IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 12, 2018, accepted June 18, 2018, date of publication June 27, 2018, date of current version August 7, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2850928

Pair Matching Strategies for Prosumer Market Under Guaranteed Minimum Trading

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The work of E. Oh was supported by the National Research Foundation of Korea through the Korean Government (Ministry of Science and ICT) under Grant 2017R1E1A1A03070136. The work of S.-Y. Son was supported by the Korea Institute of Energy Technology Evaluation and Planning and the Ministry of Trade, Industry and Energy of the South Korea under Grant 20168530050080.

ABSTRACT The need for distributed energy trading is increasing owing to the deployment of distributed renewable generators, and a new class of users, prosumers, based on them. This paper presents two pair-matching strategies for the distributed prosumer energy trading market. We first propose an energy trading rule guaranteeing a minimum trading quantity. The rule manages distributed market risk from unpredictability in the demand and supply of participants. A pair matching problem to maximize social welfare is formulated. However, it requires high computational complexity, as well as a central controller. Therefore, we propose two matching strategies considering the properties of the trading rule and the statistical characteristics of participants by modifying the problem. The proposed strategies can be applied in a distributed manner with a simple mechanism. Numerical results using the ideal and real data sets show that the proposed strategies have near optimal performance, with less than a 2% optimal gap. In addition, we discuss how distributed prosumer energy trading offers a benefit and discuss the dominant parameter for achieving that benefit.

INDEX TERMS Distributed energy market, distributed generator, energy trading, guaranteed minimum trading, prosumer, social welfare, uncertainty.

I. INTRODUCTION

With an increasing awareness of potential harmful effects on the environment, and the development of advanced grid technologies such as smart grid, distributed generators including renewable energy sources have been extensively deployed in energy systems [1]. This has resulted in significant energy security strengthening, climate-change mitigation, and economic benefits to the grid [2]. On the customer side, the expansion of distributed generators has introduced a new class of users, called prosumers, who sell domestically generated energy, usually using renewable generators such as rooftop photovoltaic power stations, as well as buy energy from the grid and/or other prosumers [3].

Prosumers' resources have low reliability according to the stochastic nature of renewable-based sources and the dependency on human behavior, and they are operated as small distributed agents with small capacity [4]. Considering these properties of prosumers, distributed or peer-to-peer (P2P) energy trading market models are suggested in place of the centralized conventional energy trading market [5]. The distributed trading with limited controllability characteristic requires more robust and efficient operation methodology than before.

In distributed trading, matching the trading pair between producers (energy sellers) and consumers (energy buyers) is one of the most important problems to be solved. Pair matching approaches have been reviewed [6]. A basic approach is a consumer selection from a producer list [7]. In this approach, after producers announce their generation types and selling price, the consumer selects the producer based on its own preference. This approach is quite simple and works well in a distributed setting. The approach selects the pair based on the historical profile or the expected average profile. In the ideal case, the performance of pair matching can be expected to be guaranteed on average, but in practical cases it is risky. In addition, it only reflects the convenience of either producers or consumers. An approach that considers both the producer and the consumer is presented [8]. Producers and consumers make contracts with a trading service provider, and the trading service provider matches the trade between the producer and the consumer. The trading pairs are matched by the service provider's rule, and the participants are directly controlled by the trading service provider. The trading service provider manages the risks that arise in practical cases because the service provider controls all parts of pair matching. In this manner, this approach could enhance the benefits of the producers and the consumers with respect to each other. However, this approach requires a central controller operated by the trading service provider. A hybrid model also considers that the trading service provider matches the trading pair, considering the consumer's prioritization [9]. This model allows participants to suggest their preference. The service provider decides the trading pair to consider the suggested preferences and the risk by the uncertainty, so this approach partially guarantees the pair matching performance in practical cases. However, it also requires a centralized controller.

The need for a central controller is related to energy trading market uncertainties. Participants and operators in the trading market try to optimize their benefits and reduce their energy trading risk, respectively. Therefore, efficient prosumer energy trading requires that the trading pair matching strategy operates in a distributed manner, considering prosumer properties as well as the trading mechanism to reduce the energy trading risk [10].

The focus of this work is to propose trading pair matching strategies for a distributed prosumer market. To do this, we first suggest an energy trading rule for the prosumer market and propose trading pair matching strategies that effectively operate in the trading environment. Both of these are summarized below:

- *Energy Trading Rule:* The distributed prosumer energy trading is high risk by virtue of its unpredictability. To manage this, we consider an energy trading rule that guarantees a minimum trading quantity. A rule based on guaranteed minimum value is often applied in many areas of social economics, such as the guaranteed minimum income and the guaranteed minimum pension, and the target is to create a system of social welfare provision [11]. In this work, the guaranteed minimum trading quantity means that the prosumer should at least guarantee the quantity of energy demand or supply that the prosumer can commit to. Otherwise, a penalty would be given. This approach manages the energy trading risk, encouraging energy sharing in the distributed prosumer energy market [12].
- *Trading Pair Matching Strategies:* Under the trading rule, an energy trading problem is formulated as a pair matching problem to maximize the social welfare that is the total benefit of participants achieved via prosumer energy trading [13]. The problem becomes a non-convex problem that requires a central controller with high computational complexity to optimally solve. Analyzing the trading rule and participant properties, we modify the problem to a simplified pair matching problem that minimizes benefit loss. The suggested pair matching strategy is solved in a distributed manner using partial information, such as the first and second statistical characteristic "mean and variance" of participants. We also present a strategy only requiring the first statistical characteristic of the participant distribution, relaxing the proposed strategy. Numerical studies using the ideal and real demand sets show that these two proposed trading pair matching strategies have near optimal performance.

TABLE 1. Notation summary.

Symbol	Description
$i \in \mathcal{P}$	Producer index
$j \in \mathcal{C}$	Consumer index
p_T	Trading price [\$/kWh]
p_G^s	Selling price to grid [\$/kWh]
p_G^b	Buying price from grid [\$/kWh]
$\hat{e}_i(t)$	Generation forecasting [kWh]
$\hat{l}_j(t)$	Load forecasting [kWh]
$e_i(t)$	Actual generation [kWh]
$l_j(t)$	Actual load [kWh]
$e_{ij}^-(t)$	Energy sold to grid by the extra generation of the producer [kWh]
$e_{ij}^+(t)$	Energy bought from grid for the minimum generation guarantee of the producer [kWh]
$l_{ji}^-(t)$	Energy sold to grid by the minimum load guarantee of the consumer [kWh]
$l_{ji}^+(t)$	Energy bought from grid by the extra consumption of the consumer [kWh]
$e_{ij}^T(t)$	Energy traded on the producer side [kWh]
$l_{ji}^T(t)$	Energy traded on the consumer side [kWh]
B_{ij}	Profit to the producer [\$]
B_{ji}	Profit to the consumer [\$]

The rest of this paper is organized as follows. Section II describes system models and the minimum guaranteed energy trading rule. Section III discusses how to design the two proposed pair matching strategies. Section IV demonstrates measurement studies using ideal and real demand profiles applied to the proposed strategies. Section V concludes the paper.

II. SYSTEM DESCRIPTION AND PROBLEM FORMULATION

A. SYSTEM MODEL

1) PLAYER MODEL

Players are defined as producers and consumers who participate in prosumer energy trading. There are sets of producers ($\mathcal{P}$) and consumers ($\mathcal{C}$). Let $i \in \mathcal{P}$ be the index of the i-th producer and $j \in \mathcal{C}$ be the index of the j-th consumer.

Before being matched for trading, players announce their first and second statistical characteristics of energy demand forecasting through the trading interval $t \in \mathcal{T} = \{1, \cdots, t, \cdots, T\}$, i.e., the generation forecasting for the producer, $\hat{e}_i(t)$ and $\sigma_i(t)$ where $i \in \mathcal{P}$, and the load forecasting for the consumer, $\hat{l}_j(t)$ and $\sigma_j(t)$ where $j \in \mathcal{C}$. These values are predicted using demand forecasting methods, such as generation forecasting methods for producers' demand [14], [15], and customer baseline load (CBL) calculation methods for customers' demand [16], [17].

2) PRICE MODEL

The price is determined by many variables, such as the fuel used, government subsidies, government and industry regulations, infrastructure, and local weather patterns. However, for residential players who have demand with small quantity, price impacts are limited and dependent on individual demand profiles, which vary from one location to another [18]. Therefore, a linear pricing model proportionally related to energy usage is considered, and its unit price is defined as follows:

- p_T [\$/kWh]: Trading price between producers and consumers, which is a selling price for producers and a buying price for consumers,
- p_G^s [\$/kWh]: Selling price to the grid,
- p_G^b [\$/kWh]: Buying price from the grid.

In order to establish a trade, each price has the relationship $p_G^s \leq p_T \leq p_G^b$. When considering a dynamic pricing model, such as real-time pricing and time-of-use pricing [19], the unit price varies through the trading time interval.

B. TRADING RULE WITH GUARANTEED MINIMUM QUANTITY

A trade with a guaranteed minimum quantity (GMQ) is considered. The GMQ means that players should guarantee at least the energy demand that they announce. At the trade between the i-th producer and the j-th consumer, the GMQ rule is applied as follows:

1) The i-th producer should supply at least the minimum value of energy between $\hat{e}_i(t)$ and $l_j(t)$.
2) The j-th consumer should purchase at least the minimum value of energy between $\hat{l}_j(t)$ and $e_i(t)$.

The values without hats, $e_i(t)$ and $l_j(t)$, express actual demand, which are the generation of producer i and the load of consumer j at time t, respectively.

There can be a mismatch between the actual demand and the traded quantity in the GMQ. Players have to buy or sell energy from the grid to compensate for this imbalance. At the trade between the i-th producer and the j-th consumer, the mismatched quantity at time t is measured as

$$e_{ij}^-(t) = \max\{0,\ e_i(t) - \max(l_j(t), \hat{l}_j(t))\}, \quad (1a)$$

$$e_{ij}^+(t) = \max\{0,\ \min(l_j(t), \hat{e}_i(t)) - e_i(t)\}, \quad (1b)$$

$$l_{ji}^-(t) = \max\{0,\ \min(e_i(t), \hat{l}_j(t)) - l_j(t)\}, \quad (1c)$$

$$l_{ji}^+(t) = \max\{0,\ l_j(t) - \max(e_i(t), \hat{e}_i(t))\}. \quad (1d)$$

From the producer aspect, $e_{ij}^-(t)$ and $e_{ij}^+(t)$ in (1a) and (1b) are the energy sold to grid by the extra generation and the energy bought from grid for the minimum generation guarantee, respectively. $l_{ji}^-(t)$ and $l_{ji}^+(t)$ in (1c) and (1d) are the energy sold to grid by the minimum load guarantee and the energy bought from grid by the extra consumption of the consumer, respectively.

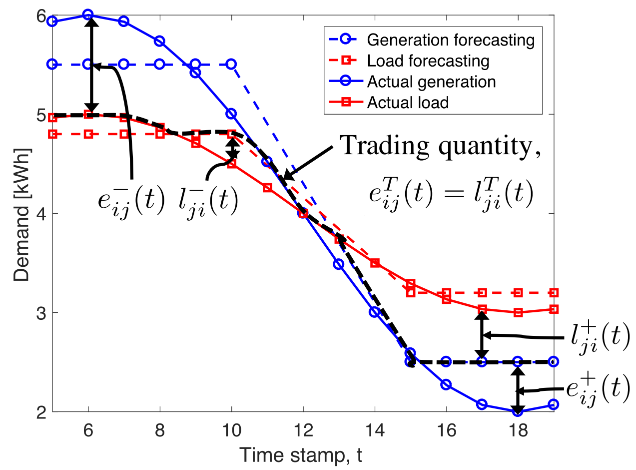


FIGURE 1. Traded and mismatched quantity example by the GMQ. Examples of the mismatched quantities, $e_{ij}^-(t)$, $l_{ji}^-(t)$, $l_{ji}^+(t)$, and $e_{ij}^+(t)$, exist at time 6, 10, 17, and 18, respectively.

Figure 1 shows an example of traded and mismatched quantities between a supplier and consumer pair by the GMQ. Dashed and solid lines express the demand forecasting and actual demand, and lines with a circle marker and with a square marker represent the value of the producer and the consumer, respectively. Examples of the mismatched quantities, $e_{ij}^-(t)$, $l_{ji}^-(t)$, $l_{ji}^+(t)$, and $e_{ij}^+(t)$, exist at time 6, 10, 17, and 18, respectively. In addition, the black dashed line indicates the traded quantity considering the GMQ constraint between the producer and consumer trading pair. The trading quantity is determined by adjusting the mismatched quantity and the actual demand.

C. PROBLEM FORMULATION

Under the GMQ, the aim of this work is to maximize social welfare determined as the sum of all player's profits. The profit is defined as the additional gain over the case of trading with the grid, such as extra income for the producer and expense savings for the consumer. At the trade between the i-th producer and the j-th consumer, profits of producer i, B_{ij}, and consumer j, B_{ji}, are written as

$$B_{ij} = \sum_{t\in\mathcal{T}} \left[\left(e_i^T(t)\,p_T + e_{ij}^-(t)\,p_G^s - e_{ij}^+(t)\,p_G^b \right) - e_i(t)\,p_G^s \right], \quad (2a)$$

$$B_{ji} = \sum_{t\in\mathcal{T}} \left[l_j(t)\,p_G^b - \left(l_{ji}^T(t)\,p_T - l_{ji}^-(t)\,p_G^s + l_{ji}^+(t)\,p_G^b \right) \right], \quad (2b)$$

where $e_{ij}^T(t) = e_i(t) - e_{ij}^-(t) + e_{ij}^+(t)$ and $l_{ji}^T(t) = l_j(t) + l_{ji}^-(t) - l_{ji}^+(t)$ are the quantities traded by the producer and consumer, respectively. According to the energy balance equation, this becomes $e_{ij}^T(t) = l_{ji}^T(t)$.

The objective function is given by

$$O(\mathbf{e}, \mathbf{l}) = \sum_{(i,j)} B_{ij} + B_{ji} \tag{3}$$

where (i, j) is the trading pair as producer i and consumer j. $\mathbf{e}$ and $\mathbf{l}$ are column vectors of the ordered producer and consumer so that each element at the same index in the vectors together represent the player pairs (e.g., i and j).

In addition, players expect to obtain positive profit through the trade, so a profit constraint is considered as

$$\begin{aligned} B_{ij} &\geq 0, \quad \forall (i,j) \in (\mathcal{P}, \mathcal{C}), \\ B_{ji} &\geq 0, \quad \forall (i,j) \in (\mathcal{P}, \mathcal{C}). \end{aligned} \tag{4}$$

In general, the social welfare maximization problem considering positive profit is formulated as:

$$\begin{aligned} \mathbf{P0:} \quad & \max_{(i,j)\in(\mathcal{P},\mathcal{C})} O(\mathbf{e}, \mathbf{l}) \\ & \text{s.t. } B_{ij} \geq 0, \quad \forall (i,j) \in (\mathcal{P}, \mathcal{C}), \\ & \qquad B_{ji} \geq 0, \quad \forall (i,j) \in (\mathcal{P}, \mathcal{C}). \end{aligned} \tag{5}$$

In (5), the social welfare maximization problem (**P0**) becomes determining the set of trading pairs between producers and consumers subject to positive profit. As shown in Figure 1, the trading quantity, which is an element of the profit function, is a non-convex function. Therefore, the problem presents as a non-convex problem. For finding the optimum set, high computational complexity is theoretically required among $|\mathcal{P}| \times |\mathcal{C}|$ combinations [20], and a controller that in practice requires information from all players is also needed. These difficulties impose a burden on the practical implementation of prosumer energy trading in a low responsibility, distributed prosumer market environment. In this paper, effective trading pair matching strategies are suggested to deal with these difficulties. To keep the notation simple, the time index t is suppressed throughout the paper.

III. TRADING PAIR MATCHING STRATEGIES

This section begins by discussing the profit of players under the GMQ mechanism. Based on the lesson, trading pair matching strategies are proposed that can be solved with low computational complexity and in a distributed manner.

A. DESIGN RATIONALE

The difficulty in solving the problem in (5) is due to the non-convexity of the players' profit B_{ij} and B_{ji} and the trading price. It is the basic element for constructing the objective to maximize social welfare, and the constraint to guarantee positive profit through trading. To design an effective strategy, the effect of the profit of players on the objective and the constraint is checked.

From (2a), the profit of producer i at time t trading with consumer j is written as

$$\begin{aligned} b_{ij} &= \left(e_i^T p_T + e_{ij}^- p_G^s - e_{ij}^+ p_G^b\right) - e_i p_G^s, \\ &= e_i(p_T - p_G^s) - e_{ij}^-(p_T - p_G^s) - e_{ij}^+(p_G^b - p_T). \end{aligned} \tag{6}$$

The mismatched quantities e_{ij}^- and e_{ij}^+ do not happen at the same time because they are the selling and buying quantities to/from the grid by the trade imbalance, respectively. Therefore, the profit in (6) can be rewritten as

$$b_{ij} = \begin{cases} e_i(p_T - p_G^s) - e_{ij}^-(p_T - p_G^s), & \text{(7a)} \\ e_i(p_T - p_G^s) - e_{ij}^+(p_G^b - p_T). & \text{(7b)} \end{cases}$$

It is generally understood that the profit in (7) is positive because the maximum value of e_{ij}^- is e_i in (1a), and the profit in (7) also becomes positive on average because the expectation of e_{ij}^+ goes to zero in (1b). This means that the profit of a producer has a positive value on average under the GMQ. In the same way, it is seen that the profit of a consumer also has a positive value on average. In addition, the profit in (6) says that to maximize the profit that is the objective of the problem in (5) becomes to minimize the mismatched quantities, such as e_{ij}^- and e_{ij}^+, as is obvious.

From these derivations, the social welfare maximization problem that considers the positive profit constraint in the GMQ can be relaxed to minimize the mismatched quantities in trading.

B. TRADING PAIR MATCHING STRATEGIES

Assuming that the demand of players has a Gaussian distribution as $e_i \sim N\left(\hat{e}_i, \sigma_{e_i}^2\right)$ and $l_j \sim N\left(\hat{l}_j, \sigma_{l_j}^2\right)$, the difference between the demand and supply, z_{ij}, is also normally distributed with mean $\mu_{z_{ij}} = \hat{e}_i - \hat{l}_j$ and variance $\sigma_{z_{ij}}^2 = \sigma_{e_i}^2 + \sigma_{l_j}^2$ [21]. In addition, the mismatched quantity between the trading pair $|z_{ij}|$ has a folded normal distribution with parameters $\mu_{z_{ij}}$ and $\sigma_{z_{ij}}$.

The expected mismatched quantity with folded normal distribution is measured as [22]

$$\begin{aligned} \mathbb{E}\left\{|z_{ij}|\right\} &= \mu_{z_{ij}}\left[1 - 2Q\left(\frac{\mu_{z_{ij}}}{\sigma_{z_{ij}}}\right)\right] + \sigma_{z_{ij}}\sqrt{\frac{2}{\pi}}\exp\left(-\frac{\mu_{z_{ij}}^2}{2\sigma_{z_{ij}}^2}\right) && \text{(8a)} \\ &\geq \mu_{z_{ij}}\left[1 - \exp\left(-\frac{\mu_{z_{ij}}^2}{2\sigma_{z_{ij}}^2}\right)\right] + \sigma_{z_{ij}}\sqrt{\frac{2}{\pi}}\exp\left(-\frac{\mu_{z_{ij}}^2}{2\sigma_{z_{ij}}^2}\right), && \text{(8b)} \\ &\approx \mu_{z_{ij}}\left[1 - \exp\left(-\frac{\mu_{z_{ij}}^2}{2\sigma_{z_{ij}}^2}\right)\right] + \sigma_{z_{ij}}\exp\left(-\frac{\mu_{z_{ij}}^2}{2\sigma_{z_{ij}}^2}\right), && \text{(8c)} \\ &= \mu_{z_{ij}}\left(1 - \alpha_{ij}\right) + \sigma_{z_{ij}}\alpha_{ij}. && \text{(8d)} \end{aligned}$$

where $Q(\cdot)$ is the tail distribution function of the standard normal distribution, $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty \exp\left(-\frac{u^2}{2}\right) du$, and $\alpha_{ij} = \exp\left(-\frac{\mu_{z_{ij}}^2}{2\sigma_{z_{ij}}^2}\right)$. From (8a) to (8b), the value is relaxed using the improved exponential bound of $Q(\cdot)$ [23]. This shows that the expected mismatched quantity comes from the α fraction of the difference of the average demand between the trading pair and its standard deviation (STD). Figure 2 presents the bound of the expected mismatched quantity varying with the

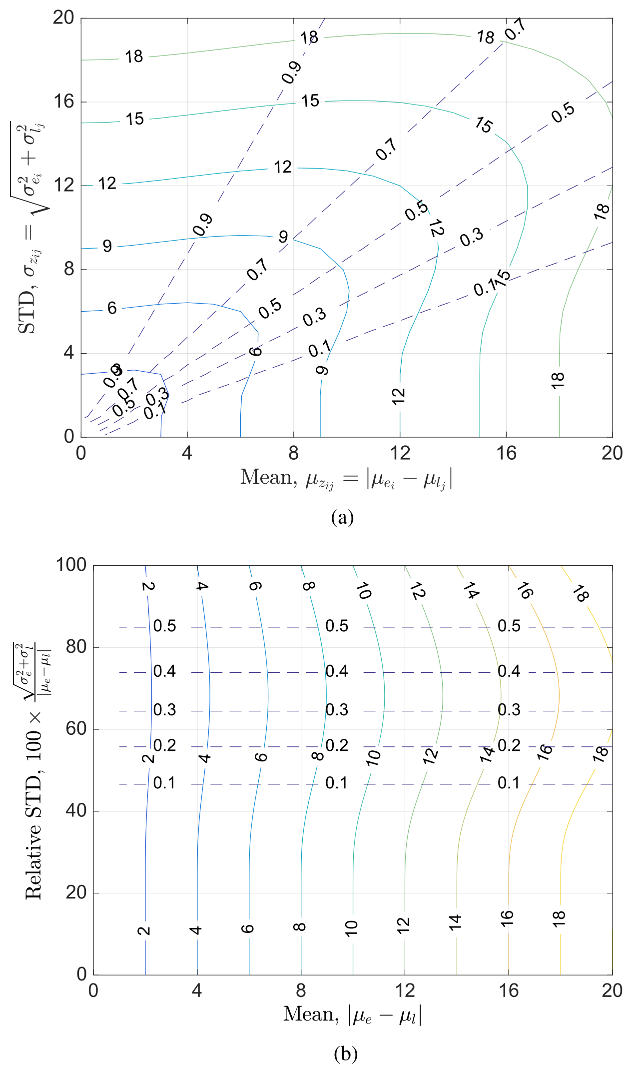


FIGURE 2. **Theoretical bound of the expected mismatched quantity in (8). Dashed lines in figures are the value of α_{ij}. Figure 2 shows that the mismatching quantity is evenly affected by the mean and STD, but the quantity depends on the difference in the average demand between the trading pair in the region below 40%, as shown in Figure 2. (a) Absolute STD. (b) Relative STD.**

difference in average demand and its STD. It says that the mismatching quantity is evenly affected by the mean and STD, and, to minimize the mismatching quantity, the mean and STD should be balanced.

Using (8), the problem of maximizing social welfare in (5) is converted to minimizing the expected mismatched quantity between the pairs, which is the first effective trading pair matching strategy,

$$\textbf{P1:} \quad \min_{(i,j)\in(\mathcal{C},\mathcal{P})} \sum_{(i,j)} |\hat{e}_i - \hat{l}_j| \left(1 - \alpha_{ij}\right) + \sqrt{\sigma_{e_i}^2 + \sigma_{l_j}^2}\,\alpha_{ij}. \tag{9}$$

Note that in (9), the trading pair matching problem based on the expected mismatched quantity (**P1**) is a convex problem constructed with convex combination sets. The problem can be solved by iterative algorithms such as the Newton method or the gradient descent method in a distributed manner [24].

To find the solution, each player selects their matching pair to minimize the mismatched quantity, and announces the information related to the selection. Using updated information, each player repeatedly selects. Based on the convex property, the solution always converges.

When the expected mismatched quantity based on the relative STD, which is the ratio of the STD over the mean, is reviewed, the quantity depends on the difference in the average demand between the trading pair in the region below 40%, as shown in Figure 2. Considering that the demand forecasting error is less than 15% of the average demand [14]–[17], it can be said that the difference in the average demand between the trading pair dominates in determining the mismatched quantity in practice. Therefore, the trading pair matching problem to minimize the expected mismatched quantity in (9) is approximated to the trading pair matching problem to minimize the difference of the average demand between the trading pair, which is the second effective trading pair matching strategy,

$$\textbf{P2:} \quad \min_{(i,j)\in(\mathcal{C},\mathcal{P})} \sum_{(i,j)} ||\hat{e}_i - \hat{l}_j||, \tag{10}$$

where $||\cdot||$ is the Euclidean norm. Similar to problem **P1**, the trading pair matching problem based on the difference of the average demand between the trading pair (**P2**) in (10) is also a convex problem that is solved by iterative algorithms in a distributed manner.

Let $(i^{(t)}, j^{(t)})$ be the pair matching at the t-th iteration. The distributed trading pair matching algorithm is sketched as follows:

Algorithm 1 Distributed Trading Pair Matching Algorithm

1: Initialize $(i^{(0)}, j^{(0)})$ that is randomly selected.
2: **do while** $(i^{(t-1)}, j^{(t-1)}) \neq (i^{(t)}, j^{(t)})$
3: $t \leftarrow t + 1$,
4: Each player i (or j) selects its own pair j (or i) to minimize (9) or (10).
5: The selected information is broadcast and updated.
6: **end do**

As mentioned above, the problem **P1** and **P2** are convex problems, so the algorithm is always converged and solved with the linear computational complexity as $\mathcal{O}(\max(|\mathcal{P}|, |\mathcal{C}|))$.

IV. NUMERICAL RESULTS

To verify the effectiveness of our work, we evaluate the performance of the proposed trading pair matching strategies using ideal and practical demand profiles and discuss which characteristics of the players affect performance, and how. The results are compared to the performance achieved by solving the problem in (5).

In the simulation, daily trading is considered as a player trading energy within the same pair for a day. The trading is measured every half hour. The trading price is assumed to be p_T = KRW 100/kWh, p_G^s = KRW 80/kWh, and

p_G^b = KRW 120/kWh,[1] which are the average electricity prices in Korea [25] and U.S [26].

A. IDEAL CASE

The demand of each player is randomly generated with a normal distributed model at each trade time and the mean of the demands varying with time according to a typical residential demand model for Korea [27]. Average daily demand and the STD of players is uniformly distributed in a specific range depending on the case. For player sets, 16 producers and consumers are basically considered, but the case for varying the set size is also described. The performances are calculated by averaging the results over 1000 days.

1) PREFERENCE

Table 2 shows the performance of the average unit profit when applying the proposed trading pair matching strategies, **P1** and **P2**, as well as the solution of the optimal problem **P0**. According to the statistics for Korea [25] and the accuracy of conventional demand forecasting methods [14]–[17], the average daily demand and relative STD of the reference case are set to 12 kWh and 15%, respectively. The performance is also measured considering high STD and low STD environments.

TABLE 2. Average unit profit [KRW/kWh].

	P0	P1	P2
[Ref. case] Daily demand: (8, 16)[kWh], Relative STD: (0, 30)[%]			
Profit of producer	18.2	18.1	18.0
Profit of consumer	18.2	18.0	18.0
Total Profit	36.4	36.1	36.0
Gain achievement [%]	91 .0	90.3	90.0
Optimal gap [%]	-	0.8	1.1
[Low STD] Daily demand: (8, 16)[kWh], Relative STD: (0, 10)[%]			
Profit of producer	19.1	19.0	19.0
Profit of consumer	19.1	19.1	19.0
Total profit	38.2	38.1	38.0
Gain achievement [%]	95.5	95.3	95.0
Optimal gap [%]	-	0.3	0.5
[High STD] Daily demand: (8, 16)[kWh], Relative STD: (20, 30)[%]			
Profit of producer	17.3	17.0	17.1
Profit of consumer	17.3	17.0	17.1
Total profit	34.6	34.0	34.2
Gain achievement [%]	86.5	85.0	85.5
Optimal gap [%]	-	1.7	1.2

Throughout the results, the producers and the consumers have similar profits because they have similar properties. In the reference case and the low STD case, results under the proposed strategies achieve more than 90% of the maximum achievable profit and have less than 1% optimal gap compared to the optimal solution of **P0**. By increasing the demand uncertainty, presented as STD, the performance is reduced in the high STD case. However, the optimal gap of the proposed strategies is still less than 2%. This verifies that the proposed strategies are well designed, and work effectively.

Comparing the results of applying **P1** and **P2**, the performance of **P1** achieves better profit than that of **P2** in the reference case and the low STD case. This is because **P1** considers both the first and second characteristics of demand, but **P2** only uses the first demand characteristic. However, when STD grows, this increases the approximation error in (8) and reduces the performance of **P1**.

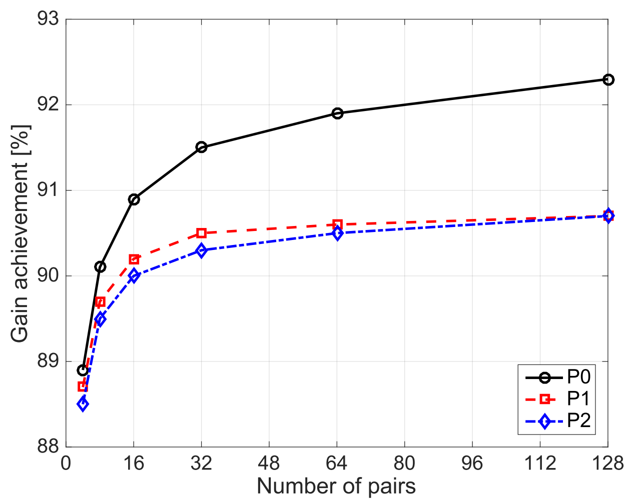


FIGURE 3. Gain achievement with varying player set size. The black line with circles, the red dashed line with squares, and the blue dash-dot line with diamonds illustrate the gain achievement by applying P0, P1, and P2, respectively.

Figure 3 shows the gain achievement related to the size of the player sets for the reference case. The circled black line, the red dashed line with squares, and the blue dash-dot line with diamonds illustrate the gain achievement by applying **P0**, **P1**, and **P2**, respectively. The performance of **P0** is enhanced by increasing the set size. To solve this problem for **P0**, perfect demand information is required, and the information improves performance with increasing multi-user diversity [28]. The proposed strategies, **P1** and **P2**, use only partial information, such as the first and second characteristics of the demand, thus the performance enhancement due to multi-user diversity is limited. However, the gain achievement gap is marginal, less than 1.5%, between the optimal solution and the proposed strategies.

2) CHARACTERISTICS

To show how players achieve profit, we observe the characteristics of matching pairs for the reference case. Pearson's linear correlation coefficient (PLCC) is used to check the relationship [29].

Table 3 presents the relationship between the matched trading pairs. **P1** and **P2** use the first and second demand characteristics of players, so the PLCC of demand characteristics between pairs is measured. The similar values of PLCC at **P0** and **P1** show that the matching pairs by **P0** and **P1**

[1] The KRW is the currency unit of South Korea ($1 = KRW 1,000).

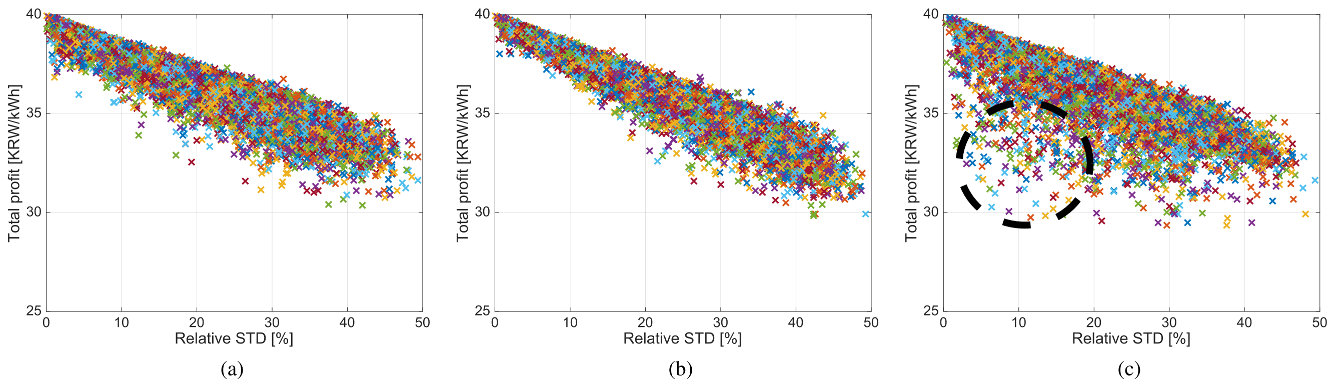


FIGURE 4. Relationship between the total profit and the relative STD of each pair. The result of P1 in Figure 4 shows higher correlation than the other results in Figure 4 and 4. (a) P0. (b) P1. (c) P2.

TABLE 3. PLCC of characteristics between matched trading pairs.

	P0	P1	P2
Average demand, $\hat{e}_i$ and $\hat{l}_j$	0.84	0.76	0.83
Relative STD, $\sigma_i/\hat{e}_i$ and $\sigma_j/\hat{l}_j$	0.45	0.56	0.01

are organized to similar sets. This verifies that our approach in converting the social welfare maximization problem to a mismatched quantity minimization problem is rational. In **P2**, the relative STD between pairs is remarkably low at 0.01, but the profit of trading is high even when considering the STD as shown above. This means that the profit of trading is highly dominated by the average demand of pairs.

TABLE 4. PLCC between total profit and characteristics of pairs.

	P0	P1	P2
Demand difference, $\mu_{z_{ij}}$	-0.56	-0.76	-0.50
Relative STD, $\sigma_{z_{ij}}/\mu_{z_{ij}}$	-0.94	-0.97	-0.82

Table 4 represents the relationship between the total profit of pairs and the matched pair's characteristics. The relationship between the profit and the STD is quite high (larger than 0.8). This says that a pair with low uncertainty (low STD) can achieve more profit because of a lesser mismatched quantity.

Figure 4 describes the relationship between the total profit (or social welfare) and the relative STD of each pair. The same as the result in Table 4, the result of **P1** in Figure 4 shows higher correlation than the other results in Figure 4 and 4. Actually, **P1** was designed considering the demand difference and the STD, so it has the highest correlation in Table 4 and Figure 4. However, the performance of **P1** is limited compared with that of **P0**, which is less related to these two characteristics, and additionally considers other information. In Figure 4, some points in bold dashed circles have low profit even though they are low STD. This point reduces the performance of **P2**, because **P2** was designed to be biased toward the demand difference only.

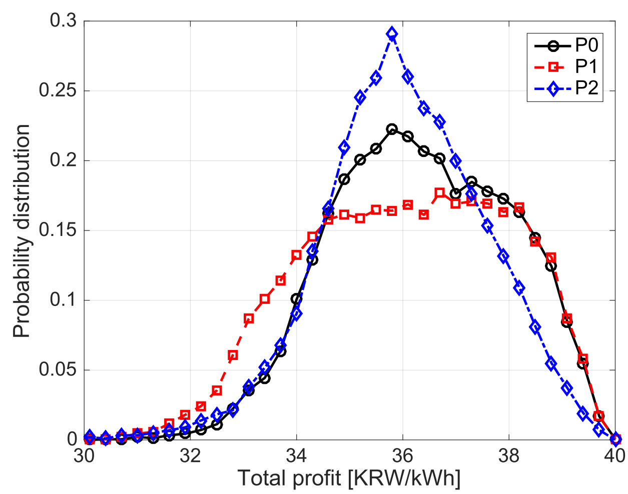
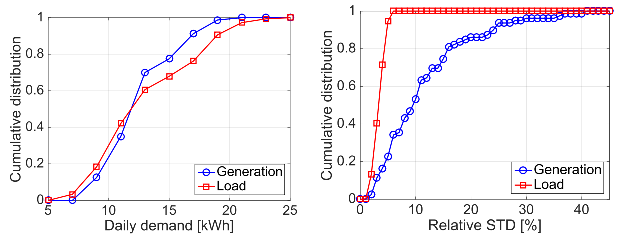


FIGURE 5. Probability distribution of the total profit of each pair. The black line with circles, the red dashed line with squares, and the blue dash-dot line with diamonds show the gain achievement by applying P0, P1, and P2, respectively.

Figure 5 shows the total profit distribution of each pair applying the strategies. The circled black line, the red dashed line with squares, and the blue dash-dot line with diamonds illustrate the gain achievement by applying **P0**, **P1**, and **P2**, respectively. Similar numbers of pairs achieve a high profit of more than 38 by **P0** and **P1**, but more pairs by **P1** achieve a profit of less than 34 than do pairs by **P0**. The opposite property appears when comparing the profit distribution by **P0** and **P2**. In addition, the profit distribution by **P2** has lower variance than that by **P1**. This means that **P2** only considers the average demand difference and ensures the average profit as the maximization of the minimum profit (max-min) operation, and **P1** with average demand difference and relative STD works as the maximization of the maximum profit (max-max) operation [30]. These results show that **P2**



(a) (b)

FIGURE 6. Real demand properties. The blue line with circles and the red line with squares represent the statistical properties of the generation and load, respectively. (a) Daily demand. (b) Relative STD.

is a more effective strategy when considering profit fairness among pairs, and **P1** is a better strategy for maximizing profit.

B. PRACTICAL CASE

For more practical results, we simulate using the sample data from real demand profiles of wind generation and building load. The wind generation was collected by the Bonneville Power Administration (BPA), United States Department of Energy [31], and the building load was recorded as part of the Korea Micro Grid Energy Project (K-MEG) [32] in 2016,. The announced generation forecasting data from BPA and the measured data applying the NYISO day-ahead CBL methodology [17] are considered. The accuracy of the generation and load forecasting corresponds to about 11% and 4% of the relative STD. The statistical properties of real demand are presented in Figure 6. The performance is averaged on the results of 30 days with 16 producer and consumer sets.

TABLE 5. Average unit profit [KRW/kWh].

	P0	P1	P2
Profit of producer	16.3	16.1	16.1
Profit of consumer	16.8	16.8	16.7
Total profit	33.1	32.9	32.8
Gain achievement [%]	82 .8	82.3	82.0
Optimal gap [%]	-	0.6	0.9

In Table 5, performance using the real data shows the same trend as that of the ideal case, and the optimal gap between the optimal solution of **P0** and the results using the proposed strategies, **P1** and **P2**, is less than 1%. This verifies that the proposed strategies work well. In addition, the results show that the consumers achieve more profit than the producers on average. This is because the consumers' STD related to mismatching is lower than that of the producers. This says once again that the profit is highly correlated to the STD.

V. CONCLUSIONS

In this study, we focused on the trading pair matching problem for social welfare maximization. First, we suggested a GMQ to manage the distributed energy trading risk. Analyzing the effect of the players' profit on the problem in the GMQ mechanism, the non-convex social welfare maximization problem was converted into a convex problem to minimize the mismatched quantity. We proposed two trading pair matching strategies based on the first and the second statistical characteristics of demand. The proposed strategies can be solved in a distributed manner with low computational complexity. We empirically showed that the proposed strategies perform close to the optimal solution for the ideal case, as well as for the practical case considering real demand profiles. In addition, we discussed the relationship between the profit and the characteristics of the matched trading pairs. This suggests guidance in designing rules for trading and matching.

REFERENCES

[1] M. S. Hossain, N. A. Madlool, N. A. Rahim, J. Selvaraj, A. K. Pandey, and A. F. Khan, "Role of smart grid in renewable energy: An overview," *Renew. Sustain. Energy Rev.*, vol. 60, pp. 1168–1184, Jul. 2016.
[2] *Energy Technology Perspectives 2015*, OECD/IEA, Paris, France, 2015.
[3] S. Grijalva and M. U. Tariq, "Prosumer-based smart grid architecture enables a flat, sustainable electricity industry," in *Proc. IEEE PES Innov. Smart Grid Technol. (ISGT)*. Anaheim, CA, USA: IEEE, Jan. 2011, pp. 1–6.
[4] A. J. D. Rathnayaka, V. M. Potdar, T. S. Dillon, O. K. Hussain, and E. Chang, "A methodology to find influential prosumers in prosumer community groups," *IEEE Trans Ind. Informat.*, vol. 10, no. 1, pp. 706–713, Feb. 2014.
[5] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nature Energy*, vol. 1, no. 4, Mar. 2016, Art. no. 16032.
[6] C. Zhang, J. Wu, C. Long, and M. Cheng, "Review of existing peer-to-peer energy trading projects," *Energy Procedia*, vol. 105, pp. 2563–2568, May 2017.
[7] Vandebron. *Switch to Good Energy Vandebron*. Accessed: May 11, 2018. [Online]. Available: https://vandebron.nl
[8] Sonnen. *SonnenCommunity*. Accessed: May 11, 2018. [Online]. Available: https://microsite.sonnenbatterie.de/en/sonnenCommunity
[9] Open-Utility. *Introducing Piclo*. Accessed: May 11, 2018. [Online]. Available: https://www.openutility.com/piclo/
[10] O. Jogunola *et al.*, "State-of-the-art and prospects for peer-to-peer transaction-based energy system," *Energies*, vol. 10, no. 12, pp. 1–28, Dec. 2017.
[11] L. Groot and R.-J. van der Veen, *Basic Income on the Agenda: Policy Objectives and Political Chances*. Amsterdam, Netherlands: Amsterdam Univ. Press, 2000.
[12] J. Lan, Y. Ma, D. Zhu, D. Mangalagiu, and T. F. Thornton, "Enabling value co-creation in the sharing economy: The case of mobike," *Sustainability*, vol. 9, no. 9, pp. 1–20, Aug. 2017.
[13] W. Miller and M. Senadeera, "Social transition from energy consumers to prosumers: Rethinking the purpose and functionality of eco-feedback technologies," *Sustain. Cities Soc.*, vol. 35, pp. 615–625, Nov. 2017.
[14] C. Wan, J. Lin, Y. Song, Z. Xu, and G. Yang, "Probabilistic forecasting of photovoltaic generation: An efficient statistical approach," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 2471–2472, May 2017.
[15] J. R. Andrade and R. J. Bessa, "Improving renewable energy forecasting with a grid of numerical weather predictions," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1571–1580, Oct. 2017.
[16] S. Mohajeryami, M. Doostan, and P. Schwarz, "The impact of customer baseline load (CBL) calculation methods on peak time rebate program offered to residential customers," *Electr. Power Syst. Res.*, vol. 137, pp. 59–65, Aug. 2016.
[17] S. Mohajeryami, M. Doostan, A. Asadinejad, and P. Schwarz, "Error analysis of customer baseline load (CBL) calculation methods for residential customers," *IEEE Trans. Ind. Appl.*, vol. 53, no. 1, pp. 5–14, Jan./Feb. 2017.
[18] S. Ong, C. Campbell, and N. Clark, "Impacts of regional electricity prices and building type on the economics of commercial photovoltaic systems," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-6A20-56461, Dec. 2012.

[19] G. Dutta and K. Mitra, "A literature review on dynamic pricing of electricity," *J. Oper. Res. Soc.*, vol. 68, no. 10, pp. 1131–1145, Oct. 2017.

[20] R. M. Karp, "Reducibility among combinatorial problems," *Complex. Comput. Comput.*, vol. 40, no. 4, pp. 85–103, 1972.

[21] A. Papoulis and S. Pillai, *Probability—Random Variables and Stochastic Processes*. New York, NY, USA: McGraw-Hill, 2002.

[22] F. C. Leone, L. S. Nelson, and R. B. Nottingham, "The folded normal distribution," *Technometrics*, vol. 3, no. 4, pp. 543–550, Apr. 1961.

[23] M. Chiani, D. Dardari, and M. K. Simon, "New exponential bounds and approximations for the computation of error probability in fading channels," *IEEE Trans. Wireless Commun.*, vol. 2, no. 4, pp. 840–845, Jul. 2003.

[24] D. P. Bertsekas and J. N. Tsitsiklis, *Parallel and Distributed Computation: Numerical Methods*. Upper Saddle River, NJ, USA: Prentice-Hall, 1989.

[25] *Statistics of Electric Power in Korea*, Korea Electr. Power Corp., Naju, South Korea, Jun. 2017.

[26] *Annual Energy Outlook*, U.S. Energy Inf. Admin., Washington, DC, USA, Feb. 2018.

[27] E. Oh, J.-B. Park, and S.-Y. Son, "Group building based power consumption scheduling for the electricity cost minimization with peak load reduction," *J. Elect. Eng. Technol.*, vol. 9, no. 6, pp. 1843–1850, Nov. 2014.

[28] S. Verdú, *Multiuser Detection*. Cambridge, U.K.: Cambridge Univ. Press, 1998.

[29] J. L. Rodgers and W. A. Nicewander, "Thirteen ways to look at the correlation coefficient," *Amer. Stat.*, vol. 42, no. 1, pp. 59–66, 1988.

[30] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[31] Bonneville Power Administration, United States Department of Energy. *WIND GENERATION & Total Load in the BPA Balancing Authority*. Accessed: May 11, 2018. [Online]. Available: http://transmission.bpa.gov/Business/Operations/Wind/

[32] E. Oh, Y. Kwon, and S.-Y. Son, "A new method for cost-effective demand response strategy for apartment-type factory buildings," *Energy Buildings*, vol. 151, pp. 275–282, Sep. 2017.

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