Joint Geometric Unsupervised Learning and Truthful Auction for Local Energy Market

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***Abstract*—Development of smart grid technologies has created a promising atmosphere for smart cities and energy trading markets. Especially, traditional electricity consumers evolve into prosumers who produce as well as consume electricity in modern power electric systems. In this evolution, the electric power industry has tried to introduce the notion of *local energy markets* for prosumers. In the local energy market, prosumers purchase electricity from distributed energy generators or the other prosumers with surplus electricity via a local power exchange center. For this purpose, this paper proposes joint *geometric clustering* and *truthful auction* schemes in the local energy markets. The proposed *clustering* scheme is designed for distribution fairness of the distributed energy generator for serving prosumers, where the scheme is inspired by expectation and maximization (EM)-based unsupervised learning. Moreover, this paper proposes an *auction* mechanism for truthful electricity trading in a local energy market. In order to guarantee truthful electricity trading, the proposed auction mechanism is constructed based on the Vickrey-Clarke-Groves (VCG) auction, which was proven to guarantee truthful operations. The Hungarian method is also considered in addition to the auction. The simulation results for the auction verify that the utilities of local market energy entities are maximized when the prosumers are truthful.**

***Index Terms*—Smart grid, Local power exchange center, Clustering, Local energy market, VCG auction.**

I. Introduction

DEVELOPMENT of smart cities and energy informatics technologies considers the clean energy agenda including climate change, transitions to low-carbon energy, and potential renewable energy resources [1], [2]. Recently, technologies related to renewable energy resources, such as advanced metering, energy storage systems (ESSs), and energy communications, have dramatically evolved [3], [4]. These developments create opportunities for energy consumers to evolve into *prosumers*. In other words, prosumers are able to consume as well as produce electricity using renewable energy resources in a smart city. As the number of prosumers increases, leading electric power companies such as the Korea Electric Power Corporation (KEPCO) have currently introduced the concept of local energy market, which allows electricity trading among prosumers. KEPCO has recently established local power exchange centers for local energy markets in Korea.

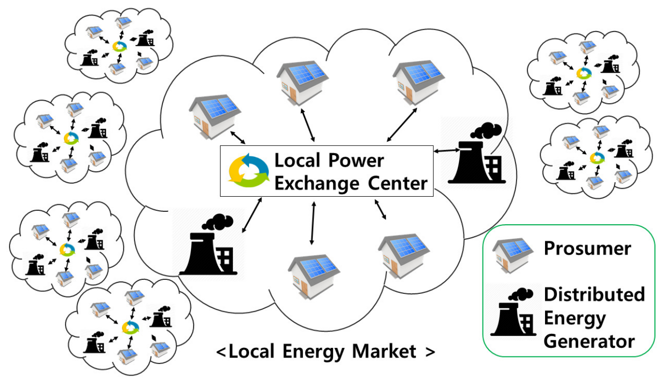

Fig. 1: A reference system model for local energy market

Fig. 1 illustrates the concept of local energy market. As presented, a local energy market consists of prosumers, distributed energy generators, and a local power exchange center. A prosumer who needs electricity can request electricity from the local energy market. Then, prosumers who produce more electricity than they need can auction their surplus electricity. At this time, the local power exchange center acts as broker for electricity trading, i.e., determining the matching and pricing for electricity trading. The previous research results of energy prosumers aimed to reduce both the cost of energy production and the usage of the power grid and thus could not consider the concept of a local power exchange center.

This paper proposes novel algorithms of *clustering* for organizing local energy markets and *auctioning* for truthful electricity trading.

For *clustering*, this paper proposes a geometric local market clustering scheme based on unsupervised learning algorithm concepts [5]. Electricity loss increases rapidly as the transmission distance increases. Therefore, prosumers are geometrically clustered. The proposed scheme clusters all prosumers based on a location when the number of clusters is given. Accordingly, the proposed scheme can be used if the electric power industry introduces any number of local energy markets.

As shown in Fig. 1, this paper assumes that several distributed energy generators are public facilities for producing electricity such as a public thermal power station. In this paper,

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the distributed energy generator has a different meaning from the distributed energy resource (DER), which refers to smaller power sources from renewable energy such as photovoltaic or wind turbines. Since the distribution of generators is important for energy market fairness, the proposed clustering scheme considers distribution fairness of the distributed energy generators. The proposed geometric clustering method has a different purpose than locational marginal pricing (LMP) [6], which is a pricing system that includes marginal costs, supply costs, and congestion in the grid under geographical considerations. i.e., the proposed clustering scheme presents the local energy market organization method considering both geographical location and fairness.

For *auctioning*, this paper proposes a truthful electricity trading scheme based on the Vickrey-Clarke-Groves (VCG) auction. The VCG auction consists of sealed-bid auctions for ensuring truthful actions in electricity trading. The VCG auction is a special case of Vickrey auction, where each bid should be the true value to maintain utility. This paper assumes that participants of the auction consist of 1) a seller who is a prosumer with surplus electricity, 2) a buyer who is a prosumer with power shortage, and 3) an auctioneer who is a local power exchange center. In the auction, buyers request the electricity demand to auctioneer, and the demand will be an item of the auction. Then, each seller will bid for item, and bidding reflects the actual cost that can be influenced by the geometric relationship with the seller along with the cost function. Therefore, the proposed scheme prevents electricity monopolies and ensures market efficiency.

In summary, the proposed schemes contribute as follows:

- *Clustering fairness:* The proposed clustering algorithm is based on the geometric information of the prosumers and finds appropriate locations for the local power exchange centers. In addition to the location information, the clustering operation functions under the consideration of fairness of distributed energy generators.
- *Truthfulness auction mechanism:* The proposed auction mechanism is constructed based on the VCG auction, which is well known for its truthfulness. Also, the truthfulness of the VCG auction has been proven [18]. Via intensive evaluations, it has been shown that the utilities of each consumer are maximized when evaluating truthful behaviors; thus, the proposed scheme is proven to be truthful.
- *Computational efficiency:* The proposed optimization problem for geometric clustering is NP-hard. Therefore, this paper proposes a scheme inspired by the expectation and maximization (EM)-based learning algorithm to solve the problem in polynomial time. In addition, the proposed auction matching is also NP-hard; thus, the proposed scheme solves the problem using the Hungarian method, which is a well-known polynomial-time method for finding matching that meets the minimum cost.

The rest of this paper is organized as follows. Section II conducts literature surveys. In Section III, a geometric clustering scheme for fairness is proposed. Section IV proposes truthful auction for energy trading. Section V evaluates the performance of the proposed clustering and auction schemes. The conclusions of this paper are given in Section VI.

II. Related Work

There have been several studies on the communications and networks of distributed micro grid systems [7]–[9]. An interconnection architecture of multiple micro grids is proposed in [7]. The proposed algorithm in [8] investigates the robust distributed control scheme to achieve the desired power regulation by coordinating distributed energy generators. The distributed controller monitors the power mismatch in neighbor micro grids and regulates power flow among different micro grids. In [9], the probabilistic minimal cut-set-based iterative methodology is proposed for micro grid interconnection planning. The interconnection planning enhances the reliability and the economic operation of micro grids. These interconnection schemes are focused on solving island problems such as low reliability and limited energy generation capability. Therefore, it is difficult to apply interconnection schemes to local energy market clustering. In [10], the micro grid clustering scheme is proposed under the consideration of communication and control requirements. They take into account the latency and reliability of the communication systems for optimization formulation. In smart city's local energy market, reliability and latency problems will be solved by a low cost, high performance network interface such as WiFi. Previous research [7]–[10] has taken into account the power quality aspects, i.e., the characteristics of the distributed power generation units, the distributed energy storage units, and the distributed reactive source for micro grid clustering.

Several studies have focused on energy market auctions [11]–[17]. In [11], a real-time implementation of multi-agent-based game theory reverse auction models is proposed for a micro grid. The proposed algorithm in [12] focused on efficient double auctions along with proportional allocation of electricity among its buyers. In [13], an auction mechanism is proposed under the consideration of Stackelberg game theory. In [14], a risk-based auction strategy is implemented in which an agent can assess the risk associated with a bid or ask under current market conditions and bid/ask accordingly to maximize the profit. These papers proposed customized auction algorithms for energy markets and analyzed the algorithms through game theory. The main purpose of these papers is to efficiently purchase the required amount of energy at the lowest cost, although the auctions did not present plans to avoid monopolistic resources. [15] proposed the reverse auction architecture based on a second-price Vickrey auction for truthful bidding. However, since the market environment in [15] consists of one buyer and multiple sellers, it is not suitable for a local energy market consisting of multiple buyers and sellers. The VCG auction is used in [16] as an auction well known for truthful trading [18]. However, detailed auction mechanisms are not presented in [16], preventing a clear understanding. In [17], the VCG auction mechanism with a linear problem is proposed, and its truthfulness is mathematically proven. In contrast with bidding done by the seller in the present paper, it is done by the buyer in [17].

III. Geometric Clustering for Local Energy Market

This section formulates optimization problems for geometric unsupervised learning, i.e., clustering, for local energy markets. The purpose of this mathematical model is to formulate local energy market clustering under the consideration of distribution fairness among distributed energy generators.

A. Motivation

This paper investigates a geometric unsupervised learning-based clustering algorithm for local energy markets. To the best of our knowledge, currently existing clustering algorithms have focused on the sustainability of clustering groups under consideration of the characteristics of each entity. However, the prosumer, an entity of the local energy market, contains the characteristic of being able to sell or buy electricity according to the situation. Therefore, this paper proposes a geometric unsupervised learning algorithm that excludes all prosumer characteristics since they are difficult to consider in existing clustering algorithms. Furthermore, the proposed algorithm is designed to consider the distribution fairness of distributed energy generators because each local energy market should be under stable and seamless energy supplies.

B. Problem Formulation

The proposed network architecture consists of prosumers and distributed generators. Each prosumer is able to generate and also consume electricity, e.g., smart homes or residential buildings with renewable energy resources. On the other hand, the distributed generators only produce energy via small generators. If the electric power industry wants to build local power exchange centers, their geographical locations and the distribution of the generators are very important in terms of trading efficiency and sustainability of local energy markets. In particular, the clustering of generators in local energy markets is very important due to the increase in power consumption depending on the distance between the sellers and buyers. In addition, the local energy market becomes unfair if the distributed energy generators are concentrated in a specific local energy market. Therefore, the proposed optimization problem aims for balance in terms of the geometric distribution of the local energy markets and ensures the fairness of the distribution of energy generators.

In order to formulate clustering models, the proposed scheme defines the notation for the set of prosumers $\mathcal{P}$, i.e.,

$$\mathcal{P} = \{p_1, p_2, \cdots, p_N\}, \tag{1}$$

where N is the total number of prosumers in the system. This paper also assumes that each prosumer p_n has a geometric location vector $\mathbf{L}^p_n$. Similar to (1), the set of distributed energy generators $\mathcal{D}$ is defined as

$$\mathcal{D} = \{d_1, d_2, \cdots, d_M\}, \tag{2}$$

where M is the total number of distributed energy generators, and d_m has geometric location vectors $\mathbf{L}^d_m$.

If the electric power industry decides to construct K local energy markets, K local power exchange centers are required. Let $\mathcal{X}$ be the set of local power exchange centers, defined as follows:

$$\mathcal{X} = \{x_1, x_2, \cdots, x_K\}, \tag{3}$$

and x_k has geometric location vectors $\mathbf{L}^x_k$.

Based on the definitions and notations, the relations between prosumers and local power exchange centers are defined as

$$r^p_{n,k} = \begin{cases} 1, & \text{if prosumer } p_n \text{ belongs to cluster } k \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

Since each prosumer should be associated with one local power exchange center, it is true that:

$$\sum\nolimits_{k=1}^{K} r^p_{n,k} = 1, \forall p_n. \tag{5}$$

Similarly, let $r^d_{m,k}$ be the relation between d_m and x_k, which is defined as an indicator function, i.e., if d_m belongs to cluster k, $r^d_{m,k} = 1$; otherwise, $r^d_{m,k} = 0$. Since each distributed energy generator should belong to one local power exchange center, it is obvious that:

$$\sum\nolimits_{k=1}^{K} r^d_{m,k} = 1, \forall d_m. \tag{6}$$

As discussed, the proposed optimization formulation aims to balance the geometric distribution of energy generators in local energy markets. Therefore, the fairness of the distribution of energy generators can be formulated as follows:

$$\sum\nolimits_{m=1}^{M} r^d_{m,k} \leq \left\lceil \frac{M \cdot \omega}{K} \right\rceil, \forall x_k, \tag{7}$$

where ω is a balance factor for the fairness in clustering, and $1 \leq \omega \leq K$. As ω becomes smaller, more fairness can be achieved, i.e., distributed energy generators are evenly distributed among clusters when $\omega = 1$, whereas all distributed energy generators belong to one cluster when $\omega = M$.

Based on this optimization design rationale, a distortion measure function $\mathcal{DMF}$, which is the sum of the geometric distances between the local energy market entities (prosumers or distributed energy generators) and local power exchange centers, ,can be defined as follows:

$$\mathcal{DMF} \triangleq \sum\nolimits_{k=1}^{K} \left(\sum\nolimits_{n=1}^{N} r^p_{n,k} ||\mathbf{L}^p_n - \mathbf{L}^x_k||^2 + \sum\nolimits_{m=1}^{M} r^d_{m,k} ||\mathbf{L}^d_m - \mathbf{L}^x_k||^2 \right). \tag{8}$$

Therefore, the optimization problem is for the minimization of $\mathcal{DMF}$ under system model constraints:

$$\underset{r^p_{n,k}, r^d_{m,k}, \mathbf{L}^x_k}{\text{minimize}} \quad \mathcal{DMF} \tag{9}$$

$$\text{subject to} \quad \sum\nolimits_{k=1}^{K} r^p_{n,k} = 1, \forall p_n \tag{10}$$

$$\sum\nolimits_{k=1}^{K} r^d_{m,k} = 1, \forall d_m \tag{11}$$

$$\sum\nolimits_{m=1}^{M} r^d_{m,k} \leq \left\lceil \frac{M \cdot \omega}{K} \right\rceil, \forall x_k \tag{12}$$

$$1 \leq \omega \leq K. \tag{13}$$

C. Expectation and Maximization (EM)-based Clustering

The optimization formulation in previous section, i.e., (9)-(13), is NP-hard due to the fact (9) is not convex; thus, it is obviously difficult to solve in polynomial-time. Therefore, this section presents the EM-based learning algorithm to solve the given optimization problem. The EM algorithm is an iterative method to find the maximum likelihood estimates of parameters [5]. The EM iteration computes the *expectation* of log-likelihood evaluated using the current estimate for the parameters, and the *maximization* of expected log-likelihood. In the expectation phase, each prosumer belongs to which cluster will be expected, i.e., finds $r^p_{n,k}$ and $r^d_{m,k}$ using the estimated locations of local power exchange centers. In the maximization phase, the locations of local power exchange centers to maximize the utility will be found, i.e., find $\mathbf{L}^x_k$ using the estimated relations between prosumers, distributed energy generators, and clusters.

Let $\mathbf{R}^x_k$ be denoted by the estimated geometric location vector of local power exchange center k inspired by the fundamental concept of EM algorithms. Then, $\mathcal{DMF}$ in (8) can be reformulated as follows by assuming that $\mathbf{L}^x_k = \mathbf{R}^x_k$, which is based to the fundamental procedures of EM algorithms:

$$\mathcal{DMF}_{exp} \triangleq \sum\nolimits_{k=1}^{K} \left(\sum\nolimits_{n=1}^{N} r^p_{n,k} ||\mathbf{L}^p_n - \mathbf{R}^x_k||^2 + \sum\nolimits_{m=1}^{M} r^d_{m,k} ||\mathbf{L}^d_m - \mathbf{R}^x_k||^2 \right), \quad (14)$$

where $\mathbf{R}^x_k$ is a constant, and (14) is defined in a closed form for $r^p_{n,k}$ and $r^d_{m,k}$. In addition, the objective function (9) can be updated as follows:

$$\underset{r^p_{n,k}, r^d_{m,k}}{\text{minimize}} \; \mathcal{DMF}_{exp}. \quad (15)$$

Let $\mu^p_{n,k}$ be the estimated relation between prosumer n and cluster k; and $\mu^d_{m,k}$ stands for the estimated relation between the distributed energy generator m and cluster k. By assuming that $r^p_{n,k}$ and $r^d_{m,k}$ are equal to $\mu^p_{n,k}$ and $\mu^d_{m,k}$, respectively, (8) can be updated as follows:

$$\mathcal{DMF}_{max} \triangleq \sum\nolimits_{k=1}^{K} \left(\sum\nolimits_{n=1}^{N} \mu^p_{n,k} ||\mathbf{L}^p_n - \mathbf{L}^x_k||^2 + \sum\nolimits_{m=1}^{M} \mu^d_{m,k} ||\mathbf{L}^d_m - \mathbf{L}^x_k||^2 \right), \quad (16)$$

where $\mu^p_{n,k}$ and $\mu^d_{m,k}$ are constants. Similarly, the objective function (9) is updated as follows:

$$\underset{\mathbf{L}^x_k}{\text{minimize}} \; \mathcal{DMF}_{max}. \quad (17)$$

Due to the fact that (16) is quadratic and thus convex, it can be solved using optimization solvers in polynomial time.

The proposed clustering algorithm for solving the optimization framework is formally described in Algorithm 1. Algorithm 1 consists of two steps, i.e., (i) initialization and (ii) EM-based geometric clustering. First, the initialization step initializes the default value for algorithm operation, i.e., it sets the vector $\mathbf{R}^x_k$ as random, which is used as a seed vector; and sets $\mathcal{DMF}_{prev}$ and $\mathcal{DMF}$ as the default values

Algorithm 1: Geometric Clustering Algorithm

Step 1: Initialization
for $k = 1 \rightarrow K$ **do**
    Set $\mathbf{R}^x_k$ as random vector.
end for
$\mathcal{DMF}_{prev} \leftarrow 0$
$\mathcal{DMF} \leftarrow \infty$
Step 2: EM-based Geometric Clustering
while $\mathcal{DMF} \neq \mathcal{DMF}_{prev}$ **do**
    $\mathcal{DMF}_{prev} \leftarrow \mathcal{DMF}$
    Step 2-1: Expectation Phase
    find $r^p_{n,k}, r^d_{m,k}$ with objective function (15)
    $\mu^p_{n,k} \leftarrow r^p_{n,k}$
    $\mu^d_{m,k} \leftarrow r^d_{m,k}$
    Step 2-2: Maximization Phase
    find $\mathbf{L}^x_k$ with objective function (17)
    $\mathbf{R}^x_k \leftarrow \mathbf{L}^x_k$
    calculate $\mathcal{DMF}$ with (8)
end while

where $\mathcal{DMF}_{prev}$ is used to determine the convergence of the EM-based geometric clustering algorithm. After completing the initialization step, the second step, EM-based geometric clustering, iteratively and successively conducts expectation and maximization until the result converges. In the expectation phase, find $r^p_{n,k}, r^d_{m,k}$ with (15), which can be obtained in polynomial time due to the fact that (14) is defined in a closed form for $r^p_{n,k}$ and $r^d_{m,k}$, i.e., the computational complexity is $O(N)$. Then, $\mu^p_{n,k}$ and $\mu^d_{m,k}$ are updated with the obtained $r^p_{n,k}$ and $r^d_{m,k}$, respectively. The updated variables will be used in the maximization phase, where $\mathbf{L}^x_k$ is calculated with (17). The optimal value of $\mathbf{L}^x_k$ can be obtained in polynomial time because (16) is convex. Then, $\mathbf{L}^x_k$ will be updated to obtained $\mathbf{R}^x_k$ to be used in the next step of the expectation phase. After completing this maximization, the proposed algorithm calculates the distortion measure function $\mathcal{DMF}$ to determine convergence. If the current distortion measure function $\mathcal{DMF}$ is equal to the previous result, a local optimal solution is found by this EM-based algorithm. Based on the calculated $r^p_{n,k}$ and $r^d_{m,k}$, the clustering local energy market entities are defined. In addition, the location of the local power exchange center is determined based on the obtained $\mathbf{L}^x_k$.

IV. Truthful Auction for Local Energy Market

This section introduces the auction models for truthful electricity trading in a local energy market. In addition, the problems are mathematically formulated and the desirable properties of the auction mechanism are presented.

A. Motivation

After determination of the local power exchange center using geometric clustering, the local power exchange center can start managing prosumers and locally form a market. This means that the local power exchange center can act as the aggregator for power trading among prosumers. A center can exchange information with the prosumers to determine appropriate market prices. For this purpose, a VCG-based auction mechanism is proposed for joint matching and price calculation. In addition, the auction mechanism guarantees the truthfulness, computational efficiency, and individual rationality[1] [18]. For auction mechanism design, this paper assumes that a seller is a prosumer with surplus electricity or a distributed energy generator, a buyer is a prosumer with power shortage, and an auctioneer is a local power exchange center. Note that the terms of seller, buyer, and auctioneer are used instead of prosumer, distributed energy generator, and local power exchange center, respectively, in the rest of this paper.

B. Problem Formulation

Prior to the explanation of the proposed truthful energy auction, a suitable formulation is defined in this section. In order to formulate the energy auction model, assume that each local energy market consists of an aggregator, a seller group $\mathcal{S}$, and a buyer group $\mathcal{B}$, where $\mathcal{S}$ consists of I sellers and is denoted as follows:

$$\mathcal{S} \triangleq \{s_1, s_2, \cdots, s_i, \cdots, s_I\}. \tag{18}$$

$\mathcal{B}$ consists of J buyers and is denoted as follows:

$$\mathcal{B} \triangleq \{b_1, b_2, \cdots, b_j, \cdots, b_J\}. \tag{19}$$

This paper also assumes that each seller s_i has surplus electricity E_i^{pro} with electricity generation cost c_i^{pro}. The electricity generation cost c_i^{pro} can be expressed by various cost functions according to energy resource type, such as in [14], [15], and the proposed auction mechanism is independent of the cost function. Therefore, the cost function is out of the scope in this paper, and any cost function can be applied to c_i^{pro}. In addition, this paper assumes that each buyer b_j needs an amount of power E_j^{con}.

In the proposed auction mechanism, each seller submits a set of bids $\mathbf{B}_i$ for each buyer, where $\mathbf{B}_i$ can be described as follows:

$$\mathbf{B}_i = \{b_{i,1}, b_{i,2}, \cdots, b_{i,J}\}, \tag{20}$$

where $b_{i,j}$ is the bid that s_i submits to b_j. Therefore, all bids submitted to the auctioneer can be denoted as follows:

$$\mathbf{B} = \bigcup_{i=1}^{I} \mathbf{B}_i. \tag{21}$$

For the proposed truthful auction mechanism, the bid is calculated by considering the electricity generation cost c_i^{pro} and the electricity loss $l_{i,j}$. This paper assumes that $l_{i,j}$ is calculated as the Euclidean distance between s_i and b_j.

Further, the amount of received electricity should be greater than the required electricity. Therefore, s_i should bid when the following constraint is satisfied:

$$E_j^{\text{con}} \le E_i^{\text{pro}} \cdot (1 - l_{i,j}). \tag{22}$$

In order to satisfy the buyer's desired amount of electricity, the seller must transmit the electricity while also considering the loss. The transmitted amount of electricity from s_i to b_j can be calculated as $E_j^{\text{con}}/(1 - l_{i,j})$. Therefore, the actual cost of electricity that generated by s_i and transmitted to b_j can be calculated as follows:

$$c_{i,j} = c_i^{\text{pro}} \cdot E_j^{\text{con}}/(1 - l_{i,j}). \tag{23}$$

In addition, the seller will not bid on the auction if its cost of electricity is more expensive than the commercial cost. Denote the commercial electricity pricing from power utility is as c^{pow} and the seller and buyer can recognize the pricing information on Internet. When b_j is supplied the electricity from power utility, the electricity bill can be calculated as follows:

$$\mathcal{P}_j = c^{\text{pow}} \cdot E_j^{\text{con}}. \tag{24}$$

Therefore, s_i should bit when the following constraint is satisfied:

$$c_{i,j} \le \mathcal{P}_j. \tag{25}$$

In the proposed auction, s_i can bid the items, that satisfy both (22) and (25). On the other hand, i.e., if s_i cannot satisfy (22) or (25), s_i should not submit a bid to b_j, i.e., $b_{i,j} = \infty$.

In this paper, s_i will bid the actual cost to b_j for a truthful of exchange, and this bidding can be calculated as follows:

$$b_{i,j} = \begin{cases} \infty, & \text{if } E_j^{\text{con}} \ge E_i^{\text{pro}} \cdot (1 - l_{i,j}), \\ \infty, & \text{else if } c_{i,j} \ge \mathcal{P}_j, \\ c_i^{\text{pro}} \cdot E_j^{\text{con}}/(1 - l_{i,j}), & \text{otherwise.} \end{cases} \tag{26}$$

Let $z_{i,j}$ be the indicator function that calculates the winning bid. If the bid $b_{i,j}$ is calculated to be the winning bid, it is set to 1, otherwise it is set to 0.

By definition, the objective of the auction is minimization of the electricity bill. Therefore, the auctioneer will calculate the winning bids that satisfy the minimum total bill; thus, the following objective function can be derived:

$$\underset{z_{i,j}}{\text{minimize}} \quad z_{i,j} \cdot b_{i,j} \tag{27}$$

$$\text{subject to} \quad \sum\nolimits_{i=1}^{I} z_{i,j} \le 1, \forall b_j \in \mathcal{B} \tag{28}$$

$$\sum\nolimits_{j=1}^{J} z_{i,j} \le 1, \forall s_i \in \mathcal{S}, \tag{29}$$

where (28) and (29) are the constraints for assuring that each seller is matched to only one buyer.

In a VCG auction, payment is calculated by the auctioneer and is different from a bid. Let $p_{i,j}$ be the calculated payment for s_i to b_j; thus, the utility of s_i is formulated as the difference between payment and cost as follows:

$$u_i = \sum\nolimits_{j=1}^{J} \left(p_{i,j} - z_{i,j} c_{i,j}\right), \forall s_i \in \mathcal{S}. \tag{30}$$

C. Truthful Auction Mechanism for a Local Energy Market

The proposed auction mechanism for truthful trading consists of three steps as follows:

1) *Auction initiation:* In this initial step, the auctioneer informs the local energy market when the auction will start. Then, sellers and buyers prepare to join the auction trading. Refer to Section IV-C1.

[1]The corresponding proof is in Appendix.

Algorithm 2: Auction Process for Truthful Trading

Step 1: Local Energy Market Auction Initiation
b_j requests the electricity demand and provides its geometric information
local power exchange center broadcasts $\mathbf{ED}$
for $i = 1 \rightarrow I$ **do**
  for $j = 1 \rightarrow J$ **do**
    s_i computes $b_{i,j}$ by (26)
  end for
  s_i submits the set of bids $\mathbf{B}_i$
end for
Step 2: Winning Bid Calculation
local power exchange center calculates the winning bids of $\mathbf{B}$ by the Hungarian method
if $b_{i,j}$ is selected **then**
  $z_{i,j} \leftarrow 1$
end if
Step 3: Payment Calculation
for $i = 1 \rightarrow I$ **do**
  for $j = 1 \rightarrow J$ **do**
    if $z_{i,j} = 1$ **then**
      $\mathbf{B} \setminus \{b_{i,j}\} \leftarrow \mathbf{B} - \{b_{i,j}\}$
      local power exchange center calculates the winning bids of $\mathbf{B} \setminus \{b_{i,j}\}$ by the Hungarian method
      if $b_{i',j'}$ is selected **then**
        $z_{i',j'} \leftarrow 1$
      end if
      Calculate the total cost $\mathcal{C}_{\mathbf{B}\setminus\{b_{i,j}\}}$ with $z_{i',j'}$;
      Calculate $p_{i,j}$ with (33);
    end if
  end for
end for
for $i = 1 \rightarrow I$ **do**
  for $j = 1 \rightarrow J$ **do**
    if $z_{i,j} = 0$ **then**
      $p_{i,j} \leftarrow 0$
    end if
  end for
end for

2) *Winning bid calculation:* In this step, the auctioneer calculates the winning bids according to the VCG auction policy for the submitted bids. Refer to Section IV-C2.
3) *Payment calculation:* In this last step, the auctioneer determines the payments for winning bids according to the VCG auction policy. Refer to Section IV-C3.

The above steps are explicitly separated by time and executed independent of each other. (i.e., the calculations of winning bid and payment are executed after the bid submissions are complete). This framework of the proposed auction satisfies the "weak truthful" properties of a VCG auction [19]. Moreover, each auction result is delivered individually, resulting in an incomplete information game which provides "strong truthfulness" in a VCG auction [19].

The details of each step are as follows. In addition, note that the proposed entire auction process for truthful trading in the local energy market is described in Algorithm 2.

1) Auction initiation: When each auctioneer (i.e., local power exchange center) wishes to initiate the auction, the auctioneer first informs the buyers and sellers, i.e., all prosumers and distributed energy generators, in the local energy market. If a prosumer wants to purchase a certain amount of electricity, it sends the relevant information (i.e., geometric location and amount of required electricity) to the auctioneer. Let $\mathcal{ED}_j$ be the request information from b_j and be represented as follows:

$$\mathcal{ED}_j \triangleq [E_j^{\text{con}}, \mathbf{L}_j^p]. \tag{31}$$

The auctioneer collects the request information of buyers as a set and informs both prosumers and distributed energy generators. Let $\mathbf{ED}$ be denoted by the set of $\mathcal{ED}_j$ as follows:

$$\mathbf{ED} = \{\mathcal{ED}_1, \mathcal{ED}_2, \cdots, \mathcal{ED}_J\}. \tag{32}$$

The seller, which can be a prosumer with surplus electricity or a distributed energy generator, calculates the bid by (26) and submits a set of bids to the auctioneer.

2) Winning bid calculation: Using the collected set of bids $\mathbf{B}$, the auctioneer determines both the winning bid and the payment. For VCG auction matching, the seller who submitted the lowest bidding is selected and wins the auction. Note that the lowest bid is the winning bid. In addition, the payment for the winning bidder is calculated based on the next lowest bid, and it is referred to as payment calculation. For winning bid calculation, the sellers and buyers are matched to minimize the total cost by solving the optimization problem (27)-(29), which is NP-hard. Therefore, this paper utilizes the winning bid calculation with the Hungarian method. Based on this Hungarian method, the proposed auction for truthful trading finds $z_{i,j}$ in polynomial time. The Hungarian method is one of the most widely known polynomial time methods for one-to-one weighted matching that guarantees the minimal total cost.

The Hungarian method is conducted in the following steps:

Step *a:* The minimum value is subtracted from each row and column of the square bid matrix with size S. That is, each row and column should have at least one value of 0.

Step *b:* Erase rows and columns that contain 0 as the minimum number of lines. If all 0s are deleted with S lines, go to Step d.

Step *c:* Find the minimum value in the elements that are not erased by the lines. This minimum value is subtracted from undeleted elements and added at the overlap of the lines. Go to Step b.

Step *d:* Look for independent 0s, which has one 0 in each row and column.

Since the Hungarian method uses a square matrix, the following steps are required when i and j are different.

i) The auctioneer creates a bid matrix of size I x J with $\mathbf{B}$
ii) If $I > J$, add the columns from $J+1$ to I to make an I x I matrix.
iii) Set any positive integer Z greater than any bids for an element of (1: I, J+1: I).
iv) After generating a matrix of size I x I, find the minimum total cost and matching through the Hungarian method.
v) Subtract $Z * (I - (J+1))$ from the total cost and exclude the elements matched with the $J+1$ to Ith columns.

As an example, the following bid matrix $\mathbf{M}$ represent the bids.

$$\mathbf{M} = \begin{bmatrix} 6 & 4 & 1 \\ 10 & 6 & 3 \\ 7 & 6 & 4 \\ 9 & 10 & 3 \end{bmatrix},$$

where sellers and buyers are indexed by rows and columns, respectively.

Before the Hungarian method, $\mathbf{M}$ is set to $\mathbf{M}'$ as follows:

$$\mathbf{M}' = \begin{bmatrix} 6 & 4 & 1 & 10000 \\ 10 & 6 & 3 & 10000 \\ 7 & 6 & 4 & 10000 \\ 9 & 10 & 3 & 10000 \end{bmatrix}.$$

Then, winning bid calculation is conducted with the Hungarian method:

$$\begin{bmatrix} 6 & 4 & 1 & 10000 \\ 10 & 6 & 3 & 10000 \\ 7 & 6 & 4 & 10000 \\ 9 & 10 & 3 & 10000 \end{bmatrix} \xrightarrow{(\textbf{Step } a)} \begin{bmatrix} 2 & 1 & 0 & 3 \\ 4 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 3 & 5 & 6 & 1 \end{bmatrix} \xrightarrow{(\textbf{Step } b)}$$

$$\begin{bmatrix} 2 & 1 & \underline{0} & 3 \\ 4 & 1 & \underline{0} & 1 \\ \underline{0} & \underline{0} & \underline{0} & \underline{0} \\ 3 & 5 & \underline{6} & 1 \end{bmatrix} \xrightarrow{(\textbf{Step } c)} \begin{bmatrix} \underline{1} & \underline{0} & \underline{0} & \underline{2} \\ \underline{3} & \underline{0} & \underline{0} & \underline{0} \\ \underline{0} & \underline{0} & \underline{1} & \underline{1} \\ \underline{2} & \underline{4} & \underline{5} & \underline{0} \end{bmatrix} \xrightarrow{(\textbf{Step } d)} \begin{bmatrix} 1 & \mathbf{0} & 0 & 2 \\ 3 & 0 & \mathbf{0} & 0 \\ \mathbf{0} & 0 & 1 & 1 \\ 2 & 4 & 5 & \mathbf{0} \end{bmatrix}$$

Independent 0s are elements of the optimal matching. As a result, the winning bids are $b_{1,2}$, $b_{2,3}$, and $b_{3,1}$ except $b_{4,4}$, with bids of 4, 3, and 7, respectively.

3) Payment calculation: The payment for the winning bid is calculated using the concept of *opportunity cost* for the theory of the VCG auction [18]. The opportunity cost in this scheme can be calculated by $\mathcal{C}_{\mathbf{B}}$ and $\mathcal{C}_{\mathbf{B}\setminus\{b_{i,j}\}}$, where $\mathcal{C}_{\mathbf{B}}$ is the sum of the winning bids as calculated by the auctioneer and $\mathcal{C}_{\mathbf{B}\setminus\{b_{i,j}\}}$ is the minimum total cost as obtained by the winning bids excluding the bid $b_{i,j}$. That is, it is true that $\mathcal{C}_{\mathbf{B}\setminus\{b_{i,j}\}} > \mathcal{C}_{\mathbf{B}}$ when $b_{i,j}$ is a winning bid. On the other hand, $\mathcal{C}_{\mathbf{B}\setminus\{b_{i,j}\}} = \mathcal{C}_{\mathbf{B}}$ when $b_{i,j}$ is not a winning bid. Let $\mathcal{C}_{\mathbf{B}} - x_{i,j}b_{i,j}$ denote the total cost (as determined by the winning bid calculation), excluding its own bid. The opportunity cost (e.g., payment) $p_{i,j}$ can be defined as the difference between $\mathcal{C}_{\mathbf{B}\setminus\{b_{i,j}\}}$ and $\mathcal{C}_{\mathbf{B}} - x_{i,j}b_{i,j}$ [18]. Therefore, it can be finally expressed as follows:

$$p_{i,j} = \mathcal{C}_{\mathbf{B}\setminus\{b_{i,j}\}} - (\mathcal{C}_{\mathbf{B}} - z_{i,j}b_{i,j}). \tag{33}$$

As an example, in the above situation with bid matrix $\mathbf{M}$, s_1's payment $p_{1,2}$ can be calculated. $\mathcal{C}_{\mathbf{B}}$ is $4+3+7=14$. $\mathbf{B}\setminus\{b_{1,2}\}$ is represented with the matrix as follows:

$$\begin{bmatrix} 6 & 10000 & 1 \\ 10 & 6 & 3 \\ 7 & 6 & 4 \\ 9 & 10 & 3 \end{bmatrix}.$$

$\mathcal{C}_{\mathbf{B}\setminus\{b_{1,2}\}}$ can be calculated by the Hungarian method as above and is $6+6+3=15$. Thus, payment $p_{1,2}$ is $15-(14-4)=5$.

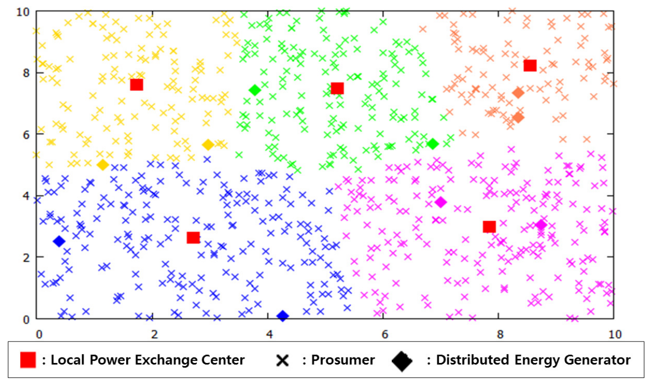

Fig. 2: Visualized results of the proposed clustering algorithm ($N=800, M=10, K=5$).

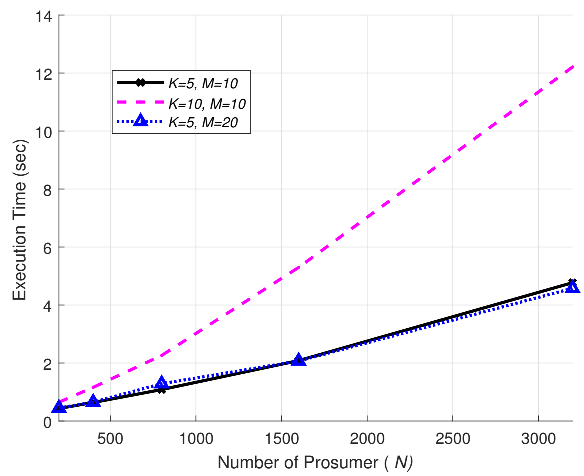

Fig. 3: Number of prosumers vs. execution time.

V. Performance Evaluation

The fine-grained evaluations of the proposed geometric clustering and truthful VCG auction algorithms were conducted, and the results are presented in this section.

A. Performance of Geometric Clustering

To evaluate the performance of the proposed EM-based clustering algorithm, C++ based customized simulator with the MOSEK optimization software tool [20] has been developed. Fig. 2 shows the visualized results of the proposed clustering algorithm when the number of clusters (denoted by K) is 5, the number of prosumers (denoted by N) is 800, and the number of distributed energy generators (denoted by M) is 10. As shown in the figure, the proposed algorithm geometrically classifies prosumers and distributed energy generators based on their geometric information/distribution and determines the appropriate locations of local power exchange centers.

To verify the computational efficiency of the proposed clustering algorithm, the execution time is measured according to the number of prosumers, as plotted in Fig. 3. For detailed simulation results, this paper simulates the proposed clustering algorithm 30 times and plots the average execution time. As shown in the figure, the execution time increases linearly when the number of prosumers increases. Therefore, the complexity of the proposed clustering algorithm is linear depending on the number of prosumers.

The execution time for $K = 5, M = 10$, where K is the number of local power exchange centers (or the number of clusters), and M is the number of distributed energy generators is similar to the time when M becomes double, i.e., $K = 5, M = 20$. Therefore, the number of distributed energy generators M cannot significantly affect the execution time of the proposed algorithm. On the other hand, the number of local power exchange centers K significantly affects the execution time, as shown in the results with $K = 10, M = 10$ in Fig. 3. This is due to the increase in the number of control variables as K increases.

B. Performance of a Truthful VCG Auction

The performance of the proposed auction scheme was verified by showing that our proposed algorithm satisfies the following two criteria: (i) computational efficiency via measurement of execution time and (ii) truthfulness.

The proposed auction scheme utilizes the Hungarian method to obtain the sum of minimum costs, as it is a well-known matching method and guarantees polynomial time operation. To demonstrate the time efficiency of the scheme with the Hungarian method, the execution time of this scheme is compared with the execution time of an auction scheme that uses a brute force method instead of the Hungarian method. The execution time comparison results are summarized in Table I. When the auction scheme uses a brute force method, the number of possible combinations exponentially increases as the number of buyers or sellers increases. This leads to sharp increases in execution time and makes it difficult to implement for real-time applications. When conducting computational simulations with brute force method for 20 sellers and 10 buyers, the execution time becomes too long to measure even in high-performance computing platforms. In addition, the execution time is about 2 seconds when the auction scheme utilizes the Hungarian method even if the number of sellers is 100 and the number of buyers is 80. Therefore, the auction scheme with the Hungarian method is efficient enough to be applied to real-world micro grid systems. Lastly, as shown in Table I, the auction with the Hungarian method is 769 times faster than the auction with the brute force method when the numbers of sellers and buyers are 15 and 5, respectively.

As mentioned earlier, when a seller submits bids where $b_{i,j} = c_{i,j}$, the seller can be considered as a truthful seller. In the auction, the winning bids are calculated along with the minimum total cost. This can result in the situation that dishonest participants submit bids lower than the true cost; this can be represented using the untrue ratio introduced in [18]. For example, a case in which a seller with an untrue ratio less than 1 (e.g., $\frac{b_{i,j}}{c_{i,j}} < 1$) means that the submitted bids are smaller than the true cost. This seller can be treated as a dishonest participant and can reduce system stability and trust. However, this dishonest participant cannot guarantee its maximum utility. On the other hand, we can consider a case in which a seller can submit a bid with an untrue ratio greater

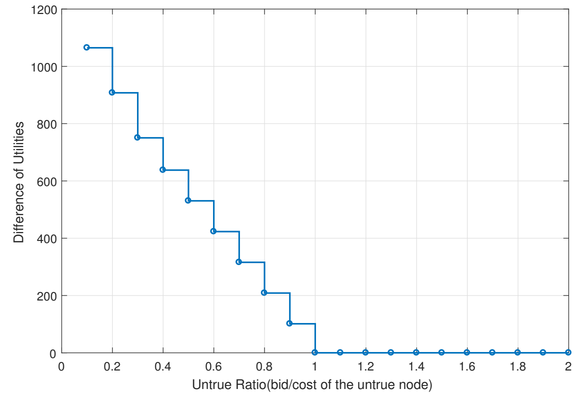

Fig. 4: Truthfulness evaluation with difference between utilities.

than 1 (e.g., $\frac{b_{i,j}}{c_{i,j}} > 1$). This indicates that the seller submits a bid greater than the true cost. There are two situations in this case: one in which the untrue bid is selected as the winning bid, and another where it is not. Even if the untrue bid is selected as the winning bid, the seller's utility is the same as when it submits a true bid. In addition, the VCG-based auction calculates the winning bid with the minimum total cost; thus, a bigger bid is disadvantageous. The ineffectiveness of an untrue bid in a VCG-based auction is mathematically proven in [18]. It is assumed that all participants want to maximize their utility. The truthfulness can be guaranteed by showing that the utilities are maximized when they are honest.

The simulation was performed as follows. There are 100 sellers and 80 buyers that want to participate in the auction. Each buyer's power demand is randomly set between 10 and 100, each seller's power generation cost is randomly set between 500 and 1000, and the power loss between the buyer and seller is set between 0 and 1. A certain seller is set to be unfaithful, and it submits a bid with an untrue ratio between 0.1 and 2.0. As shown in Fig. 4, as the untrue ratio decreases (e.g., 0.9-0.1), the utility difference increases. If the seller bids with an untrue ratio larger than 1 (e.g., 1.1-2.0), this is unreasonable, and it will not be considered. In addition, the probability of being selected as the winning bid is lowered by increasing the bid. Therefore, the seller's utility will be maximized only when it bids truthfully.

In auction mechanisms, all sellers are fair when they are honest. In order to formulate the *fairness*, Jain s fairness index is used and is formulated as follows [21]:

$$\mathcal{J}(u_1, u_2, \cdots, u_I) = \frac{\left(\sum_{i=1}^{I} u_i\right)^2}{I \sum_{i=1}^{I} u_i^2}$$

where I denotes the number of sellers and u_i denotes the number of times the ith seller is matched. The index ranges from 0 to 1 and is maximized when all sellers are matched the same number of times. When 15 sellers bid and match to 10 buyers, only unfaithful seller s_5 submits bids with untrue ratios; the auction is conducted 100 times at each untrue ratio. In Fig. 5, the highest result close to 1 when the untrue ratio is

TABLE I: Auction Execution Times with the Brute Force Method and the Hungarian Method

Brute Force Method			**Hungarian Method**		
# sellers	# buyers	Execution time (sec)	# sellers	# buyers	Execution time (sec)
10	5	0.1728	10	8	0.0096
15	5	10.2340	15	5	0.0133
10	8	12.5485	100	80	2.0135

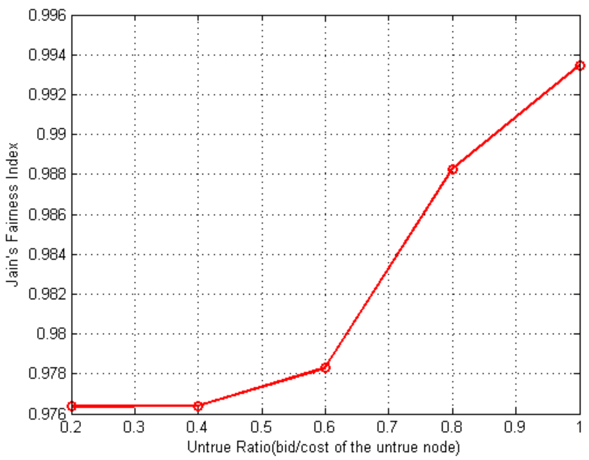

Fig. 5: Jain's fairness index.

1, which means that all sellers bid honestly. This indicates that all sellers are awarded a similar number of times. If a seller who wants to monopolize the power selling with lower bids, it can be monopolized. However, it is clear that this unfaithful behavior can be prevented because it will result in lowering the utility of cheating seller.

VI. Concluding Remarks

In this paper, optimization formulation and corresponding polynomial time algorithms were proposed for geometric clustering and truthful auction in local energy markets. For clustering in a local energy market, the optimization problem considers the fairness of the distributed energy generator and distribution. To solve the clustering optimization problem, this paper proposes an EM-based geometric unsupervised learning algorithm. Through intensive simulations of clustering using the MOSEK optimization software tool, this paper shows that the proposed algorithm can sufficiently cluster a local energy market. In addition, this paper proposes a truthful mechanism based on the VCG auction to calculate the price that effectively guarantees the lowest cost in the local energy market. The additional data-intensive performance evaluation of the auction mechanism shows that the proposed algorithm is optimal in terms of network stability when all deployed elements are truthful.

In our future research, it is important to design and optimize the local energy trading systems under the consideration of the electricity generation cost. In addition, the proposed auction can be expanded to double auction and item can be modeled as set of electricity.

Appendix

Theorem 1: The proposed auction is individual rational for each seller.

Proof 1: The auction is individual rational when all agents have positive utilities for the bid [18], [22]. In the proposed auction, the utility of the seller can be determined separately in two cases: i.e., 1) a bid is selected or 2) all bids are not selected. Suppose that the seller i bids the winning bid to buyer j. In this case, $p_{i,j} \geq b_{i,j}$ according to (34). Therefore, the utility is positive ($u_i \geq 0$) according to (30). On the other hand, let us suppose that all bids of the seller i are not selected. Since all bids are not selected, $\sum_{j=1}^{J} p_{i',j} = 0$ and $\sum_{j=1}^{J} z_{i',j} = 0$. Therefore, the utility can be calculated as follows:

$$\begin{aligned} u_{i'} &= \sum\nolimits_{j=1}^{J} (p_{i',j} - z_{i',j} c_{i',j}) \\ &= \sum\nolimits_{j=1}^{J} (0 - 0 \cdot c_{i',j}) = 0. \end{aligned}$$

Consequently, $u_i \geq 0, \forall s_i \in \mathcal{S}$ is satisfied in all cases.

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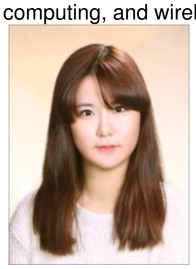

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