

# Optimal Offer Strategies for Energy Storage System Integrated Wind Power Producers in the Day-Ahead Energy and Regulation Markets

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**Abstract** – We make optimal consecutive offer curves for an energy storage system (ESS) integrated wind power producer (WPP) in the co-optimized day-ahead energy and regulation markets. We build the offer curves by solving multi-stage stochastic optimization (MSSO) problems based on the scenarios of pairs consisting of real-time price and wind power forecasts through the progressive hedging method (PHM). We also use the rolling horizon method (RHM) to build the consecutive offer curves for several hours in chronological order. We test the profitability of the offer curves by using the data sampled from the Iberian Peninsula. We show that the offer curves obtained by solving MSSO problems with the PHM and RHM have a higher profitability than offer curves obtained by solving deterministic problems.

**Keywords:** Wind power producers, Energy storage system, Day-ahead market, Progressive hedging method, Offer curve, Rolling horizon method, Multi-stage stochastic optimization.

## 1. Introduction

Wind power has rapidly developed during the past several decades. For example, the wind power capacity in the United States was about 2.5 GW in 2000 but 82 GW in 2016 [1]. Furthermore, the amount of annual wind energy generation was about 5.6 TWh in 2000 but 227 TWh in 2016 [2].

To monetize this wind energy, wind power producers (WPP)s, like conventional generators, can participate in the day-ahead (DA) market and then the WPPs submit offer curves to an independent system operator (ISO) 24 hours before the DA market is settled. The offer curve represents the offer amount at the given DA price. When the DA market is settled, the DA price is cleared, and the dispatch amount of each generator is determined by the offer amount at the DA price in the submitted offer curve.

In this process, WPPs have studied several methods to build profitable offer curves by overcoming the disadvantages of wind power. In particular, the worst disadvantage is relatively low forecasting accuracy. Although various methods have been studied in order to improve the forecasting accuracy, there is still influential forecasting errors [3]. In the real-time (RT) market, if there is an imbalance between the offer amount and actual generated output, there will be a penalty. Therefore, the WPPs have studied how to build an offer curve that mitigates the effect of uncertainty of wind power on their profits.

The most common method is to build an offer curve that is linearly proportional to the inverse of the cumulative distribution function of wind power forecasts [4]. In this process, the profits of WPPs are formulated as a function of the RT price and wind power output, and the offer curve in a closed form is obtained by differentiating the profit [5]. This idea has been extended further. A set of wind power scenarios was used to consider risks from the empirical distribution of wind power forecasts [6]. Furthermore, a bilevel stochastic mixed-integer optimization problem was used to build the optimal offer curve [7]. The upper problem maximized the profit of WPPs, but the lower problem cleared the DA and RT markets.

In addition, the WPPs could increase profits further by considering the correlation between the RT prices and wind power outputs [8]. Moreover, the wind power forecasts could be fit for other distributions, which have higher likelihoods [9]. The more accurate the distribution of wind power forecasts the WPPs have, the higher the WPPs' profits are. Furthermore, the WPPs could consider the risks of paying the penalty for an imbalance between the dispatch level and actual generated wind power by modifying the offer curve based on the conditional value at risk [10].

External hardware can also be used to maximize WPPs' profits. The WPPs can increase profits further by utilizing an energy storage system (ESS). Since the ESS can charge and discharge energy with a very fast ramping rate, the ESS can help WPPs to control outputs to avoid penalties for imbalances and to participate in regulation markets [11]. In this process, the WPPs should consider the characteristics of the ESS, such as a round-trip efficiency, life cycle, and ramping rate [12].

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By following this strategy, the wind turbine market is also moving to ESS-integrated turbines. For example, GE has already been manufacturing ESS-integrated wind turbines [13]. Therefore, the need for strategies for ESS-integrated wind farms has been increasing.

Many strategies have already been studied. In [14], the offer amounts of ESS-integrated WPPs were optimized to maximize the expected profits in the DA market. Furthermore, in [15], the offer curve for the DA market based on the operation of the ESS in the RT market was proposed. In addition, in [16], it was shown that the ESS-integrated WPPs can participate in the energy and regulation markets through an advanced control algorithm to earn extra profits. However, it would be more robust to uncertain future events if wind power scenarios were considered in the framework of a multi-stage stochastic optimization (MSSO) problem.

In this paper, therefore, we build offer curves for ESS-integrated WPPs so that they can maximize their profits in the co-optimized DA energy and regulation markets. The uncertain market situations are captured by considering scenarios from the distributions of wind power and RT price forecasts. The processes of building an offer curve based on the scenarios are designed in a MSSO problem in five stages. We use the progressive hedging method (PHM) in [17] to solve the MSSO problem and rolling horizon method (RHM) to build consecutive offer curves for three hours in chronological order. Finally, our proposal is verified for two weeks on the data sampled from the Iberian Peninsula. Our contributions are summarized as follows:

- We build a more profitable offer curve by considering as many uncertain market scenarios as possible by solving the MSSO problem.
- We use the PHM to solve the MSSO problem with many scenarios within a reasonable amount of time within a parallel computing environment.
- We use the RHM to build consecutive offer curves in chronological order to consider the step-wise ESS operation.
- We increase the profitability of ESS-integrated WPP by participating in the regulation market.

This paper is organized as follows. In Section 2, we describe the formulation of a MSSO based on the scenarios of RT price and wind power forecasts. In Section 3, we explain the PHM and RHM. In Section 4, we show the results of case studies. In Section 5, we conclude this paper and present future work.

## 2. Problem Formulation

In this section, we formulate the MSSO problem to build an offer curve, which can maximize the profit of the ESS-integrated WPP in the co-optimized DA energy and

regulation markets.

From this point forward in this paper, the term WPP will represent an ESS-integrated WPP. We also describe how to generate scenarios of wind power and RT price forecasts from their joint distribution.

### 2.1 Objective Function

In the DA market, when the WPP bids  $B^{da}$ , the naive profit of WPP  $J(\pi^{da}, B^{da})$  is formulated at the DA price  $\pi^{da}$  as

$$J(\pi^{da}, B^{da}) = \pi^{da} \cdot B^{da}. \quad (1)$$

However, the actual generated output can differ from  $B^{da}$  because of wind power uncertainty. Therefore, the WPP considers the penalties for imbalances between forecasted and actual outputs. Because of penalties for these imbalances, the WPP should sell the residual energy at a lower price than the RT price when it generates more than  $B^{da}$ . On the contrary, the WPP should compensate for insufficient energy by paying at a higher price than the RT price when it generates less than  $B^{da}$ . If we consider the imbalances, (1) becomes

$$J(\pi^{da}, B^{da}) = \left[ \begin{array}{l} \pi^{da} \cdot B^{da} \\ +\lambda^+ \cdot \max(P^{da} - B^{da}, 0) \\ -\lambda^- \cdot \max(B^{da} - P^{da}, 0) \end{array} \right], \quad (2)$$

where  $P^{da}$  is the actual generated output. The  $P^{da}$  consists of the wind power output  $W^{da}$ , ESS charging rate  $QC^{da}$ , and ESS discharging rate  $QD^{da}$  as

$$P^{da} = W^{da} - QC^{da} + QD^{da}. \quad (3)$$

The RT price with a penalty for underbidding  $\lambda^+$  is determined by subtracting the penalty from the RT price. Furthermore, the RT price with a penalty for overbidding  $\lambda^-$  is determined by adding the penalty to the RT price. The RT prices with penalties are given as

$$\lambda^+ = \lambda^{rt} \cdot (1 - e^+), \quad (4)$$

$$\lambda^- = \lambda^{rt} \cdot (1 + e^-), \quad (5)$$

where  $e^+$  and  $e^-$  are a ratio of penalty to the RT price. They are 0.1 and 0.15 respectively in this paper.

We also consider WPP's profit in the regulation market. The WPP sets aside enough storage to follow the regulation signal based on the historical regulation utilization factor (RUF), which is the ratio between the procured and deployed amounts. However, the WPP has no information about the RUFs when they participate in the DA market. Therefore, although the sum of the RUF for the regulation up  $d^{ru}$  and down  $d^{rd}$  should always be one, we consider that two RUFs should always become one in this study to make a simple problem. Then we can re-formulate (2) with

RUFs as

$$J(\pi^{da}, B^{da}) = \begin{bmatrix} \pi^{da} \cdot B^{da} \\ + \lambda^+ \cdot \max(P^{da} - B^{da}, 0) \\ - \lambda^- \cdot \max(B^{da} - P^{da}, 0) \\ + (\pi^{ru} + d^{ru} \cdot \lambda^{rt}) \cdot B^{ru} \\ + (\pi^{rd} - d^{ru} \cdot \lambda^{rt}) \cdot B^{rd} \end{bmatrix}. \quad (6)$$

### 2.2 Multi-stage Stochastic Optimization Problem

In this study, we use the MSSO to determine the offer amounts and storage operations. The MSSO problem determines the optimal decision at present by considering decisions about possible future events with probabilistic density functions in a stepwise fashion. In the stochastic approach, the possible future events are represented as a scenario tree. In the stepwise approach, the decision at the current stage depends on the decision at the previous stage in a scenario tree.

We change our problem as a MSSO problem to maximize the WPP’s expected profit under a scenario tree, in which each level of branches represents a set of stages  $H$ . The scenario tree can be decomposed into a set of scenarios  $S$  as shown in Fig. 1.

That is, we can rewrite all variables as a form containing stage and scenario. For example, we rewrite the offer amount for the DA energy market  $B^{da}$  as  $B_{t,k}^{da}$  at the given stage  $t$  and scenario  $k$ , where  $\forall t \in H$  and  $\forall k \in S$ .

### 2.3 Wind Power Output and RT Price Scenarios

In order to minimize the effect of forecasting errors on the profit, we synthesize wind power and RT price scenarios based on the joint distribution of wind power and RT price forecasts and determine the optimal offer amount based on these scenarios. If a WPP determines an optimal

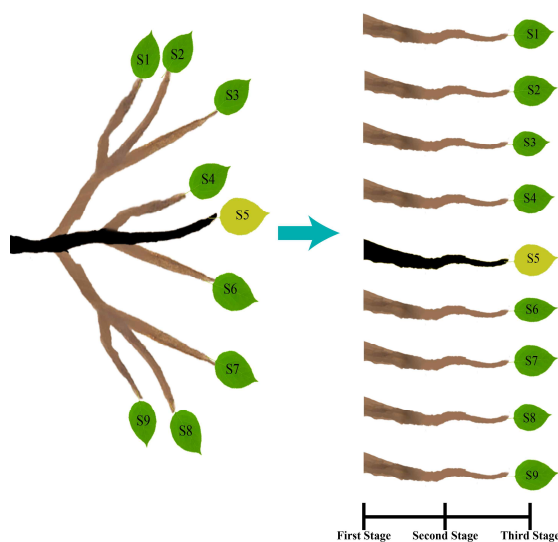


Fig. 1. A scenario tree and its decomposed scenarios

offer amount based on a single pair of wind power and RT price forecasts under any forecasting error, the WPP will have a profit less than the expectation. We also consider the correlation between wind power outputs and RT prices to build offer curves based on more realistic data and to have plausible pairs of wind power and RT price forecasts.

The process of generating scenarios is as follows. First, we sequentially predict the point forecasts of wind power output and RT prices using the persistent method based on data from the Iberian Peninsula. Then, we calculate the forecasting errors by subtracting the point forecasts from the actual values. From the empirical joint distribution of wind power and RT price forecasting errors, we oversample 100,000 forecasting errors and build the histogram of joint error distribution in Fig. 2. Second, we superpose the point forecasts and error distribution and obtain the joint distribution of wind power and RT price forecasts. Third, we generate scenarios and their probabilities from the joint distribution. Scenarios consist of a pair of forecasted wind power output and RT price, and each scenario has its own probability. Finally, we repeat this process to the number of stages and build a scenario tree by branching scenarios in series.

Although the wind power and RT price scenarios are introduced to reflect risks from uncertain situations, they increase the complexity of the MSSO problem. Furthermore, by solving the MSSO problem, we try to find the optimal expected profit based on many scenarios in different stages, it has decision variables whenever the scenario tree is split for all stages. That is, the MSSO problem becomes a very big problem and requires heavy computational resources. Therefore, we need an algorithm to decompose the MSSO problem for each scenario to better handle the complexity of the MSSO.

### 2.4 Constraints

There are constraints to make an offer curve based on ESS operations for all scenarios. In the DA market, the

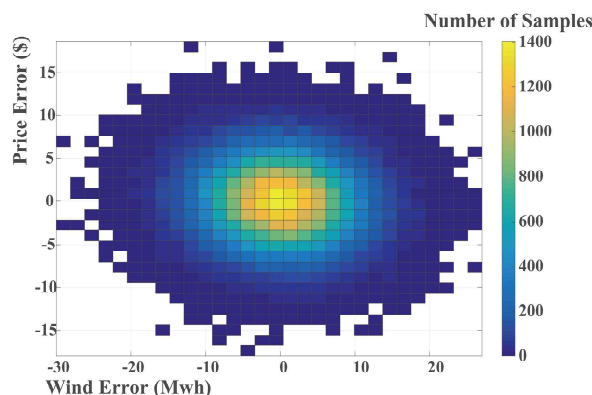


Fig. 2. Two-dimensional histogram of 100,000 samples of wind power and RT price forecasting errors based on data from the Iberian Peninsula

sum of wind power forecast  $w_{t,k}^f$ , charging amount  $QC_{t,k}$ , and discharging amount  $QD_{t,k}$  will be used to provide the offer amounts for the DA energy market, regulation up market, and the regulation down market as follows:

$$w_{t,k}^f = W_{t,k}^{da} + W_{t,k}^{ru} - W_{t,k}^{rd}, \quad \forall t \in H, \forall k \in S, \quad (7)$$

$$QC_{t,k} = QC_{t,k}^{da} + QC_{t,k}^{ru} - QC_{t,k}^{rd}, \quad \forall t \in H, \forall k \in S, \quad (8)$$

$$QD_{t,k} = QD_{t,k}^{da} + QD_{t,k}^{ru} - QD_{t,k}^{rd}, \quad \forall t \in H, \forall k \in S. \quad (9)$$

It should be noted that the WPP must not participate in the regulation up and down markets simultaneously. The binary indicator for regulation markets  $Z_{t,k}$  determines the bidding position in the regulation market as

$$0 \leq B_{t,k}^{ru} \leq b^{\text{lim}} \cdot Z_{t,k}, \quad \forall t \in H, \forall k \in S, \quad (10)$$

$$0 \leq B_{t,k}^{rd} \leq b^{\text{lim}} \cdot (1 - Z_{t,k}), \quad \forall t \in H, \forall k \in S, \quad (11)$$

where offer amounts for the regulation market  $B_{t,k}^{ru}$  and  $B_{t,k}^{rd}$  are determined respectively as

$$B_{t,k}^{ru} = W_{t,k}^{ru} - QC_{t,k}^{ru} + QD_{t,k}^{ru}, \quad \forall t \in H, \forall k \in S, \quad (12)$$

$$B_{t,k}^{rd} = W_{t,k}^{rd} - QC_{t,k}^{rd} + QD_{t,k}^{rd}, \quad \forall t \in H, \forall k \in S. \quad (13)$$

Constraints from (10) to (13) are also applied to  $W_{t,k}^{ru}$ ,  $W_{t,k}^{rd}$ ,  $QC_{t,k}^{ru}$ ,  $QC_{t,k}^{rd}$ ,  $QD_{t,k}^{ru}$ , and  $QD_{t,k}^{rd}$  respectively. Furthermore, the WPP considers the specifications of the battery, such as a state of charge (SOC), round-trip efficiency, charging & discharging rate, and maximum & minimum energy limits as follows:

$$Soc_{t,k} = Soc_{t-1,k} - \eta \cdot QC_{t,k} + \frac{QD_{t,k}}{\eta}, \quad (14)$$

$$\forall t \in \{2, \dots, \tau\}, \forall k \in S,$$

$$0 \leq QC_{t,k} \leq q^{\text{lim}}, \quad \forall t \in H, \forall k \in S, \quad (15)$$

$$0 \leq QD_{t,k} \leq q^{\text{lim}}, \quad \forall t \in H, \forall k \in S, \quad (16)$$

$$l \leq Soc_{t,k} \leq u, \quad \forall t \in H, \forall k \in S. \quad (17)$$

We also substitute the second and third terms of the max function in (6) as

$$\lambda_{t,k}^+ \cdot \max(P_{t,k}^{da} - B_{t,k}^{da}, 0) - \lambda_{t,k}^- \cdot \max(B_{t,k}^{da} - P_{t,k}^{da}, 0) \\ = \lambda_{t,k}^+ \cdot (P_{t,k}^{da} - B_{t,k}^{da} + \alpha_{t,k}^+) + \lambda_{t,k}^- \cdot (P_{t,k}^{da} - B_{t,k}^{da} + \alpha_{t,k}^-) \quad (18)$$

with the constraints below:

$$\alpha_{t,k}^+ \geq 0, \quad \forall t \in H, \forall k \in S, \quad (19)$$

$$\alpha_{t,k}^- \leq 0, \quad \forall t \in H, \forall k \in S, \quad (20)$$

$$P_{t,k}^{da} - B_{t,k}^{da} + \alpha_{t,k}^+ \geq 0, \quad \forall t \in H, \forall k \in S, \quad (21)$$

$$P_{t,k}^{da} - B_{t,k}^{da} + \alpha_{t,k}^- \leq 0, \quad \forall t \in H, \forall k \in S, \quad (22)$$

$$a_{t,k}^+ + \alpha_{t,k}^- = B_{t,k}^{da} - P_{t,k}^{da}, \quad \forall t \in H, \forall k \in S, \quad (23)$$

where,  $a_{t,k}^+$  and  $a_{t,k}^-$  are variables whose lower terms play the same role as the upper terms in (18). If  $a_{t,k}^+$  is nonzero, then  $a_{t,k}^-$  is zero, and if  $a_{t,k}^-$  is nonzero, then  $a_{t,k}^+$  is zero as a result of (19)-(23), so either  $a_{t,k}^+$  or  $a_{t,k}^-$  is always equal to  $B_{t,k}^{da} - P_{t,k}^{da}$ , regardless of a sign of  $B_{t,k}^{da} - P_{t,k}^{da}$  in (23).

Furthermore, we block the simultaneous charging and discharging by subtracting the sum of the charging and discharging amounts multiplied by a very small number  $m$ .

Finally, the MSSO problem of maximizing the WPP's profit can be formulated as:

$$\max \sum_{k=1}^K \sum_{t=1}^{\tau} \begin{bmatrix} \pi_{t,k}^{da} \cdot B_{t,k}^{da} \\ + \lambda_{t,k}^+ \cdot (P_{t,k}^{da} - B_{t,k}^{da} + \alpha_{t,k}^+) \\ - \lambda_{t,k}^- \cdot (P_{t,k}^{da} - B_{t,k}^{da} + \alpha_{t,k}^-) \\ + (\pi_{t,k}^{ru} + d_{t,k}^{ru} \cdot \lambda_{t,k}^{rt}) \cdot B_{t,k}^{ru} \\ + (\pi_{t,k}^{rd} - d_{t,k}^{rd} \cdot \lambda_{t,k}^{rt}) \cdot B_{t,k}^{rd} \\ - m \cdot (QC_{t,k} + QD_{t,k}) \end{bmatrix}. \quad (24)$$

### 3. Solution of Optimization Problem

In this section, we describe the PHM, which is used to solve the MSSO problem, and the rolling horizon method (RHM), which is used to build consecutive offer curves in chronological order. The overall process of calculating an offer curve through the PHM and RHM is shown in Fig. 3.

#### 3.1 Progressive Hedging Method

The key idea of the PHM is to solve several sub-

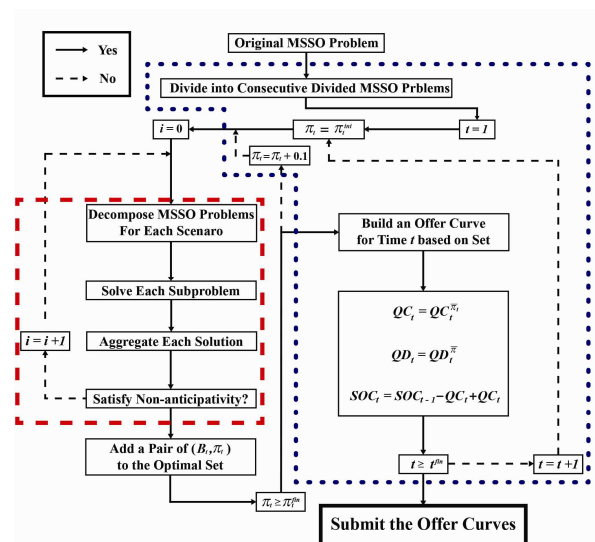


Fig. 3. Flowcharts to build consecutive offer curves by using progressive hedging (dash line) and rolling horizon (dotted line) methods

problems for each scenario and each iteration until an intermediate solution is converged to a final solution instead of solving the MSSO problem itself. The scenarios are obtained by decomposing a scenario tree. An intermediate decision is obtained by averaging individual decisions of sub-problems with probabilities of scenarios. For each iteration, an intermediate decision is updated, and it becomes the final solution when it satisfies the stopping criterion for convergence. In this study, when the difference between the previous and new intermediate decisions is less than a predetermined threshold, the iteration stops.

### 3.2 Non-anticipativity Constraint

By decomposing the MSSO problem into several small sub-problems, we can reduce the computational time. However, this leads to the need for a non-anticipativity constraint that combines the solutions of the sub-problems by following the structure of a scenario tree. If scenarios shared the same branches in the scenario tree, they should have the same decisions at those branches. If the stages share the same branches, the non-anticipativity constraint forces the equality constraints among decision variables at each stage after weighting by the corresponding scenario probability.

The non-anticipativity constraint is represented as:

$$\mathbf{I}y^n = \mathbf{J}y_k, \tag{25}$$

where  $\mathbf{J}$  represents the probabilities of scenarios.

However, the non-anticipativity constraint destroys the parallel structure among scenarios. This contradiction can be avoided by relaxing this constraint through the Lagrangian dual. The non-anticipativity constraint is placed in the objective function with Lagrangian  $\lambda_k^n$ , for  $k$ th scenario an  $n$ th iteration. Each scenario has a different  $\lambda_k^n$  because such scenario has a different  $y_{t,k}$ . Furthermore,  $\lambda_k^n$  should be updated for each iteration because the intermediate decision also changes.

In summary, the PHM can be formulated as:

$$\min_y \sum_{k=1}^K \rho_k \left[ \sum_{t=1}^T f_t(y_{t,k}, y_{t+1,k}, k) + L_k \right], \tag{26}$$

$$L_k = \lambda_k^n (y_k - \hat{y}^n) + \frac{r}{2} \|y_k - \hat{y}^n\|^2, \tag{27}$$

$$h_\tau(x_{\tau,\kappa}, x_{\tau+1,\kappa}, k) \leq 0, \tag{28}$$

$$\forall n = 1, \dots, M, \quad \forall t = 1, \dots, \tau - 1, \quad \forall k = 1, \dots, \kappa,$$

where  $y_k = [y_{1,k}, \dots, y_{\tau,k}]$  is the solution of sub-problems,  $\hat{y}^n = [y_1^n, \dots, y_\tau^n]$  is the intermediate decision, and  $\rho_k$  is a probability of each scenario. Furthermore,  $L_k$  represents the relaxed non-anticipativity condition. In this process, the projected value of the intermediate decision is used to take advantage of the recursive calculation

through the proximal point algorithm [18]. Finally, the difference between the intermediate decision and the decision variables at each stage is included in an objective function as a cost. It should be noted that the quadratic term with a step size  $r$  is added to have a faster and more stable convergence rate [19]. Finally, for each  $k$ , we solve (26), and the intermediate decision can be obtained as:

$$\hat{y}^{n+1} = \mathbf{J}y_k. \tag{29}$$

Furthermore,  $\lambda_k^n$  can be updated as:

$$\lambda_k^{n+1} = \lambda_k^n + r(y_k - \hat{y}^{n+1}). \tag{30}$$

In summary,  $\hat{y}^{n+1}$  is updated first by using the results of several sub-problems, and the difference between the updated  $\hat{y}^{n+1}$  and the solution of sub-problems  $y_k$  is used to update  $\lambda_k^n$ . We repeat this process for each iteration  $n$  until  $\hat{y}^{n+1}$  satisfies the stopping criterion. The convergence is secured by the relaxed non-anticipativity condition through the proximal point algorithm, which is the key contribution of the PHM [20].

In our study, however, the binary indicator  $Z_{t,k}$  does not have the same value in all sub-problems. Since solutions of sub-problems are averaged, the intermediate decision binary is neither zero nor one. We solve this problem via approximation. Finally, the MSSO problem can be solved through the PHM with the non-anticipativity constraint.

### 3.3 Offer Curve Generation

We use MSSO problems to build offer curves. At every possible DA price, we solve the MSSO problem to find optimal ESS operations and an optimal energy offer amount so that the offer curve consists of the pair of DA price and offer amount. We repeat this process for a set of DA prices to get several offer amounts. The set of DA prices consists of prices that differ by 0.1 euros from 10 euros less than the forecasted RT price to 10 euros more than the forecasted RT price. After solving the MSSO for every price in the set, we can get an offer curve at the given time by plotting the DA prices with respect to the offer amounts.

### 3.4 Rolling Horizon Method

We use the RHM in [21] to build consecutive offer curves in chronological order by solving MSSO problems without actual ESS operations at present. When the consecutive offer curves are built, after the offer curve for the current hour is built, we build the offer curve for the next hour by solving the MSSO problem through the PHM. However, in this process, the initial SOC level for the next hour is not determined yet because the storage operation for the current hour can be determined after the DA price is

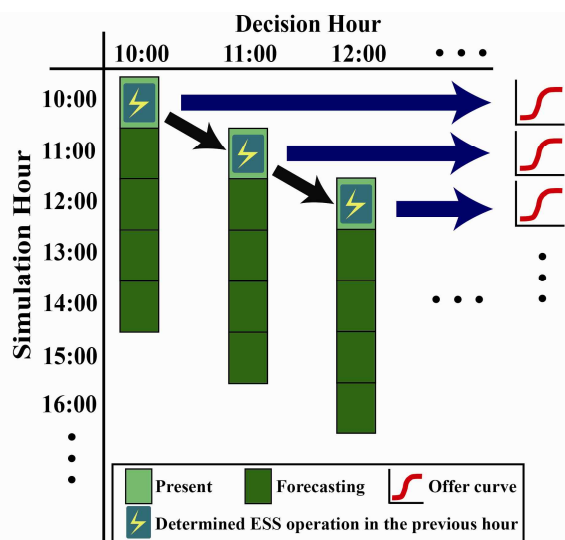


Fig. 4. The consecutive process of the RHM

determined. In this process, the actual DA price is assumed to be the forecasted DA price. Since we build the offer curve by solving MSSO problems through the PHM, we need a set of DA price forecasts for a given time.

In the RHM, the initial SOC level of the ESS for the MSSO problem at the next hour is fixed at the result of ESS operation for the MSSO problem with the DA price forecast at the next hour. Then, we shift an hour again after fixing the ESS operation in the current hour and build the offer curve for the next hour. In this study, we repeat this process for three hours in a series. Fig. 4 shows that the offer curves are built based on the previous ESS operation.

It should be noted that we fix the current ESS operation to build a next offer curve by considering the possible ESS operation, but not to fix an ESS operation schedule. In other words, the fixed ESS operation is a virtual operation, which is assumed to solve the next MSSO problem, so the actual ESS operation in the RT may differ from the fixed operation.

#### 4. Case Studies

In this section, we simulate several cases and compare profits to show the profitability of the PHM and RHM in building the offer curves for the DA energy and regulation markets. We formulate four cases as the MSSO problems and simulate in the DA and RT markets. The WPPs' profits in all cases are finalized after simulated operations in the DA and RT markets.

##### 4.1 Case Structure

In the simulation, four cases are simulated to prove the profitability of the PHM and RHM in building the offer curves for the DA energy and regulation markets. We summarize the overall simulation process in this study in

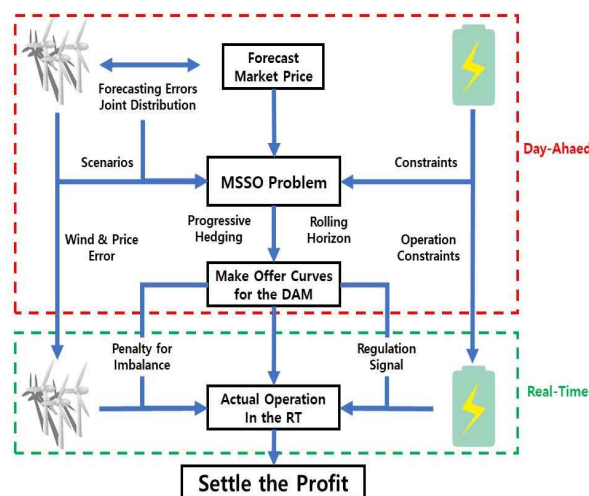


Fig. 5. Overall simulation process

Fig. 5.

In all cases, four same ESS-integrated WPPs are assumed. They have a wind farm, which has a capacity of 200 MW, and an ESS, which has a size of 50 MWh, a rate of 25 MW, and a round-trip efficiency of 90%. Furthermore, the maximum and minimum energy limits of the ESS are 10% and 90% of its size, respectively.

Furthermore, an offer curve for every hour is built based on the forecasted RT prices and wind power scenarios. The price scenarios for the DA energy and regulation markets are synthesized based on the sampled data from the Iberian Peninsula. Particularly, wind power scenarios are also made by scaling down based on the sampled data from the Iberian Peninsula. The scenario trees for each given time are made in a form with 91 nodes and 81 scenarios, which have probability, respectively, including the subsequent 2 hours for the simulation in the DA and RT markets.

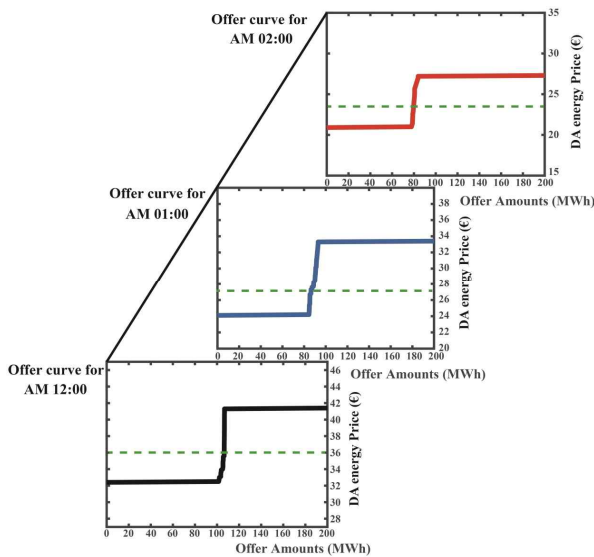
In order to calculate profits, the ESS operations in the RT are determined by solving the three-stage stochastic optimization problems based on the offer amounts in the DA markets. We obtain the actual ESS operation in the RT market by solving a MSSO problem for the RT market by considering the generated wind power, actual DA price, actual RT price, determined offer amounts, RUFs, and penalty. Finally, we settle the WPPs' profits based on the simulation results. After the benefits of all cases have been calculated, we demonstrate the effectiveness of the proposed strategy by comparing each case.

##### 4.2 Result Analysis

We simulate for two weeks based on data from the Iberian Peninsula for each case to obtain the WPPs' profits. Although all four ESS-integrated WPPs have wind farm and battery of the same characteristics, they participate in the markets in different ways. The results of all cases are also presented in Table 1. In particular, if the RHM is used, the initial SOC at the next hour is fixed at the result of the

**Table 1.** WPPs’ profits of each case in two weeks

	Case 1	Case 2	Case 3	Case 4
Energy market	O	O	O	O
Regulation market	O		O	O
Rolling horizon method	O	O		O
Stochastic	O	O	O	
Profit in the DA energy market (€)	1,306,084	1,596,650	1,349,413	1,188,392
Profit in the regulation market (€)	658,266	0	478,544	657,701
Total profit (€)	1,964,350	1,596,650	1,827,957	1,846,093



**Fig. 6.** Consecutive offer curves in Case 1

ESS operation in the previous hour. On the other hand, if the RHM is not used, the initial SOC is fixed at 50% without considering the previous ESS operation.

In Case 1, the WPP builds three offer curves for three hours by solving a five-stage stochastic optimization for each hour. It should be noted that the offer curves are generated for the first three hours, not for 24 hours, to reduce the computational time. The optimal amount in the first hour is obtained by solving the first MSSO problem. Then, by fixing the SOC in the second problem at the SOC in the first problem, the optimal amount in the second hour is obtained by solving the second MSSO problem. Finally, the offer curves for given hours are obtained by repeating this process. Three offer curves in chronological order, for example, are plotted in Fig. 6.

In order to show the profitability of participating in the regulation market, we compare the WPPs’ profit in Case 1 and Case 2. Participating in the regulation market yields a 23% higher profit for the WPP than participating only in the energy market. Although the profit of Case 2 in the DA energy market is 22% higher than the profit of Case 1 in the same market, Case 1 has earned the profit in the regulation market, which is enough to compensate the gap.

It shows that WPPs can earn more profits by participating in the regulation market.

In addition, to show the effectiveness of the RHM, we compare WPP’s profits in Case 1 and Case 3. The WPP’s total profit in Case 3 is 7% less than the profit in Case 1, and the WPP’s profit in the regulation market in Case 3 is 37.3% less than in Case 1. This suggests that the proposed ESS operation assumption is similar to an actual operation and can yield a higher profit than the case without the RHM in the regulation market. It shows that WPPs can maximize their profits in the regulation market by scheduling ESS operations more accurately.

Finally, to show the effectiveness of the MSSO with the PHM, we compare the WPPs’ profit in Case 1 and Case 4. Each WPP’s profit in the regulation market in Case 4 and Case 1 is similar. However, the profit in Case 1 is 10% higher than the profit in Case 4 in the DA energy market. The reason is that the WPP in Case 1 predicts uncertain future events more accurate than the WPP in Case 4 by using scenarios that reflect the forecasting errors. It shows that the scenarios reflecting forecasting errors can contribute the WPP’s profits in the DA energy market.

## 5. Conclusion

We propose a novel offer curve generation strategy for the ESS-integrated WPP by using the RHM. The strategy is obtained by solving the MSSO problem, whose solution is obtained through the PHM within a parallel computing environment. We show that the offer curve based on many scenarios has a higher profit than the offer curve based on a single scenario. We also show that the accurate forecasts through the many scenarios and the accurate ESS operation through the RHM can increase WPPs’ profits in the DA energy and regulation markets, respectively. The computational time increases if many scenarios are used, but the computational time is still modest since the problem is solved within a parallel computing environment. In future work, we will extend the proposed strategy in the RT market. Furthermore, we will study how to stabilize binary or integer intermediate variables in the MSSO problems with the PHM. Currently, since the intermediate decision variables are averaged in the PHM, the binary or integer variables cannot have stable values in the PHM.

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## Nomenclature

### Indices and Index Sets:

$k \in S$  Wind and price scenarios  $S = \{1, \dots, \kappa\}$   
 $t \in H$  Time  $H = \{1, \dots, \tau\}$

### Parameters:

$\eta$  Round-trip efficiency of battery  
 $u$  Maximum energy limit of battery  
 $l$  Minimum energy limit of battery  
 $q^{\text{lim}}$  Maximum rate of battery operation  
 $b^{\text{lim}}$  Maximum offer amount for regulation market  
 $\rho_k$  Probability for  $k$ th scenario  
 $\pi_{t,k}^{\text{da}}$  Day-ahead (DA) energy price at time  $t$  for  $k$  th scenario  
 $\pi_{t,k}^{\text{ru}}$  Regulation up (RU) price at time  $t$  for  $k$  th scenario  
 $\pi_{t,k}^{\text{rd}}$  Regulation down (RD) price at time  $t$  for  $k$  th scenario  
 $\lambda_{t,k}^{\text{rt}}$  Real-time price at time  $t$  for  $k$  th scenario  
 $\lambda_{t,k}^+$  Price with a penalty for underbidding at time  $t$  for  $k$  th scenario  
 $\lambda_{t,k}^-$  Price with a penalty for overbidding at time  $t$  for  $k$  th scenario  
 $w_{t,k}^f$  Forecasted wind power output at time  $t$  for  $k$  th scenario  
 $d_{t,k}^{\text{ru}}$  RU utilization factor at time  $t$  for  $k$  th scenario  
 $d_{t,k}^{\text{rd}}$  RD utilization factor at time  $t$  for  $k$  th scenario

### Decision Variables:

$W_{t,k}^{\text{da}}$  Wind power output for DA market at time  $t$  for  $k$  th scenario  
 $W_{t,k}^{\text{ru}}$  Wind power output for RU market at time  $t$  for  $k$  th scenario  
 $W_{t,k}^{\text{rd}}$  Wind power output for RD market at time  $t$  for  $k$  th scenario  
 $B_{t,k}^{\text{da}}$  Offer amount for DA market at time  $t$  for  $k$  th scenario  
 $B_{t,k}^{\text{ru}}$  Offer amount for RU market at time  $t$  for  $k$  th scenario  
 $B_{t,k}^{\text{rd}}$  Offer amount for RD market at time  $t$  for  $k$  th scenario  
 $QC_{t,k}$  Total charging amount of battery at time  $t$  for  $k$  th scenario  
 $QC_{t,k}^{\text{da}}$  Charging amount for DA market at time  $t$  for  $k$  th scenario  
 $QC_{t,k}^{\text{ru}}$  Charging amount for RU market at time  $t$  for  $k$  th scenario  
 $QC_{t,k}^{\text{rd}}$  Charging amount for RD market at time  $t$  for  $k$  th scenario  
 $QD_{t,k}$  Total discharging amount of battery at time  $t$  for  $k$  th scenario  
 $QD_{t,k}^{\text{da}}$  Discharging amount for DA market at time  $t$  for  $k$  th scenario  
 $QD_{t,k}^{\text{ru}}$  Discharging amount for RU market at time  $t$  for  $k$  th scenario

$QD_{t,k}^{\text{rd}}$  Discharging amount for RD market at time  $t$  for  $k$  th scenario  
 $Soc_{t,k}$  State of charge of battery at time  $t$  for  $k$  th scenario  
 $Z_{t,k}$  Binary indicator for regulation market at time  $t$  for  $k$  th scenario

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