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Joint Demand Response and Energy Trading for Electric Vehicles in Off-grid System

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ABSTRACT This paper proposes a joint demand response and energy trading for electric vehicles in an off-grid system. We consider isolated microgrid in a region where, at a given time, some renewable energy generators have superflous energy for sale or to keep in storage facilities, whereas some electric vehicles wish to buy additional energy to meet their deficiency. In our system model, broker lead the market by determining the optimal transaction price by considering a trade-off between commission revenue and power reliability. Buyers and sellers follow the broker's decision by independently submitting a transaction price to the broker. Correspondingly transaction energy is allocated to the buyers in the proportion to their payment, whereas the revenue is allocated to the sellers in proportion to their sales. We investigated the economic benefits of such a joint demand response and energy trading by analyzing its hierarchical decision-making scheme as a single-leader-heterogeneous multi-follower Stackelberg game. With demonstrating an existence of a unique Stackelberg equilibrium, we show that the transaction price in the proposed market model is up to 25.8% cheaper than the existing power market. In addition, we compare the power reliability results with other algorithm to show the suitability of proposed algorithm in the isolated microgrid environment.

INDEX TERMS Smart grid, electricity market, Electric vehicle, Stackelberg game, Off-grid system

I. INTRODUCTION

DUE to the energy efficiency improvement of renewable energy sources achieved using modern communication technologies and battery systems, electric vehicles (EVs) that are powered via fast charging devices or off-vehicle sources are envisioned as the next-generation transportation paradigm [1], [2]. Because of the EVs' environmental benefits, such a paradigm shift has been rapidly realized due to the increasing environmental concerns regarding the emissions generated by the conventional gasoline-powered transport sector [3]. Nevertheless, the inconspicuous proliferation of EVs may change the energy consumption pattern in existing power systems and increase peak demand. Accordingly, the necessity of additional charging facilities as well as energy generation for stable energy supplement to EVs should be emphasized [4].

This new paradigm in the transportation system faces technical issues with regard to efficient charging demand management of EVs. It is more challenging in off-grid systems for isolated regions (e.g., island region, isolated local area) , which are physically isolated power system in which additional energy supply from the maingrid is limited and satisfy the requirement of energy consumption according to distributed generators installed in the region [5], [6].

In an off-grid system (also called a microgrid without support from the maingrid), there are various forms of demand and supply problems in the literature that aim to optimize the operation of diesel generators or energy storage as backup energy supplements [7]. More recently, due to the high costs associated with the operation of such a backup system, a deregulated market-based approach that considers the demand of EVs known as energy trading in EVs is considered as a promising cost-effect maneuver [8]–[10]. In [8]–[10], the authors proposed an auction method to manage energy supplement in a region. However, the auction is a method of inducing power transaction through voluntary price competition of market participants. As a result, auction based trading models cause unstable power supplement problem in the case that power supply is limited environment such as an isolated microgrid.

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In order to solve this problem, some papers have proposed the control of EV power purchase decision using demand response (DR) market [11]–[13]. In general, the proposed DR markets reduce power consumption of consumers based on an incentive that determined by the system operator. However, the DR method has a limiting factor in that it cannot induce power consumption reduction beyond a consumer's purpose. In other words, if the inconvenience caused by reducing the actual power consumption is greater than the incentive that the consumer receives, the consumer does not proceed to participate DR market. Specifically, in the case of an off-grid system, it is hard to meet the power stability just applying the DR market. Therefore the control of overall demand from EVs while conducting energy trading is inevitable to increase the probability of stabilizing the power system. Accordingly, the joint demand response and energy trading of EVs should be considered in the design of more reliable energy trading market behavior among these vehicles in an off-grid system.

In this regard, this paper proposes a joint demand response and energy trading market model for EVs in an off-grid system. The proposed model simultaneously optimizes peer to peer energy trading and DR market to balance the energy demand and supply in the off-grid system. Under the optimized transaction price, EV charging facilities optimally determine the amount of energy to buy from the market while directly controlling the charging demands through the demand response of EVs.

The remainder of this report is divided into multiple sections. Section II summarizes the results of previous researches on energy supply in an off-grid system and EV charging facilities. In Section III, we describe the proposed EV market model and provide the details of energy management in the system. In Section IV, we suggest an approach for operating a market using heterogeneous Stackelberg game theory. Numerical results are presented in Section V. Finally, the main conclusions are summarized in Section VI.

II. RELATED WORK

Currently, EVs consume a large portion of energy in the system. They are advantageous in terms of environmental friendliness, low noise production, and the capability to manage their power reliability in the system. However, there are problems associated with EV use such as the energy consumption is unstable and difficult to predict [14]. Given that EVs are sensitive to the operational decisions of their owners, it is difficult to accurately predict energy consumption. Therefore, additional facilities such as storage or the installation of auxiliary generators are required to manage energy supply in the system [15]. However, the construction of additional facilities requires monetary consideration and can be time-consuming [16]. Therefore, in most practical cases, various approaches to control energy transaction depending on price have been studied. The most well-known approach to control energy supply is the dynamic pricing mechanism [17], which focuses on the determination of a transaction price to stabilize energy supply [9], [18]–[20]. Wei Yuan $et\ al$, [18] proposed a charging control method for EVs based on the location of facilities and the charging rate by combining Hotelling and Stackelberg game theory. Peer to peer direct energy trading among EVs has been proposed by Jiawen Kang $et\ al$ [9] to satisfy the energy supply and demand of EVs according to energy transaction required to maximize the profit of an individual participant. The game-theoretic energy consumption scheduling framework presented by Ziming Zhu $et\ al$, [19] regulates the energy consumption of an individual consumer according to price adjustment from local system operators. Based on this approach, the authors proposed a method to reduce the reliance on existing power systems and satisfy energy supply from the region. The work of Sung-Guk Yoon $et\ al$ [20] suggests a model for at-home EV charging using Stackelberg game to control the energy consumption of EVs. Their approach involved the mathematical formulation of the profit of energy retailers and the total charge of consumers to simultaneously consider both sides of the utility structure of users. Nevertheless, none of the previous works considers the characteristics of an off-grid system when additional energy supply from the maingrid is limited. In addition, there is insufficient consideration of the situation whereby the total energy supply from a generator is less than the total consumption. These characteristics should be considered to design more practical market models for off-grid systems to manage the energy supply of EVs.

In the case of an off-grid system in which it is difficult to stabilize the system based on the energy supply facilities, a method of controlling the energy consumption via the DR market can be applied. Several studies have been conducted to stabilize the power system by controlling the energy required and the charging time period. Shao $et\ al$, [11] proposed a power stabilization scheme based on the DR signal that considered the analysis of energy supply in the region and energy consumption of each element (e.g., heating, ventilation, & air conditioning, water heater, EV). The study accounts for the energy supply in the region and various energy consumption resources. However, there is limited analysis of characteristics of EV such as time constraint, or battery limitation. Shafie $et\ al$ derive two different DR market models [12] including incentive-based DR market and price-based DR market. In their publication, the authors considered the battery characteristics and the uncertainty of EV operation to deduce practical results. In the work by Pal $et\ al$ [13], a method is proposed for the trade energy between a neighborhood based on the load required by considering the fixed energy transaction charge. They considered the energy balance in own facility and derive an appropriate strategy for the individual user according to individual profit. However, in these conventional studies, there is insufficient consideration given to the power reliability of the system and the applicability of the charging facility in a real system. In addition, to apply the DR mechanism, it is necessary to consider the user's dissatisfaction factor according to the charging time and the delay in the facility. In addition, this report addresses the issue that there are no published works that consider the consumer's perspective with respect to simultaneously maximizing the total profit via energy transmission and a reduction of the participating DR market.

In summary, main contributions of this investigation are summarized as follows:

- Unlike the existing EV energy trading researches [8]–[13] that deal only with either energy trading or demand reduction, we propose a way to deal with both considerations simultaneously by determining proper transaction price.

- Based on the proposed approach, a broker manages energy trading in the off-grid system by determining the transaction price required to maintain a balance between energy demand and supply with the consideration of each participant's profit simultaneously.
- Specifically, the broker also receives a part of transaction price during the market management process as a market commission. Therefore, the profit structure of broker, which was not covered in previous researches, was also reflected as an important factor in determining the transaction price in the paper.
- For a given transaction price, the EV charging facility determines the amount of energy to buy from the market while directly controlling charging demands via the demand response of the EVs. In this case, the penalty costs associated with a reduction of the charging demands via the demand response are considered in the buyers' utility function [21]
- In the case of sellers that used to conduct power transactions, we considered the case that various strategies were conducted due to the energy storage system and renewable generator. Sellers can maximize their profit by selling or storing power generated from renewable generator, considering the amount of power stored in the energy storage device and the expected market price in the future time period. In the paper, we mathematically modeled whole of the factors to maximize individual seller's profit.
- The proposed EV energy trading system is formulated as a Stackelberg game model in which the broker is considered as a leader, and both sellers and buyers are considered as heterogeneous followers. This report reveals the existence of a unique Stackelberg equilibrium (SE) which derive the maximizing the profit of each market participant and stability of the power supply in the system.

III. SYSTEM MODEL

In this report, we consider multiple EV charging facilities that are deployed in an off-grid system as illustrated in Fig. 1. Each facility participates in the market as a buyer and determines the energy that is necessary to meet charging demands of EVs. In this case, the charging demands due to an EV cluster at each EV charging facility are determined based on the coverage of the EV charging facilities. In addition, buyers will determine the purchase amount and voluntary reductions depending on the DR incentive and transaction price that announced by broker in the market. Sellers are players who own renewable generators and energy storage that determine the transaction energy quantity to sell by considering a market prce, which is decided by the broker. In the proposed system, the broker is an independent system operator (e.g., California ISO) that determines the market price based on the power reliability and it's profit from commission. Since sellers and buyers conduct transactions based on broker's decision, which is useful for deriving optimal strategies based on hierarchical analysis. Therefore, we analyzed the framework through the Stackelberg game [22]–[24].

As shown in Fig 1, we would like to analyze each market participant's strategy and result according to the give market price in a specific time period. Therefore, we denote $\mathcal{T}$ as set of time that the market is held. Therefore, we set $t \in \mathcal{T}$ in the equations. In the market, the broker determines a transaction price $p(t)$ to maximize profit considering the market commission ω_{tr} (widely used in the practical market. see, e.g., [25]–[27]) and the DR incentive p_{dr} while maintaining a balance between the energy demand and the supply in the off-grid system. As a set of market participants, we define $\mathcal{I}$ and $\mathcal{J}$ as the set of buyers and sellers, respectively. For each $i \in \mathcal{I}$, we denote $\mathcal{L}_i$ as the set of EVs in the charging facility i. Since in the actual power system, it is impossible to reflect whole of the characteristics of individual EVs with different purpose, we set the charging facility as an aggregator trading the energy in the market with considering the average characteristics of the EVs. In addition, the number of EVs in the charging facility i is denoted as $|\mathcal{L}_i| = R_i$. For each $i \in \mathcal{I}$ and each $r \in \mathcal{L}_i$, we denote a ratio of residual energy from EV r's in the charging facility i as $SOC_{i,r}(t)$ throughout this report. In addition, for each $i \in \mathcal{I}$, we define $\hat{E}_i(t)$ as the average charging demand required at the EV charging facility i. Let $\gamma_{buy,i}(t)$ be the portion of $\hat{E}_i(t)$ that the buyer i decides to buy from the market where the range of $\gamma_{buy,i}(t)$ is $[0, 1]$. In this case, by considering the cost associated with the control of the EV's charging demand via DR, the buyer determines the amount of energy to buy from the market, i.e., $\gamma_{buy,i}(t)\hat{E}_i(t)$. In the case of a seller, we define $E_j(t)$ as the

TABLE 1: Summary of major symbols

Symbol	*Definition*
N	Number of charging facilities participate in market as buyers
$\mathcal{I}$	Set of buyers in the market
i	Number of buyers, i.e., i = 1,2,...,N
M	Number of renewable generators participate in market as sellers
$\mathcal{T}$	Set of time that the market is held
t	Time index that market held, i.e., t = 1,2,...,T
$\mathcal{J}$	Set of sellers in the market
j	Number of sellers, i.e., j = 1,2,...,M
R_i	Number of electric vehicles attempting to charge at facility i
$\mathcal{L}_i$	Set of EVs in charging facility i
r	Number of electric vehicles, i.e., r = 1,2,...,R_i
$SOC_{i,r}(t)$	State of charge of electric vehicle r in charging facility i at time t
a_1	Weight factors to determine dissatisfaction cost
ω_{tr}	Transaction fee for the profits of market participants gain by proceeding in the market
$\gamma_{sell,j}(t)$	Seller j's weight for amount of energy sold at time t
$\gamma_{buy,i}(t)$	Buyer i's weight for amount of energy bought at time t
$p_{d,i}(t)$	Discomfort cost for buyer i who want to reduce their buying quantity voluntarily at time t
$p_{grid}(t)$	Power purchase price from maingrid at time t
$p(t)$	Transaction price in the market at time t
p_{dr}	Demand response incentive according to event signal
$E_j(t)$	Seller j's selling amount of energy
$\hat{E}_i(t)$	Buyer i's buying amount of energy
$\lambda(t)$	Average arrival rate EVs per unit length of boundary at time t
E_{ev}	Average energy necessity of EVs
d	Average moving distance of EVs
η	Energy efficiency of EVs
A_i	Coverage of EV charging facility i

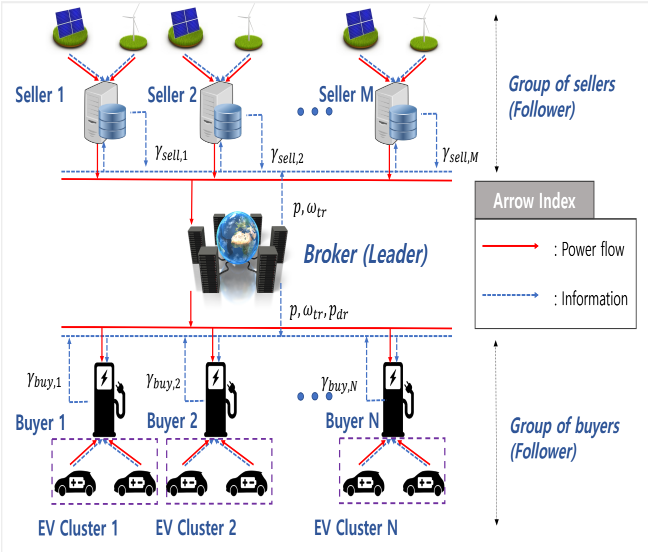

FIGURE 1: Suggested energy trading among off-grid system.

amount of energy generated by seller $j \in \mathcal{J}$. Let $\gamma_{sell,j}(t)$ be the proportion of $E_j(t)$ that the seller j decides to sell in the market where the range of the value is $[0, 1]$. Therefore, $E_j(t)\gamma_{sell,j}(t)$ has the implicit meaning of the amount of energy to sell to the market.

A. ENERGY REQUIREMENT OF CHARGING FACILITIES

To focus on the main contribution of this paper, we consider homogeneous EV cases, i.e., each EV travels the same constant average driving distance d with efficiency η (distance per kWh). The average amount of electricity required for each EV can then be given as:

$$E_{ev} = \frac{d}{\eta}. \tag{1}$$

As in [18], it is assumed that the number of EVs, which are parked in the facilities, is determined by the coverage of the EV charging facilities. Correspondingly, the coverage of the EV charging facility (buyer) $i \in \mathcal{I}$ is denoted as A_i and the average number of EV inflows to the charging facility per unit area at time t is given by λ. The average charging demand required at the EV charging facility (buyer) $\hat{E}_i(t)$ is then given as:

$$\hat{E}_i(t) = A_i \lambda(t) E_{ev}. \tag{2}$$

B. UTILITY FUNCTION OF THE BUYERS

As previously indicated, each EV charging facility plays the role of a buyer in the market. In the limited power environment where additional power supply from the maingrid restricted, the buyer's strategy is to trade power directly from other utilities or reduce their own power supply. Therefore, the buyer determines the transaction quantity $\gamma_{buy,i}(t)\hat{E}_i(t)$ by determining the optimal value of $\gamma_{buy,i}(t)$ under the given $p(t)$, ω_{tr}, and p_{dr} to maximize its own utility. Our design of the utility function for buyer i, $i \in \mathcal{I}$, considers three terms. The first term represents the quantification of the satisfaction of buyer i that is achieved from buying energy $\hat{E}_i(t)\gamma_{buy,i}(t)$in the market instead of the maingrid. The second term represents the incentives received from the broker by achieving demand reduction $(1-\gamma_{buy,i}(t))\hat{E}_i(t)$ via DR. The last term represents the cost of the dissatisfaction associated with the EV clusters via demand reduction using DR.

In this context, as in [21], we model this cost as a quadratic function of the amount of reduced energy per EV, which can be simplified as $(\frac{(1-\gamma_{buy,i}(t))\hat{E}_i(t)}{R_i})$. Specifically, we define $p_{d,i}(t) = \frac{1}{R_i}\sum_{r=1}^{R_i} \alpha_1 \frac{1}{SOC_{i,r}(t)}$ by considering an average ratio of the residual energy of the EVs where α_1 is the weight factor to consider the state of the EV user of the charge value into the dissatisfaction cost. In addition to this EV case, such a quadratic model has been widely used in other fields [28]–[30]. Correspondingly, for each $i \in \mathcal{I}$, the utility function of the buyer i is defined as follows:

$$\begin{aligned} U_{buy}(\gamma_{buy,i}(t), p(t)) = {} & p_{grid}(t)\hat{E}_i(t)\gamma_{buy,i}(t) \\ & - p(t) \times (1+\omega_{tr})\hat{E}_i(t)\gamma_{buy,i}(t) \\ & + p_{dr}(1-\gamma_{buy,i}(t))\hat{E}_i(t) \\ & - p_{d,i}(t)(\frac{(1-\gamma_{buy,i}(t))\hat{E}_i(t)}{R_i})^2 \end{aligned} \tag{3}$$

where $p_{d,i}(t) \geq 0$ is the weighting factor of the penalty costs at the charging facility.

C. UTILITY FUNCTION OF THE SELLERS

For each $j \in \mathcal{J}$, we consider the following utility function:

$$\begin{aligned} U_{sell}(\gamma_{sell,j}(t), p(t)) = {} & p(t)(1-\omega_{tr})E_j(t)\gamma_{sell,j}(t) \\ & + \ln(1+(1-\gamma_{sell,j}(t))E_j(t)) \end{aligned} \tag{4}$$

to quantify the total revenue from the energy sales $E_j(t)\gamma_{sell,j}(t)$ to the market and the logarithm based satisfaction derived by the seller j from the stored energy $(1-\gamma_{sell,j}(t))E_j(t)$ as in [23]. Correspondingly, the proposed utility function designed in this way aims to achieve a balance between energy sales and the satisfaction derived from storing the energy given that the two terms conflict with each other. In the equation (4), according to a given transaction price $p(t)$, sellers determine the $\gamma_{sell,j}(t)$ to maximize their own utility by considering the market commission ω_{tr}.

D. UTILITY FUNCTION OF THE BROKER

In the proposed market model, the broker has an important role in maintaining the balance between energy demand and supply in the off-grid system by determining a suitable transaction price $p(t)$. In this context, the broker is motivated to maximize the revenue from the market commission ω_{tr} by promoting energy trading between sellers and buyers. To model this perspective, the proposed utility considers two terms. The first term and the second term represent the market commission from sellers and buyers, respectively. Accordingly, the utility function of the broker is defined as

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follows:

$$U_{bro}(p(t),\gamma_{i\in N},\omega_{j\in M}) = \omega_{tr}p(t)\sum_{j=1}^{M}\gamma_{sell,j}(t)E_j(t) + \omega_{tr}p(t)\sum_{i=1}^{N}\gamma_{buy,i}(t)\hat{E}_i(t). \quad (5)$$

where $p_{min}(t) \leq p(t) \leq p_{grid}(t)$, $p_{min}(t)$ and $p_{grid}(t)$ are boundary conditions according to the practical energy cost in the EV charging facility. According to the boundary condition, the transaction price in the off-grid system should be lower than buying from the maingrid, otherwise, there is no motivation to buy energy from the sellers.

In order to consider the power reliability in the power system from the viewpoint of active power, we provide the following constraint that the power supply in the isolated microgrid is larger than the total power demand which are determined by the optimal price $p(t)$.

$$E_{rel}(t) = \sum_{j=1}^{M}\gamma_{sell,j}(t)E_j(t) - \sum_{i=1}^{N}\gamma_{buy,i}(t)\hat{E}_i(t) \geq 0 \quad (6)$$

IV. GAME-THEORETIC ANALYSIS

The management of energy trading among the distributed generation companies and EV facilities via a broker over a particular time interval can be considered as a hierarchical non-cooperative decision problem that can be analyzed as a single leader multi-follower Stackelberg game.

A. PRELIMINARIES

Stackelberg game is a representative non-cooperative game model in which the participants have different utilities and are classified into leaders and followers according to their interest. In the original work of H. von Stackelberg, he suggested a market with a duopoly situation in which only two firms are present. In the case of his proposed approach, a small firm (follower) observes the decision of a large firm (leader) and chooses a quantity. Such a leader and follower game model can be found in existing power systems. In particular, the expansion of the distributed generation of resources and various competitive energy markets have led researchers to use the leader-followers game model [23], [24], [31]. In general, Stackelberg game assumes that each market participant has the intention of achieving maximum profit with selfish behavior. In addition, for EV energy trading market models, there are few studies on the modeling of non-cooperative markets using Stackelberg game theory [18], [24]

In our problem, we consider that the broker assumes the role of leader, and sellers and buyers in the market assume the role of followers. Given that sellers and buyers have different purposes in terms of participating in the market, they choose their transaction quantity independently depending on their own strategy. In particular, buyers and sellers submit their $\gamma_{buy,i}(t)$ and $\gamma_{buy,i}(t)$, respectively, which aims to maximize each utility function U_{buy} and U_{sell} defined in (4), and (3). In the broker's game, the broker develops a strategy $p(t)$ depending on the decisions of buyers and sellers. Consequently, to solve for the Stackelberg equilibrium in our problem, we use a backward induction technique. To apply the method, we first find the best response of sellers and buyers from the follower-level game, then we apply the value to the utility function of the broker and optimize it correspondingly.

B. NON-COOPERATIVE GAME OF FOLLOWER - CASE OF SELLERS

Definition 1: The best response function $B_{sell,j}(\mathbf{p})$ of seller j as a follower is the best strategy for seller j given the leader's strategy $\mathbf{p}$. By definition, we have:

$$B_{sell,j}(\mathbf{p}) = \underset{\gamma_{sell,j}(t)}{\text{argmax}}\, U_{sell}(\gamma_{sell,j}(t),\mathbf{p}) \quad (7)$$

Definition 2: The optimal best response of the sellers is derived according to the optimal strategies ω^* with the property given by the leader's strategy $\mathbf{p}$. Therefore, we have:

$$\omega_j^* = B_{sell,j}(\mathbf{p}^*) \qquad \forall j \in M \quad (8)$$

Lemma 1: The utility of seller j is strictly concave, which could be used to derive the global optimal value. *Proof:* : Given equation (4), we have

$$U_{sell}(\gamma_{sell,j}(t),\mathbf{p}) = p(t)(1-\omega_{tr})E_j(t)\gamma_{sell,j}(t) \quad (9)$$
$$+ \ln(1+(1-\gamma_{sell,j}(t))E_j(t)). \quad (10)$$

Taking the first and second derivatives of $F(\gamma_{sell,j}(t),\mathbf{p})$ with respect to $\gamma_{sell,j}(t)$, we have

$$\frac{\partial U_{sell}(\gamma_{sell,j}(t),\mathbf{p})}{\partial\gamma_{sell,j}(t)} = (1-\omega_{tr})p(t)E_j(t) \quad (11)$$
$$-\frac{E_j(t)}{1+(1-\gamma_{sell,j}(t))E_j(t)} \quad (12)$$

$$\frac{\partial^2 U_{sell}(\gamma_{sell,j}(t),\mathbf{p})}{\partial\gamma_{sell,j}(t)^2} = -\frac{E_j^2}{(1+(1-\gamma_{sell,j}(t))E_j(t))^2} \quad (13)$$

Given that $\gamma_{sell,j}(t)$ has a value between 0 and 1, the right side of equation (13) always has a value less than 0. Therefore, the utility function of the seller j is strictly concave on $\gamma_{sell,j}(t)$. After proving that $U_{sell}(\gamma_{sell,j}(t),\mathbf{p})$ is concave, we solve the problem as follows:

1) Derive the maximum value using the first derivative.
2) Check the maximum value is within constraints

Based on equation (11), the best response function of seller j could be derived by setting the right hand-side of the equation as equal to zero.

$$(1-\omega_{tr})p(t)E_j(t) - \frac{E_j(t)}{1+(1-\gamma_{sell,j}(t))E_j(t)} = 0 \quad (14)$$
$$\therefore \gamma^*_{sell,j}(t) = 1 + \frac{1}{E_j(t)} - \frac{1}{(1-\omega_{tr})p(t)E_j(t)}.$$

In equation (14), we could derive the optimal value of $\gamma^*_{sell,j}(t)$. Given that the value of $\gamma^*_{sell,j}(t)$ should be located between 0 and 1, we must ensure that the optimal transaction quantity satisfies the constraint.

Value comparison: In the case of equation (4), we have confirmed that the function is concave and that it assumes a

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certain optimal value based on the derivative process. In addition, we need to show that $\gamma^*_{sell,j}(t)$ satisfies the constraint that $0 \leq \gamma^*_{sell,j}(t) \leq 1$, given that there is the restriction that sellers cannot sell more energy than they have, or purchase energy from the market. Therefore, we could check that ω^*_j satisfies the constraints in the equation.

$$0 \leq \gamma^*_{sell,j}(t) = 1 + \frac{1}{E_j(t)} - \frac{1}{(1-\omega_{tr})p(t)E_j(t)} \leq 1 \tag{15}$$

In equation (15), given that $0 \leq \omega_{tr} \leq 1$ and $p(t)$ are normalized values between 0 and 1, it can be determined that $\gamma^*_{sell,j}(t)$ has a lower value compared with 1. In addition, the minimum transaction price required to satisfy a given condition can be derived as follows

$$\begin{aligned}\gamma^*_{sell,j}(t) &= 1 + \frac{1}{E_j(t)} - \frac{1}{(1-\omega_{tr})p(t)E_j(t)} \qquad (16)\\ &= \frac{1}{E_j(t)}(1 + E_j(t) - \frac{1}{(1-\omega_{tr})p(t)})\\ &= \frac{1}{E_j(t)}(1 + E_j(t) - \frac{1}{(1-\omega_{tr})p(t)}) \geq 0\\ \therefore p(t) &\geq \frac{1}{(1-\omega_{tr})(1+E_j(t))}\end{aligned}$$

From the equation (16), $p(t)$ should be greater than or equal to $\frac{1}{(1-\omega_{tr})(1+E_j(t))}$, otherwise, sellers are not willing to sell their energy to the market. Hence, even though the theoretical lower bound of $p(t)$ can be 0, it should be updated as (16).

C. NON-COOPERATIVE GAME OF FOLLOWER - CASE OF BUYERS

Definition 3: In the case of buyers, depending on the best response function $B_{buy,i}(\mathbf{p})$ of buyer i, it is possible to derive an optimal strategy $\gamma_{buy,i}(t)$ according to the leader's strategy $\mathbf{p}$. Under this condition, we have

$$B_{buy,i}(\mathbf{p}) = \underset{\gamma_{buy,i}(t)}{\operatorname{argmax}} U_{buy}(\gamma_{buy,i}(t), \mathbf{p}) \tag{17}$$

Definition 4: As discussed in the preceding section, the best responses of buyers are derived as optimal strategies γ derived by the leader's strategy $\mathbf{p}$. In this case, we have optimal value as follows:

$$\gamma^*_{buy,i} = B_{buy,i}(\mathbf{p}^*) \qquad \forall i \in N \tag{18}$$

Lemma 2: The utility function of $U_{buy}(\gamma_{buy,i}(t), p)$ is strictly concave on $\gamma_{buy,i}(t)$. In this case, we could prove the concavity of the function and could determine the optimal value as mentioned in Section IV-B.

Proof: : In equation (3), we could take the first and second derivatives of $U_{buy}(\gamma_{buy,i}(t), \mathbf{p})$.

$$\begin{aligned}\frac{\partial U_{buy}(\gamma_{buy,i}(t),\mathbf{p})}{\partial \gamma_{buy,i}(t)} &= (p_{grid}(t) - p(t) \times (1+\omega_{tr}))\hat{E}_i(t) \qquad (19)\\ &+ 2p_{d,i}(t)\big((1-\gamma_{buy,i}(t))\frac{\hat{E}_i(t)}{R_i}\big)\frac{\hat{E}_i(t)}{R_i}\\ &- p_{dr}\hat{E}_i(t)\end{aligned}$$

$$\frac{\partial^2 U_{buy}(\gamma_{buy,i}(t),\mathbf{p})}{\partial \gamma_{buy,i}(t)^2} = -2p_{d,i}(t)\frac{\hat{E}_i(t)^2}{R_i^2} \tag{20}$$

In the equation (20), regardless of the value of $\gamma_{buy,i}(t)$, we can ensure that the second derivative term is always less than zero, i.e., the utility function of the buyer i is strictly concave for $\gamma_{buy,i}(t)$. Therefore, according to the first derivative in equation (19), we could determine the optimal value of $\gamma^*_{buy,i}(t)$ as follow:

$$\begin{aligned}&(p_{grid}(t) - p(t)\times(1+\omega_{tr}))\hat{E}_i(t) - p_{dr}\hat{E}_i(t) \qquad (21)\\ &\quad + 2p_{d,i}(t)\big((1-\gamma_{buy,i}(t))\frac{\hat{E}_i(t)}{R_i}\big)\frac{\hat{E}_i(t)}{R_i} = 0\\ &\therefore \gamma^*_{buy,i}(t) = 1 + \frac{p_{grid}(t) - p(t)\times(1+\omega_{tr}) - p_{dr}}{2p_{d,i}(t)\hat{E}_i(t)}R_i^2\end{aligned}$$

As can be seen in equation (21), we could determine the optimal value of $\gamma^*_{buy,i}(t)$. Given that we restrict the buyers' reverse power flow in the system, we have to check that $\gamma^*_{buy,i}(t)$ is located between 0 and 1.

Value comparison: Considering the prevention of reverse power flow of a buyer in the system, we could set the constraint of the bidding quantity of buyer i

$$0 \leq \gamma^*_{buy,i}(t) \leq 1. \tag{22}$$

Given that $\gamma^*_{buy,i}(t)$ is a dependent variable of $p(t)$, equation (22) could be expressed using the variable $p(t)$ as

$$0 \leq 1 + \frac{p_{grid}(t) - p(1+\omega_{tr}) - p_{dr}}{2p_{d,i}(t)\hat{E}_i(t)}R_i^2 \leq 1. \tag{23}$$

In equation (23), the sides of the equation are developed using variable $p(t)$ and it is possible to induce the following:

$$\frac{1}{1+\omega_{tr}}(p_{grid}(t) - p_{dr}) \leq p(t) \tag{24}$$

$$p(t) \leq \frac{1}{1+\omega_{tr}}(\frac{2p_{d,i}(t)\hat{E}_i(t)}{R_i^2} + p_{grid}(t) - p_{dr}) \tag{25}$$

As shown in equation (24) and (25), $p(t)$ should satisfy certain constraints. Specifically, equation (24) can be an lower-bound value of $p(t)$ to encourage buyers to participate in the market.

D. NON-COOPERATIVE GAME OF LEADER- CASE OF BROKER

By replacing $\gamma^*_{buy,i}$ and $\gamma^*_{sell,j}(t)$ into equation (5) and (6), we can reconstruct an equation of the broker's utility as follows:

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Problem 1:

$$\max_{p(t)} \quad \omega_{tr}p(t)\,(\sum_{j=1}^{M}\gamma^*_{sell,j}(t)E_j(t)+\sum_{i=1}^{N}\gamma^*_{buy,i}(t)\hat{E}_i(t)) \tag{26}$$

$$s.t. \quad \sum_{j=1}^{M}\gamma^*_{sell,j}(t)E_j(t)-\sum_{i=1}^{N}\gamma^*_{buy,i}(t)\hat{E}_i(t)\geq 0 \tag{27}$$

$$p_{min}(t)\leq p\leq p_{grid}(t) \tag{28}$$

$$\frac{1}{(1-\omega_{tr})(1+E_j(t))}\leq p(t) \tag{29}$$

$$\frac{1}{1+\omega_{tr}}(p_{grid}(t)-p_{dr})\leq p(t) \tag{30}$$

$$p(t)\leq \frac{1}{1+\omega_{tr}}(\frac{2p_{d,i}(t)\hat{E}_i(t)}{R_i^2}+p_{grid}(t)-p_{dr}) \tag{31}$$

Equation (27) refers to power reliability in isolated microgrid system which mentioned in III-D. Also, equation (28) is a boundary condition of the normalized transaction price $p(t)$ mentioned in Section III. In addition, equation (29)-(31) are constraints of $p(t)$ acquired from previous sub-sections.

In equation (26), given that ω_i^* and γ_i^* are dependent variables of the transaction price $p(t)$, we could reformulate the equation using the formula for $p(t)$. Therefore, the utility function of the broker could be reformulated as

$$\begin{aligned} U_{bro} &= \omega_{tr}p(t)(\sum_{j=1}^{M}E_j(t)+M-\frac{M}{(1-\omega_{tr})p(t)}) \\ &+\omega_{tr}p(t)(\sum_{i=1}^{N}\hat{E}_i(t)+\sum_{i=1}^{N}\frac{p_{grid}(t)-p_{dr}}{2p_{d,i}(t)}R_i^2 \\ &-\sum_{i=1}^{N}\frac{(1+\omega_{tr})p(t)}{2p_{d,i}(t)}R_i^2) \end{aligned} \tag{32}$$

In the equation (32), given that there are too many fixed constraint values, we set $k(t)=\sum_{i=1}^{N}\frac{R_i^2}{2p_{d,i}(t)}$ for ease of understanding. The problem in equation (26)-(28) is a convex optimization because it satisfies the standard form of the convex optimization problem as follows:

1) The object function in equation (26) is convex
2) Inequality constraints of broker are linear or convex form

Given that the equation in **Problem 1** is formed using the variable $p(t)$, we could derive the optimal transaction price $p^*(t)$ according to the first derivative equation (33).

$$\begin{aligned} \frac{\partial U_{bro}}{\partial p(t)} &= \omega_{tr}\sum_{j=1}^{M}E_j(t)+\omega_{tr}M+\omega_{tr}k(t)(p_{grid}(t)-p_{dr}) \\ &+\omega_{tr}\sum_{i=1}^{N}\hat{E}_i(t)-2\omega_{tr}(1+\omega_{tr})kp(t) \end{aligned} \tag{33}$$

$$\frac{\partial^2 U_{bro}}{\partial p(t)^2}=-2\omega_{tr}(1+\omega_{tr})k \tag{34}$$

The second derivative equation (34) is less than 0 for variable $p(t)$ which shows that the objective function of the broker satisfies the constraint of concavity. Therefore, we could determine the optimal transaction price p^* based on the first derivative equation (33).

$$\begin{aligned} \frac{\partial U_{bro}}{\partial p(t)} &= \omega_{tr}\sum_{j=1}^{M}E_j(t)+\omega_{tr}M+\omega_{tr}k(t)(p_{grid}(t)-p_{dr}) \\ &+\omega_{tr}\sum_{i=1}^{N}\hat{E}_i(t)-2\omega_{tr}(1+\omega_{tr})kp(t)=0 \\ \therefore p^*(t) &= \frac{\sum_{j=1}^{M}E_j(t)+M+\sum_{i=1}^{N}\hat{E}_i(t)}{2(1+\omega_{tr})k(t)}+\frac{(p_{grid}(t)-p_{dr})R_i^2}{2(1+\omega_{tr})} \end{aligned} \tag{35}$$

Based on the equation (35), we could determine the optimal transaction price that maximizes the broker's profit in a given environment. By substituting the result value for the constraints in equation (27) - (31) by variable $p^*(t)$, we could determine the Stackelberg equilibrium whereby the strategy of leader and followers converges with the consideration of power reliability. Therefore, we could convert variable $\gamma^*_{sell,j}(t)$ and $\gamma^*_{buy,i}(t)$ in equation (27) in terms of $p^*(t)$ which derived in equation (14) and (21). Therefore, we could reformulate the equation (27) as

$$\begin{aligned} &\sum_{j=1}^{M}\gamma^*_{sell,j}(t)E_j(t)-\sum_{i=1}^{N}\gamma^*_{buy,i}(t)\hat{E}_i(t) \\ &=\sum_{j=1}^{M}E_j(t)-\sum_{i=1}^{N}\frac{p_{grid}(t)-p_{dr}-(1+\omega_{tr})p(t)}{2p_{d,i}(t)}R_i^2 \\ &-\frac{M}{(1-\omega_{tr})p(t)}+M-\sum_{i=1}^{N}\hat{E}_i(t) \\ &=L(t)-\frac{M}{(1-\omega_{tr})p(t)}+k(t)(1+\omega_{tr})p(t) \\ &=\frac{1}{p(t)}(k(t)(1+\omega_{tr})p^2(t)+L(t)p(t)-\frac{M}{(1-\omega_{tr})})\geq 0 \end{aligned} \tag{36}$$

$$\therefore \quad p^*(t)\geq\frac{\sqrt{L^2+\frac{4M}{(1-\omega_{tr})}(1+\omega_{tr})k(t)}-L(t)}{2k(t)(1+\omega_{tr})} \tag{37}$$

In equation (37), $L(t)$ is the sum of the constant variable $\sum_{j=1}^{M}E_j(t)+M-l(p_{grid}(t)-p_{dr})-\sum_{i=1}^{N}\hat{E}_i(t)$ to simplify the formula. According to the equation, it is possible to set a minimum transaction price to satisfy the power supply and demand in the system. With the consideration of the boundary constraints in equation (27)-(30), we can obtain the optimal transaction price as depicted in algorithm 1.

Corollary 1: A unique Stackelberg equilibrium exists in the proposed heterogeneous multi-followers energy trading game.

According to algorithm (1), we could ascertain that a unique Stackelberg equilibrium exists in the proposed heterogeneous multi-followers energy trading game.

V. NUMERICAL RESULTS

In this section, we provide numerical simulation results to illustrate that the suggested market mechanism is appropriate in an off-grid system. We are interested in system reliability and the net profit of participants according to the market operation in an off-grid system.

Algorithm 1 Decision of SE

$Initialization$:

(a) Initialize transaction price p^* from the equation (35).

(b) Initialize the lower bound constraints in equation (29),(30), and (37).

(c) Initialize the upper bound constraint in equation (31).

$l_1(t) \leftarrow \frac{1}{(1-\omega_{tr})(1+E_j(t))}$

$l_2(t) \leftarrow \frac{1}{1+\omega_{tr}}(p_{grid}(t) - p_{dr})$

$l_3(t) \leftarrow \frac{\sqrt{L^2+\frac{4M}{(1-\omega_{tr})}(1+\omega_{tr})l-L}}{2l(1+\omega_{tr})}$

$r_1(t) \leftarrow \frac{1}{1+\omega_{tr}}(\frac{2p_{d,i}(t)\hat{E}_i(t)}{R_i^2} + p_{grid}(t) - p_{dr})$

$l(t) \leftarrow \max(l_1(t), l_2(t), l_3(t), p_{min}(t))$

$r(t) \leftarrow \min(r_1(t), p_{grid}(t))$

if $l(t) < p^*(t) < r(t)$ **then**

  $\bar{p(t)}^* = p(t)^*$

else if $r(t) < p^*(t)$ **then**

  $\bar{p}^*(t) = r(t)$

else

  $\bar{p}^*(t) = l(t)$

end if

$\gamma^*_{buy,i}(t) = 1 + \frac{p_{grid}(t) - \bar{p}^*(t)(1+\omega_{tr}) - p_{dr}}{2p_{d,i}(t)\hat{E}_i(t)} R_i^2$

$\gamma^*_{sell,j}(t) = 1 + \frac{1}{E_j(t)} - \frac{1}{(1-\omega_{tr})\bar{p}^*(t)E_j(t)}$

return $\bar{p}^*(t), \gamma^*_{buy,i}, \gamma^*_{sell,j}(t)$

In all the simulation results, the maximum transaction price $p_{grid}(t)$ is set as $\$0.37/kWh$ considering the EV charging rate announcement from the *Pacific Gas and Electric (PG&E)*. In addition, we set a minimum trading price $p_{min}(t)$ as half of C_{grid} in the simulation considering the reselling price that seller directly sell their surplus energy into maingrid [32]. The DR incentive for the diminishing load consumption of buyers is set as $\$0.1/kWh$ in the system. In addition, to determine the EV user's dissatisfaction cost, we set the number of EVs in the facility to between 8 - 10 users and the weight factor α_1 to determine the dissatisfaction cost is set to 0.025. To consider the characteristics of the EV charging facilities, we set $A = 5.0km$, $\eta = 5km/kWh$, $d = 100km$ and the number of charging facilities in the region is 10. For the case of renewable generation, we assume that the average renewable energy generation in the region is $80kWh$ and the number of facilities is 10.

A. CORRELATION BETWEEN VARIABLES

As depicted in Section III, the decision of transaction price and energy quantity that covered in this paper is closely related to the average residual energy in EVs or energy price in the market.

In Fig. 2, we could examine the relationship between the EVs' average remaining energy in the facility and the transaction price $p(t)$ in the market. In the general, The SoC value is used to determine the average discomfort cost $p_{d,i}(t)$ in equation (3), and at the same time, influences the determination of the auxiliary variable k. Based on the relationship among the variables, we could examine whether $SOC_{i,r}(t)$ affects the boundary condition in equation (31), (37) and determine the optimal transaction price p^* in equation (35). According to

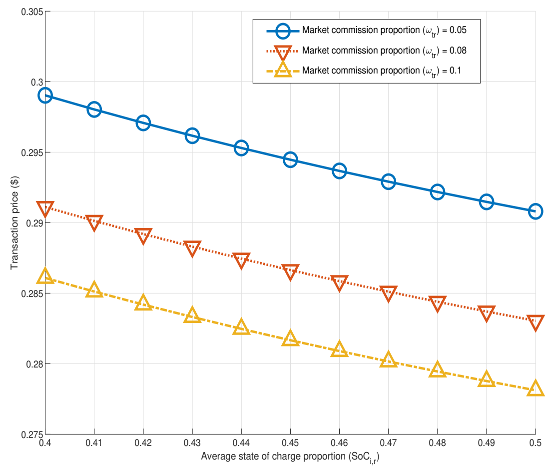

FIGURE 2: Relationship between the transaction price and the DR incentive in the market

equation (37), it can be determined that increasing the value of $SOC_{i,r}(t)$ leads to a reduction in the transaction price at the whole of different commission proportion. In addition, we can see that the commission fee ω_{tr} affects the transaction price such that the larger the ω_{tr}, the lower the transaction price $p^*(t)$ in the figure. According to the results, we could confirm that the increase of the commission fee leads to a faster decrease in the transaction price as depicted in equation (35).

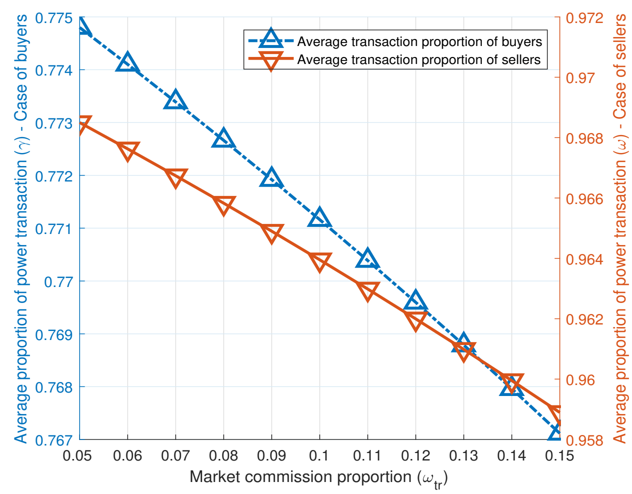

FIGURE 3: Proportion of energy transaction to changes in the DR incentive

As mentioned in Fig. 2, an increment of $SOC_{i,r}(t)$ leads to a decrease in the transaction price. To examine the strategy change of other participants according to the SOC variation, Fig. 3 shows the result of trading proportion change when $\omega_{tr} = 0.05$. As shown in equation (14), sellers are sensitive to the transaction price so that the sale volume sharply decreases according to the decrease of this price. For the case

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of buyers, the transaction price is also inversely related to the amount of the transaction price as depicted in equation (21), so that a increment of commission fee leads to a reduction in buyers' power purchases.

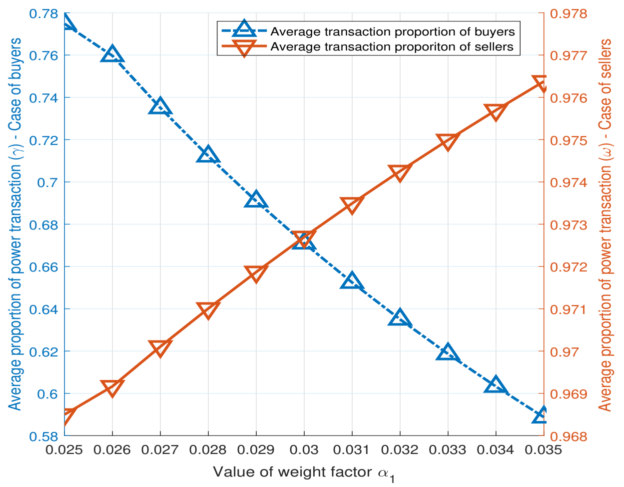

FIGURE 4: Transaction variation due to buyer's average dissatisfaction cost

As mentioned in equation (3), α_1 is an auxiliary variable that directly affect to decide the dissatisfaction cost that occur if the buyer does not receive enough power. Since this dissatisfaction cost is an important factor that directly determining the transaction price in the market, it can be concluded that it also affects the power transaction amount of the sellers and buyers as shown in **Algorithm 1**. As a result, an increment in the weight factor α_1 would lead to an increase in transaction price as depicted in equation (35). In this case, since sellers and buyers react sensitively to the transaction price, the opposite results are shown in Fig. 4.

B. REVENUE ANALYSIS OF INDIVIDUAL MARKET PARTICIPANT

For market participants, regardless of power system they are interested in the profits that they will receive over the existing market. Since the actual amount of energy transaction is determined by the status of each participant, it is possible to make a preliminary prediction of individual profits and market operation result using current users' status.

In Fig. 5, we analyze the profit of individual market participants according to a given market environment. In the simulation, we set the broker 's commission proportion associated with the transaction price as $\omega_{tr} = 0.05$. In addition, coverage of each charging facility A_i is set between $4.0km$ - $6.0km$ and renewable energy generation is between $80kWh$ - $120kWh$. In this environment, the transaction price in the market is \$0.2943 with the consideration of various factors in the environment. In addition, we set the total amount of generated energy as $688kWh$ and the energy requirement from the entire charging facility as $802kWh$, where the required energy in the region is higher than the total supply. In this case, the voluntary reduction in energy consumption of incentive-based buyers is necessary to stabilize the energy supply in the system. Consequently, a reduced transaction

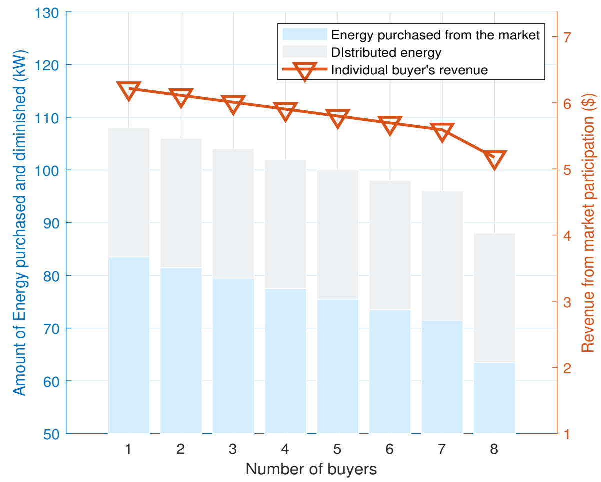

FIGURE 5: Transaction results and revenue of the buyers according to participation in the market

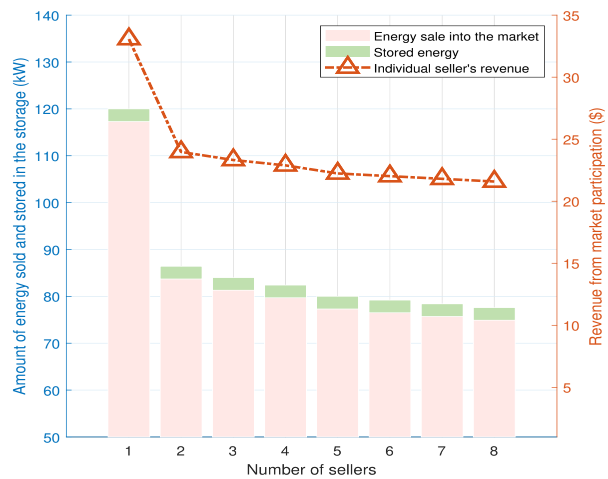

FIGURE 6: Sales revenue and volume of sellers that participate in the market

price and DR incentive change the buyer's total power consumption to $605.9312kWh$. Based on the simulation result, it is evident that the individual buyer's purchase power volume and profit are derived as expected from equation (21). It is also evident that the larger the initial desired purchase amount $\hat{E}_i$, the greater the power purchase proportion and profit from the market.

In Fig. 6, we can also examine the sales revenue and volume of sellers in the market. Given that the sale volume of the seller is determined according to their generation amount and transaction price as depicted in equation (14). The sales ratio also decreases in proportion to a decrease in the sales volume. In addition, as previously indicated, in the case of sellers, the sale volume decreases according to the increment of the transaction price. In addition, the total sales energy in the market is $666.4554kWh$, which is larger than the total

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demand in the system that satisfies the stable energy supply.

C. ANALYZING THE RESULTS OF DAILY MARKET OPERATIONS

In the case of EV fare, time of use pricing, which charges differently depending on the time periods, is applied in the PG & E. If energy purchase price from the maingrid is charged differently according to the time period, different results can be obtained depending on the amount of energy held by sellers and the amount of renewable energy generation. In this Section, we will analyze the transaction price and the power reliability results according to market price which compared with different algorithm according to the change of environment in each time period.

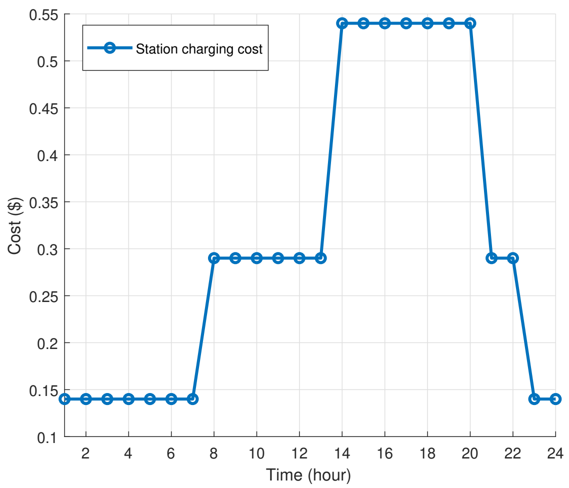

FIGURE 7: Time of use pricing for EV published by PG&E

In Fig. 7, we could check the energy purchase from maingrid that announced by PG&E. The price is determined by the consideration of total energy consumption in the system. In addition, PG&E decided different rates for charging at home or at station according to the user decision. Here, we only cover *station charging cost* which depicted in Fig. 7.

In our system model, seller sales in the market are based on the remaining energy in storage and the renewable energy generation. In Fig. 8, we could check the average value of power generation from PV generator over a month period from 8 buildings collected from KAIST in South Korea. In the simulation, we consider PV generators which have the maximum power generation as $80kWh$ - $100kWh$ per hour. In Fig. 8, we could check that the most PV generators started to generate after at 9 o'clock, and decreased their generation drastically after at 14 o'clock. Since the renewable energy is not further generated, the sellers' strategy will be limited, so we only deal with the results between 9 and 14 o'clock when the renewable energy generation exists.

In Fig. 9, we illustrate the trading results in comparison with the *Cournot model* that depicted in [33]. In the simulation, a *Proposed model* means the simulation results derived from the proposed market environment which considered power reliability in the system. The *Cournot model* is the case that determines the transaction price depending on the total deficit and surplus energy as described in [33]. The

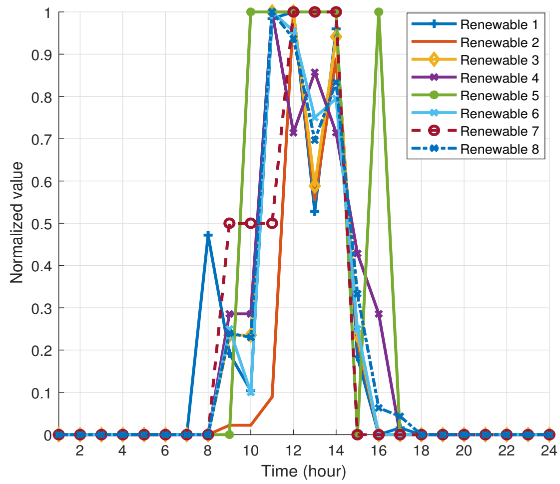

FIGURE 8: Sales revenue and volume of sellers that participate in the market

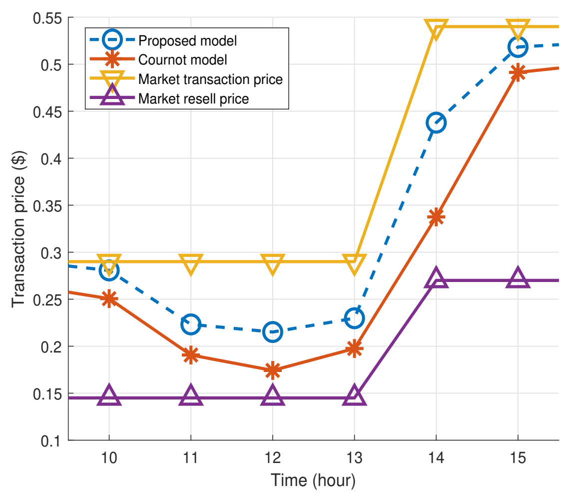

FIGURE 9: Sales revenue and volume of sellers that participate in the market

Market transaction price is the price charged by PG&E for supplying energy into EVs from maingrid. The *Market resell price* is the price that seller resells the surplus energy into the maingrid [32]. In whole of the time period, we could check that the *Proposed model* and the *Cournot model* are located between the market prices. In particular, we can check that the transaction price in the *Cournot model* has a lower price than that of the *Proposed model*. In this case, if we apply *Cournot model* to determine transaction price, the sellers' sale energy in the proposed market would decreases while the buyers' desired energy purchase increases and results in an energy imbalance problem.

As mentioned in Section I, the advantage of the Stackelberg game model is that it limits the follower's options through the leader's strategy. Thus, it is possible to derive results that are more appropriate for the actual power system

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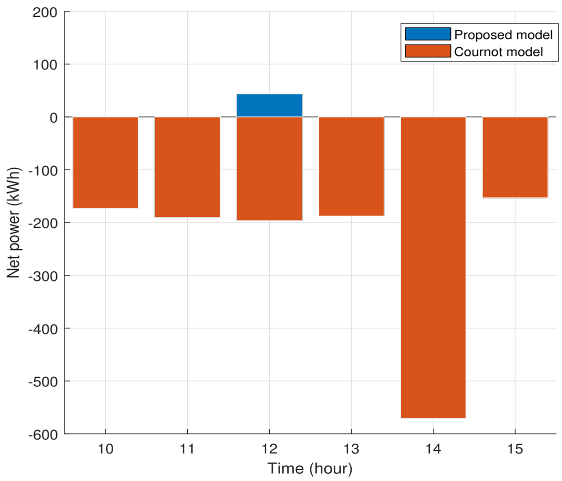

FIGURE 10: Sales revenue and volume of sellers that participate in the market

environment than conventional methods, where market prices are voluntarily determined. As can be seen in Fig. 10, we show the simulation results of power supply and demand in the system when applying the *Proposed model* and *Cournot model*. In the case of *Cournot model*, it represents that it requires more power than the power supplied to the actual system. On the other hand, when the *Proposed model* is applied, power supply and demand are the same in most time period. The reason is that the power reliability suggested in equation (6) is excluded in the case of *Cournot model*. According to the result, we could check that the proposed model is more proper in the practical environment.

In order to implement the proposed model in practical environment, we have to manage various heterogeneous data. That is, research on data security and management should be preceded. In academia, various researches have been proposed in terms of data processing using blockchain or federated learning in [34]–[36]. The research on the EV trading platform considering the data security will be conducted in the future.

VI. CONCLUSION

In this report, we address a method to supply energy to multiple charging facilities in an off-grid environment. Using the heuristic Stackelberg game model, actual buyers can choose strategies associated with self-degrading energy consumption based on DR incentive and purchasing energy. In addition, sellers are also allowed to choose their own strategies according to revenue from the sale of energy or the increase of their satisfaction based on charging operation. With the consideration of the net profit of the broker in the system, this approach allows each participant in the market to maximize their own profits while stabilizing the energy supply and demand in an independent energy environment.

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