

Distribution Locational Marginal Price (DLMP) is a mathematical method for setting the wholesale electric energy prices and for reflecting the value of electric energy at different locations in a distribution system corresponding to Locational Marginal Price (LMP) in a transmission system [12]. In a transmission system, if there is no any congestion and losses, all LMPs would be the same called Market Clearing Price (MCP) because it reflects only the cost of serving the next increment of the load, otherwise, the bus price will differ. Generally, LMPs are different among locations due to transmission losses and constraints for preventing the next cheapest MW of electric energy to reach all locations in this system. Therefore, when the next cheapest MW can reach all locations, the cost of physical transmission losses will result in different LMPs across this system. Obviously, understanding cost of energy, a congestion charge, and transmission system losses is the three most important components of LMPs calculation. In addition, day-ahead and real-time LMPs and DLMPs are two different types of methods for calculating prices in a power system. However, they are based on the same basic calculation using the different nodal prices, optimizing the dispatches and minimizing the costs for energy, congestion, and losses [13].

In order to implement this distributed price mechanism layer, the consensus + innovations approach for distributed multi-agent coordination is introduced in this chapter [14]. The main idea of this approach is to optimize the global value according to local and neighborhood information autonomously. In general, the updated item of each iterations of λ and P at different time scale are given by (1) and (2). Equation (1) shows that 1) there are i iteration numbers, j nodes and t hours; 2) α_i and β_i are tuning parameters to 0 when iteration goes to infinity; 3) ω_j is a set of communication neighborhood which comes from physical entity modeling topology connection. It is a projection operation in equation (2) for power injected/consumed $P_{j,t}^{i+1}$ onto the interval $[P_{n,t}^{min}$, $P_{n,t}^{max}]$ using new $\lambda_{j,t}^{i+1}$ value and generator cost parameter a_n and b_n:

$$\lambda_{j,t}^{i+1} = \lambda_{j,t}^{i} - \beta_i \sum_{l\in\omega_j} (\lambda_{j,t}^{i} - \lambda_{l,t}^{i}) - \alpha_i \sum_{n\in\Omega_j} P_{n,t}^{i} \quad (1)$$

$$P_{j,t}^{i+1} = \underset{P_{n,t}^{min} \leq P_{n,t} \leq P_{n,t}^{max}}{\boldsymbol{arg} \quad \boldsymbol{min}} \parallel P_{n,t}^{i} - \frac{\lambda_{j,t}^{i+1} - b_{n,t}}{a_{n,t}} \parallel^2 \quad (2)$$

In our DCOPF case [15]–[17], the quadratic cost function is used to model the generation costs for each component n from Figure 1 given by:

$$C_n(P_n) = \frac{1}{2} a_n P_n^2 + b_n P_n + c_n \quad (3)$$

Where a_n,b_n, $c_n \geq 0$

In this layer, the goal is to determine the DLMPs for each node which minimizes the total system cost. The marginal cost function is given by:

$$\frac{dC_n(P_n)}{dP_n} = a_n P_n + b_n = \lambda_n \quad (4)$$

where P_n is limited to $\underline{P}_n$ and $\overline{P}_n$; when $\underline{P}_n \geq 0$, it is for generator; when $\overline{P}_n \leq 0$, it is for load; and when $\underline{P}_n \leq 0$, $\overline{P}_n \geq 0$ it is for storage or battery.

The mathematical problem formulation of generation costs modeling can be expressed by:

$$obj: \qquad \min_{P_n} \sum_{n \in \Omega_G} (\frac{1}{2} a_n P_n^2 + b_n P_n + c_n) \quad (5)$$

$$s.t: \qquad \underline{P}_n \leq P_n \leq \overline{P}_n \qquad \forall n \in \Omega_G \quad (6)$$

$$\theta_1 = 0 \quad (7)$$

$$-\overline{P}_{kj} \leq \frac{\theta_k - \theta_j}{X_{kj}} \leq \overline{P}_{kj} \qquad \forall kj \in \Omega_L \quad (8)$$

$$\sum_{n \in \Omega_G} P_n - P_{Load_k} = \sum_{j \in \Omega_k} \frac{\theta_k - \theta_j}{X_{kj}} \qquad \forall n \in \Omega_N \quad (9)$$

where: P_n:generation at generator n
- a_n, b_n, c_n: quadratic cost parameter of generator n
- P_{Load_k}: load at but k
- θ_k: angle at bus k
- X_{kj}: reactance of line between bus k and j
- $\underline{P}_n$, $\overline{P}_n$: generation min, max at generator n
- -$\overline{P}_{kj}$, $\overline{P}_{kj}$: line capacity between bus k and j
- Ω_k: set of all bus connected to bus k
- Ω_N: set of all nodes
- Ω_G: set of all generators
- Ω_L: set of all line segments

The Lagrange function for this generation cost minimizing problem is given by:

$$\begin{aligned}\mathcal{L} = &\sum_{n \in \Omega_G} (\frac{1}{2} a_n P_n^2 + b_n P_n + c_n) + \\ &\sum_{n \in \Omega_G} \mu_n^+ (P_n - \overline{P}_n) + \sum_{n \in \Omega_G} \mu_n^- (-P_n - \underline{P}_n) + \\ &\sum_{i=1}^{\Omega_N} \lambda_k (-\sum_{n \in \Omega_G} P_n + P_{Load_k} + \sum_{j \in \Omega_k} \frac{\theta_k - \theta_j}{X_{kj}}) + \\ &\sum_{kj \in \Omega_L} \mu_{kj} (\frac{\theta_k - \theta_j}{X_{kj}} - \overline{P}_{kj}) + \\ &\sum_{kj \in \Omega_L} \mu_{kj} (-\frac{\theta_k - \theta_j}{X_{kj}} - \overline{P}_{kj}) + \lambda_1 \theta_1\end{aligned} \quad (10)$$

where λ and μ are Lagrange multipliers. The first order optimality conditions are given by:

$$\frac{d\mathcal{L}}{dP_n} = a_n P_n + b_n + \mu_n^+ - \mu_n^- - \lambda_n = 0 \quad (11)$$

$$\frac{d\mathcal{L}}{d\lambda_k} = -\sum_{n \in \Omega_G} P_n + P_{Load_k} + \sum_{j \in \Omega_i} \frac{\theta_k - \theta_j}{X_{kj}} = 0 \quad (12)$$

$$\frac{d\mathcal{L}}{d\theta_k} = \lambda_k \sum_{j \in \Omega_k} \frac{1}{X_{kj}} - \sum_{j \in \Omega_k} \lambda_k \frac{1}{X_{kj}} + \sum_{j \in \Omega_k} (\mu_{kj} - \mu_{jk}) \frac{1}{X_{kj}} = 0 \quad (13)$$

$$\frac{d\mathcal{L}}{d\lambda_1} = \theta_1 = 0 \quad (14)$$

$$\frac{d\mathcal{L}}{d\mu_n^+} = P_n - \overline{P}_n \leq 0 \quad (15)$$

$$\frac{d\mathcal{L}}{d\mu_n^-} = -P_n - \underline{P}_n \leq 0 \quad (16)$$

$$\frac{d\mathcal{L}}{d\mu_{kj}} = \frac{\theta_k - \theta_j}{X_{kj}} - \overline{P}_{kj} \leq 0 \quad (17)$$

$$\frac{d\mathcal{L}}{d\mu_{kj}} = -\frac{\theta_k - \theta_j}{X_{kj}} - \overline{P}_{kj} \leq 0 \quad (18)$$

Now, DCOPF is applied into case into the equation (1) and (2) of distributed consensus + innovations approach. Then, the updated Lagrange multipliers $\lambda_{j,t}^{i+1}$, $P_{j,t}^{i+1}$, $\theta_{j,t}^{i+1}$, $\mu_{ij,t}^{i+1}$ and $\mu_{ji,t}^{i+1}$ are given by:

$$\begin{aligned}\lambda_{j,t}^{i+1} = \lambda_{j,t}^{i} - \beta_i (\lambda_{j,t}^{i} \sum_{j \in \Omega_k} \frac{1}{X_{kj}} - \sum_{j \in \Omega_k} \lambda_{j,t}^{i} \frac{1}{X_{kj}} + \\ \sum_{j \in \Omega_k} (\mu_{kj,t} - \mu_{jk,t}) \frac{1}{X_{kj}}) - \\ \alpha_i (\sum_{n \in \Omega_G} P_{n,t}^{i} - P_{Load_k} - \sum_{j \in \Omega_k} \frac{\theta_{k,t}^{i} - \theta_{j,t}^{i}}{X_{kj}})\end{aligned} \quad (19)$$

$$P_{n,t}^{i+1} = \underset{P_{n,t}^{min} \leq P_{n,t} \leq P_{n,t}^{max}}{\boldsymbol{arg} \quad \boldsymbol{min}} \parallel P_{n,t}^{i} - \frac{\lambda_{j,t}^{i+1} - b_{n,t}}{a_{n,t}} \parallel^2 \tag{20}$$

$$\theta_{j,t}^{i+1} = \theta_{j,t}^{i} - \gamma(-\sum_{n\in\Omega_G} P_{n,t}^{i+1} + P_{Load_k} + \sum_{j\in\Omega_k} \frac{\theta_{k,t}^{i} - \theta_{j,t}^{i}}{X_{kj}}) \tag{21}$$

$$\mu_{kj,t}^{i+1} = \underset{\mu_{kj,t}^{min} \leq \mu_{kj,t} \leq \mu_{kj,t}^{max}}{\boldsymbol{arg} \quad \boldsymbol{min}} \parallel \mu_{kj,t}^{i} - \delta(\overline{P}_{kj} - \frac{\theta_{k,t}^{i+1} - \theta_{j,t}^{i+1}}{X_{kj}}) \parallel^2 \tag{22}$$

$$\mu_{jk,t}^{i+1} = \underset{\mu_{jk,t}^{min} \leq \mu_{jk,t} \leq \mu_{jk,t}^{max}}{\boldsymbol{arg} \quad \boldsymbol{min}} \parallel \mu_{jk,t}^{i} - \delta(\overline{P}_{jk} - \frac{\theta_{k,t}^{i+1} - \theta_{j,t}^{i+1}}{X_{kj}}) \parallel^2 \tag{23}$$

1) $\overline{P}_{ij}$ and $\overline{P}_{ji}$ are the line limits between feeder i and j. They are 500 kW;

2) Ω_i is a set of communication neighborhood which comes from physical entity modeling topology connection;

3) Ω_N, Ω_G, and Ω_L are set of nodes, generators and line segments;

4) new updated value is used for next step calculation such as $\lambda_{j,t}^{i+1}$ in (20), $P_{n,t}^{i+1}$ in (21) and $\theta_{j,t}^{i+1}$ and $\theta_{j,t}^{j+1}$ in (22) and (23);

5) α, β,γ, and, δ are the four key tunning parameters to impact the convergence. They are set to:

$$\alpha = \frac{0.55}{i^{0.98}} \qquad \beta = \frac{0.2}{i^{0.001}}$$
$$\gamma = \frac{0.05}{i^{0.001}} \qquad \delta = \frac{0.008}{i^{0.001}}$$

DCOPF is applied into the consensus + innovations approach flow chart, it shows in Figure 2. The updated terms $\lambda_{j,t}^{i+1}$, $P_{n,t}^{i+1}$, $\theta_{j,t}^{i+1}$, $\mu_{ij,t}^{i+1}$ and $\mu_{ji,t}^{i+1}$ are according to equations (19) - (23).

III. Case studies

In this section, two cases (normal and congested) are provided to apply the distributed algorithm. The test system is a modified IEEE 13 node test feeder system which is shown in Figure 3. We consider two MGs and three PV panels as distributed generators in this power system topology. And, it can be noticed that there are several generators on nodes 650, 646, 633, 684, 692, and 680 respectively. Node 650 is connected to the main grid; node 646, 633, and 684 are the solar PV generators; node 692 and 680 are microgrids.The generation cost parameters and limitation data are shown in Table I. Load are on nodes of 646, 645, 632, 634, 611, 671, 675, and 652 proportionally. The load data are given in Table II. The line segment and impedances configuration parameters such as line impedances, connections and length, please see in [18].

For those two cases, we simulated 24 hours (t = 24) for them. The generation units output and DLMPs of the two cases

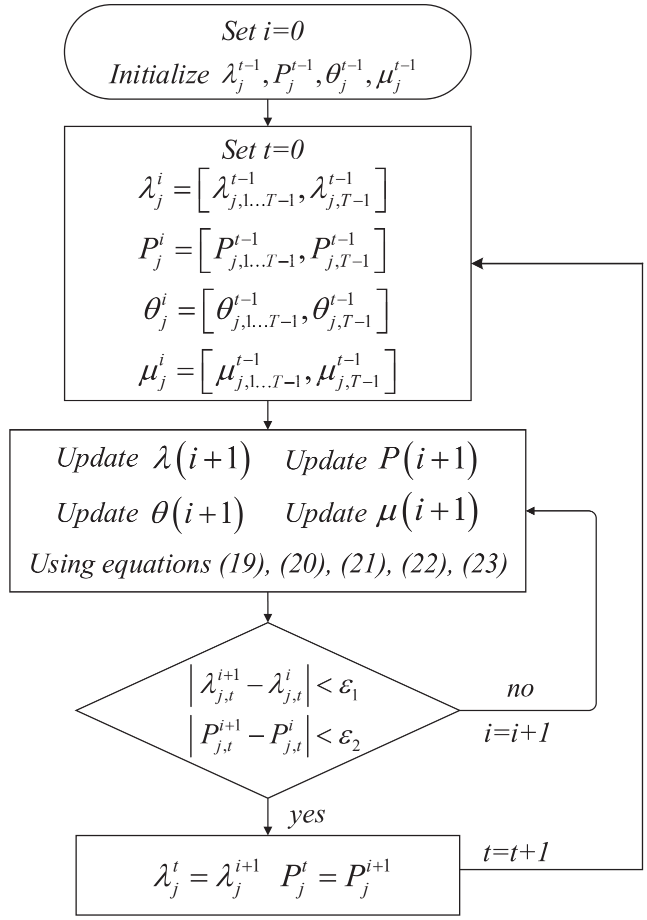

Fig. 2. DCOPF consensus + innovations approach flow chart

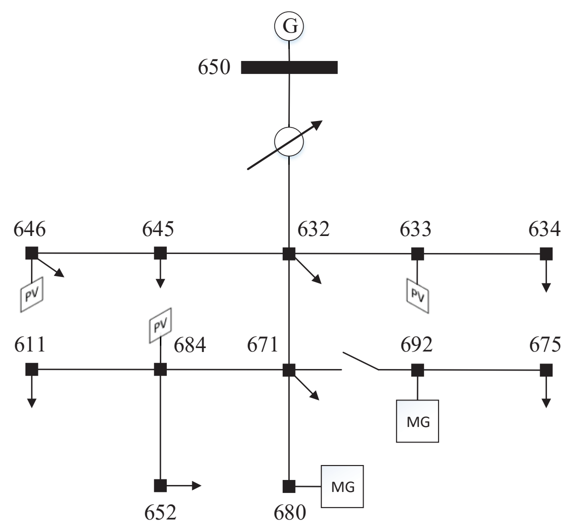

Fig. 3. Modified IEEE 13 node test feeder system topology

TABLE I
GENERATOR PARAMETERS

Node	a_n ($\$/pu^2$)	b_n($\$/pu$)	c_n	$\overline{P_n}$ (kW)
Sourcebus.1	0.36	20.7	0	1100
646.3	0.056	3.5	0	185
633.1	0.07	4.0	0	185
684.1	0.058	3.5	0	185
692.1	0.082	4.5	0	600
692.2	0.082	4.5	0	600
692.3	0.082	4.5	0	600
680.1	0.068	3.0	0	550
680.2	0.068	3.0	0	550
680.3	0.068	3.0	0	550

TABLE II
LOAD PARAMETERS

Node	a_n ($\$/pu^2$)	b_n($\$/pu$)	c_n	$\overline{P_n}$ (kW)
646.2	0.084	8.0	0	-230
645.2	0.074	7.0	0	-170
632.1	0.068	6.4	0	0
634.1	0.08	7.5	0	-160
634.2	0.06	6.3	0	-120
634.3	0.07	8.0	0	-90
611.3	0.076	7.0	0	-80
671.1	0.07	7.5	0	-385
671.2	0.08	8.0	0	-385
671.3	0.07	7.2	0	-220
675.1	0.064	6.8	0	-485
675.2	0.04	7.5	0	-68
675.3	0.06	8.0	0	-212
652.1	0.065	6.9	0	-128

are shown in Figure 4 and 5 respectively (The top two lines are MGs, the middle three lines are PVs, and the bottom line is generator). In Figure 5 (congested case), the generation output of three PVs are 0 at hour 9 and 10, and the generation of the generator which is connected to the main grid is 0 at hour 18 and 19. And Figure 6 and 7 show the 1000th iteration of distributed DLMPs for normal and congested case respectively. It can be noticed that the prices increase when PV power are lost such as at hours 9 and 10 apparently.

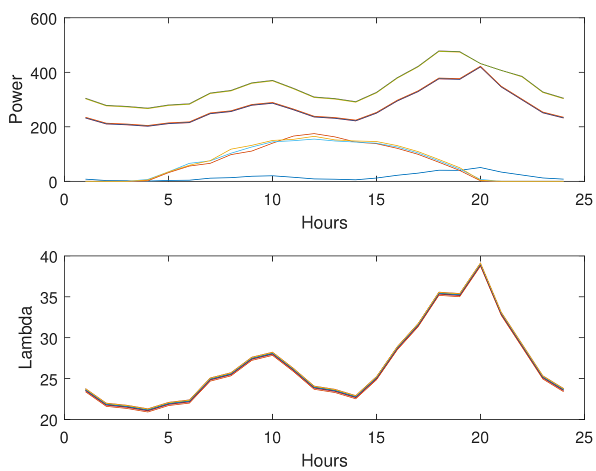

Fig. 4. Power and DLMPs of each generation unit

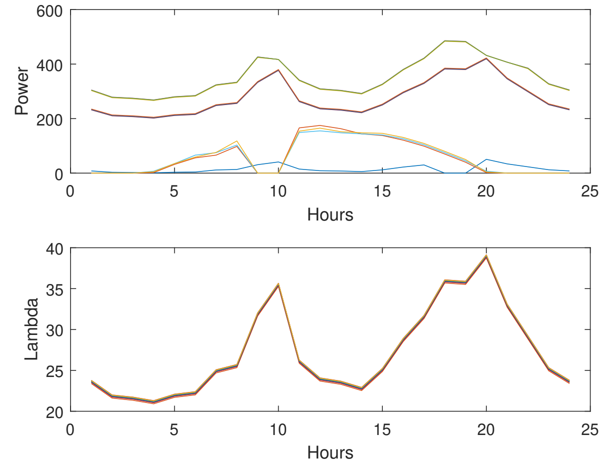

Fig. 5. Power and DLMPs of each generation unit in congested case

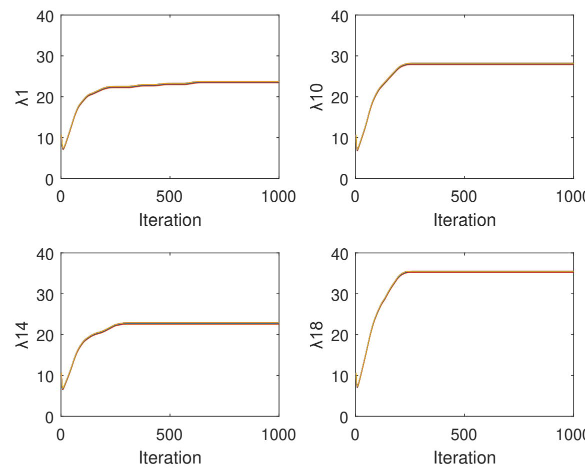

Fig. 6. The 1000th iteration of DLMPs of each generation unit at hour 1, 10, 14, and 18

A nodejs (A web programming language) case study named Distribution Power Trading (DPT) platform will be shown in this section. Blockchain server is a server to access Ethereum private chain and get the database of blocks, transactions and smart contracts, etc.. Distributed DLMPs server is to read MATLAB OPF results calculated by consensus + innovation algorithm. Contract server connects the database between blockchain server and distributed DLMPs server to finish transactions. The three servers are controlled by nodejs controller, and then, shown on web localhost:3000.

The Ethereum private chain is created by GO language and Geth commands. The results of distributed DLMPs and units power generation from MATLAB algorithm are given in Figure 2 and sent to servers. In servers, we use module-view-controller approach to create the user interface on the web localhost:3000. The home page of the user interface is shown in Figure 8 to show the accounts. At the beginning, the balance is 0 except Miner account. Andt then, each account can

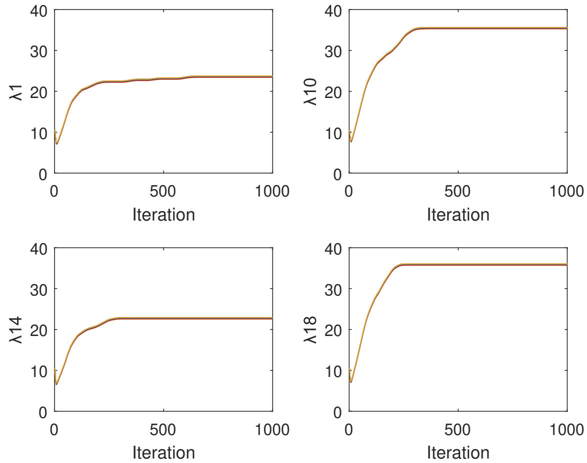

Fig. 7. The 1000th iteration of DLMPs of each generation unit in congested case

exchange with others. The blocks and transactions information can be found in BLOCK and TXs page. They are not shown in the paper becasue of the pages limitation.

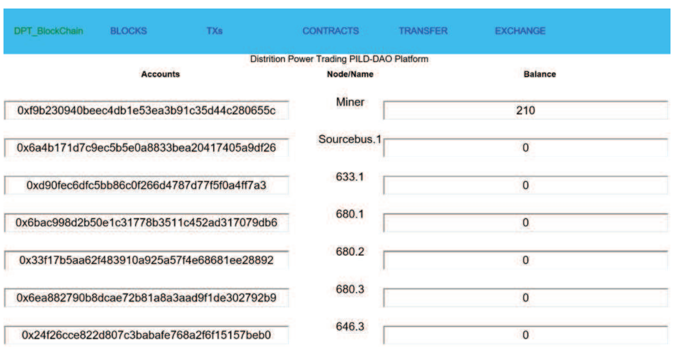

Fig. 8. The home page of distribution power trading platform

Conclusion

In conclusion, the three layers in the new architecture of small-scale microgrid energy market based on PILT-DAO are introduced in this paper. There are 3 PVs and 2 MGs in the modified IEEE 13 node test feeder system topology. In the price mechanism layer, the consensus + innovations approach calculates DLMPs for one normal case and one contingency case. Blockchain technology used on Ethereum platform connects consensus + innovations algorithm in PILT-DAO market layer. In addition, a case study of small-scale microgrid energy market based on PILT-DAO is shown in Figure 8. The research done in this paper demonstrates that the new market structure can reduce the operation cost and increase the transaction security and transparency between DG suppliers with PILT-DAO blockchain technology.

However, several aspects of research are still needed in the future. They are:

1) Calculate the DLMPs under linearized ACOPF constraints using the distributed consensus + innovation algorithm;
2) Apply a new distributed algorithm to ED, DCOPF, and ACOPF;
3) Improve the user interface of distribution power trading based on PILT-DAO.

Acknowledgment

This work is supported by US National Science Foundation grant 1429093.

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