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Optimal energy procurement with long-term photovoltaic energy contracts considering generation uncertainty: A two-dimensional auction approach

Jihyeok Jung [a], Chan-Oi Song [b], Deok-Joo Lee [a,*], Kiho Yoon [b]

[a] Department of Industrial Engineering, Seoul National University, 1, Gwanak-ro, Gwanak-gu, Seoul, 08820, Republic of Korea
[b] Department of Economics, Korea University, 145, Anam-ro, Seongbuk-gu, Seoul, 02841, Republic of Korea

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ABSTRACT

The procurement auction scheme for long-term photovoltaic (PV) energy contracts is being implemented in various countries to ensure stable profits for potential PV generators. However, in most of these auction formats, there is a deficiency in that they consider only the contract price and capacity, neglecting to account for the uncertainty of generation efficiency. In this regard, this study proposes a procurement auction scheme for long-term photovoltaic (PV) energy contracts based on mechanism design theory. We developed a two-dimensional auction model in which PV generators bid their cost and capacity. The energy buyer then determines the winners and enters into contracts with them for a fixed period. We incorporated the capacity factor into the payoff functions of both the buyer and the sellers to reflect different generation efficiencies of generators. Following the revelation principle, we characterized the incentive-compatible, individually rational direct mechanism that maximizes the buyer's expected payoff during the contract period. We also proposed a computation algorithm to implement the auction. Numerical analysis using data from the Korean PV auction market suggested that the proposed model demonstrates results similar to the uniform price auction in terms of the levelized cost of electricity and contract price, and these results are lower than those of the Vickrey auction. Furthermore, despite the fact that the proposed auction results in a slight increase in social costs (approximately 1% more than the Vickrey auction), it maximizes the expected procured electricity and the auctioneer's payoff.

1. Introduction

In the midst of the ongoing trend towards an increase of renewable energy (RE)-based electricity generation, photovoltaic (PV) energy has achieved the fastest growth due to its advantages of convenient installation and low maintenance cost. In 2021, the global PV power capacity increased by 140 GW, accounting for 60% of the newly installed RE capacity [1]. The amount of generated electricity also increased from 1.0 EJ (10^{18} J) in 2011 to 5.4 EJ in 2021 [2]. Along with this trend of the energy transition, the RE generation of Korea also shows a fast increase from 3 million toe[1] in 2012 to 12 million toe in 2020, where PV energy took the largest share at 34% [3]. However, despite the advantages of PV energy, its generation is constrained by solar irradiation, resulting in high volatility depending on regional characteristics, climate uncertainty, and seasonal influences. These physical limitations of PV energy generation expose PV generators to uncertain investment, which becomes a barrier that hinders potential PV generators from entering the electricity market [4].

To deal with this problem, many countries are now implementing various support policies such as Feed-in-Tariff (FiT) and Renewable Portfolio Standard (RPS), both of which aim to preserve the profitability of PV generators by purchasing their electricity at a price premium (FiT) or issuing a certificate that allows them to obtain additional income (RPS) [5]. These subsidies result in producers receiving payments beyond the price in the wholesale electricity market. However, a challenge arises in determining the appropriate level of this premium. To address this issue, procurement auction mechanisms between PV generators and the energy buyer have been recently paid much attention, which allows the premium to be determined with the spontaneous offers by generators [6].

In this auction, the generators bid their desired contract capacity and electricity price, and the winners to be decided by some specific auction rules have the right to sell their entire amount of solar power at a fixed contract price for a long period of time (10–20 years). This auction system is being conducted for renewable energy (RE)

* Corresponding author.
E-mail addresses: firedaeman@snu.ac.kr (J. Jung), gnos@korea.ac.kr (C.-O. Song), leedj@snu.ac.kr (D.-J. Lee), kiho@korea.ac.kr (K. Yoon).

[1] Toe is an acronym of 'ton of equivalent', which is a unit of energy and is defined as the amount of energy released by burning 1 ton of crude oil.

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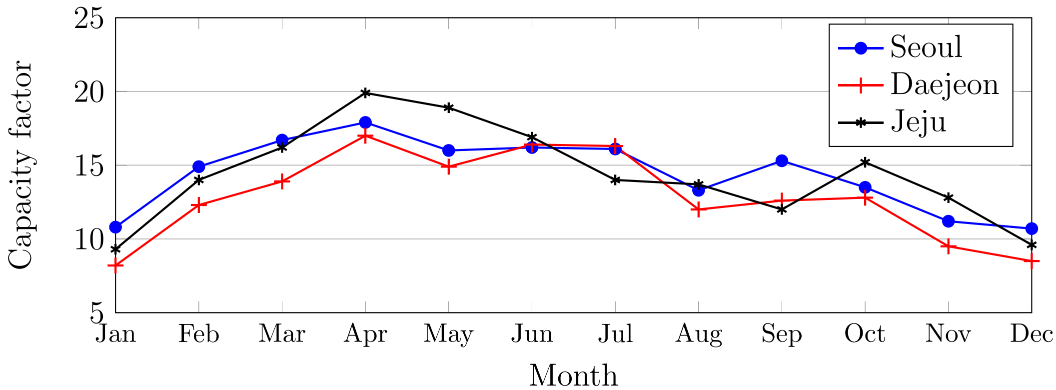

Fig. 1. Capacity factors of some regions of Korea in 2021.

resources in various countries, and the most prevalent auction rule is to determine the winners based on their bid price [7]. In the case of Korea, the long-term contract auction scheme for RE is currently being implemented only for PV energy generators. PV generators with a capacity ranging from 3 kW to over 20 MW are eligible to participate in the auction under the current scheme. The winner determination rule for the Korean PV auction is also based on the bid price submitted by bidders, and the bid price becomes the contract price of the winning bidders [8].

This price-based auction rule aims to secure PV energy supply at the possibly lowest cost and it is most prevalent because of its simplicity of implementation. Accordingly, there exist various studies on the bidding strategies of generators under this price-based rule [9,10]. However, considering that the purpose of implementing these PV auctions is to secure and expand PV generation rather than simply procuring electricity at a lower cost, this cost-minimizing approach to selecting winning bidders based solely on bid price may not be appropriate. Instead, it is necessary to employ a more complex approach that considers PV generation efficiency as well as bid price to ensure that solar power can be procured efficiently. Therefore, this study suggests incorporating generation efficiency as a key element in the auction, which has not been considered in previous research.

There are several indicators that measure the power generation efficiency of energy resources. Among them, the *capacity factor* represents the ratio of the actual generation of energy resources to the maximum possible amount that could be generated in a given time period [11]. The capacity factor of PV energy is affected by regions, weather, and the quality of panels, and it generally ranges from 10% to 25%. Fig. 1 illustrates the different values of capacity factors in several regions in Korea. Seoul is in the northern region, Daejeon is in the central region, and Jeju is in the southern area of Korea [12]. The average capacity factors are shown to be different by region. Given that the current price-based auction system cannot differentiate between bidders who bid the same capacity and price but have different efficiencies, it is necessary to design an enhanced auction scheme that also could consider generation efficiency by estimating the capacity factor of each bidder with a proper method. Towards this end, the mechanism design theory can be applied to design a proper PV long-term procurement auction that maximizes the auctioneer's benefits from the PV procurement and satisfies several desirable properties, such as making the bidders report their true values and participate in the auction voluntarily.

In this study, we propose an optimal procurement auction scheme for PV long-term contracts using the two-dimensional auction model in which the energy buyer makes contracts for a specified capacity and the bidders bid their costs and contract capacities. The auction model in this study addresses the energy buyer's goal of maximizing payoff while considering the constraints of incentive compatibility and individual rationality for PV generators. Additionally, we consider the uncertainty of PV generation by estimating the capacity factors of PV generators and reflecting the estimated values in the payoff functions of the buyer and sellers.

The contributions of this study to the current literature are as follows:

- First, we figure out the optimal allocation rule and pricing rule of the two-dimensional procurement auction in which bidders bid their contract price and capacity. We demonstrate that the proposed model satisfies the required properties in mechanism design even when capacity overbidding is allowed.
- Second, we propose a new auction rule that enables the buyer to identify favorable bidders by considering the bidders' expected generation efficiency. To this end, we suggest a proper evaluation method that integrates the efficiency levels and bid information of the bidders.
- Lastly, considering the implementation issue, we proposed a discriminatory auction scheme suitable for PV long-term contracts, the most popular support scheme for renewable energy generators, by suggesting an efficient computation algorithm.

The rest of this paper is organized as follows. In Section 2, we review the previous research related to the theory of payoff maximizing auctions and its application to the energy sector. In Section 3, the economic environment of the auction is presented. In Section 4, the optimal allocation rule and pricing rules are derived from several characterizations of the proposed mechanism. In Section 5, the estimation of capacity factors and numerical analysis are presented. In Section 6, we conclude the paper. All proofs of the propositions are presented in Appendix.

2. Literature review

The procurement mechanism for the PV long-term contracts involves several characteristics. First, the optimality of the auction for the buyer should be guaranteed. Second, the bidders have multidimensional attributes. Third, they have limited capacity to produce electricity. In this respect, we first review the related works in mechanism design theory, which stem from the characterization of the optimal auction as suggested by Myerson [13]. Subsequently, we briefly review the recent research that investigates the auction scheme for supporting renewable energy generation.

After Myerson [13] initially proposed the optimal auction to maximize the seller's expected revenue, characterizing the optimal auction rule for one-dimensional bidder types, this approach has become fundamental in the design of optimal auction rules. Concerning the analysis of a multi-dimensional environment, Che [14] presented the model where bidders report both quality and cost and showed that the first and second-scoring auctions implement the optimal mechanism. Maskin et al. [15] came up with the monopolist's nonlinear pricing problem in this two-dimensional setting. Furthermore, Asker and

Cantillon [16] characterized the optimal auction with two-dimensional type space, where each bidder has private information about their fixed cost and marginal cost.

Another aspect inspired by Myerson's work is the optimal auction for a multi-unit environment. Maskin and Riley [17] generalized the optimal auction for multi-unit homogeneous items based on symmetric, independent, and risk-neutral bidder assumptions. The work of Iyengar and Kumar [18] is the most similar work to our research, as they presented a model where the buyer intends to procure divisible goods from producers with limited capacity. The model depicts each bidder's type as the production capacity and cost. But, their approach has a limitation in assuming that bidders cannot overbid their capacity. Gautam et al. [19] extended Iyengar and Kumar [18] by considering volume discounts, and they revealed several properties in this setting. Meanwhile, the work of Malakhov and Vohra [20,21] handled the multi-dimensional type space of bidders as discrete values and reformulated the problem as linear programming of the shortest path problem.

The theoretical work on optimal auction design for multi-unit items with multi-dimensional type spaces has found applications in several industrial fields. Prasad and Rao [22] designed an optimal two-dimensional auction for resource allocation in cloud computing, where cloud vendors bid on both their cost and quality of service. Chatzopoulos et al. [23] applied the auction framework to smart contracts on a blockchain, designing a cost-minimizing auction scheme for an Internet service provider who selects contractors based on their cost and task-of-interest as part of the type space. Also, Bhat et al. [24] designed an optimal two-dimensional procurement auction where the buyer's reward is stochastic and suggested the algorithm to compute the mechanism outcome of Iyengar and Kumar [18]. While there have been several studies exploring the application of two-dimensional auction design, relatively few attempts have been made to design an optimal auction for renewable energy support schemes.

However, our research can be justified by examining studies that apply mechanism design to other renewable energy and power markets. Kreiss et al. [10] applied a simple first-price and second-price auction format to a general renewable energy auction with a risk of non-realization by winning bidders, revealing that physical and financial pre-qualifications can achieve a high realization rate. Additionally, Matthäus et al. [25] modeled PV generation uncertainty as a real option and analyzed the non-realization behaviors of winning bidders. Khazaei and Zhao [9] addressed the problem of aggregating uncertain renewable energy by designing an efficient indirect mechanism for an aggregator receiving information from renewable energy producers. Kröger et al. [26] designed a discriminatory auction for onshore wind, considering the spatial characteristics of the generators, and their simulation demonstrated a reduction in consumer costs of approximately 13%. While not directly related to renewable energy support schemes, Zou et al. [27] developed an optimal mechanism for operating a distributed energy system using Myerson's model, which shares similarities with the model we propose.

In addition to efforts in designing renewable energy auctions at a theoretical level, there have been studies evaluating ongoing renewable energy auctions through data analysis. For example, Batz Liñeiro and Müsgens [28] decomposed German onshore wind auction data into individual levels and examined which design elements of the auction influenced the success or failure of the auctions. Diniz et al. [29] investigated the effect of auction design elements using project-level auction data from Brazil, finding that a preliminary transmission capacity phase in an auction improves outcomes. Fleck and Anatolitis [30] scrutinized 269 auction rounds from 20 European countries and discovered that not all conducted auctions align with the results of theoretical work.

3. Model

3.1. Auction environment

We consider the PV generation market, in which potential PV generators seek to enter into a long-term contract with an energy buyer to supply energy for T periods. The market comprises n PV generators (sellers) indexed by $i \in I := \{1, 2, \dots, n\}$ and one buyer. Each generator i has private information regarding its desired PV capacity $K_i \in [0, \bar{K}]$ for the contract and the cost $c_i \in [\underline{c}, \bar{c}]$ to purchase and maintain one unit of PV panel. Here, c_i can be interpreted as the total cost of ownership.[2] Therefore, the total cost for operating K_i units of panels equals $c_i K_i$. We denote the type of generator i as $b_i := (c_i, K_i)$, $b = (b_i)_{i\in I}$ as the type profile, and $\mathbb{B} = ([\underline{c}, \bar{c}] \times [0, \bar{K}])^n$ as the type space. Prior to actual generation, the total expected electricity generated by generator i during T periods can be computed as

$$\sum_{t=1}^{T} \left[(1-d)^t \times H \times \eta_i^t\right] \times K_i, \tag{1}$$

where H represents the total hours of a unit period, d is the average degradation rate of PV panels, and η_i^t is the expected capacity factor of PV panels for generator i during period t, estimated before the auction begins. The expected capacity factor η_i^t represents the efficiency of PV panels owned by generator i during period t, and it varies among PV generators and over time due to geographic and climatic conditions. To compute the expectations before the auction, the information and methods used for predicting each generator's capacity factor are made available to all market participants. Therefore, the sequence $\left[\eta_i^t\right]_{t=1}^{T}$ for all generators is considered public information.

Along with the Bayesian game structure, generator i cannot know the types of other generators, $b_{-i} = (c_j, K_j)_{j\in I\setminus\{i\}}$. Each generator treats the type of the other generator b_j as a random variable with $F_j(c_j, K_j)$ as the joint cumulative distribution function and $f_j(c_j, K_j)$ as the joint density function. Besides, we assume that the type of each bidder is independent of the others. The buyer aims to enter into contracts with the PV generators for a maximum capacity of $\tilde{K}$ units through the auction. The contract lasts for T periods, during which the buyer should purchase all the electricity generated by the contracted PV generators. One unit of electricity generated by PV will benefit the buyer by reducing the cost of thermal power generation, denoted as c_0.

Furthermore, we assume that the buyer can infer the actual operating capacity of the contracted generator without incurring additional observation costs, and the buyer can observe the true capacity of a small number of winning bidders at a negligible cost. These assumptions will assist us in constructing a commitment rule to prevent bidders from engaging in overbidding behaviors.

3.2. Procurement mechanism

In this section, we define the procurement auction and the payoff function of the PV generators, with several properties that the mechanism should satisfy. Using the revelation principle [13], we restrict our consideration to a direct mechanism. Let $\Gamma = (a, p)$ be a procurement mechanism, where $a(b) = \left(a_i(b)\right)_{i\in I} : \mathbb{B} \to \mathbb{R}_+^n$ is an allocation rule, and $p(b) = \left(p_i(b)\right)_{i\in I} : \mathbb{B} \to \mathbb{R}_+^n$ is a pricing rule. Note that $a_i(b)$ and $p_i(b)$ describe bidder i's capacity to be contracted and the unit price of electricity generated. If the energy buyer and bidder i enter into a contract after the auction with (a_i, p_i), the entire electricity generated from the PV panel with a capacity of a_i will be sold at the unit price p_i. After the procurement mechanism $\Gamma = (a, p)$ is implemented, the winner of the auction is expected to generate $\left[(1-d)^t \times H \times \eta_i^t\right] a_i(b)$ units at period t and receive $p_i(b)$ for each unit. Then, bidder i's ex-post

[2] Total cost of ownership is an estimation of the overall cost associated with purchasing, maintaining, and retiring a product over its entire lifecycle.

payoff is defined as the expected present value of the contract. When bidder i reports $(\hat{c}_i, \hat{K}_i)$ but its true type is (c_i, K_i), its ex-post payoff is defined as

$$u_i(\hat{c}_i, \hat{K}_i | c_i, K_i, b_{-i}) = \left[\alpha_i p_i((\hat{c}_i, \hat{K}_i), b_{-i}) - c_i\right] a_i((\hat{c}_i, \hat{K}_i), b_{-i}). \tag{2}$$

Here, $\alpha_i = \sum_{t=1}^{T} \frac{(1-d)^t \times H \times \eta_i^t}{(1+r)^t}$ and r is a discount rate. Furthermore, if we consider a sealed-bid auction, the bidders do not know the other bidders' types at the bidding stage. Therefore, bidder i would behave to maximize the interim payoff. When bidder i reports $(\hat{c}_i, \hat{K}_i)$ but its true type is (c_i, K_i), its interim payoff can be defined as follows.

$$U_i(\hat{c}_i, \hat{K}_i | c_i, K_i) = \mathbb{E}_{b_{-i}}\left[u_i(\hat{c}_i, \hat{K}_i | c_i, K_i, b_{-i})\right]. \tag{3}$$

For convenience, denote the interim payoff of bidder i when the bidder reports its type truthfully as $U_i(c_i, K_i) := U_i(c_i, K_i | c_i, K_i)$.

Meanwhile, the sole buyer, who wishes to secure $\tilde{K}$ units of PV capacity through this procurement auction, must find a direct revelation mechanism Γ that maximizes its expected payoff, denoted as $\Pi(\Gamma)$. The procurement of electricity from bidder i provides a benefit of c_0, and the buyer must pay $p_i(b)$. If we define the buyer's payoff function as the expected present value of the PV long-term contract procurement auction with a discount rate r, the buyer's optimization problem can be formulated as follows.

$$\max_{\Gamma} \quad \Pi(\Gamma) = \mathbb{E}_b\left[\sum_{i=1}^{n} \alpha_i (c_0 - p_i(b)) a_i(b)\right] \tag{4}$$

$$\text{s.t.} \quad (c_i, K_i) \in \underset{(\hat{c}_i, \hat{K}_i) \in [\underline{c}, \bar{c}] \times [0, \tilde{K}]}{\operatorname{argmax}} \{U_i(\hat{c}_i, \hat{K}_i | c_i, K_i)\}, \quad \forall i \in I, \tag{5}$$

$$U_i(c_i, K_i) \geq 0, \quad \forall i \in I, \tag{6}$$

$$0 \leq a_i(b_i, b_{-i}) \leq K_i, \quad \forall i \in I, \tag{7}$$

$$\sum_{i=1}^{n} a_i(b) \leq \tilde{K}. \tag{8}$$

There are several properties that we require the mechanism $\Gamma = (a, p)$ to satisfy. Constraint (5) indicates that the truthful bidding strategy should be a Bayesian Nash equilibrium because we focus on the direct revelation mechanism. This constraint is known as *Bayesian incentive compatibility* (BIC). Constraint (6) means that the mechanism should ensure that every generator in the market participates in the auction voluntarily, also known as *individual rationality* (IR). Lastly, Constraint (7) implies that the allocation amount of each bidder is non-negative and cannot exceed its capacity. We define this constraint as *feasibility*. Then, denote the optimal solution to the above problem as $\Gamma^* = (a^*, p^*)$. We refer to $\Gamma^* = (a^*, p^*)$ as the optimal procurement mechanism.

4. Analysis

4.1. Characterization

In this section, we present the characterization of the buyer's problem with an analogy to Myerson [13] and Iyengar and Kumar [18]. To this end, we define the expected allocation of bidder i as $A_i(\hat{c}_i, \hat{K}_i) = \mathbb{E}_{b_{-i}}\left[a_i\left((\hat{c}_i, \hat{K}_i), b_{-i}\right)\right]$, when the bidder reports its type as $(\hat{c}_i, \hat{K}_i)$. Then, if the procurement auction satisfies the BIC condition, we can obtain the following lemma.

Lemma 1. *If $\Gamma = (a, p)$ is an incentive compatible mechanism, then*

(a) $\forall i \in I$, $A_i(c_i, K_i)$ is non-increasing in c_i for fixed K_i;
(b) $U_i(c_i, K_i) = U_i(\bar{c}, K_i) + \int_{c_i}^{\bar{c}} A_i(\tau, K_i) d\tau$.

Part (a) of Lemma 1 implies that the expected allocated capacity of every bidder decreases as its bidding cost increases. Also, part (b) of Lemma 1 corresponds to the revenue equivalence theorem, implying that the interim utility is determined solely by the expected allocation for any mechanism satisfying BIC. Using this fact, we can obtain the following theorem.

Theorem 1. *If a direct mechanism $\Gamma = (a, p)$ is incentive compatible, the expected payoff of the buyer (or auctioneer), $\Pi(\Gamma)$, has the form of*

$$\Pi(\Gamma) = \mathbb{E}_b\left[\sum_{i=1}^{n} H_i(c_i, K_i) a_i(b_i, b_{-i})\right] - \sum_{i=1}^{n} U_i(\bar{c}, K_i), \tag{9}$$

where $H_i(c_i, K_i) = \alpha_i c_0 - \left(c_i + \frac{F_i(c_i|K_i)}{f_i(c_i|K_i)}\right)$. We refer $H_i(c_i, K_i)$ as the virtual marginal profit from generator i.

Theorem 1 possesses an important property for finding the optimal allocation and pricing rule: while the original problem involves two types of decision variables, a and p, the modified problem only has one type of decision variable, a. Therefore, the only remaining aspect in solving the buyer's problem is to find the optimal allocation rule.

4.2. Optimal mechanism

In this section, we present the optimal procurement mechanism $\Gamma^* = (a^*, p^*)$ under the *regularity condition*, which we define here. To this end, we first examine the relaxed problem where $H_i(c_i, K_i)$ of all bidders are known to the buyer, and the non-increasing property of the optimal expected allocation is relaxed. It is worth noting that since $U_i(\bar{c}, K_i) \leq U_i(c_i, K_i)$ for every (c_i, K_i) by Lemma 1, it is obvious that the optimal mechanism should satisfy $U_i(\bar{c}, K_i) = 0$. Using these facts and Theorem 1, constraints (5) and (6) are integrated into the objective function, and the buyer's problem is relaxed as follows.

$$\max_{a} \quad \sum_{i=1}^{n} H_i(c_i, K_i) a_i(b_i, b_{-i}) \tag{10}$$

$$\text{s.t.} \quad (7), (8)$$

The buyer can arrange the bidders in descending order of $H_i(c_i, K_i)$ using a mapping $\xi : I \to I$ with the following property.

$$H_{\xi(i)}(c_{\xi(i)}, K_{\xi(i)}) \geq H_{\xi(j)}(c_{\xi(j)}, K_{\xi(j)}) \text{ whenever } 1 \leq i \leq j \leq n \tag{11}$$

Without loss of generality, assume that $H_i(c_i, K_i) \geq 0$ for every bidder $i \in I$, and $H_i(c_i, K_i) \neq H_j(c_j, K_j)$ whenever $i \neq j$. Let l^* be the positive integer satisfying $\sum_{i=1}^{l^*-1} K_{\xi(i)} \leq \tilde{K} \leq \sum_{i=1}^{l^*} K_{\xi(i)}$. Define $\xi^{-1}(i : (c_i, K_i), b_{-i})$ as the ranking of bidder i when its type is (c_i, K_i), and the others are b_{-i}. The optimal solution to the relaxed problem can be described as follows.

Lemma 2. *The optimal allocation rule a^* for the relaxed problem with the objective function presented in (10) is*

$$a_i^*(b) = \begin{cases} K_i & \text{if } \xi^{-1}(i : (c_i, K_i), b_{-i}) < l^* \\ \tilde{K} - \sum_{i=1}^{l^*-1} K_{\xi(i)} & \text{if } \xi^{-1}(i : (c_i, K_i), b_{-i}) = l^* \\ 0 & \text{if } \xi^{-1}(i : (c_i, K_i), b_{-i}) > l^* \end{cases} \tag{12}$$

The optimal allocation rule is to accept offers in order of bidders' virtual marginal profits until the contracted capacity exceeds the predetermined amount $\tilde{K}$. Additionally, since the allocation rule is a point-wise maximizer for each $b \in \mathbb{B}$ and the expected payoff of the buyer is a convex combination of every $f(b)$, it follows that $a^* \in \operatorname{argmax}_a \mathbb{E}_b[\sum_{i=1}^{n} H_i(c_i, K_i) a_i(b_i, b_{-i})]$.

To guarantee that the optimal allocation rule a^* in the relaxed problem is also optimal in the original problem, we need to demonstrate that $A_i^*(b_i) := \mathbb{E}_{b_{-i}}\left[a_i^*(b_i, b_{-i})\right]$ is non-increasing in c_i. To this end, we will focus on the type space that satisfies the following regularity condition.

Assumption 1 (*Regularity Condition*). $\frac{F_i(c_i|K_i)}{f_i(c_i|K_i)}$ is non-decreasing in c_i and non-increasing in K_i for all $i \in I$.

The monotonicity for c_i holds when the reverse hazard rate $\frac{f_i(c_i|K_i)}{F_i(c_i|K_i)}$ is non-increasing in c_i, and the monotonicity for K_i holds if c_i and K_i are affiliated.[3] Under the regularity condition, it can be directly observed that the virtual marginal profit $H_i(c_i, K_i)$ is non-increasing with respect to c_i and non-decreasing with respect to K_i. Therefore, the ranking of bidder i, i.e., $\xi^{-1}(i)$, preserves these monotonic properties. Hence, we can obtain the following Lemma 3, which includes the non-increasing property of the optimal allocation rule.

Lemma 3. *Under the regularity condition, for every $i \in I$,*

(a) $a_i^*((c_i, K_i), b_{-i})$ is non-increasing in c_i for fixed K_i and b_{-i};
(b) $a_i^*((c_i, K_i), b_{-i})$ is non-decreasing in K_i for fixed c_i and b_{-i};
(c) $A_i^*(c_i, K_i)$ is non-increasing in c_i for fixed K_i;
(d) $A_i^*(c_i, K_i)$ is non-decreasing in K_i for fixed c_i

Lemma 3 demonstrates that the obtained allocation rule presented in (12) can be optimal in the original problem by introducing the regularity assumption. Then, the only remaining part to derive an optimal procurement mechanism under the regularity condition is to construct an adequate pricing rule p^*. However, it has been found that with the pricing rule alone, truth-telling is not necessarily a Bayesian Nash equilibrium because bidders can make overbids on contract capacity to raise their priorities. Nevertheless, due to the feasibility condition, there is a physical limitation for PV generators to sign long-term contracts with more than their desirable capacity. Therefore, we construct an additional proviso rule, together with the pricing rule, for the bidders who make overbids on their capacity, and this proviso rule prevents them from overbidding. The next theorem describes the optimal mechanism.

Theorem 2. *Under the regularity condition, the following pricing rule p^* with the allocation rule a^* suggested in (12) constitute the incentive compatible, individually rational, feasible, and payoff-maximizing auction $\Gamma^* = (a^*, p^*)$ with the proviso ρ:*

$$p_i^*\left((c_i, K_i), b_{-i}\right) = \frac{1}{\alpha_i}\left(c_i + \int_{c_i}^{\bar{c}} \frac{A_i^*(\tau, K_i)}{A_i^*(c_i, K_i)} d\tau\right), \ \forall i \in I \tag{13}$$

ρ is an additional proviso rule containing the following commitments.

(1) The auctioneer is going to examine $\hat{K}_{l^*}$, which is the bidding capacity of the last winner.
(2) If bidder i is revealed to overbid her capacity K_i, the winner is obliged to provide the auctioneer with the capacity $\min\{K_i, \bar{a}\}$ at the price $\frac{\underline{c}}{\alpha}$, where $\bar{a}$ is the assigned capacity according to the auction result.

The proposed proviso in Theorem 2 plays a role in prohibiting bidders from overbidding their capacity. Unlike Iyengar and Kumar [18], which assumed that overbidding is not allowed, we allow bidders to strategically overbid, and they are prevented from capacity overbidding by the proviso rule. Bidders can overbid their capacity, and there are three possible cases. First, the bidder wins the auction with $a_i^* < K_i$. Second, the bidder wins the auction with $a_i^* > K_i$ Third, the bidder loses the auction despite overbidding. Since we assume that the buyer can observe the operating capacity of generators, and examination is done with zero cost, the first case is prevented by the first proviso, and the second case is prevented by the second proviso.

We emphasize that every agent participating in the auction knows that the cost and time for observation are zero. This implies that after the winner determination, the buyer will always try to examine the last winner. Therefore, the buyer will always fulfill its declared commitments and the bidders will believe that the commitment will always be kept, which means that the proviso rule exists and works effectively. This assumption is much more rational than that of Iyengar and Kumar [18], in which the overbidding strategy is assumed to be perfectly prevented by penalties alone, as it has ambiguous aspects with respect to the scale of the penalty.

Although Theorem 2 states that the optimal procurement mechanism comprises the allocation rule a^*, the pricing rule p^*, and the proviso ρ, Bayesian implementation has several weaknesses. In practice, it may be less robust to the strategic behaviors of bidders, as there is a possibility that any bidder may misreport its type if the bidder anticipates other bidders to do so as well. Additionally, it is worth noting that the mathematical expression of p^* contains the expected allocation A^*. As the type space of bidders is a *continuum*, computing A^* becomes intractable when the number of participants increases. To cope with these problems, we introduce the stronger concept of incentive compatibility: *dominant strategy incentive compatibility* (DSIC), which is defined as follows.

$$\forall i \in I, \ \forall \hat{b}_{-i} \in \mathbb{B}_{-i}, \ (c_i, K_i) \in \underset{\hat{c}_i, \hat{K}_i \in [\underline{c}, \bar{c}] \times [0, \bar{K}]}{\operatorname{argmax}} \{u_i(\hat{c}_i, \hat{K}_i | c_i, K_i, \hat{b}_{-i})\}. \tag{14}$$

Then, the next theorem proposes the DSIC procurement mechanism.

Theorem 3. *Under the regularity condition, the following pricing rule p^{**} with the allocation rule a^* suggested in (12) and the proviso ρ suggested in Theorem 2 constitutes the dominant strategy incentive compatible, individually rational, feasible, and payoff-maximizing auction $\Gamma^* = (a^*, p^{**})$ with the proviso ρ:*

$$p_i^{**}\left((c_i, K_i), b_{-i}\right) = \begin{cases} \frac{1}{\alpha_i}\left(c_i + \int_{c_i}^{\bar{c}} \frac{a_i^*((\tau, K_i), b_{-i})}{a_i^*((c_i, K_i), b_{-i})} d\tau\right) & \text{if } a_i^* > 0 \\ 0 & \textit{otherwise}. \end{cases} \tag{15}$$

The proposed mechanism in Theorem 3 has an important property that the pricing scheme p^{**} is composed of the deterministic function a^*, which allows us to calculate the pricing rule using a formula from Bhat et al. [24]. To describe the complete algorithm of the auction process, we need the inverse function of the virtual marginal profit for fixed capacity as follows.

$$z = H_i(c_i, K_i) \leftrightarrow H_i^{-1}(z) = c_i, \ \forall c_i \in [\underline{c}, c] \text{ for fixed } K_i \tag{16}$$

The proposed algorithm for the optimal auction is described in Algorithm 1. The time complexity to compute the allocation and payment for each bidder is $O(n \log n)$ because both rules require a sorting algorithm. Therefore, the total complexity of the auction is $O(n^2 \log n)$.

5. Numerical analysis

In this section, we verify the completeness of the proposed algorithm for the optimal procurement auction of PV long-term contracts and compare its effectiveness with some benchmark auction formats, such as uniform price auction and Vickrey auction. We conduct a numerical experiment using realistic data from the historical data of the Korean long-term contract auction. To achieve this, we first introduce the mathematical definitions of the benchmark auctions. Subsequently, we organize the parameters used in our numerical experiments and then present the results and their implications. All computations were conducted using Python. The prediction of capacity factors was done using the PyTorch package, and the auction simulation was performed using the Scipy and Numpy packages.

5.1. Benchmark auctions

To evaluate the effectiveness of the proposed auction, we construct benchmark auction models for comparison. While it is necessary to consider auctions with two-dimensional bidding forms to ensure a fair comparison, existing well-known multi-unit auction models may violate the incentive compatibility condition when they are two-dimensional.

[3] Random variables $x \in X$ and $y \in Y$ whose joint density function is $f(x,y)$ are affiliated if $f(x_1,y_1)f(x_2,y_2) \le f(\max\{x_1,x_2\},\max\{y_1,y_2\}) f(\min\{x_1,x_2\},\min\{y_1,y_2\})$ for any $x_1, \ x_2 \in X$ and $y_1, \ y_2 \in Y$ [31].

Algorithm 1 Implementation of the optimal auction

Input: $\tilde{K}$, c_0; $b_i = (c_i, K_i)$, α_i for $i \in I$

function Auction(I, b, α, $\tilde{K}$, c_0)

  Compute the allocation $a^* =$ Allocation(I, b, α, $\tilde{K}$, c_0)

  for $i \in I$ **do**

    if $a_i^* > 0$ **then**

      Compute the allocation without i,

      $a_{-i}^{**} =$ Allocation($I \setminus \{i\}$, b_{-i}, $\tilde{K}$, c_0, α_{-i})

      Define the redistributed allocation $r_{-i} = a_{-i}^{**} - a_{-i}^*$

      $p_i^{**} = \frac{1}{\alpha_i a_i^*} \sum_{j \in I \setminus \{i\}} r_j \max\{H_i^{-1}(H_j(c_j, K_j)), \bar{c}\} + (a_i^* - \sum_{j \in I \setminus \{i\}} a_j^{**})\bar{c}$

    end if

  end for

  return Contract (a_i^*, p_i^{**}) for $i \in I$

end function

function Allocation(I^θ, b^θ, $\tilde{K}^\theta$, c_0^θ, α^θ)

  for $i \in I^\theta$ **do**

    $H_i = c_0^\theta \alpha_i^\theta - \left(c_i^\theta + \frac{F_i(c_i^\theta | K_i^\theta)}{f_i(c_i^\theta | K_i^\theta)}\right)$

  end for

  Define ξ: $H_{\xi(i)}(c_{\xi(i)}^\theta, K_{\xi(i)}^\theta) \geq H_{\xi(j)}(c_{\xi(j)}^\theta, K_{\xi(j)}^\theta)$ for $i, j \in I^\theta$ and $i \leq j$

  for $i \in I^\theta$ **do**

    if $H_{\xi(i)} \geq 0$ and $\tilde{K}^\theta \geq 0$ **then**

      $a_{\xi(i)}^\theta = \min\{K_{\xi(i)}^\theta, \tilde{K}^\theta\}$; $\tilde{K}^\theta \longleftarrow \tilde{K}^\theta - a_{\xi(i)}^\theta$

    end if

  end for

  return a_i^θ for $i \in I^\theta$

end function

Therefore, we consider auctions with one-dimensional bidding forms to prevent such occurrences, where bidders have one-dimensional private information on their costs, while their information on desirable capacities is public. By reducing the type dimension, we are able to utilize existing multi-unit auction models instead of the policy cost that bidders must secure their PV capacity before participating. We consider three well-known auction types: (1) Receive-as-bid auction, (2) Uniform price auction, and (3) Vickrey auction.

However, Ausubel et al. [32] noted that in a multi-unit receive-as-bid auction, equilibrium strategies do not generally exist when the capacities of bidders are different. Therefore, we only considered the other two auction models that satisfy DSIC and IR conditions. The auction scheme for the uniform price auction was taken from McAfee [33]. In this auction, the winners are selected by ordering the bids by Levelized Cost of Electricity (LCOE) in ascending order, which represents the total costs associated with the generation facilities required to produce 1 kWh of electricity. The contract price of each winner is determined as the lowest LCOE among the losing bidders. Note that LCOE can be calculated as $\frac{c_i}{\alpha_i}$ for each bidder i. On the other hand, the Vickrey auction selects winners by ordering the bids by the capacity cost c_i to minimize the social cost and determines the contract price of winners based on their marginal contributions to the system. We omit the proofs of the characteristics of the benchmark auction models. The definitions of the two benchmark models are as follows.

Definition 1 (*Uniform Price Auction*)**.** Reorder bidders based on their LCOEs, i.e., $\frac{c_{[1]}}{\alpha_{[1]}} \leq \frac{c_{[2]}}{\alpha_{[2]}} \leq \cdots \leq \frac{c_{[n]}}{\alpha_{[n]}}$. Define l^U such that $\sum_{i=1}^{l^U-1} K_{[i]} \leq \tilde{K} \leq \sum_{i=1}^{l^U} K_{[i]}$. Then, a dominant strategy incentive compatible and individually rational uniform price auction $\Gamma^U = (a^U, p^U)$ has the following form:

$$a_i^U = \begin{cases} K_i & \text{if } [i] \leq l^U \\ 0 & \text{otherwise} \end{cases}, \quad p_i^U = \begin{cases} \frac{c_{[l^U+1]}}{\alpha_{[l^U+1]}} & \text{if } a_i^U > 0 \\ 0 & \text{otherwise.} \end{cases}$$

Definition 2 (*Vickrey Auction*)**.** Reorder bidders based on their costs, i.e., $c_{[1]} \leq c_{[2]} \leq \cdots \leq c_{[n]}$. Define l^V such that $\sum_{i=1}^{l^V-1} K_{[i]} \leq \tilde{K} \leq \sum_{i=1}^{l^V} K_{[i]}$. Then, a dominant strategy incentive compatible and individually rational Vickrey auction $\Gamma^V = (a^V, p^V)$ has the following form:

$$a_i^V = \begin{cases} K_i & \text{if } [i] < l^V \\ \tilde{K} - \sum_{j=1}^{l^V-1} K_{[j]} & \text{if } [i] = l^V \\ 0 & \text{otherwise} \end{cases}, \quad p_i^V = \frac{1}{\alpha_i a_i^V}\left(\sum_{j \neq i} c_j a_j^{V \setminus \{i\}} - \sum_{j \neq i} c_j a_j^V\right),$$

where $a^{V \setminus \{i\}}$ is a Vickrey allocation conducted without bidder i.

5.2. Experiment parameters

In this section, we organize the parameters used for the numerical experiment. To conduct an experiment that reflects real-world conditions as closely as possible, we determined the parameters based on historical data from the Korean PV market. This data primarily consists of the results of the PV long-term contract auction held in the second half of 2021. Firstly, we generate the bidders' type profiles from the type distributions. Furthermore, we propose a time-series model to estimate the capacity factor of each bidder, which is a key factor in determining the winner. Lastly, we determine the other necessary parameters for the suggested auction process.

In order to generate bidders' information, we fully incorporate the current PV auction system of Korea. In this system, participants are divided into several groups based on their bidding capacity range, and the auctioneer then evenly allocates the total capacity to each group to ensure equal competition rates across the groups. Therefore, we divide bidders into four groups (denoted as A, B, C, and D) based on their capacity range and assume that each group installs different types of PV panels. We do not consider PV generators whose contract capacity exceeds 20 MW, as we regard them as large-scale operators who are not eligible for support through PV long-term contracts. Additionally, we assume that the cost and capacity are independent within each group.

To conduct numerical experiments, we construct two scenarios in which the marginal distributions of the cost follow a normal distribution in the first scenario and a uniform distribution in the second scenario. In each scenario, the standard deviation of the cost in each group is set to be 10% of the mean. Additionally, the capacity follows a uniform distribution in both scenarios. All the assumptions regarding capacity and cost for each group are derived from Korea Energy Economics Institute [34] and Korea New and Renewable Energy Center [35]. For details about the distributions used in the numerical experiment, please refer to Table 1.

Next, we adopt the Auto-regressive Neural Network model (AR-Net) proposed by Triebe et al. [36] to estimate the expected capacity factor of each bidder during the contract period at the beginning of the auction. AR-Net is a feed-forward neural network whose structure is based on the classic auto-regressive model. Although many factors affect the generation efficiency of PV panels such as daily weather and PV panel performance, the main driver is daylight time which highly depends on the season. Therefore, we use time-series data of monthly capacity factors to estimate future PV generation efficiency. To train the model, historical data on monthly capacity factors from the last 5 years of 17 different administrative districts in Korea is used. This data is obtained from Electric Power Statistics Information System [12].

We trained the model using the previous four years and tested it using the data from the last year. The hyperparameters of the AR-Net

Table 1
The bidders' type distributions.

Group	Number of bidders	Capacity (kW)	Cost (10^3 KRW[a])	
			Scenario 1	Scenario 2
A	4000	$U[3, 100]$	$N(2300, 230^2)$	$U[2300 - 230\sqrt{3}, 2300 + 230\sqrt{3}]$
B	3000	$U[100, 1000]$	$N(2100, 210^2)$	$U[2100 - 210\sqrt{3}, 2100 + 210\sqrt{3}]$
C	1000	$U[1000, 3000]$	$N(1800, 180^2)$	$U[1800 - 180\sqrt{3}, 1800 + 180\sqrt{3}]$
D	20	$U[3000, 20000]$	$N(1700, 170^2)$	$U[1700 - 170\sqrt{3}, 1700 + 170\sqrt{3}]$

[a] KRW is a monetary unit of Korea and 1 USD ≃ 1300 KRW as of Dec, 2022.

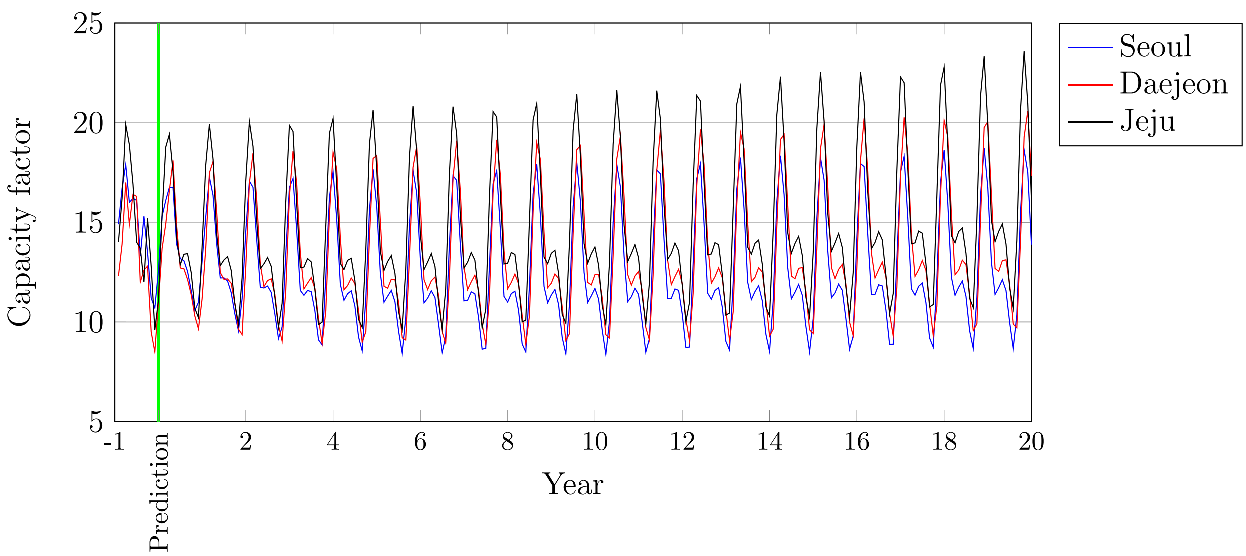

Fig. 2. Prediction of the capacity factor for the next 20 years.

Table 2
Parameters for numerical example of PV auction.

Parameters	Values
$\tilde{K}$ (kW)	2,000,000
T (months)	240
c_0 (10^3 KRW)	0.3
r (monthly)	0.4%
d (monthly)	0.05%

were determined through several trials to balance the train and test errors, using mean squared error (MSE) as a loss function. We set the time lag as 12 and used a neural network structure with 2 layers, each containing 20 nodes. The training was performed based on the Adam optimizer with a learning rate of 0.5% for 500 epochs. After training the AR-Net model, the capacity factors for the next 20 years in 17 regions of Korea were predicted. Fig. 2 shows representative examples of monthly capacity factor predictions for three different regions, which were introduced in Section 1. The final training MSE is 2.1194, and the test MSE is 4.9533, which implies that the average prediction errors are in the range of 2.5%.

The only remaining part is to determine the regions of the bidders, which will determine α_i. The regions of bidders are randomly selected in proportion to the cumulative PV installation of panels in each of the 17 regions of Korea, as depicted in Fig. 3. The total capacity to be allocated in the procurement auction experiment is set to 2,000,000 kW, which is redistributed to each group in proportion to the sum of the bidders' capacities of each group so that the competition rate for each group can be constant. The other parameters for the numerical experiment are listed in Table 2.

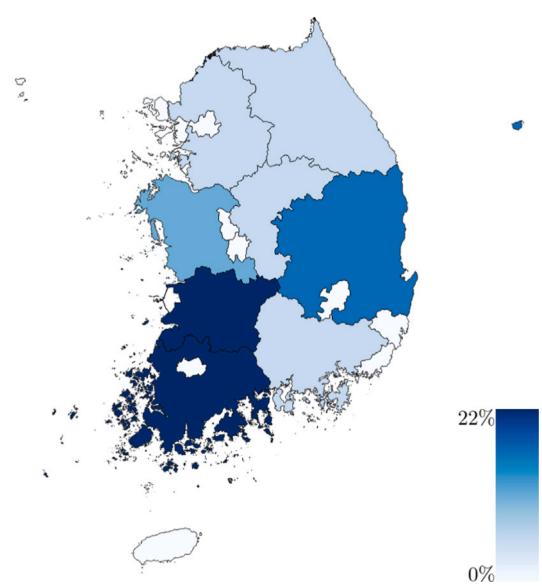

Fig. 3. Proportion of cumulative PV installation in Korea.

5.3. Experiment results

The primary results of the simulation are presented in Table 3. In both scenarios, the total capacity allocated to each group is similar at equilibrium, although the selected bidders differ. Furthermore, despite the challenge of incorporating various realistic parameters, the average winning prices are shown to be at a similar level to the actual Korean PV auction in 2021, where the average winning price was 143.1 KRW/kWh.

Regarding the relationship between the winning price and LCOE, the difference between them can be interpreted as the information rent, which has two characteristics. First, regardless of the cost distribution,

Table 3
Primary results of the proposed auction.

Group	Number of winners	Competition rate	Total allocation (kW)	Average LCOE of winners (KRW/kWh)	Average receipts (KRW/kWh)	Average NPV of winners (10^3 KRW)
Scenario 1						
A	1956	2.045:1	99,828	135.0	147.6	10,058
B	1437	2.088:1	802,316	123.0	134.7	103,664
C	478	2.092:1	988,701	105.7	115.1	318,609
D	11	1.818:1	109,155	106.1	113.7	1,327,920
Scenario 2						
A	1984	2.016:1	100,649	134.5	148.1	10,931
B	1468	2.044:1	815,475	122.7	134.7	107,316
C	486	2.058:1	977,801	105.5	115.8	324,481
D	10	2.000:1	106,075	101.8	114.4	2,239,025

Table 4
Comparison for average LCOEs and receipts of the auctions (Unit: KRW/kWh).

Results	Group	Scenario 1			Scenario 2		
		Proposed	Uniform	Vickrey	Proposed	Uniform	Vickrey
Average LCOE (std.)	A	135.0 (9.1)	135.0 (9.1)	136.1 (10.6)	134.5 (8.2)	134.5 (8.2)	135.4 (9.7)
	B	123.0 (8.6)	122.8 (8.5)	124.0 (10.1)	122.6 (7.3)	122.6 (7.3)	123.3 (8.5)
	C	105.7 (7.0)	105.5 (6.9)	106.6 (8.3)	105.5 (6.2)	105.4 (6.1)	106.3 (7.3)
	D	106.1 (6.7)	106.1 (6.7)	107.5 (6.9)	101.7 (6.2)	101.6 (5.9)	102.8 (6.9)
Average receipt (std.)	A	147.6 (0.7)	147.6 (–)	147.8 (6.8)	148.1 (0.1)	148.0 (–)	148.4 (6.7)
	B	134.7 (1.0)	134.2 (–)	134.9 (6.3)	134.7 (0.6)	134.6 (–)	134.6 (6.1)
	C	115.1 (1.6)	114.8 (–)	115.6 (5.4)	115.8 (1.3)	115.6 (–)	116.2 (5.3)
	D	113.7 (0.7)	114.3 (–)	114.3 (5.2)	114.4 (1.8)	114.5 (–)	118.3 (4.9)

the information rent tends to increase as group capacity decreases. This is because costs tend to rise as capacity decreases, resulting in a higher price premium for truthful reports from bidders. Second, although the mean and standard deviation of the cost distribution in the two scenarios are equal, the information rent in the uniform distribution tends to be greater than in the normal distribution due to its higher variation in information uncertainty (e.g., $\Pr\left(|\frac{x-\mu}{\sigma}| \le 1\right) \simeq 68\%$ in the normal distribution; $\simeq 58\%$ in the uniform distribution).

Next, we compare the outcomes of the proposed model with the benchmark models in multiple aspects to verify the performance of the proposed optimal PV auction. First, Table 4 organizes the average LCOEs and receipts of the winning bidders in each auction format. It consistently demonstrates the lowest average LCOEs in both scenarios across all groups. However, it does not show a significant difference in the LCOEs of the proposed model, and the average contract price is also similar between the two auctions, although the proposed auction receives two-dimensional bids. On the other hand, the Vickrey auction, which has an allocation rule that minimizes social costs, shows that the overall LCOEs and contract prices are higher than those of the other two auctions.

Moreover, these results are validated by comparing the standard deviation of winning bidders' LCOE and receipts. In the case of LCOE, the proposed auction and the uniform auction show similar levels across all groups, indicating that nearly identical bidders are awarded. However, in the case of the Vickrey auction, we observe a larger deviation in LCOE compared to the other two auctions, suggesting that the system may have lower stability. Additionally, in terms of receipts, the proposed auction exhibits a significantly lower standard deviation compared to the Vickrey auction. Since both auctions are discriminatory auctions, a low standard deviation indicates that the winning bidders' receipts are similar, implying a more fair and envy-free auction mechanism.

The overall social outcomes of the auctions are summarized in Fig. 4. The total social cost, as described in (a), is minimized in the Vickrey auction due to its defined allocation rule. The proposed auction increases the social cost by about 1% higher than the minimum social cost in both scenarios, which is the highest among the three auction formats. Meanwhile, the expected procured electricity by the contract, as described in (b), is maximized in the proposed auction, followed by the uniform price auction format and the Vickrey auction. This is because the unit benefits c_0 for the government's purchase of one unit of electricity generated by PV is generally higher than the LCOE of PV. Therefore, the government aims to secure as much PV energy as possible in our proposed auction. Finally, the auctioneer's payoff is, of course, maximized in the proposed auction, but the uniform price auction format exhibits a similar level, whereas the Vickrey auction is almost 20 billion KRW lower than the proposed one.

Taken together, these results confirm that our proposed auction, despite adopting a discriminatory auction scheme, can increase both expected procured electricity and the buyer's payoff compared to the uniform and Vickrey auction formats. Since all individual rational (IR) conditions are met, sellers do not refuse market participation even when their costs increase. Therefore, we can conclude that this auction scheme offers various advantages.

6. Conclusion

The expansion of renewable energy generation is considered one of the challenges in the pursuit of carbon neutrality. Photovoltaic energy, the predominant source of renewable power generation, faces high uncertainties concerning power generation and profitability, necessitating the implementation of appropriate support policies. This study designed a procurement auction for PV long-term contracts in a direct revelation environment in which bidders bid on their desirable PV capacity and the life cycle cost. Focusing on the uncertainty of PV generation, we defined the payoffs of bidders and the auctioneer to quantify the expected net present values during the entire contract period. To find the optimal mechanism from the government's perspective, we identified key characteristics of the incentive-compatible, individually rational, feasible and payoff-maximizing mechanism within a two-dimensional framework. Additionally, we proposed a computational algorithm to determine the winning bids along with their corresponding contract prices. We also developed prediction methods for estimating future PV generation using time-series models.

The study identified the optimal allocation and pricing rules for a procurement auction of PV long-term contracts to incentivize truthful reporting of costs and capacities by bidders while maximizing the

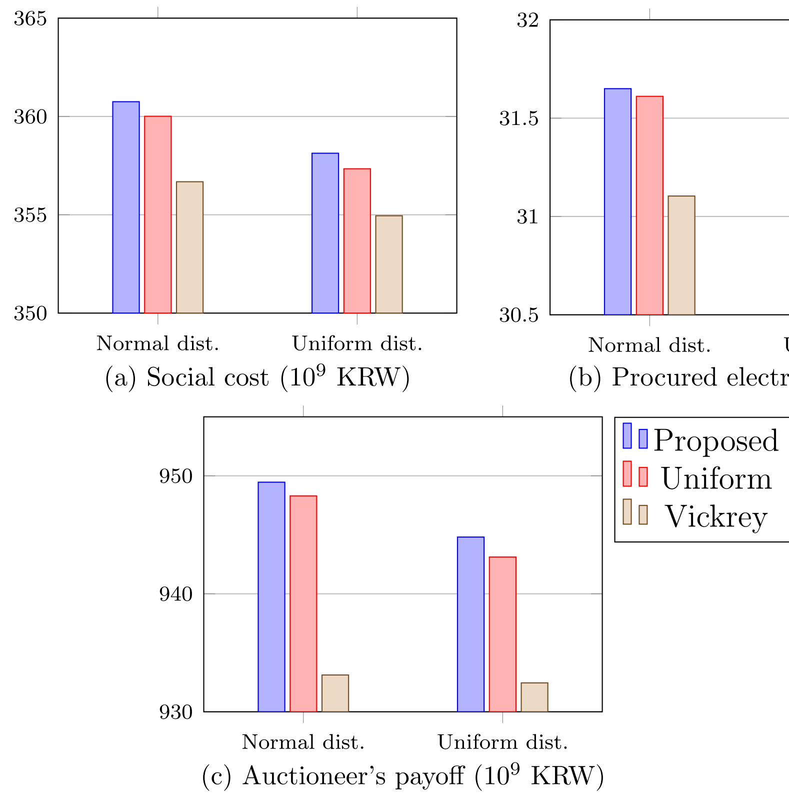

Fig. 4. The social outcomes of each auction format.

auctioneer's expected payoff and ensuring compliance with certain conditions. Incorporating information rents, the auctioneer can maximize its expected payoff by ordering the bidders with their virtual marginal profit. Numerical analysis using realistic parameters retrieved from the Korean PV energy market revealed that small-capacity generators tend to receive higher contract prices, and the proposed two-dimensional auction model showed similar LCOEs and receipts to the uniform price auction and lower than those in the Vickrey auction. Although the proposed model had the highest total cost, it resulted in higher expected PV electricity procurement and the buyer's payoff.

While this study proposed a novel approach to designing a two-dimensional procurement auction in a discriminatory format that considers the unique characteristics of PV energy generation, there are several areas for improvement. Firstly, we assumed that generators would fulfill their entire production under the contract, but they may strategically choose to break the contract based on market conditions. Future research could explore how to account for this strategic behavior. Secondly, while we used real data to make predictions about future PV generation using a time series model, future research could derive payoff functions and auction rules using a more sophisticated stochastic model. Furthermore, it is theoretically challenging to find an indirect mechanism that can implement the direct mechanism we proposed in a unit payment setting, unlike a lump-sum payment setting suggested in Iyengar and Kumar [18]. However, proposing an appropriate indirect mechanism is crucial for enhancing the implementability of the auction scheme. Therefore, it is essential to investigate this aspect in future work.

CRediT authorship contribution statement

Jihyeok Jung: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization. **Chan-Oi Song:** Conceptualization, Methodology, Formal analysis, Writing – original draft. **Deok-Joo Lee:** Writing – review & editing, Supervision, Project administration. **Kiho Yoon:** Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

Proof of Lemma 1.

Remark. If $\Gamma = (a, p)$ is incentive compatible, then

(a) $U_i(c_i, K_i)$ is convex in c_i;
(b) For any $\epsilon > 0$, $U_i(c_i, K_i) - U_i(c_i - \epsilon, K_i) \le -\epsilon A_i(c_i, K_i) \le U_i(c_i + \epsilon, K_i) - U_i(c_i, K_i)$.

Proof of Remark. Let $\Gamma = (a, p)$ be an incentive compatible mechanism. Then, truthful bidding maximizes the interim payoff of every bidder $i \in I$, which means

$$U_i(c_i, K_i) = \sup_{(\hat{c}_i, \hat{K}_i) \in [\underline{c}, \bar{c}] \times [0, \bar{K}]} \left\{ U_i(\hat{c}_i, \hat{K}_i | c_i, K_i) \right\} \tag{A.1}$$

Meanwhile, the payoff of bidder i for any reported type $(\hat{c}_i, \hat{K}_i)$ is

$$U_i(\hat{c}_i, \hat{K}_i | c_i, K_i) = \mathbb{E}_{b_{-i}} \left[\alpha_i p_i((\hat{c}_i, \hat{K}_i), b_{-i}) a_i((\hat{c}_i, \hat{K}_i), b_{-i}) \right] - c_i A_i(\hat{c}_i, \hat{K}_i), \tag{A.2}$$

which implies that $U_i(\hat{c}_i, \hat{K}_i|c_i, K_i)$ is affine in c_i. Therefore, for any $c_i', c_i'' \in [\underline{c}, \bar{c}]$ and $t \in [0,1]$, we have the following.

$$U_i(\hat{c}_i, \hat{K}_i|tc_i' + (1-t)c_i'', K_i) = tU_i(\hat{c}_i, \hat{K}_i|c_i', K_i) + (1-t)U_i(\hat{c}_i, \hat{K}_i|c_i'', K_i) \le tU_i(c_i', K_i) + (1-t)U_i(c_i'', K_i). \quad (A.3)$$

Because $tU_i(c_i', K_i) + (1-t)U_i(c_i'', K_i)$ is an upper bound for any reported type, it also holds when bidder i reports true type. Then, we get

$$U_i(tc_i' + (1-t)c_i'', K_i) \le tU_i(c_i', K_i) + (1-t)U_i(c_i'', K_i), \quad (A.4)$$

which proves that $U_i(c_i, K_i)$ is convex with respect to c_i. Further, for any $\epsilon > 0$, we have

$$\begin{aligned} U_i(c_i+\epsilon, K_i) &\ge U_i(c_i, K_i|c_i+\epsilon, K_i) \\ &= \mathbb{E}_{b_{-i}}\left[\alpha_i p_i\left((c_i, K_i), b_{-i}\right) a_i\left((c_i, K_i), b_{-i}\right)\right] - (c_i+\epsilon)A_i(c_i, K_i) \\ &= U_i(c_i, K_i) - \epsilon A_i(c_i, K_i), \end{aligned} \quad (A.5)$$

Similarly, we have

$$\begin{aligned} U_i(c_i-\epsilon, K_i) &\ge U_i(c_i, K_i|c_i-\epsilon, K_i) \\ &= \mathbb{E}_{b_{-i}}\left[\alpha_i p_i\left((c_i, K_i), b_{-i}\right) a_i\left((c_i, K_i), b_{-i}\right)\right] - (c_i-\epsilon)A_i(c_i, K_i) \\ &= U_i(c_i, K_i) + \epsilon A_i(c_i, K_i), \end{aligned} \quad (A.6)$$

which completes the proof of the remark.

Then, if we divide the inequality (b) of the Remark by $\epsilon > 0$ and take the limit to zero, we have

$$\lim_{\epsilon\to 0} \frac{U_i(c_i, K_i) - U_i(c_i-\epsilon, K_i)}{\epsilon} \le -A_i(c_i, K_i) \le \lim_{\epsilon\to 0} \frac{U_i(c_i+\epsilon, K_i) - U_i(c_i, K_i)}{\epsilon} \quad (A.7)$$

By (a) of the Remark, $U_i(c_i, K_i)$ is convex in c_i and thus differentiable almost everywhere. If $U_i(c_i, K_i)$ is differentiable in a certain point c_i, then the limit of (A.7) is

$$\frac{\partial U_i(c_i, K_i)}{\partial c_i} = -A_i(c_i, K_i) \quad (A.8)$$

Then, the convexity of $U_i(c_i, K_i)$ in c_i implies that $A_i(c_i, K_i)$ is non-increasing in c_i. Also, $U_i(c_i, K_i)$ can be described as

$$\int_{c_i}^{\bar{c}} -A_i(\tau, K_i)d\tau = \int_{c_i}^{\bar{c}} \frac{\partial U_i(\tau, K_i)}{\partial c_i} d\tau = U_i(\bar{c}, K_i) - U_i(c_i, K_i), \quad (A.9)$$

i.e., $U_i(c_i, K_i) = U_i(\bar{c}, K_i) + \int_{c_i}^{\bar{c}} A_i(\tau, K_i)d\tau$. ■

Proof of Theorem 1. By Lemma 1, under an incentive compatible mechanism $\Gamma = (a, p)$,

$$\mathbb{E}_{b_{-i}}\left[\alpha_i p_i\left(b_i, b_{-i}\right) a_i(b_i, b_{-i})\right] = c_i A_i(c_i, K_i) + U_i(\bar{c}, K_i) + \int_{c_i}^{\bar{c}} A_i(\tau, K_i)d\tau. \quad (A.10)$$

Then, the objective function of the buyer can be rewritten as follows.

$$\begin{aligned} \Pi(\Gamma) &= \mathbb{E}_b\left[\sum_{i=1}^n \alpha_i(c_0 - p_i(b))a_i(b)\right] \\ &= \mathbb{E}_b\left[\sum_{i=1}^n \alpha_i c_0 a_i(b)\right] \\ &\quad - \sum_{i=1}^n \mathbb{E}_{b_i}\left[c_i A_i(c_i, K_i) + U_i(\bar{c}, K_i) + \int_{c_i}^{\bar{c}} A_i(\tau, K_i)d\tau\right] \\ &= \mathbb{E}_b\left[\sum_{i=1}^n \left(\alpha_i c_0 - c_i\right) a_i(b) - \sum_{i=1}^n U_i(\bar{c}, K_i)\right] \\ &\quad - \sum_{i=1}^n \mathbb{E}_{b_i}\left[\int_{c_i}^{\bar{c}} A_i(\tau, K_i)d\tau\right] \end{aligned} \quad (A.11)$$

Also, $\mathbb{E}_{b_i}\left[\int_{c_i}^{\bar{c}} A_i(\tau, K_i)d\tau\right]$ can be computed as

$$\begin{aligned} \mathbb{E}_{b_i}\left[\int_{c_i}^{\bar{c}} A_i(\tau, K_i)d\tau\right] &= \int_0^{\bar{K}}\int_{\underline{c}}^{\bar{c}}\left[\int_{c_i}^{\bar{c}} A_i(\tau, K_i)d\tau\right] f_i(c_i, K_i)dc_i dK_i \\ &= \int_0^{\bar{K}}\int_{\underline{c}}^{\bar{c}} A_i(\tau, K_i)\int_{\underline{c}}^{\tau} f_i(c_i, K_i)dc_i d\tau dK_i \\ &= \int_0^{\bar{K}}\int_{\underline{c}}^{\bar{c}} A_i(\tau, K_i)\frac{F_i(\tau|K_i)}{f_i(\tau|K_i)} f_i(\tau|K_i)d\tau f_i(K_i)dK_i \\ &= \mathbb{E}_b[a_i\left((c_i, K_i), b_{-i}\right)\frac{F_i(c_i|K_i)}{f_i(c_i|K_i)}]. \end{aligned} \quad (A.12)$$

Combining (A.11) and (A.12), we have

$$\Pi(\Gamma) = \mathbb{E}_b\left[\sum_{i=1}^n \left(\alpha_i c_0 - \left(c_i + \frac{F_i(c_i|K_i)}{f_i(c_i|K_i)}\right)\right) a_i(b) - \sum_{i=1}^n U_i(\bar{c}, K_i)\right] \quad ■ \quad (A.13)$$

Proof of Lemma 2. We can refer to the relaxed problem as the primal problem. We assume without loss of generality that $H_i(c_i, K_i) \ge 0$ for all $i \in I$. Using the solution suggested in Lemma 2, the objective function value is given by $\sum_{i=1}^{l^*-1} H_{\xi(i)}(c_{\xi(i)}, K_{\xi(i)})K_{\xi(i)} + H_{\xi(l)}(c_{\xi(l)}, K_{\xi(l)})(\tilde{K} - \sum_{i=1}^{l^*-1} K_{\xi(i)})$. If we derive the dual problem of the relaxed problem, we obtain

$$\min_{\mu,\lambda_i} \quad \tilde{K}\mu + \sum_{i=1}^n K_i\lambda_i \quad (A.14)$$

$$\text{s.t.} \quad \mu + \lambda_i \ge H_i(c_i, K_i), \ \forall i \in I \quad (A.15)$$

$$\mu \ge 0, \ \lambda_i \ge 0, \ \forall i \in I. \quad (A.16)$$

From (A.15) and (A.16), we can transform $\lambda_i = \max\{0, H_i(c_i, K_i) - \mu\}$ and the dual problem is reduced to

$$\min_{\mu\ge 0} \quad \tilde{K}\mu + \sum_{i=1}^n K_{\xi(i)}\max\{0, H_{\xi(i)}(c_{\xi(i)}, K_{\xi(i)}) - \mu\}. \quad (A.17)$$

Then, if we set $\mu^* = H_{\xi(l^*)}(c_{\xi(l^*)}, K_{\xi(l^*)})$, the objective function value of the dual problem is the same as that of primal problem: $\tilde{K}H_{\xi(l^*)}(c_{\xi(l^*)}, K_{\xi(l^*)}) + \sum_{i=1}^{l^*-1} K_{\xi(i)}H_{\xi(i)}(c_{\xi(i)}, K_{\xi(i)}) - \sum_{i=1}^{l^*-1} K_{\xi(i)}H_{\xi(l^*)}(c_{\xi(l^*)}, K_{\xi(l^*)})$, which is exactly same with the objective function value of the primal problem. Therefore, by the strong duality, the solution proposed in Lemma 2 is optimal. ■

Proof of Lemma 3. Assume that the regularity condition holds. Fix K_i and b_{-i}. Let $c_i \le c_i'$ and denote the corresponding rankings as $\xi_1^{-1}(i)$ and $\xi_2^{-1}(i)$. Then, we have $\xi_1^{-1}(i) \le \xi_2^{-1}(i)$. If $\xi_1^{-1}(i) \le l^*$, according to the definition of a^*, we have

$$a_i^*\left((c_i, K_i), b_{-i}\right) = \begin{cases} K_i & \text{if } \xi_1^{-1}(i) < l^* \\ \tilde{K} - \sum_{j=1}^{l^*-1} K_j & \text{if } \xi_1^{-1}(i) = l^* \end{cases} \ge a_i^*\left((c_i', K_i), b_{-i}\right). \quad (A.18)$$

If $\xi_1^{-1}(i) > l^*$, then, again by the definition of a^*,

$$a_i^*\left((c_i, K_i), b_{-i}\right) = a_i^*((c_i', K_i), b_{-i}) = 0. \quad (A.19)$$

For all cases, $c_i \le c_i'$ implies $a_i^*\left((c_i, K_i), b_{-i}\right) \ge a_i^*\left((c_i', K_i), b_{-i}\right)$, which proves (a). The proof of (b) is omitted because it is analogous to (a).

(c) comes directly from (a). For fixed K_i, $c_i \le c_i'$ implies $a_i^*\left((c_i, K_i), b_{-i}\right) \ge a_i^*\left((c_i', K_i), b_{-i}\right)$ for any b_{-i}. Therefore, by the definition of A^*, we have

$$A_i^*(c_i, K_i) = \mathbb{E}_{b_{-i}}\left[a_i^*\left((c_i, K_i), b_{-i}\right)\right] \ge \mathbb{E}_{b_{-i}}\left[a_i^*\left((c_i', K_i), b_{-i}\right)\right] = A_i^*(c_i', K_i). \quad (A.20)$$

One can easily show that (b) implies (d). ■

Proof of Theorem 2.

Step 1. *$\Gamma^* = (a^*, p^*)$ with proviso ρ is feasible and incentive compatible.*

To prove incentive compatibility, we consider a bidder $i \in I$. Assuming all bidders except i play truthfully, let bidder i's bid and true type be $(\hat{c}_i, \hat{K}_i)$ and (c_i, K_i), respectively. Under Γ^*, bidder i's interim payoff is given by

$$\begin{aligned} U_i(\hat{c}_i, \hat{K}_i | c_i, K_i) &= (\hat{c}_i - c_i) A_i^*(\hat{c}_i, \hat{K}_i) + \int_{\hat{c}_i}^{\bar{c}} A_i^*(\tau, \hat{K}_i) d\tau \\ &= (\hat{c}_i - c_i) A_i^*(\hat{c}_i, \hat{K}_i) - \int_{c_i}^{\hat{c}_i} A_i^*(\tau, \hat{K}_i) d\tau + \int_{c_i}^{\bar{c}} A_i^*(\tau, \hat{K}_i) d\tau \\ &\leq \int_{c_i}^{\bar{c}} A_i^*(\tau, \hat{K}_i) d\tau \end{aligned} \tag{A.21}$$

The last inequality holds because the function $A_i^*(c_i, K_i)$ is non-increasing in c_i by the part (c) of Lemma 3. Also, notice that $U_i(c_i, K_i) = \int_{c_i}^{\bar{c}} A_i^*(\tau, K_i) d\tau$. Now, we shall show

$$\int_{c_i}^{\bar{c}} A_i^*(\tau, \hat{K}_i) d\tau \leq \int_{c_i}^{\bar{c}} A_i^*(\tau, K_i) d\tau = U_i(c_i, K_i). \tag{A.22}$$

For $\hat{K}_i \leq K_i$, by (d) of Lemma 3, we have $A_i^*(\tau, \hat{K}_i) \leq A_i^*(\tau, K_i)$. By integrating both sides of the inequality, one can see that (A.22) holds. Consider the overbidding cases. Suppose bidder i overbids her capacity. Without loss of generality, i bids $(c_i, \hat{K}_i)$ where $\hat{K}_i > K_i$. In case of i wins the procurement with $a_i^*((c_i, \hat{K}_i), b_{-i}) > K_i$, the overbidding is directly observed and her payoff equals $(\alpha_i \frac{\underline{c}}{\alpha} - c_i) K_i$. Since $\alpha = \sup_{i \in I} \{\alpha_i, 1\}$, it follows that

$$(\alpha_i \frac{\underline{c}}{\alpha} - c_i) K_i \leq (\underline{c} - c_i) K_i \leq 0 \tag{A.23}$$

If i wins the procurement with $a_i^*((c_i, \hat{K}_i), b_{-i}) < K_i$, her payoff equals

$$(\alpha_i \frac{\underline{c}}{\alpha} - c_i) a_i^*((c_i, \hat{K}_i), b_{-i}) \leq (\underline{c} - c_i) a_i^*((c_i, \hat{K}_i), b_{-i}) \leq 0 \tag{A.24}$$

Finally, it is clear that if i loses the procurement with bid $(c_i, \hat{K}_i)$, she gets 0. For all cases, overbidding yields payoffs less or equal to 0. This shows that bidder i has no incentive to report its capacity not dishonestly. Furthermore, the mechanism is feasible since it is incentive compatible.

Step 2. *$\Gamma^* = (a^*, p^*)$ with proviso ρ is individually rational.*

Since $\forall c \in [\underline{c}, \bar{c}]$, the expected allocation $A_i^*(c, K_i) \geq 0$. Therefore, we have $U_i(c_i, K_i) = \int_{c_i}^{\bar{c}} A_i^*(\tau, K_i) d\tau \geq 0$ for every type $(c_i, K_i) \in [\underline{c}, \bar{c}] \times [0, \bar{K}]$.

Step 3. *$\Gamma^* = (a^*, p^*)$ with proviso ρ maximizes the buyer's payoff.*

Consider any feasible mechanism. By the revelation principle, there exists a corresponding direct revelation mechanism $\Gamma = (a, p)$ which ensures the same result. Then, by the revenue equivalence theorem,

$$\begin{aligned} \Pi(\Gamma) &= \mathbb{E}_b \left[\sum_{i=1}^n H_i(c_i, K_i) a_i(b) - \sum_{i=1}^n U_i(\bar{c}, K_i) \right] \\ &\leq \mathbb{E}_b \left[\sum_{i=1}^n H_i(c_i, K_i) a_i^*(b) \right] = \Pi(\Gamma^*). \end{aligned} \tag{A.25}$$

The last equality holds since $U_i(\bar{c}, K_i) = \int_{\bar{c}}^{\bar{c}} A_i^*(\tau, K_i) d\tau = 0$. ■

Proof of Theorem 3. The proof is similar to the proof of Theorem 2. Let $\hat{b}_{-i}$ denote the reported types of the other bidders for $i \in I$. The ex-post payoff of bidder i when bidding $(\hat{c}_i, \hat{K}_i)$ and having a true type of (c_i, K_i) can be expressed as follows.

$$\begin{aligned} u_i((\hat{c}_i, \hat{K}_i) | c_i, K_i, \hat{b}_{-i}) &= (\hat{c}_i - c_i) a_i^*((\hat{c}_i, \hat{K}_i), \hat{b}_{-i}) + \int_{\hat{c}_i}^{\bar{c}} a_i^*((\tau, \hat{K}_i), \hat{b}_{-i}) d\tau \\ &\leq \int_{c_i}^{\bar{c}} a_i^*((\tau, \hat{K}_i), \hat{b}_{-i}) d\tau \end{aligned} \tag{A.26}$$

The last inequality is held by part (a) of Lemma 3. Clearly, by the proviso ρ, overbidding $\hat{K}_i > K_i$ yields non-positive payoff. Also, by part (b) of Lemma 3, we can rule out the underbidding $\hat{K}_i \leq K_i$. So, we have

$$\int_{c_i}^{\bar{c}} a_i^*((\tau, \hat{K}_i), b_{-i}) d\tau \leq \int_{c_i}^{\bar{c}} a_i^*((\tau, K_i), b_{-i}) d\tau = u_i(c_i, K_i) \tag{A.27}$$

which proves that truth-telling is a weakly dominant strategy for all bidders. The other properties are analogous to the proof of Theorem 2. ■

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