A Decentralized P2P Electricity Market Model for Microgrids

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***Abstract*—Inspired by the online peer-to-peer (P2P) goods trading that has become increasingly popular in the recent years, in this paper we propose a decentralized P2P electricity marketing mechanism for a microgrid (MG) consisting of networked prosumer (consumers with distributed generation capability) clusters by incorporating Blockchain technology and Smart Contracts (SC). Our proposed electricity marketing mechanism is a two-level hierarchical one: In the upper level, the aggregators (AGGs) cooperate with each other and in the lower level, the local PRs maximize their financial profits via P2P energy trading. This mechanisms potentially results in price of anarchy instances in which the targets of the two level players will be contradictory. To address this issue, we assume that there exists a single universal cost function for both levels of the game. In our simulations, we evaluate the performance of our proposed P2P electricity marketing mechanism in maximizing the self-sufficiency of the microgrid and minimizing the side effects of the discriminatory pricing.**

***Index Terms*—P2P Electricity Market, Price of Anarchy, Blockchain, Electricity Market, Aggregator, Distributed Energy Resources (DERs)**

I. INTRODUCTION

Various smart grid techniques have been developed to provide novel analysis and operating tools by leveraging the potentials of the Distributed Energy Resources (DERs) and enhancing the capabilities of the modern power systems in addressing the dramatically increased energy demand. In this manner, we propose a decentralized P2P real-time electricity marketing mechanism for MGs by exploiting Blockchain techniques. Considering the effectiveness of implementing the P2P electricity marketing mechanism is dependent on the high penetration of the DERs, in our paper we assume that the consumers also have DERs such as solar photovoltaic (PV) panels and wind turbines (WT). The authors believe that this assumption is consistent with the evolution of the modern power systems. *Prosumer*(PR) is used to refer to a consumer who owns the DER units. The Blockchain technologies [1] have been developed to provide immutable, public, and decentralized ledger that can be employed to securely record the individual transaction in our P2P energy trading mechanism. In our Blockchain-enabled mechanism, the valuable transactions are determined by using a smart contract (SC) in which all PRs agree to the general algorithm while they may differ in terms of pricing strategies and levels. The cost of financial mining in the Blockchain is carried out by PRs financial transactions' taxation. Our main contribution in this paper is to design an automated P2P direct electricity trading mechansim on the Blockchain platform which brings about various advantages; The decentralized P2P electricity markets potentially reduce the transmission losses and dissipation due to relative short and reduced transmission lines [2], support peak shaving by enabling DG integration into the grid in large scale [3], [4] and helps to dencentralize hierarchical control systems by distributing the generation into a wider portfolio [5] while current centralized algorithms limit DRM (Demand Response Management) programs in the market due to centralized price-based algorithms [4]. The control system in centralized markets is limited to hierarchical control systems and (Very Limited) multi-agent ones [6] and the load profile will always be subject to change from top to bottom. The power outputs of DER units, such as PVs and WTs, can be extremely volatile which introduce significant uncertainties that are unacceptable for detailed financial planning. To address this issue, various solutions have been proposed; *Su et al.* use reserve fast ramping spinning generators to support the system in the times of power generation loss [7]. Although this system is deemed to be reliable, its implementation is expensive and costly. The utilization of load AGGs is proposed in [8] in which load AGGs are market entities that own distributed energy storage systems and sign long-term contracts with local PRs. The incentivize completion of the contract varies from case to case. Additionally, many market designers have been using the financial compensation as the restitution tool for the said rights to incentivize PRs to participate in these types of programs [8], and [9]. *Chang et al.* in [9] proposed a different approach for developing load control algorithms in which they used aggregated loads belonging to various MGs as virtual power plants (VPPs). They also developed a method to minimize the transmission loss to maximize financial gain.

In this paper, we propose a two-level hierarchical energy trading mechanism. In the lower-level, we model the interactions between the PRs within the same MGs by defining a competitive game theoretical mechanism with price discrimination. The competitive nature of the game theoretical model in the lower level automatically solves the issue of lack of incentives for the PRs to take part in the game. Considering that the PRs may lack either time or expertise to constantly engage in the real-time energy transactions, in our model we use Smart Contracts (SCs) for a network of PRs, where status of each PR in the market and energy trading transactions they make is recorded and updated in real time. It is well known that most electricity markets use the uniform pricing for achieving the inherent optimal load profile [10] and removing abnormal load harmonics [11]. The decentralized and P2P nature of price discrimination led us to develop a cooperative game between the AGGs in the upper level of the market structure to minimize the effects of discriminatory pricing and the load increase, and maximize the financial restitution and profits of PRs in the lower-level game. The rest of the paper is organized as follows. In Section II, we will introduce the structure of the MG and the dynamics of the energy storage system. In Section III, we will describe the electricity pricing method and the various strategies of the PRs as well as electricity market trade and optimal decision-making algorithm for an efficient dispatch. The simulation results and the conclusions will be shown in Sections IV and V.

II. THE MICROGRID STRUCTURE

A. The Structure of the Microgrid

In our proposed mechanism, a cost-efficient load profile assessment and planning for renewable energy systems is achieved by leveraging the AGGs in the MG model. In our mechanism, we assume that the AGGs have the following three rights: (1) controlling the interruptible loads (ILs), (2) managing the distributed generations, and (3) taking a pre-determined percentage of each financial transaction as taxation over the associated cluster for maintaining the operations and managing the P2P energy trading. Each AGG is the responsible party for a group of geographically associated PRs that we call *cluster*. Furthermore, we assume that an Automatic Metering Infrastructure (AMI) is implemented in the MG and each PR is connected to their respective AGG and other PRs via high-speed data connection. The electricity consumption level and the cost of generating or purchasing the energy of the individual PRs are announced via that data system to the associated AGGs. One of the essential challenges in designing the decentralized electricity markets is the extremely high, complexity chain of actions that may occur. To tackle this

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challenge, we incorporate the concept of the cloud of energy proposed in [12]. Each cluster of the PRs is equipped with a decentralized Energy Storage System (ESS) that is shared among the PRs within the cluster and, is utilized by the associated AGG for either transferring the energy between local PRs or buying/selling energy to other clusters. Each AGG owns a set of spinning generators whose costs are supported by the taxation of lower-level financial transactions.

B. Dynamics of the ESS and P2P Energy Transfer

In our framework, we assume that each PR *i* of Cluster *j* has its own energy storage unit. The overall ESS capacity of the cluster can be calculated as:

$$ESS_j = \sum_{i=1}^{N_j} ESS_{i,j} \tag{1}$$

where N_j is the number of PRs in Cluster *j*. Additionally, each PR has three pre-defined possible actions regarding the energy storage system: (1) charging it, (2) using its resources to supply their demand, or (3) a hybrid status, in which the individual PRs can act according to the following three essential rules:

I) If the level of local energy storage of PR *i* in the Cluster *j* is larger than $X_u(i,j)$ percent, then this PR must go to the local market as a seller.

II) If the local energy storage unit has fallen below this second threshold $X_d(i,j)$, the PR *i* needs to go to the market to charge its storage system. The system is defined in a manner which, if the level of local storage gets close to the lower threshold, it means that its demand has already surpassed its generation capability.

III) If the ESS charge is lesser than the upper threshold and larger that lower bar, it will follow the following algorithm for its charge and discharge, based on the finite difference of supply-demand function:

$$C_{i,j}^{t_n} = \lim_{h \to 1} \left(\frac{\Delta_h \left(G_{i,j}^{t_n} - D_{i,j}^{t_n} \right)}{h} \right) \tag{2}$$

where $G_{i,j}^{t_n}$ is the generation level of PR *i* of Cluster *j* at the Time-step t_n and $D_{i,j}^{t_n}$ is the demand level of the said PR at the same time period. We choose *h* as the difference duration to converge to minimum difference possible which will be *1*, in order to increase the accuracy and speed of the system response to generation/demand changes. The values of $X_u(i,j)$ and $X_d(i,j)$ which are the *sharing ratios* are determined by the PRs based on their level of willingness to share their resources with the market. The charge-discharge in the hybrid mode is determined according to the following rules: (1) if $C_{i,j}^{t_n} \geq 0$, the PR will start engaging in the market as a seller of energy, (2) if $C_{i,j}^{t_n} < 0$, the PR will continue storing the residential local storage unit to prevent further discharge of the battery, and (3) if $C_{i,j}^{t_n} = 0$, (a subset of situation (1)), it means the market has reached a balance over a certain price and trade will start to occur. This specific situation will be discussed further in III-A, and III-C. Furthermore, if there are not sufficient demand in the market for excessive generation, the PRs can continue to charge their own ESSs. The competition between the PRs is encouraged by leveraging the resources in the local shared ESS. We name the energy storage, momentarily level of each PR *i* of Cluster *j* which contains N_j PRs at any given moment t_n as $R_{i,j}^{t_n}$, and we also denote the amount that each PR brings to the market at any given period t_n as $S_{i,j}^{t_n}$ and it can be calculated as:

$$S_{i,j}^{t_n} = \left\{ \begin{array}{l} \left[\begin{array}{l} \frac{1}{2}\left(1 - sgn\left(X_u(i,j) - R_{i,j}^{t_n}\right)\right) \times \\ \left(R_{i,j}^{t_n} - \left(\frac{X_u(i,j)\, ESS_i}{100}\right)\right) \end{array} \right] + \\ \left[\begin{array}{l} \frac{1}{4}\left(1 - sgn\left(R_{i,j}^{t_n} - X_u(i,j)\right)\right) \times \\ \left(1 + sgn\left(C_{i,j}^{t_n}\right)\right) \left(\left(\frac{X_u(i,j)\, ESS_i}{100}\right) - R_{i,j}^{t_n}\right) \end{array} \right] \end{array} \right\} \tag{3}$$

It should be noted that, if the PR is not sharing any resources with the market which happens in the second situation, its contribution to the market would obviously be zero and thus the inclusion of a third term in Eq. (9), which is always zero, is not necessary. Also, the total tradable, shared resources of Cluster j consisting of N_j PRs, is denoted as $E_j^{t_n}$ and it can be calculated as:

$$E_j^{t_n} = \sum_{i=1}^{k} S_{i,j}^{t_n} \tag{4}$$

III. The Electricity Market Model

In our work, the AGG other than the aforementioned tasks, acts as the auctioneer in each cluster and clears each financial transaction at a distinct price according to price discrimination at the lower level. Furthermore, the AGG of each cluster arranges the seller bids from the least to the highest and buyer bids in reverse. The pricing algorithm for individual PRs is as follows: We denote the maximum value of buyers bids as P_m and the cost of generation is assumed to be independent of each PR's DER unit output level due to relative small size, and is shown by $Q_{i,j}^{t_n}$. Since the bids for generation and demand are made locally, the generation/demand prediction is not required. In other words, even though the generation capabilities of PRs is subject to volatility in future horizons due to inherent fluctuations in PV and WT units power outputs, when the seller PR signs the contract for a certain period in the future, he will always honor it one way or another, either using their storage or buying from real-time market to honor their pledge. The seller will fulfill its responsibility with regards to the contract using either its DER unit, local storage unit or in the worst-case scenario, reducing its demand. This enables us to have deterministic values for trades at each energy trading period. Each PR is trying to maximize its profit while its associated AGG targets at supporting the total demand of the cluster at any given time iteration (period). This interest conflict can result in a pure *price of anarchy* situation in the auction for all PRs. The pricing of each PR is modeled by using three strategies: withholding, predatory (undercutting) and timid [11].

A. Pricing Strategies

1) Predatory Pricing: The objective of PR *i* in this strategy is to sell at a lower price than other PRs in the market in order to either gain power over the market by eliminating other competitors or to sell the energy at a price to gain a risk-free moderate profit that is acceptable to the PR but is not feasible to other competitors. The predatory price P_p in our model it is determined based on the minimum costs of the energy generation of PR *i* and the maximum buyer bids given by the local PRs. The predatory pricing has the constraint defined as follows:

$$Q_{i,j}^{t_n} \leq P_p < \frac{1}{2}\left(P_m + Q_{i,j}^{t_n}\right) \tag{5}$$

$$P_m > Q_{i,j}^{t_n} \tag{6}$$

Since the predatory pricing strategy achieves the lowest value amongst all models of pricing, if no buyers' bid is acceptable for this strategy the PR *i* will not sell energy at that given time.

2) Withholding Pricing: In this strategy, PR *i* aims to maximize its profit by suggesting a higher price comparing to other bids for their energy. The goal of this strategy is to sell at a higher price to either compensate the lower number of sales in case of being undercut by other competitors or to gain maximum authority over market if no other seller is active. The withholding price is defined as follows:

$$P_w \geq P_m \tag{7}$$

3) Timid Pricing: Timid Pricing refers to the strategy that achieves the price between the predatory price and the maximum buying bid and can be modeled as follows:

$$\frac{1}{2}\left(P_m + Q_{i,j}^{t_n}\right) \leq P_T < P_m \tag{8}$$

As mentioned earlier, the trade mechanism employed in this paper is an automated one that occurs independent of momentary decisions of the buyer and/or seller PRs in order to facilitate a trade system on the SC. This mechanism is dependent only on the strategies, sharing ratios as mentioned in section II-B as well as generation/demand of the PRs and maximum price and individual cost of generation. The decision-making procedure for individual seller PRs is described in II-B. The pricing for seller PRs is dependent on parameters and concepts introduced separately in II-A, II-B, and III-A, but in order to present a unified vision for the price, we can write the price of electricity as:

$$P_{i,j}^{t_n} = \left\{ \begin{array}{l} \left[\begin{array}{l} \frac{1}{2}\left(1 - sgn\left(P_p(i,j) - \frac{1}{2}\left(P_m + Q_{i,j}^{t_n}\right)\right)\right) P_p(i,j) + \\ \frac{1}{2}\left(1 - sgn\left(P_m - P_w(i,j)\right)\right) P_w(i,j) + \end{array} \right] \\ \left[\begin{array}{l} \frac{1}{4}\left(1 + sgn\left(P_T(i,j) - \frac{1}{2}\left(P_m + Q_{i,j}^{t_n}\right)\right)\right) \times \\ \left(1 + sgn\left(P_m - P_T(i,j)\right)\right)\right) \times P_T(i,j)) \end{array} \right] \end{array} \right\} \tag{9}$$

The price for each individual PR depending on their strategy differs and is pre-determined by the seller PR. The case for buyer PRs is slightly different and works based on two main parameters, availability of the resource and reputation of the seller and it can be described in Fig. 1.

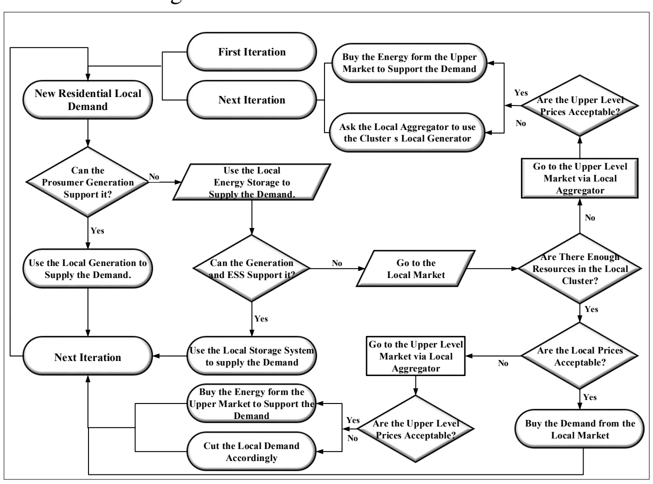


Fig. 1: Buyer Prosumer Decision-making Process

B. *Blockchain-Based Trade Mechanism*

The Blockchain enables various functionalities that were not possible in the centralized markets or even coalitions such as robust security of information, decentralized validation of transactions, market decentralization, and etc. The Blockchains provide the possibility of practical implementation of discrimination-based price market. Furthermore, there is no need for a coalition of a cooperative pool of PRs to take shape and the profit allocation will be completely fair and intrinsic to the system. The pricing policies for each PR is defined as a variable that they can simply choose in the SC, as well as announcing and updating their sharing ratios and other information regarding their participation. These information can easily be acquired and announced in the market by using the SC. Based on their level of electricity generation, their cost of generation, their selected policy, and the sharing ratios that are announced in the SC, the PRs can go to the market to either sell their excessive generation or to buy energy to supply their demand in the future iterations based on the following priorities: (1) Local PR generation, (2) Local PR ESS, (3) Local cluster market (If the prices are acceptable and/or there is enough resources in the local cluster), and (4) Upper-level market by asking the AGG. The details of market mechanism including the pricing algorithm and decision-making procedure of the individual buyer PRs is shown in Fig. 1. At each iteration, each seller PR, gives its excessive electricity to the AGG and receives a unit, which is called *coin* and has the value proportional to the amount of the shared energy, from the AGG. The authors would like to mention that the concept of coin is equivalent to "*Renewable Energy Certificates*" proposed in [13] that refers to a pre-determined amount of energy. In the market, PR acting as a buyer, called buyer PR, joins the pool of local seller PRs and based on the required energy demand and the reliability coefficients of each seller that are defined in the SC, buys its required coins from any seller that it deems appropriate. In the next stage, the buyer PR goes to the AGG with the bought coins and demands energy for the coins. By leveraging the coins, we effectively eliminate disparities in load balance, frequency, and voltage that may raise in P2P electricity market mechanism. There are issues that may occur during this transaction, most noticeable of all is that the local pool of sellers pricing is not acceptable to buyers which is the equivalent of:

$$P_m < Q_{i,j}^{t_n} \tag{10}$$

To tackle this issue, there is another option for a buyer to go directly to the AGG and ask for resources. Since the AGG owns nothing other than the reserve generators and its rights, it cannot sell from the shared ESS to the buyer (The shared pool of resources belongs to the sellers and coin owners.), so it must go to the upper market and ask for resources in the upper-level market between other AGGs as a *buyer AGG*. The reserve generators only functionality is for the conditions, where there aren't sufficient resources in the both lower and the upper levels. In our modeling, we name the generator output power as λ_j. The cost of this generator should be compensated by the taxation that is agreed upon earlier. The size of generation of this reserve is proportional to the rate of taxation τ_j:

$$\lambda_j = \frac{\tau_j}{m}\left(\sum_{t_n=t_0}^{t_n+24}\left(\sum_{i=1}^{k} D_{i,j}^{t_n}\right)\right) \tag{11}$$

where m is the financial efficiency ratio of the generator and is assigned as a weight to the system. In our model simulation, we set m as 2. Since the AGGs have no goal of financial profit, they only sell the energy at the price that is based on their maximum local PRs price. The market clears at distinct prices for each AGG and each AGG has no strategy except the one that is enforced by its local PRs via their local pricing algorithms. Moreover, the AGGs obviously have no authority to sell the energy at a lower price than their clusters maximum price. We believe this assumption is reasonable since: (1) An AGG cannot enforce a price to its seller PRs. (2) The AGG cannot impose any financial loss to its local cluster other than agreed upon, tax rate. (3) Each AGG may not use its local seller PRs who sell at lower prices to sell to other AGGs because the first priority for each PR is the local cluster and inside the local cluster, there are local buyers that may use that lower priced energy. The lower-level local market and upper-level AGG market are both cleared simultaneously.

C. *The Electricity Market Optimization Problem*

Since our market uses price discrimination, the total cost of energy for all PRs and their level of satisfaction will be different from the optimized values [11] usually associated with uniform pricing. To strike this issue, we introduce a social satisfaction factor for the PRs in the system performance cost function which will also include their total cost of energy. The social satisfaction index $\phi_{i,j}$, is dependent on the level of demand cuts that the cluster undergoes and is different from perceived reputation of sellers which is a constant value. The cost function for the performance of the system is defined by also considering total power consumption in each iteration and the individual financial gain of all PRs in the cluster. Since the market uses a simultaneous method for price clearing, in both upper and lower levels, we use a single cost function for both levels of the market to optimize the system status at any given moment. We know that the profit of each seller is determined by its strategy and its generation supply curve, so for Cluster *j*, we have:

$$T_{i,j}^{t_n} = \left(1 - \frac{\tau_j}{100}\right)(S_{i,j}^{t_n})(\,P_{i,j}^{t_n}) \tag{12}$$

Using Eq. (12), we can determine the total sales of all PRs Y_j, of Cluster *j*:

$$Y_j \;= \sum_{t_n=1}^{t_f} \sum_{i=1}^{N_j} (V_i) \left(T_{i,j}^{t_n}\right) \tag{13}$$

where V_i is the perceived *reputation* coefficient of each PRs that each buyer PR considers when selecting a seller. The value of V_i is fixed for each seller PR and is used as a weight parameter in the decision-making procedure for buyers. The total cost of energy for all PRs of Cluster *j*, is dependent on their demand as well as the price that they pay for energy which can be calculated as:

$$W_j = \sum_{t_n=1}^{t_f} \left[\left(\sum_{i=1}^{N_j} \left(\,D_{i,j}^{t_n}\right) \left(P_i \left(\,C_j^{t_n} = 0\right)\right) \right) \right] \tag{14}$$

where:

$$C_j^{t_n} = \sum_{i=1}^{N_j} C_{i,j}^{t_n} \tag{15}$$

As shown in Eq. (15), the total cost of demand is calculated by the intersection price point of the demand and supply curves multiplied by the total demand in all iterations. The demand and supply curves for each PR may vary but we design them based on the maximum price point of each buyer PR P_m and minimum generation cost of seller PRs, $Q_{i,j}^{t_n}$ in respectively linearized demand and supply curves. The total cost of generation for a Cluster *j*, can be calculated as:

$$Z_j \;= \sum_{t_n=1}^{t_f} \sum_{i=1}^{N_j} \left(Q_{i,j}^{t_n}\right) \tag{16}$$

The PRs main goal is financial gain, so the following cost function, which is utility function from the perspective of PRs of one cluster *j*, should be maximized:

$$U_j \;= Y_j \;-\; (W_j \;+ Z_j) \tag{17}$$

As mentioned earlier, the AGGs mainly focus on maximizing the feasibility of the grid and this comes through that maximum ratio of the demand of the cluster is supported and the PRs have had minimum demand cuts and since the reason behind the demand cuts is the high price of energy, we can calculate the cost function from the perspective of an AGG. First, the total cut needs to be calculated:

$$\phi_{i,j}^{t_n} = \frac{1}{2}\left[1 - \operatorname{sgn}\left(C_{i,j}^{t_n}\right)\right] \left[\sum_{t_n=1}^{t_f} \left(C_{i,j}^{t_n}\right) \right] \tag{18}$$

$$\phi_j \;= \sum_{t_n=1}^{t_f} \sum_{i=1}^{N_j} \left(\phi_{i,j}^{t_n}\right) \tag{19}$$

The summation of all demand cuts are considered as the indexes of the system reliability, where lower total demand cut points at a more self-sufficient, feasible and reliable system and higher one shows a less reliable system. The difference in the price and the cost of energy that forced a buyer PR to cut its demand instead of buying it, can be modeled as:

$$O_j = \left(\phi_{i,j}^{t_n}\right) \left(\min_i \;\left(Q_{i,j}^{t_n}\right) - P_m \right) \tag{20}$$

The main constraint of the utility function comes from self-sufficiency of the MG. Therefore, based on Eqs. (17) and (20), we can derive the final cost function for the PRs of cluster *j* and their associated AGG:

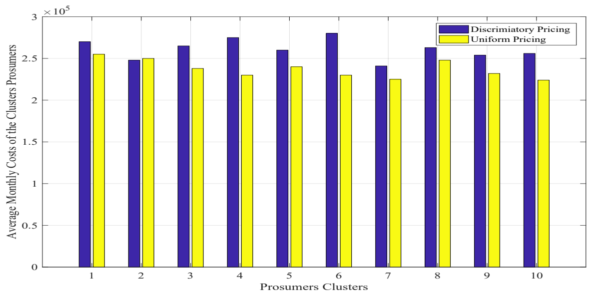
$$\underset{\tau_j}{Maximize} : \quad U_j - O_j \tag{21}$$

$$Subject\, to: \;\; (Y_j + \lambda_j) - \left(\sum_{i=1}^{N_j} \left(\,D_{i,j}^{t_n}\right) \right) \geq 0 \tag{22}$$

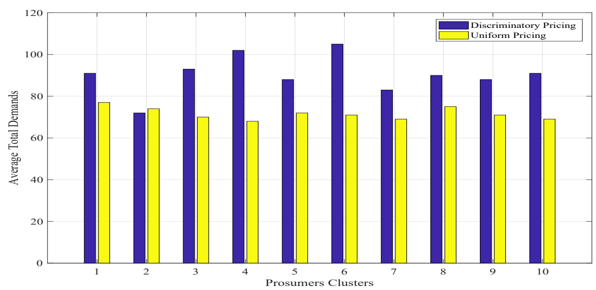
As defined in Eqs. (21) and (22), if the total generation of the cluster does not satisfy the total demand of it, the system will ask for resources from other clusters and if that attempt is not successful, finally it will go to its own reserve generators and in such situations, obviously, an optimized dispatch is not the first priority for the system. In the next section, the simulation results of the model and general conclusions are presented.

IV. Simulation Results

In this section, we evaluate our proposed mechanism by considering a MG consisting of ten PR clusters. In each cluster, there are PRs that are equipped with small PV panels with a nominal power output of 2.5 kWh. As stated in previous sections, the PRs are in geographically close locations so they will face similar weather and financial situations, but their load profiles are different. We use the datasets from the day ahead forecasts of Solar PV panels for the state of Ohio in the April of 2006, from National Renewable Energy Laboratory (NREL) archive [14] to normalize and correctly simulate (based on time of the day and the day in the month) power outputs of each PR's DER unit. The simulations are conducted for a sample period of 24 hours that is divided to 24 time iterations in the day ahead market. At the start of each period, PRs can go to the market to buy their demand for the same period tomorrow from the local pool of local cluster's PRs, while the upper-level market is an expensive real-time option. To achieve a context for the actual price of energy and simulate the interactions within the upper and lower levels of day-ahead and real-time market, we use the PJM locational marginal pricing dataset in the same period (i.e. April of 2006) for OhioHub. We simulate the average total costs of each cluster for every 24 hours and compare the simulation results to the values that are achieved via standard uniform pricing. In our simulations, the system never shifts to emergency reserves , which illustrates the effectiveness of our mechanism in improving the feasibility and reliability of the electricity market for distribution power systems. From Fig. 2 (a), we can observe that the total costs of energy of the PRs of the cluster, due to the demand rise for each PR, have an increment with an average rate of 20.68 % compared with centralized real-time uniform pricing which can be explained by price discrimination. Discriminatory pricing reduces the total financial optimality of the system at the price of nearly total freedom of PRs in their functionality. In the next step, we compare the total average



(a)



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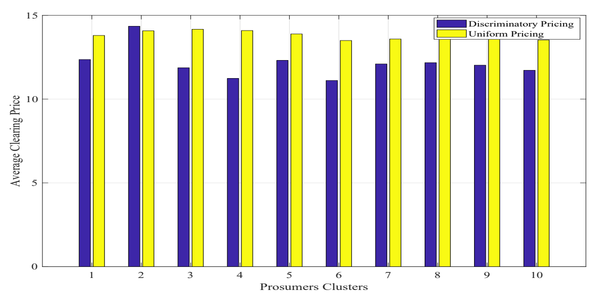

(c)

Fig. 2: The Average (a) Costs of a Clusters Prosumers for Ten Clusters, (b) Total Demand for All Clusters, (c) Price for All Clusters Prosumers per Hour

demand load of clusters in our decentralized discriminatory pricing method versus uniform pricing. In our system,the individual PRs can act as either buyers or sellers in the market. Furthermore, as shown in Fig. 2 (b), the decentralized P2P marketing algorithm proposed in our system modeling efficiently reduces the optimality of the demand profile and will cause a surge in the electricity consumption rate for relatively all of the PRs. From Fig. 2 (b), we can also see that due to the price discrimination in our decentralized P2P marketing model, the load peak for the cluster will increase as well but at a rate of only 9.37 %. This result is reasonable since the inherent price discrimination creates will create zones with PRs that, based on their reputation, will engage only in mutual financial transaction mostly with each other; This issue will result in increased demand in the system during peak hours. The other parameter that is affected by our modeling is the average price of electricity. In our model, while the price discrimination might hint to increased price, it is expected that the we witness lower **average** prices comparing to the centralized markets which have to compensate for transmission losses and infrastructural costs and it would also be compatible to individual rationality and incentive compatibility principle for individual PRs. In Fig. 2,(c) it can be seen in remotely all instances the average prices for consumers is lower than that of central markets. It should be noted that the individual prices for transactions is volatile and highly dependent on the preferences of each PR and it might be higher or lower than the average values of Fig. 2 (c).

In this paper, we propose a Blockchain-enabled mechanism for decentralized P2P energy marketing, in which the price discrimination is determined based on the decision-making of the individual residential PRs and the energy trading transactions are implemented autonomously via smart contracts. As shown in the simulation results, the main target of the upper-level of the market which is the self-sufficiency of the MG is reached. The lower level's PRs financial turn over is also acceptable and total freedom for all PRs is ensured but this comes at the cost of lower financial turnover, an increase in demand and higher load peak. In the current context, as shown in simulation results, the mechanism is capable of minimizing the total cost and load peak increase, to a certain extent which both the demand peak and costs are lower than centralized flat-priced traditional markets and only lack behind real-time uniform markets. This is an acceptable compromise for decentralization of the market. In our ongoing work, we are extending the work in this paper by considering including more practical measures and regulations in the model and implementing P2P electricity marketing for a set of residential MGs in urban environment with more restrictions and constraints.

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