An Incentive Compatible Profit Allocation Mechanism for Renewable Energy Aggregation

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Abstract—**Profit allocation mechanism (PAM) for aggregating renewable power producers (RPPs) to participate in two-settlement power markets is studied. As opposed to assuming all renewable generation forecast information are publicly known, with a PAM, the aggregator elicits private forecast information from the RPPs, participates in the power markets, and allocate profit to each RPP. A novel profit allocation mechanism is proposed that simultaneously achieves four design goals: truthfulness, individual rationality, social welfare maximization, and budget balance. The proposed PAM is evaluated using the forecast and generation data from ten wind power producers in PJM, and is observed to closely follow the ideal fair profit allocation derived by assuming all forecast information are public.**

I. Introduction

Integration of renewable energies from sources such as wind and solar into the electric grid plays a key role in achieving a sustainable energy future. Unlike conventional generation, these renewable energies are inherently not controllable, and yet have highly variable and uncertain output. In particular, wind and solar generation forecast is typically much less accurate than load forecast [1]. Such uncertainty raises significant challenges for using renewable energies to serve power demands reliably. While there are a range of technologies for compensating for the uncertainty of renewable energies, such as fast-ramping generators, energy storage and demand response [2], [3], [4], [5], [6], challenging issues of their cost and capacity remain to be solved. On the other hand, aggregation of statistically diverse renewable energy sources can effectively reduce their generation uncertainty. If fully exploited, renewable energy aggregation can greatly reduce the requirement and cost of using other means of compensation for the uncertainty.

The benefit of renewable energy aggregation has been demonstrated in a number of studies. For renewable power producers (RPPs) to sell reliable power in forward power markets, aggregation of multiple RPPs reduces their generation uncertainty and brings significant increase to their total profit. A central question is thus how to *allocate* such economic benefit to the RPPs in an aggregation, in other words, how to *value* the contribution of each RPP to an aggregation. A coalitional game approach for profit allocation among RPPs was introduced in [7], and it is shown that the core of the game is non-empty. Using an instrument named risky power contract, it is shown that there is a *unique* fair profit allocation to each contributing RPPs in an aggregation, determined by the competitive equilibrium of the risky power market [8]. While the above works guarantee a stable profit allocation (i.e., in the core) in an "ex-ante" sense (i.e., in expectation), other works that discuss "ex-post" (i.e., for each realization) individual rationality include [9], [10]. A key lesson learned from the renewable energy aggregation studies is that the fair valuation of each contributing RPP critically depends on the *probabilistic properties* of the uncertain generation. In particular, a lower variance of an RPP's generation, and/or a more negative/less positive correlation of its generation with other RPPs', lead to a higher valuation of this RPP.

A primary assumption made by existing renewable energy aggregation studies is that the probability distributions of the RPPs' forecast generation, which are *random variables* when selling in the forward markets, are *public* information that everyone agrees on. This is however a simplification of the reality, as different entities can often have different information and forecast of future generation. For example, in CAISO, the operator asks wind power producers to provide their own generation forecast [11]. This leads to a fundamental incentive compatibility issue: If private information from RPPs are used in determining profit allocation in an aggregation, it is to the advantage of an RPP to report whatever information (e.g., claiming, even if it's not true, that its forecast generation has a lower variance and is negatively correlated with others) that can lead to a higher profit allocated to itself. It is thus crucial to design profit allocation mechanisms (PAMs) so that RPPs are incentivized to report their true information on generation forecast. Mechanism for eliciting forecast information of RPPs has been studied in [12]. However, it does not consider the alternative of an RPP leaving an aggregation and separately selling power in power markets, or whether its profit allocation is close to the fair profit allocation for renewable energy aggregation.

In this paper, we first formulate the mechanism design problem of profit allocation for aggregating RPPs. As opposed to assuming that generation forecast information are publicly known, we design the PAM to elicit the private forecast information from RPPs. We propose a PAM to simultaneously achieve four design goals: a) RPPs are willing to report their private forecast information truthfully, b) RPPs are willing to form an aggregation as opposed to sell power separately in power markets, c) Full benefit of aggregation is achieved as if all RPPs fully cooperate with each other in a grand coalition, and d) the profit obtained by the aggregation is always equal to the sum of the profits allocated to all participating RPPs. We evaluate the proposed PAM with the wind power data (forecast and generation) from ten wind power producers in PJM [13]. It is shown that the proposed PAM allocates profit very closely to the ideal fair profit allocation obtained by assuming all information are public.

II. Problem Formulation

A. Renewable Power Producers in a Two Settlement Market

We consider RPPs participating in a two-settlement power market consisting of a day ahead (DA) market and a real time (RT) market. We assume that the RPPs are price takers.

Without considering aggregation, RPPs sell power in the DA market separately. In the DA market, RPP i's generation at the time of interest in the next day is modeled as a random variable, denoted by X_i. Based on all forecast information it has on X_i, RPP i commits certain level of power s_i in the DA market. At the delivery time, RPP i sees its actual realized generation x_i. If there is a shortfall, i.e., $s_i - x_i > 0$, RPP i is responsible for the difference and buys the corresponding amount in the RT market, and if otherwise, it sells the surplus $x_i - s_i$. The profit of RPP i who separately participates in the DA-RT market is:

$$\mathcal{P}_i^{sep} = p^d s_i - p^{r,b} \left(s_i - x_i\right)_+ + p^{r,s} \left(x_i - s_i\right)_+ , \quad (1)$$

where p^d is the DA price, $p^{r,b}$ and $p^{r,s}$ are the RT prices of buying and selling power, $p^{r,b} > p^d > p^{r,s}$, and $(\cdot)_+ = \max(0, \cdot)$. Since there is uncertainty of RPP i's generation X_i one day head of delivery, RPP i needs to commit in the DA market somewhat conservatively. Based on the DA forecast probability distribution of X_i, the optimal level of commitment, denoted by s_i^*, can be solved as a news-vendor problem [14], [15] (see Remark 1 below).

B. Aggregation of RPPs and Profit Allocation

The benefit of aggregation stems from the inherent uncertainty of the renewable power sources. An aggregator aggregates multiple RPPs so that their statistical diversity helps reduce the uncertainty of their generation. By selling power in the DA-RT market jointly and sharing the risk in an aggregation, a higher total profit can be achieved for the RPPs. The key question that an aggregator faces is how to allocate the total profit to the RPPs in an aggregation. Prior works primarily assumed that the forecast joint probability distribution function (PDF) of RPPs' future generation are public information known to the aggregator and the RPPs. Based on this, fair profit allocation is shown to critically depend on this joint PDF. In particular, for an aggregation of N RPPs under a unique fair profit allocation, RPP i has an expected profit $\mathcal{P}_i^{fair,exp} = p_i^* \mu_i$, where $\mu_i = \mathbb{E}[X_i]$, and p_i^* is a "competitive price" computed based on the joint PDF of $X_1, \ldots, X_N$ and the power market prices (see [8] for details).

However, it is a simplification to assume that the forecast joint PDF of RPPs' generation are public information on which everyone agrees. For RPP i, there can be private information that only RPP i itself knows. Such information can determine the true uncertainty of its generation X_i as well as its correlation with other RPPs' generation. As a result, the aggregator would need to a) elicit such private forecast information from the RPPs in order to make more informed decisions in the DA market, and b) incorporate the elicited information in computing the profit allocation to the RPPs.

C. Aggregation and Profit Allocation with Private Information Elicited

We consider an aggregator aiming to aggregate N RPPs. The aggregation and profit allocation procedure consists of the following steps: 1) One day ahead, the RPPs report their forecast information, denoted by I_i^R to the aggregator, (note that this reported information are not necessarily their true information I_i^T,) 2) Based on the joint PDF determined by these reported information, on behalf of the RPPs, the aggregator sells a commitment s_A in the DA market, 3) At RT, the aggregator combines the actual realized generation from the RPPs, $x_1, \ldots, x_N$, supplies the committed power s_A, and resolves the imbalance $s_A - \sum_{i=1}^N x_i$ in the RT market, 4) The aggregator accrues a total profit of $\mathcal{P}_A$ from participating the two-settlement market, and allocates profit $\mathcal{P}_1, \ldots, \mathcal{P}_N$ to the RPPs. The general structure of the aggregation and profit allocation procedure in shown in Fig. 1.

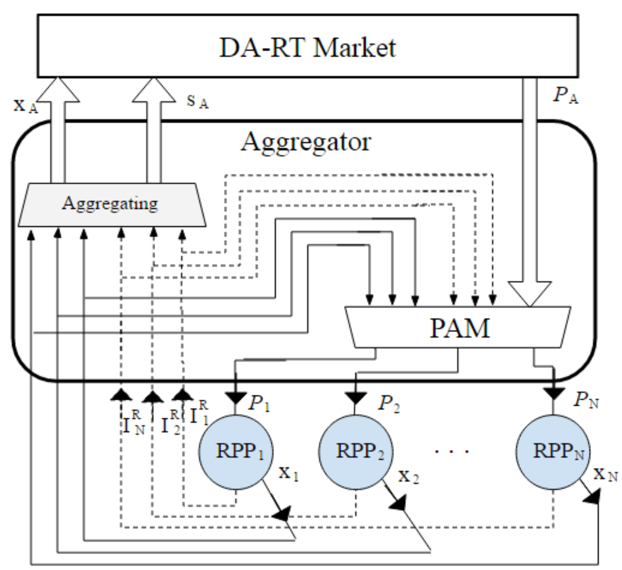

Fig. 1. The general structure of aggregation and profit allocation mechanism.

The key task for the aggregator is the mechanism by which it allocates profit to all the RPPs. In designing the PAM, we would like to achieve the following goals:

1) ***Truthfulness***: It is optimal for the RPPs to report to the aggregator their *true private information*, i.e., $I_i^R = I_i^T, \forall i$.
2) ***Individual rationality***: An RPP cannot get a higher expected profit by leaving the aggregation and separately selling power in the DA-RT markets.

3) ***Social welfare maximization*:** The total profit of the RPPs achieves the maximum as if they fully cooperate as a grand coalition.
4) ***Budget balance*:** The allocated profit to the RPPs $\{\mathcal{P}_i\}$ exactly sum to the profit earned by the aggregator $\mathcal{P}_A$.

III. Profit allocation mechanism design

Assuming truthfulness, the profit allocation schemes developed in [7], [8] achieve individual rationality, social welfare maximization, and budget balance. However, without assuming it, truthfulness is not necessarily achieved. In this section, we first introduce a simple PAM to achieve truthfulness, which does not necessarily achieve individual rationality. Extending this, we propose a PAM that achieves all the design goals.

A. Profit Allocation Based on Realized Generation

Truthfulness itself can be achieved with a simple idea: allocate profit based on the *realized* generation of the RPPs, namely, $\{x_1, \ldots, x_N\}$. In particular, a simple and intuitive mechanism is to let profit allocated to RPP i be

$$\mathcal{P}_i = \frac{x_i}{\sum_j x_j} \mathcal{P}_A, \tag{2}$$

where $\mathcal{P}_A$ is the profit earned by the aggregator. This PAM achieves truthfulness, and the intuition is the following: Since what RPP reports to the aggregator has no influence at all on the actual realized generation $\{x_i\}$, it is to the interest of each RPP to report information so that the *only other factor* that influences its profit – $\mathcal{P}_A$ – is maximized. As the aggregator depends on the reported information $\{I_i^R\}$ to maximize $\mathcal{P}_A$, and $\mathcal{P}_A$ is clearly maximized *only if no false information is used*, it is optimal for each RPP to report its true information to the aggregator, i.e., $I_i^R = I_i^T$.

It is immediate to see that this simple PAM achieves budget balance. However, it does not necessarily achieve individual rationality and hence social welfare maximization.

B. The Proposed Profit Allocation Mechanism

The key idea to achieve individual rationality is to guarantee the profit to each RPP that would be obtained if it separately sells power in the DA-RT market.

Specifically, based on the received reported information $\{I_j^R\}$, the aggregator commits the *optimal* DA contract $s_A^*\big(\{I_j^R\}\big)$ by solving the news-vendor problem [14], and collects the following profit after resolving the aggregate imbalance in the RT market:

$$\mathcal{P}_A^* = p^d s_A^* \left(\{I_j^R\}\right) - p^{r,b}\Big(s_A^*\left(\{I_j^R\}\right) - \sum_{j=1}^N x_j\Big)_+ + p^{r,s}\Big(\sum_{j=1}^N x_j - s_A^*\left(\{I_j^R\}\right)\Big)_+ \tag{3}$$

To allocate $\mathcal{P}_A^*$, the aggregator employs the following procedure. First, each RPP i is allocated the amount that it can *maximally* earn if it were to separately sell power in the DA-RT market *based on its reported information* I_i^R:

$$\mathcal{P}_i^{sep,*} = p^d s_i^*\left(I_i^R\right) - p^{r,b}\big(s_i^*\left(I_i^R\right) - x_i\big)_+ + p^{r,s}\big(x_i - s_i^*\left(I_i^R\right)\big)_+ \tag{4}$$

where $s_i^*\left(I_i^R\right)$ is the optimal commitment by RPP i if it separately sells in the DA-RT markets based on I_i^R. Then, the *remaining* profit $\mathcal{P}_A^* - \sum_{i=1}^N \mathcal{P}_i^{sep,*}$ (which will be shown later to be always nonnegative in expectation) is allocated based on the *realized* generation of the RPPs as in the last subsection.

Accordingly, the complete PAM is as follows:

$$\mathcal{P}_i = \mathcal{P}_i^{sep,*} + \frac{x_i}{\sum_j x_j}\left(\mathcal{P}_A^* - \sum_{j=1}^N \mathcal{P}_j^{sep,*}\right). \tag{5}$$

Remark 1: The optimal commitment s_i^* for RPP i to sell in the DA market can be solved by a news-vendor problem [14]:

$$\begin{aligned} s_i^* &= \arg\max_{s_i} \mathbb{E}\left[\, p^d s_i - p^{r,b}\left(s_i - X_i\right)_+ + p^{r,s}\left(X_i - s_i\right)_+\right] \\ &= F_i^{-1}\left(\frac{p^d - p^{r,s}}{p^{r,b} - p^{r,s}}\right), \end{aligned} \tag{6}$$

where F_i is the cumulative distribution function (CDF) of the forecast generation of RPP i, X_i.

In an aggregation, the aggregator also uses (6) to compute the optimal commitment s_A^* for the aggregation, based on the CDF F_A of the aggregate generation $\sum_{i=1}^N X_i$.

C. The Proposed PAM Achieves the Design Goals

We now show that the proposed PAM (5) achieves all the four design goals.

Theorem 1: The proposed profit allocation mechanism achieves truthfulness, individual rationality, social welfare maximization, and budget balance.

Proof: i) *Truthfulness*: Consider RPP i. Assume that all other RPPs report their true information. We have:

$$\begin{aligned} \mathcal{P}_i &= \mathcal{P}_i^{sep,*} + \frac{x_i}{\sum_j x_j}\left(\mathcal{P}_A^* - \sum_{j=1}^N \mathcal{P}_j^{sep,*}\right) \\ &= \frac{\sum_{j\neq i} x_j}{\sum_j x_j}\mathcal{P}_i^{sep,*} + \frac{x_i}{\sum_j x_j}\mathcal{P}_A^* - \frac{x_i}{\sum_j x_j}\sum_{j\neq i}\mathcal{P}_j^{sep,*} \end{aligned} \tag{7}$$

Note that $\{x_j\}$ are the actual realized generation that do not depend on what information the RPPs report. In addition, for RPP i, the last term $\sum_{j\neq i}\mathcal{P}_j^{sep,*}$ does *not* depend on its reported information I_i^R (but on others' reported information $I_j^R, j \neq i$). Therefore, RPP i would like to report its information such that the expected $\mathcal{P}_i^{sep,*}$ and $\mathcal{P}_A^*$ are maximized. Now, we notice that a) as $\mathcal{P}_i^{sep,*}$ (4) is based on the DA commitment $s_i^*\left(I_i^R\right)$ computed according to its *reported information* I_i^R, it is maximized when RPP i reports the true information $I_i^R = I_i^T$, and b) as $\mathcal{P}_A^*$ (3) is the aggregator's profit whose commitment s_A^* is based on the reported information, similar to the argument in Section III-A, it is also maximized when RPP i report its true information $I_i^R = I_i^T$.

ii) *Individual Rationality*: Here, we consider that the RPPs report their true information as we proved above. We need to prove that $\mathbb{E}[\mathcal{P}_A^* - \sum_{j=1}^N \mathcal{P}_j^{sep,*}] \geq 0$. This is immediate as $\mathbb{E}[\mathcal{P}_A^*]$ is the *maximum* expected profit that the aggregation can achieve, whereas $\sum_{j=1}^N \mathcal{P}_j^{sep,*}$ is *some* expected profit that the aggregation can achieve. A detailed proof is given below:

$$\begin{aligned}\mathcal{P}_A^* &= p^d s_A^*\left(\{I_j^R\}\right) - p^{r,b}\Big(s_A^*\left(\{I_j^R\}\right) - \sum_{j=1}^N x_j\Big)_+ \\ &\qquad + p^{r,s}\Big(\sum_{j=1}^N x_j - s_A^*\left(\{I_j^R\}\right)\Big)_+ \\ &\geq p^d \sum_{j=1}^N s_j^*\left(I_j^R\right) - p^{r,b}\Big(\sum_{j=1}^N s_j^*\left(I_j^R\right) - \sum_{j=1}^N x_j\Big)_+ \qquad (8) \\ &\qquad + p^{r,s}\Big(\sum_{j=1}^N x_j - \sum_{j=1}^N s_j^*\left(I_j^R\right)\Big)_+ \\ &\geq p^d \sum_{j=1}^N s_j^*\left(I_j^R\right) + \sum_{j=1}^N \Bigg(- p^{r,b}\Big(s_j^*\left(I_j^R\right) - x_j\Big)_+ \qquad (9) \\ &\qquad + p^{r,s}\Big(x_j - s_j^*\left(I_j^R\right)\Big)_+ \Bigg) \\ &= \sum_{j=1}^N \mathcal{P}_j^{sep,*}.\end{aligned}$$

(8) is because $s_A^*\left(\{I_j^R\}\right)$ is by definition the optimal DA commitment for the aggregation, whereas $\sum_{j=1}^N s_j^*\left(I_j^R\right)$ is some feasible commitment. To see (9), let us define a function $f(\Delta) = -p^{r,b}(\Delta)_+ + p^{r,s}(-\Delta)_+, \Delta \in \mathbb{R}$. Note that a) $f(\Delta)$ is concave since $p^{r,b} \geq p^{r,s}$, and b) $f(\alpha\Delta) = \alpha f(\Delta), \forall \alpha \geq 0$. With these two properties, by Jensen's inequality, $f(\sum_{j=1}^N \Delta_j) \geq \sum_{j=1}^N f(\Delta_j), \forall \Delta_1, \ldots, \Delta_N$. This then implies (9).

iii) *Budget balance*: It is by design achieved.

iv) *Social welfare maximization*: From i), ii) and iii), it is immediate that the total profit of the RPPs achieves the maximum as if all of them fully cooperate as a grand coalition. ∎

IV. Simulation

A. Data description and simulation setup

We perform the simulation using the NREL dataset [13] based on ten wind power producers (WPPs) located in PJM. For each WPP, both the hourly DA forecast and actual realized generation are available. The generation of the WPPs are modeled as follows:

$$W_i\left(t\right) = \widehat{W}_i\left(t\right) + \epsilon_i\left(t\right),$$

where $\widehat{W}_i$ is the (point) forecast power of WPP i, and ϵ_i is the forecast error, i.e., the difference between the realization and the forecast of generation. For numerical simplicity, we model the forecast error vector using a zero mean jointly Gaussian distribution, $N(0, \Sigma)$. We fit the covariance matrix Σ using the data of these ten WPPs in Jan. 2004. We then run the simulation using the data of the ten WPPs in Feb. 2004. Note that the jointly Gaussian forecast error model does *not* affect the wind power *forecast and generation* data that we use in the simulation. This model only affects how WPPs model their forecast errors when determining DA commitments. To simulate the interactions with the DA-RT markets, we employ the hourly DA and RT locational marginal prices (LMPs), during Feb. 2004, from where the ten WPPs are located. As these ten WPPs are located close to each other, they faced the same LMPs. For each hour of Feb. 2004, the aggregator has the total wind energy forecast $\sum_{i=1}^{10} \widehat{W}_i$, the learned covariance matrix of the forecast errors Σ, and the DA, RT prices. Based on these, the aggregator sets an optimal contract in the DA market (cf. Remark 1), and also resolves any imbalance between the current hour's generation and the DA contract committed one day ago.

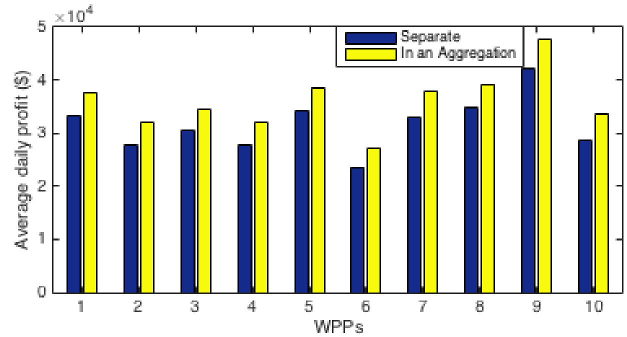

Fig. 2. Comparison of average daily profits of the WPPs.

The comparison between a) the average daily profit of each WPP if it separately participates in the DA-RT markets, and b) when the ten WPPs form an aggregation and each is paid according to the proposed profit allocation mechanism (5), is shown in Fig. 2. It demonstrates the individual rationality achieved by the proposed PAM, as each WPP's allocated profit in the aggregation is greater than its profit when it separately participates in the DA-RT markets. We also know from Theorem 1 that the maximum total profit is achieved as if all WPPs fully cooperate as a grand coalition.

Furthermore, we are interested in comparing the profit allocation under the proposed PAM (5) that elicits truthful private information vs. the fair profit allocation *assuming* that all information are public, i.e., truthfulness is enforced, (see [8] for details). This is plotted in Fig. 3. Note that the proposed PAM and the fair profit allocation assuming truthfulness both achieve the same maximum total profit, and are hence allocating the same amount of total profit among the ten WPPs. From Fig. 3, it is interesting to see that the proposed PAM allocates profit very closely to the fair profit allocation derived by assuming all information are public.

To take a closer look at how the proposed PAM approximately follows the fair profit allocation, we plot in Fig. 4 the

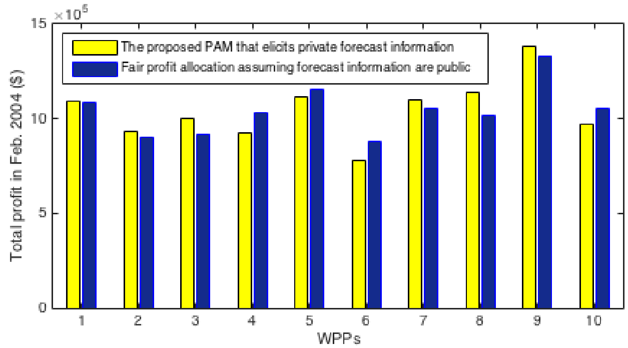

Fig. 3. Comparison of the proposed PAM and the fair PAM that assumes truthfulness.

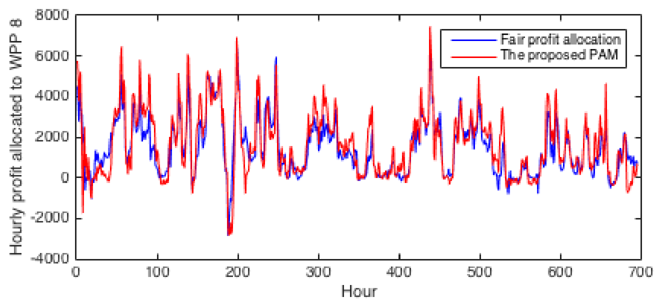

Fig. 4. Comparison of the profits of WPP_8, the proposed PAM vs. the fair PAM that assumes truthfulness.

traces of profit allocation by the two mechanisms for WPP 8 (who experiences the largest difference between the two as observed from Fig. 3), for a total of 696 hours in Feb. 2004. We observe that, again, the proposed PAM follows the fair profit allocation very closely over time.

We further know from prior work that the fair profit allocation assuming truthfulness is *in the core* of the coalitional game of aggregating RPPs [8]. We note that being in the core implies individual rationality for a PAM, and is thus a stronger requirement. An interesting future direction is to find a PAM that, in addition to achieving all the design goals in this work, also achieves being in the core. From the numerical proximity between the proposed PAM and the fair profit allocation, we see that the proposed PAM approximately achieves being in the core.

V. Conclusion

We have proposed a profit allocation mechanism (PAM) for aggregating multiple renewable power producers (RPPs), so that the aggregation participates in two-settlement power markets based on the *private information elicited* from the RPPs on their generation forecast. The proposed PAM achieves a) truthfulness, i.e., it elicits the true private forecast information from the RPPs, b) individual rationality, i.e., it allocates to each RPP a profit that is in expectation no less than what it would obtain by separately participating in the power markets, c) social welfare maximization, i.e., the maximum total profit is achieved for the RPPs as if they fully cooperate as a grand coalition, and d) budget balance, i.e., the total profit earned by the aggregator is always equal to the sum of the profits allocated to all the RPPs. The performance of the proposed PAM is demonstrated using wind power forecast and generation data from ten WPPs in PJM. It is observed that the proposed PAM that elicits true private information closely follows the ideal fair profit allocation that assumes all forecast information are public.

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