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Optimal Bidding Strategies for Wind Power Producers in the Day-ahead Electricity Market

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Abstract: Wind Power Producers (WPPs) seek to maximize profit and minimize the imbalance costs when bidding into the day-ahead market, but uncertainties in the hourly available wind and forecasting errors make the bidding risky. This paper assumes that hourly wind power output given by the forecast follows a normal distribution, and proposes three different bidding strategies, *i.e.*, the expected profit-maximization strategy (EPS), the chance-constrained programming-based strategy (CPS) and the multi-objective bidding strategy (ECPS). Analytical solutions under the three strategies are obtained. Comparisons among the three strategies are conducted on a hypothetical wind farm which follows the Spanish market rules. Results show that bid under the EPS is highly dependent on market clearing price, imbalance prices, and also the mean value and standard deviation of wind forecast, and that bid under the CPS is largely driven by risk parameters and the mean value and standard deviation of the wind forecast. The ECPS combining both EPS and CPS tends to choose a compromise bid. Furthermore, the ECPS can effectively control the tradeoff between expected profit and target profit for WPPs operating in volatile electricity markets.

Keywords: wind power; bidding; day-ahead electricity market; risk; chance-constrained programming; multi-objective optimization

List of symbols

R	profit in single period [€], a random variable
P_b	quantity bid into day-ahead market in single period [MW]
P_t	real power generated by the concerned wind farm [MW]
I_c	Imbalance costs in single period [€]
P_{max}	rated power of the concerned wind farm [MW]
λ_s	day-ahead market price in single period [€/MWh]
λ_{sell}	price of positive imbalances incurred in single period [€/MWh]
λ_{buy}	price of negative imbalances incurred in single period [€/MWh]
μ_t	mean value of wind power forecast in single period t [MW]
δ_t	standard deviation of wind power forecast in single period t [MW]
J	target profit in single period [€]
β	confidence level, $\beta \in [0,1]$
$f(P_t)$	probability density function of random variable P_t
$h(R)$	probability density function of random variable R
$H(R)$	cumulative distribution function of random variable R
$\Pr\{A\}$	probability of event A
$F_1(P_b)$	expected profit function in single period [€]
$F_2(P_b)$	target profit function in single period [€]
$G(P_b)$	weighted sum of $F_1(P_b)$ and $F_2(P_b)$
α	weight assigned to $G(P_b)$
F_i^{max}	maximal value of single objective, $i = 1,2$
F_i^{min}	minimal value of single objective, $i = 1,2$
u_{F_i}	membership function of F_i
u_D	normalized membership function
M	number of nondominated solutions
N_{obj}	number of objectives, in this article, $N_{obj} = 2$

1. Introduction

Encouraged by hospitable legal and financial policies, the worldwide installation of wind power has increased significantly over the past several years. In some markets like the Spanish market and Nordic power market, wind power producers (WPPs) have the option to bid in the electricity market or to sell all the energy to the market operator. When bidding into the electricity market, WPPs commit power production to the market operator for scheduling. However, due to the intermittency and unpredictability of wind power generation, the final power delivered usually differs from the power committed in the day-ahead market. This energy deviation results in imbalance costs, which must be paid by those who produce the wind power [1,2]. Although the accurate prediction of wind power generation (forecasted by WPPs) can reduce the imbalance costs to some extent, prediction precision is limited to the forecast length [3]; furthermore, optimal bids often do not coincide with the best predictions [4]. Thus, WPPs tend to find optimal bids which take into account both the maximal profit and minimal imbalance costs.

As the installation capacity of wind power has increased in recent years, so have researchers' interests in proposing bidding strategies in the short-term electricity market for WPPs [5–9]. In [5], a bidding strategy using Markov probabilities for a wind farm in the United Kingdom to determine the best energy contract level was presented; this study demonstrated how a change in market closure delay and in the number of trades per day affects the overall expected imbalance costs for the wind farm. A probability density function representing the accuracy of the prediction model was defined as a Beta function in [6], and a probabilistic methodology to estimate the energy costs associated with the prediction errors was similarly proposed. Reference [7] presented a general methodology for deriving optimal bidding strategies based on probabilistic forecasts of wind production; modeling of the potential WPP sensitivity to regulation costs was also discussed. Matevosyan and Soder [8] utilized the ARMA model to simulate scenarios for wind speed forecasting errors, and developed a bidding strategy as a stochastic mixed integer programming problem to maximize expected profit and minimize the imbalance costs for WPPs. A stochastic programming approach was proposed to generate the optimal offers under uncertainty in wind generation and electricity prices [9].

The aforementioned literatures take into account the imbalance costs caused by the stochastic nature of wind, without considering however the risk that WPPs face with regard to the bidding process itself. Risk and profit are two conflicting objectives, as high profit is usually accompanied by high risk. It is critical for WPPs to be able to estimate their expected risk during the bidding process.

Optimal trading strategies for wind generation that consider the risk to power producers have been extensively researched [10–20]. In [10], different risk management approaches for wind trading in the electricity market were discussed, and the utility function method was considered to be more effective than the mean variance model. Xue *et al.* [11] defined the power producer's attitude towards risk as the membership function based on the fuzzy set theory, and subsequently proposed a multi-objective optimal bidding strategy; this fuzzy optimization method was extended to coordinated trading of wind generators and an energy storage device (ESD) in [12], which took into account the risk quantified by computing expected energy not served (EENS). Bidding strategies based on utility and the conditional value at risk (CVaR) were derived to study the optimal bidding strategies for WPPs in [13,14]. Reference [15] developed optimal bidding strategy including various trading floors based on the scenario method, and α -CVaR was used to calculate the expected profit of the $(1 - \alpha)100\%$ scenarios with lowest profit similar to that reported in [16]. In [17], a CVaR constrained for the bid that maximized the expected revenue was proposed as a way of reducing the risk. Catalao *et al.* [18] provided a two-stage stochastic programming approach for WPPs considering uncertainties related to electricity market and wind power generation, and also incorporated the risk aversion by limiting the volatility of the expected profit through the CVaR methodology. Reference [19] presented new analytical expressions for determining the optimal forward market strategy for wind generators under the risk-neutral and risk-averse cases, and the methods required specification only of the expected real-time prices given the forward price and wind output. Wang *et al.* [20] established a two-stage optimization model based on chance-constrained programming for unit commitment with uncertain wind power output, and described risk as the probability that a specific bidding strategy was accepted. In [21], a decision-making model for investing wind farm based on real options was presented and a risk profile characterization of the model was developed. These bidding strategy-specific studies provide a valuable framework for our own research in this field.

In this article, hourly wind power output is assumed to follow a normal distribution [22–24], and three different bidding strategies are developed for WPPs to derive optimal day-ahead bids in the Spanish market. In fact, these strategies can be applied to any market with some minor adjustment. This article is organized as follows: A description of the problem, including the market framework and a basic model, is provided in Section 2. Section 3 describes the modeling details of three different bidding strategies, along with proposed model-specific solutions. Bidding results are compared in a case study in Section 4. Lastly, Section 5 summarizes our conclusions.

2. Problem Description

2.1. Market Framework

Consider a pool-based electricity market in which power suppliers submit day-ahead bids for each hour before closure of the day-ahead market (e.g., 10 AM). Unlike conventional generators, WPPs are generally regarded as price-takers, and are often not allowed to bid multiple price/quantity pairs. After a certain time of day (e.g., 3 PM), the market operator aggregates the hourly bids to determine the hourly market clearing prices (λ_s , MCPs) and the volumes being traded by identifying the point at which the supply bids and demand cross. Afterwards, the balancing market is carried out closer to real-time; this helps ensure that there is a real-time balance between generation and demand by offsetting the deviations between the real-time generation and the energy program cleared in the day-ahead market [15]. With such a market structure, the gap between the time at which the bids are submitted and the beginning of the energy delivery period is 14–38 hours [8]; the wind power forecast length should also be within this range. Because of the significant time gap, some markets include an intra-day market, where all producers correct their bids using more recent and accurate predictions. These actions are intended to reduce the differences between the expected production and the schedule cleared in the day-ahead market.

The objective of WPPs is to maximize their expected profits from trading energy in the day-ahead market while also minimizing the imbalance costs incurred in the balancing market. Different markets apply different imbalance penalty rules. In the Spanish market, the price for the positive energy deviation (higher real-time generation than scheduled) λ_{sell} and the price for the negative energy deviation (lower real-time generation than the energy program cleared) λ_{buy} are settled for each hour. The imbalance price mechanism depends on the sign of imbalance of the whole system imbalance [15]. Specifically, when the system imbalance is positive (generation is greater than demand), those suppliers who generate more power than scheduled are penalized by λ_{sell} , while those who generate less power than scheduled are not penalized. These latter sellers help to alleviate the positive system imbalance and are paid by λ_s . The opposite holds true when the system imbalance is negative, (*i.e.*, generation is less than demand).

From the above imbalance mechanism, a reasonable relation among λ_s , λ_{sell} and λ_{buy} can be expressed in the following inequation [11]:

$$0 \leq \lambda_{sell} \leq \lambda_s \leq \lambda_{buy} \quad (1)$$

In this paper, we don't focus on the prediction of prices, market clearing prices and the imbalance prices are considered to be given data, which can be derived from prediction models.

2.2. Profit of Wind Power Producers

Consider a WPP that bids the quantity of p_b into the day-ahead market for period t , but actually generates p_t . Since there are no inter-temporal constraints [8], we can formulate an hourly bidding problem. Solving the problem for each hour will give a day-ahead bidding strategy. The profit of the WPP for period t is described as follows:

$$R = p_b \lambda_s + I_c \quad (2)$$

where R is the profit which means the income from all markets, not the profit after taking into account production costs of generation. I_c is the imbalance costs resulting from the balancing process. Here, I_c is given by:

$$I_c = \begin{cases} \lambda_{buy}(p_t - p_b), & p_t \leq p_b \\ \lambda_{sell}(p_t - p_b), & p_t > p_b \end{cases} \quad (3)$$

Note that p_t is a random variable and cannot be obtained in day-ahead. We assume that it follows normal distribution [22–24]. Then we have:

$$p_t \sim N(\mu_t, \delta_t^2) \quad (4)$$

The mean value μ_t and the standard deviation δ_t of hourly wind power forecast are assumed to be given data.

3. Mathematical Formulation

This section proposes three different bidding strategies for wind power producers to use when participating in the day-ahead market, *i.e.*, the expected profit-maximization strategy (EPS), the chance-constrained programming-based strategy (CPS) and the multi-objective bidding strategy (ECPS). The EPS aims to maximize the expected profit and is a risk-neutral strategy. The CPS calculates the maximum target profit considering the risk which is defined as the probability that target profit cannot be realized. The ECPS combines the EPS and the CPS, and is formulated as a multi-objective model.

3.1. Expected Profit-Maximization Bidding Strategy

Let us denote the probability density function (PDF) by $f(p_t)$; in turn, this gives us an expected profit of a WPP as follows:

$$\begin{aligned} E[R] &= p_b \lambda_s + E[I_c] \\ &= p_b \lambda_s + \int_{-\infty}^{p_b} (p_t - p_b) \lambda_{buy} f(p_t) dp_t + \int_{p_b}^{+\infty} (p_t - p_b) \lambda_{sell} f(p_t) dp_t \end{aligned} \quad (5)$$

where $E[R]$ is the mathematical expectation of the random variable R . The right side of the equal sign in (5) is a function of p_b , and we denote it by:

$$F_1(p_b) = p_b \lambda_s + \int_{-\infty}^{p_b} (p_t - p_b) \lambda_{buy} f(p_t) dp_t + \int_{p_b}^{+\infty} (p_t - p_b) \lambda_{sell} f(p_t) dp_t \quad (6)$$

Thus, the EPS could be derived by maximizing $F_1(p_b)$, as shown in (7):

$$\begin{aligned} & \max_{p_b} F_1(p_b) \\ & s.t. \ 0 \leq p_b \leq p_{\max} \end{aligned} \quad (7)$$

The first derivative and the second derivative of objective function $F_1(p_b)$ are shown in (8) and (9):

$$dF_1(p_b) / dp_b = \lambda_s - \lambda_{buy} \int_{-\infty}^{p_b} f(p_t) dp_t - \lambda_{sell} \int_{p_b}^{+\infty} f(p_t) dp_t \quad (8)$$

$$d^2 F_1(p_b) / dp_b^2 = -\lambda_{buy} f(p_b) + \lambda_{sell} f(p_b) \quad (9)$$

It can be seen that $d^2 F(p_b) / dp_b^2 \leq 0$ in (9), so $F_1(p_b)$ is concave in p_b . The model in (7) can be easily solved; its optimal solutions are listed in (10) below:

$$p_b^* = \begin{cases} \text{arbitrary, } p_b^* \in [0, p_{\max}], \ \lambda_{sell} = \lambda_s = \lambda_{buy} \\ \Phi^{-1}\left(\frac{\lambda_s - \lambda_{sell}}{\lambda_{buy} - \lambda_{sell}}\right)\delta_t + \mu_t, & \lambda_{sell} + (\lambda_{buy} - \lambda_{sell})\Phi\left(-\frac{\mu_t}{\delta_t}\right) \leq \lambda_s \leq \lambda_{sell} + (\lambda_{buy} - \lambda_{sell})\Phi\left(\frac{p_{\max} - \mu_t}{\delta_t}\right) \\ 0, & \lambda_s < \lambda_{sell} + (\lambda_{buy} - \lambda_{sell})\Phi\left(-\frac{\mu_t}{\delta_t}\right) \\ p_{\max}, & \lambda_s > \lambda_{sell} + (\lambda_{buy} - \lambda_{sell})\Phi\left(\frac{p_{\max} - \mu_t}{\delta_t}\right) \end{cases} \quad (10)$$

where $\Phi(x)$ is the standard normal distribution function, and $\Phi^{-1}(x)$ is the inverse function of $\Phi(x)$.

From (9), we know that under EPS, the optimal bids are related to the MCP, imbalance prices, mean value, and standard deviation of wind power. The optimal objective $F_1(p_b^*)$ can also be easily calculated. The EPS does not consider risk faced by WPPs, so it is also called a risk-neutral strategy.

3.2. Chance-Constrained Programming-Based Bidding Strategy

In this section, we propose a chance-constrained programming-based bidding considering risk faced by WPPs in bidding process.

3.2.1. Cumulative Distribution of Random Variable R

From (2), (3), and (4), we get:

$$R = \begin{cases} (\lambda_s - \lambda_{sell})p_b + \lambda_{sell}p_t, & p_b \leq p_t \\ (\lambda_s - \lambda_{buy})p_b + \lambda_{buy}p_t, & p_t > p_b \end{cases} \quad (11)$$

It is known that R is a random function of P_t with a given P_b , and that it follows the normal distribution with the following distributed parameters:

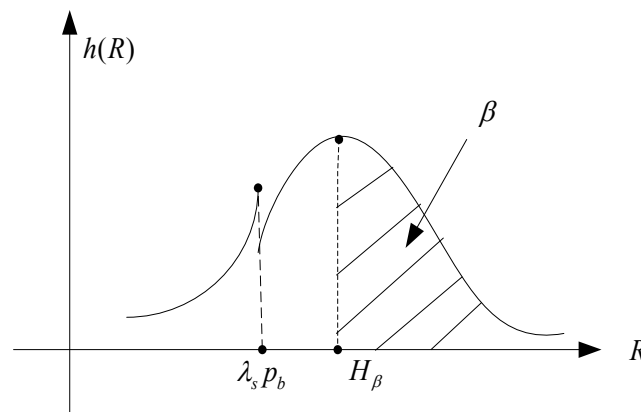
$$R \sim \begin{cases} N((\lambda_s - \lambda_{buy})p_b + \lambda_{buy}\mu_t, \lambda_{buy}^2\delta_t^2), & R \leq \lambda_s p_b \\ N((\lambda_s - \lambda_{sell})p_b + \lambda_{sell}\mu_t, \lambda_{sell}^2\delta_t^2), & R > \lambda_s p_b \end{cases} \quad (12)$$

As is commonly known, the cumulative distribution of a random variable should be equal to 1. However, the cumulative distribution of a variable y with similar distributed parameters as shown in (11) may not be equal to 1. For example, assuming that x follows normal distribution *i.e.*, $x \sim N(0,1)$, considering $y = \begin{cases} x, & x \leq 5 \\ 2x - 5, & x > 5 \end{cases}$, then we obtain that y follows the normal distribution ($y \sim N(0,1)$) when

$x \leq 5$, and that y follows the normal distribution ($y \sim N(0,4)$) when $x > 5$. However, this is not true, because $\int_{-\infty}^{+\infty} yf(y) \neq 1$. So, the cumulative distribution of R must be discussed.

For simplicity, let us introduce the following notations $h(R)$ and $H(R) = \begin{cases} H_1(R), & R \leq \lambda_s p_b \\ H_2(R), & R > \lambda_s p_b \end{cases}$ as representations of the PDF and cumulative distribution function (CDF) of R . A schematic diagram of the PDF of R is shown in Figure 1.

Figure 1. A schematic diagram of the PDF of R .



Let $\Pr\{R \leq \lambda_s P_b\} = \rho_1$ and $\Pr\{R > \lambda_s P_b\} = \rho_2$. From $\Pr\{R \leq \lambda_s P_b\} = \rho_1$, we are able to ascertain that $\lambda_s P_b$ is the lower quantile of R i.e., $H_1(\lambda_s P_b) = \rho_1$, after normalizing $H_1(\lambda_s P_b)$, results in $\Phi\left(\frac{\lambda_s p_b - ((\lambda_s - \lambda_{buy})p_b + \lambda_{buy}\mu_t)}{\lambda_{buy}\delta_t}\right) = \rho_1$, i.e., $\rho_1 = \Phi\left(\frac{p_b - \mu_t}{\sigma_t}\right)$. Similarly, from $\Pr\{R > \lambda_s P_b\} = \rho_2$, we have $\rho_2 = 1 - \Phi\left(\frac{p_b - \mu_t}{\sigma_t}\right)$. Since $\rho_1 + \rho_2 = 1$, the cumulative distribution of R is thus equal to 1.

3.2.2. Formulation of the CPS

The model (7) only takes into account the expected profit without considering the risk faced by a WPP in the bidding process. As previously noted, higher profit is usually accompanied by higher risk. In this section, risk is defined as the probability that the target profit cannot be realized. Here we introduce a chance-constrained programming-based bidding model to obtain the CPS as formulated in (13):

$$\begin{cases} \max_{p_b} \bar{J} \\ \text{s.t. } \Pr\{R \geq \bar{J}\} \geq \beta \\ 0 \leq p_b \leq p_{\max} \end{cases} \quad (13)$$

where $\bar{J}$ is the target profit, and β is the probability that $\bar{J}$ can be realized. Definitions of other parameters can be found in the section above.

Rewrite $\Pr\{R \geq \bar{J}\} \geq \beta$ as follows:

$$\Pr\{R \leq \bar{J}\} \leq 1 - \beta \quad (14)$$

$1 - \beta$ describes the risk that the target profit cannot be realized; this varies from 0 to 1. The model (13) proposed a method to measure risk quantitatively.

Now we discuss the general solution for the optimization problem in the model. From Figure 1, when $H^{-1}(1 - \beta) \geq \lambda_s P_b$, we have:

$$\frac{\lambda_s p_b - \mu_r}{\delta_r} \leq \Phi^{-1}(1 - \beta) \quad (15)$$

where μ_r and δ_r can take any distributed parameter of (12), and $\Phi^{-1}(1 - \beta)$ is the upper quantile of a standard normal distribution, then we get $p_b \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t$. Under this condition, the maximal $\bar{J}$ should be greater than or equal to $\lambda_s P_b$; thus, R follows the below distribution *i.e.*, $R \sim N((\lambda_s - \lambda_{sell})p_b + \lambda_{sell}\mu_t, \lambda_{sell}^2\delta_t^2)$, resulting in:

$$\frac{\bar{J} - [(\lambda_s - \lambda_{sell})p_b + \lambda_{sell}\mu_t]}{\lambda_{sell}\delta_t} \leq \Phi^{-1}(1 - \beta) \quad (16)$$

i.e., $\bar{J} \leq \Phi^{-1}(1 - \beta)\lambda_{sell}\delta_t + (\lambda_s - \lambda_{sell})p_b + \lambda_{sell}\mu_t$.

Similarly, when $H^{-1}(1 - \beta) < \lambda_s P_b$, we have $p_b \geq \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, and R follows the normal distribution below, *i.e.*, $R \sim N((\lambda_s - \lambda_{buy})p_b + \lambda_{buy}\mu_t, \lambda_{buy}^2\delta_t^2)$, then we get $\bar{J} \leq \Phi^{-1}(1 - \beta)\lambda_{buy}\delta_t + (\lambda_s - \lambda_{buy})p_b + \lambda_{buy}\mu_t$.

From the above discussion, we learn that maximal $\bar{J}$ is a function of p_b ; thus, let us denote:

$$F_2(p_b) = \begin{cases} \Phi^{-1}(1 - \beta)\lambda_{sell}\delta_t + (\lambda_s - \lambda_{sell})p_b + \lambda_{sell}\mu_t, & 0 \leq p_b \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t \\ \Phi^{-1}(1 - \beta)\lambda_{buy}\delta_t + (\lambda_s - \lambda_{buy})p_b + \lambda_{buy}\mu_t, & \Phi^{-1}(1 - \beta)\delta_t + \mu_t < p_b \leq P_{\max} \end{cases} \quad (17)$$

Then the model (13) can be transformed into the model (18) as follows:

$$\begin{cases} \max_{p_b} F_2(p_b) \\ s.t. 0 \leq p_b \leq p_{\max} \end{cases} \quad (18)$$

Figure 2 shows $F_2(p_b)$ as a function of p_b . It is not difficult to obtain the analytical solutions of model (18); the results of these calculations are listed in Table 1.

Figure 2. Function F_2 versus P_b .

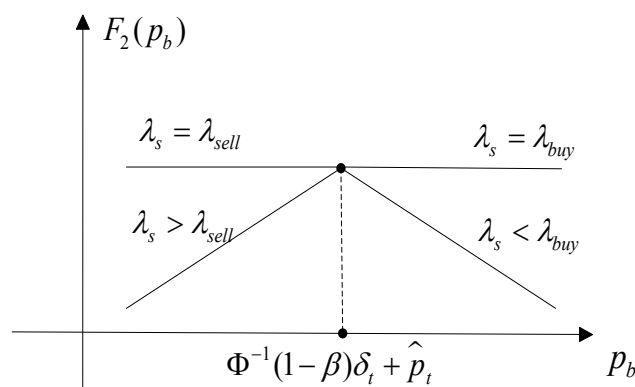


Table 1. Optimal results of chance-constrained programming-based bidding model.

Range of β	Relationship among λ_s , λ_{sell} and λ_{buy}	Optimal solution, P_b^*	$F_2(P_b^*)$
$[0, 1 - \Phi(\frac{p_{\max} - \mu_t}{\delta_t})]$	$\lambda_s > \lambda_{sell}$	$p_{\max}$	$\Phi^{-1}(1 - \beta)\lambda_{sell}\delta_t +$ $(\lambda_s - \lambda_{sell})p_{\max} + \lambda_{sell}\mu_t$
	$\lambda_s = \lambda_{sell}$	$\forall p_b^* \in [0, p_{\max}]$	$\lambda_s[\Phi^{-1}(1 - \beta)\delta_t + \mu_t]$
$(1 - \Phi(\frac{-\mu_t}{\delta_t}), 1]$	$\lambda_s < \lambda_{buy}$	0	$\Phi^{-1}(1 - \beta)\lambda_{buy}\delta_t + \lambda_{buy}\mu_t$
	$\lambda_s = \lambda_{buy}$	$\forall p_b^* \in [0, p_{\max}]$	$\lambda_s[\Phi^{-1}(1 - \beta)\delta_t + \mu_t]$
$[1 - \Phi(\frac{p_{\max} - \mu_t}{\delta_t}), 1 - \Phi(\frac{-\mu_t}{\delta_t})]$	$\lambda_{sell} = \lambda_s = \lambda_{buy}$	$\forall p_b^* \in [0, p_{\max}]$	$\lambda_s[\Phi^{-1}(1 - \beta)\delta_t + \mu_t]$
	$\lambda_{sell} = \lambda_s < \lambda_{buy}$	$\forall p_b^* \in [0, \Phi^{-1}(1 - \beta)\delta_t + \mu_t]$	$\lambda_s[\Phi^{-1}(1 - \beta)\delta_t + \mu_t]$
	$\lambda_{sell} < \lambda_s = \lambda_{buy}$	$\forall p_b^* \in [\Phi^{-1}(1 - \beta)\delta_t + \mu_t, p_{\max}]$	$\lambda_s[\Phi^{-1}(1 - \beta)\delta_t + \mu_t]$
	$\lambda_{sell} < \lambda_s < \lambda_{buy}$	$\Phi^{-1}(1 - \beta)\delta_t + \mu_t$	$\lambda_s[\Phi^{-1}(1 - \beta)\delta_t + \mu_t]$

It can be seen from Table 1 that the optimal bids under the CPS are related to β , prices, and the distributed parameters.

3.3. Multi-Objective Bidding Strategy

3.3.1. Multi-Objective Bidding Model

In this section, we present ECPS based on a multi-objective bidding model that takes into account both expected profit and risk. The multi-objective model is formulated as follows:

$$\begin{cases} \max_{p_b} [F_1(p_b), F_2(p_b)] \\ s.t. 0 \leq p_b \leq p_{\max} \end{cases} \quad (19)$$

where $F_1(p_b)$ and $F_2(p_b)$ are as defined in Sections 3.1 and 3.2. Since $F_1(p_b)$ and $F_2(p_b)$ are concave functions, we convert the problem to a single-function objective through the weighted sum of the objective functions (19)–(20):

$$\begin{cases} \max_{p_b} G(p_b) \\ s.t. 0 \leq p_b \leq p_{\max} \end{cases} \quad (20)$$

$$G(p_b) = (1 - \alpha)F_1(p_b) + \alpha F_2(p_b) \quad (21)$$

where α is the weight selected from [0.0 1.0]. A set of non-dominated solutions can be obtained by varying α through this weighted sum method. When $\alpha = 0$, the model (20) changes into the model (7), and when $\alpha = 1$, it changes into the model (18). Furthermore, model (20) is expressed as shown below:

When $p_b \geq \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, (20) can be rewritten as follows:

$$\begin{cases} \max_{p_b} G_1(p_b) \\ s.t. 0 \leq p_b \leq p_{\max} \end{cases} \quad (22)$$

where $G_1(p_b) = \alpha[\Phi^{-1}(1 - \beta)\lambda_{buy}\delta_t + (\lambda_s - \lambda_{buy})p_b + \lambda_{buy}\mu_t] + (1 - \alpha)F_1(p_b)$. When $p_b \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, (20) can be rewritten as follows:

$$\begin{cases} \max_{p_b} G_2(p_b) \\ \text{s.t. } 0 \leq p_b \leq p_{\max} \end{cases} \quad (23)$$

where $G_2(p_b) = \alpha[\Phi^{-1}(1-\beta)\lambda_{sell}\delta_t + (\lambda_s - \lambda_{sell})p_b + \lambda_{sell}\hat{p}_t] + (1-\alpha)F_1(p_b)$. The first derivative and second derivative of the objective functions $G_1(p_b)$ and $G_2(p_b)$ are shown below:

$$dG_1(p_b)/dp_b = \lambda_s - \alpha\lambda_{buy} - (1-\alpha)\lambda_{buy}\int_{-\infty}^{p_b} f(p_t)dp_t - (1-\alpha)\lambda_{sell}\int_{p_b}^{+\infty} f(p_t)dp_t \quad (24)$$

$$dG_2(p_b)/dp_b = \lambda_s - \alpha\lambda_{sell} - (1-\alpha)\lambda_{buy}\int_{-\infty}^{p_b} f(p_t)dp_t - (1-\alpha)\lambda_{sell}\int_{p_b}^{+\infty} f(p_t)dp_t \quad (25)$$

$$d^2G_1(p_b)/dp_b^2 = -(1-\alpha)\lambda_{buy}f(p_b) + (1-\alpha)\lambda_{sell}f(p_b) \leq 0 \quad (26)$$

$$d^2G_2(p_b)/dp_b^2 = -(1-\alpha)\lambda_{buy}f(p_b) + (1-\alpha)\lambda_{sell}f(p_b) \leq 0 \quad (27)$$

The solutions of the models (22) and (23) are presented in the next section.

3.3.2. Solution of Multi-objective Bidding Model

In this section, the general solution for a multi-objective bidding model is developed, and the solution is also analyzed in detail for several cases. Specifically, the following details are presented:

$$(1) \lambda_{sell} = \lambda_s = \lambda_{buy}$$

Since $dG_1(p_b)/dp_b = dG_2(p_b)/dp_b = 0$, thus, $\forall \beta \in [0,1]$ and the optimal bid is arbitrary p_b^* , and $p_b^* \in [0, p_{\max}]$, and the maximal value of each objective: $F_1^* = \lambda_s\mu_t$, $F_2^* = \lambda_s[\Phi^{-1}(1-\beta)\delta_t + \mu_t]$.

$$(2) \lambda_{sell} < \lambda_{buy}$$

Case (1) $\Phi^{-1}(1-\beta)\delta_t + \mu_t < 0$, i.e., $0 \leq 1-\beta < \Phi(-\frac{\mu_t}{\delta_t})$

If $0 \leq p_b \leq p_{\max}$, we apply the model (22). For simplicity, let us denote $\int_{-\infty}^{p_b} f(p_t)dp_t = z_1$, then $dG_1(p_b)/dp_b = \lambda_s - \alpha\lambda_{buy} - (1-\alpha)\lambda_{buy}z_1 - (1-\alpha)\lambda_{sell}(1-z_1)$.

- Case (1a) if $\lambda_{sell} \leq \lambda_s < \alpha\lambda_{buy} + (1-\alpha)\lambda_{sell}$, we have $dg_1(p_b)/dp_b < 0$, the function $G_1(p_b)$ is monotonically decreasing, we get $p_b^* = 0$, and $G_1^* = G_1(0)$.
- Case (1b) if $\alpha\lambda_{buy} + (1-\alpha)\lambda_{sell} \leq \lambda_s \leq \lambda_{buy}$, from, $dg_1(p_b)/dp_b = 0$, we have $z_1 = \frac{\lambda_s - \alpha\lambda_{buy} - (1-\alpha)\lambda_{sell}}{(1-\alpha)(\lambda_{buy} - \lambda_{sell})}$,

and $0 \leq z_1 \leq 1$, the extreme point $p_b = \Phi^{-1}(z_1)\delta_t + \mu_t$. Three cases are considered further:

if $\Phi^{-1}(z_1)\delta_t + \mu_t < 0$, $p_b^* = 0$, $G_1^* = G_1(0)$;

if $0 \leq \Phi^{-1}(z_1)\delta_t + \mu_t \leq p_{\max}$, $p_b^* = \Phi^{-1}(z_1)\delta_t + \mu_t$, $G_1^* = G_1(\Phi^{-1}(z_1)\delta_t + \mu_t)$;

if $\Phi^{-1}(z_1)\delta_t + \mu_t > p_{\max}$, $p_b^* = p_{\max}$, $G_1^* = G_1(p_{\max})$.

Case (2) $\Phi^{-1}(1-\beta)\delta_t + \mu_t > p_{\max}$, i.e., $\Phi(\frac{p_{\max} - \mu_t}{\delta_t}) < 1-\beta \leq 1$

If $0 \leq p_b \leq p_{\max}$, we can apply the model (23). For simplicity, let us denote $\int_{-\infty}^{p_b} f(p_t)dp_t = z_2$ then $dg_2(p_b)/dp_b = \lambda_s - \lambda_{sell} - (1-\alpha)(\lambda_{buy} - \lambda_{sell})$.

- Case (2a) if $(1 - \alpha)\lambda_{buy} + \alpha\lambda_{sell} \leq \lambda_s \leq \lambda_{buy}$, $dg_1(p_b)/dp_b > 0$, the objective function is monotonically decreasing, we get $p_b^* = p_{max}$, $G_2^* = G_2(p_{max})$.
- Case (2b) if $\lambda_{sell} \leq \lambda_s \leq (1 - \alpha)\lambda_{buy} + \alpha\lambda_{sell}$, from $dg_2(p_b)/dp_b = 0$, we have $z_2 = \frac{\lambda_s - \lambda_{sell}}{(1 - \alpha)(\lambda_{buy} - \lambda_{sell})}$,

and $0 \leq z_2 \leq 1$. Three cases are considered further:

if $\Phi^{-1}(z_2)\delta_t + \mu_t < 0$, $p_b^* = 0$, $G_2^* = G_2(0)$;

if $0 \leq \Phi^{-1}(z_2)\delta_t + \mu_t \leq p_{max}$, $p_b^* = \Phi^{-1}(z_2)\delta_t + \mu_t$, $G_2^* = G_2(\Phi^{-1}(z_2)\delta_t + \mu_t)$;

if $\Phi^{-1}(z_2)\delta_t + \mu_t > p_{max}$, $p_b^* = p_{max}$ and $G_2^* = G_2(p_{max})$.

Case (3) $0 \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t \leq p_{max}$, i.e., $\Phi(\frac{-\mu_t}{\delta_t}) \leq 1 - \beta \leq \Phi(\frac{p_{max} - \mu_t}{\delta_t})$

Let us divide the interval $0 \leq p_b \leq p_{max}$ into $0 \leq p_b \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t$ and $\Phi^{-1}(1 - \beta)\delta_t + \mu_t \leq p_b \leq p_{max}$; thus, we can solve the models (22) and (23), respectively.

- Case (3a) $0 \leq p_b \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t$

In this case, we apply model (23), and then two more cases are considered:

- (i) if $(1 - \alpha)\lambda_{buy} + \alpha\lambda_{sell} \leq \lambda_s \leq \lambda_{buy}$, the optimal bid is $p_b^* = \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, and $G_2^* = G_2(\Phi^{-1}(1 - \beta)\delta_t + \mu_t)$;

- (ii) if $\lambda_{sell} \leq \lambda_s \leq (1 - \alpha)\lambda_{buy} + \alpha\lambda_{sell}$. Three cases are considered further:

if $\Phi^{-1}(z_2)\delta_t + \mu_t < 0$, $p_b^* = 0$, $G_2^* = G_2(0)$;

if $0 \leq \Phi^{-1}(z_2)\delta_t + \mu_t \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, $p_b^* = \Phi^{-1}(z_2)\delta_t + \mu_t$ and $G_2^* = G_2(\Phi^{-1}(z_2)\delta_t + \mu_t)$;

if $\Phi^{-1}(z_2)\delta_t + \mu_t > \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, $p_b^* = \Phi^{-1}(1 - \beta)\delta_t + \mu_t$ and $G_2^* = G_2(\Phi^{-1}(1 - \beta)\delta_t + \mu_t)$.

- Case (3b) $\Phi^{-1}(1 - \beta)\delta_t + \mu_t \leq p_b \leq p_{max}$

In this case, we apply the model (22). Similarly, as in Case (3a),

- (i) if $\lambda_{sell} \leq \lambda_s < \alpha\lambda_{buy} + (1 - \alpha)\lambda_{sell}$, the optimal bid is $p_b^* = \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, and $G_1^* = G_1(\Phi^{-1}(1 - \beta)\delta_t + \mu_t)$.

- (ii) if $\alpha\lambda_{buy} + (1 - \alpha)\lambda_{sell} \leq \lambda_s \leq \lambda_{buy}$. Three cases are considered further:

if $\Phi^{-1}(z_1)\delta_t + \mu_t < \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, $p_b^* = \Phi^{-1}(1 - \beta)\delta_t + \mu_t$, $G_1^* = G_1(\Phi^{-1}(1 - \beta)\delta_t + \mu_t)$;

if $\Phi^{-1}(1 - \beta)\delta_t + \mu_t \leq \Phi^{-1}(z_1)\delta_t + \mu_t \leq p_{max}$, $p_b^* = \Phi^{-1}(z_1)\delta_t + \mu_t$ and $G_1^* = G_1(\Phi^{-1}(z_1)\delta_t + \mu_t)$;

if $\Phi^{-1}(z_1)\delta_t + \mu_t > p_{max}$, $p_b^* = p_{max}$, and $G_1^* = G_1(p_{max})$.

From the above discussion, we have shown that when $0 \leq \Phi^{-1}(1 - \beta)\delta_t + \mu_t \leq p_{max}$, the maximal value of the objective is $\max\{G_1(p_b^*), G_2(p_b^*)\}$, and that the corresponding p_b^* is the optimal bid.

3.3.3. Best Compromise Solution

The solution obtained from the multi-objective model is a Pareto-optimal set of non-dominated solution, from which WPPs should choose a solution as the final decision. This section proposed a method based on fuzzy theory to determine the best compromise solution [25]. Each objective function of the m -th solution is represented by a membership function $u_{F_i}^m$ defined as:

$$u_{F_i}^m = \begin{cases} 0 & F_i \leq F_i^{\min} \\ \frac{F_i - F_i^{\min}}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 1 & F_i \geq F_i^{\max} \end{cases} \quad (28)$$

where $F_i^{\max}$ is the objective value only considering objective i , and $F_i^{\min}$ is the objective value considering other objectives except objective i . Thus, we can obtain $0 \leq u_{F_i} \leq 1$, in which $u_{F_i} = 1$ reflects that the decision maker is totally satisfied with the objective and $u_{F_i} = 0$ reflects the opposite.

For each non-dominated solution m , the normalized membership function u_D^m is calculated by:

$$u_D^m = \frac{\sum_{i=1}^{N_{obj}} u_{F_i}^m}{\sum_{m=1}^M \sum_{i=1}^{N_{obj}} u_{F_i}^m} \quad (29)$$

where M is the number of non-dominated solutions. The best compromise solution is the one having the maximum of u_D^m .

4. Numerical Simulation

Simulations are performed on a hypothetical wind farm with an installed capacity of 200 MW. The bidding problem is analyzed for one day using 24 hourly cases which are general and representative. Hourly mean values and standard deviations of wind power for the day are assumed to be obtained from historical data as shown in Table 2 [23].

Table 2. Hourly expected value and standard deviation of day-ahead wind power forecast.

Hour	Expected value/MW	Standard deviation/MW	Hour	Expected value/MW	Standard deviation/MW
1	70.0	31.37	13	133.0	84.76
2	45.5	27.32	14	129.5	87.06
3	24.5	21.53	15	147.0	96.39
4	28.0	24.61	16	140.0	97.62
5	42.0	32.08	17	133.0	98.6
6	59.5	40.5	18	108.5	92.18
7	70.0	46.63	19	84.0	83.86
8	80.5	52.49	20	77.0	82.92
9	94.5	59.78	21	66.5	79.4
10	112.0	68.26	22	42.0	65.2
11	126.0	75.22	23	35.0	61.34
12	139.5	80.23	24	63.0	84.53

Hourly MCPs based on the spot prices on 08/03/2012 provided by the European Power Exchange (EPEX SPOT SE) [26] and the hypothetical imbalance prices which follow the relation set forth in (1) are listed in Table 3. Note that there is both an up- and down regulating price for each hour in Table 3, in fact, our strategies can still work when there is only either up- or down-regulation price for each hour.

Table 3. Hourly day-ahead market price and imbalance prices.

t	λ_s (€/MWh)	λ_{sell} (€/MWh)	λ_{buy} (€/MWh)	t	λ_s (€/MWh)	λ_{sell} (€/MWh)	λ_{buy} (€/MWh)
1	53.54	25.23	59.56	13	52.02	35.43	71.32
2	49.72	24.12	62.69	14	49.72	36.65	68.56
3	41.6	23.16	59.68	15	45.36	38.26	72.63
4	38.1	20.16	55.79	16	42.57	37.42	74.2
5	35.07	24.68	56.2	17	41.66	35.87	75.36
6	38.2	27.56	61.32	18	45.63	34.39	67.74
7	42.57	30.2	62.28	19	52.01	42.16	79.68
8	49.72	32.59	65.2	20	59.28	40.68	74.8
9	53.54	35.63	68.21	21	59.28	37.33	70.12
10	53.54	38.65	70.81	22	53.54	32.1	66.37
11	53.54	38.55	70.71	23	52.64	24.63	62.09
12	53.54	39.1	73.36	24	45.92	27.65	65.07

We first present results for one individual hour (*i.e.*, period 2), looking at how the objective functions in the three tested bidding strategies change as functions of day-ahead bid quantity. Then, we discuss how the risk $1 - \beta$ and standard deviation of wind power forecast affect optimal decision making. Finally, we calculate the optimal bidding decisions for all the hours of the day.

We first present results for one individual hour (*i.e.*, period 2), looking at how the objective functions in the three tested bidding strategies change as functions of day-ahead bid quantity. Then, we discuss how the risk $1 - \beta$ and standard deviation of wind power forecast affect optimal decision making. Finally, we calculate the optimal bidding decisions for all the hours of the day.

In period 2, the mean value and the standard deviation of wind power forecast are 45.5 MW and 27.32 MW, respectively. MCP, the price for the positive energy, and the price for the negative energy are 49.72 €/MWh, 24.12 €/MWh, and 62.69 €/MWh, respectively. Figure 3 shows the change trend of expected profit under EPS. The expected profit first increases and then decreases; the optimal bid quantity is 57.05 MW and is greater than the mean value (45.5) in period 2. This shows that larger bid quantity does not lead to larger expected profit because of the imbalance costs, as is shown in Figure 4.

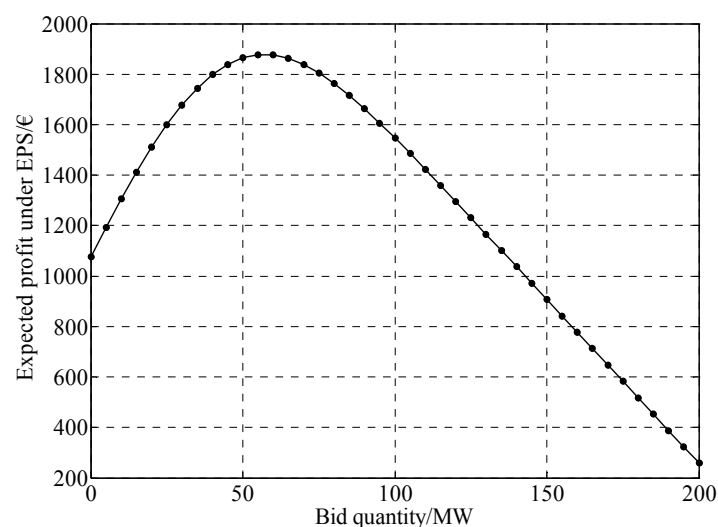
Figure 3. Expected profit under the EPS *versus* bid quantity.

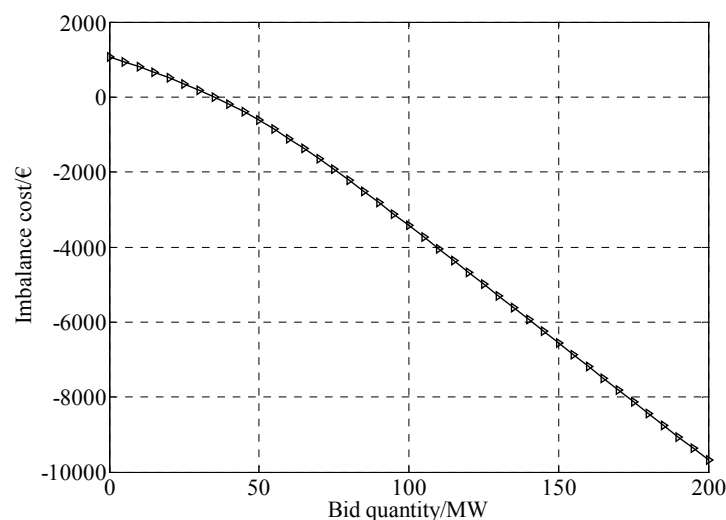
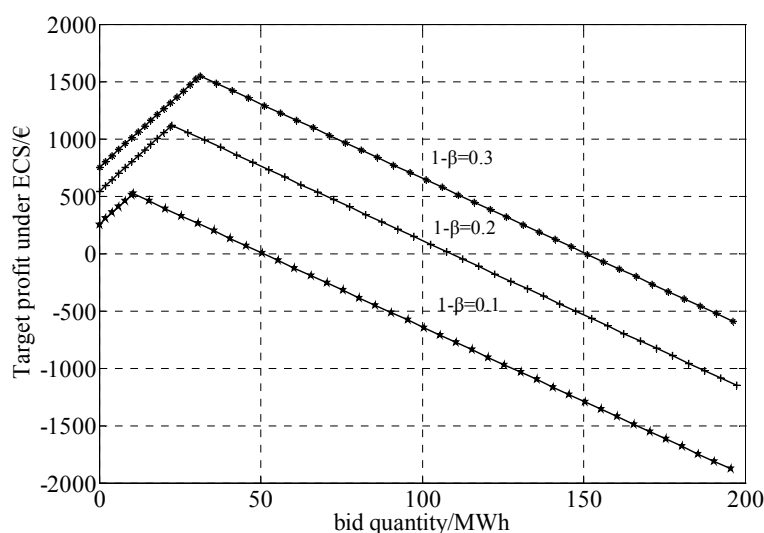
Figure 4. Imbalance costs *versus* bid quantity under the EPS.

Figure 5 shows the change trend of target profit as a function of bid quantity with different risk parameters; due to the imbalance costs, it has a trend similar to that of expected profit under the EPS, and the optimal bid quantity under the CPS increases when the risk parameter increases.

The maximal optimal bid quantity with different $1 - \beta$ is 31.17 MW ($1 - \beta = 0.3$), which is smaller than the mean value. With the risk increasing, the target profit which a WPP can realize also increases. This is in accordance with the notion that high risk leads to high profit. In addition, the CPS can also help a WPP to set appropriate target values, for example, when a WPP is willing to face very low risk ($1 - \beta = 0.1$), then the maximal reasonable target profit is 521.46 €. If the target profit is set higher than 521.46 €, the risk the WPP faces will thus increase.

Figure 5. Target profit under the CPS *versus* bid quantity with different $1 - \beta$.

Figures 6 and 7 show how the expected profit and target profit change as a function of bid quantity with $1 - \beta = 0.1$ under the ECPS. As is shown, the expected profit and target profit are two conflicted objectives when the bid quantity varies from 10.48 to 57.05 MW. The expected profit increases monotonically *versus* the bid quantity, while the target profit decreases monotonically.

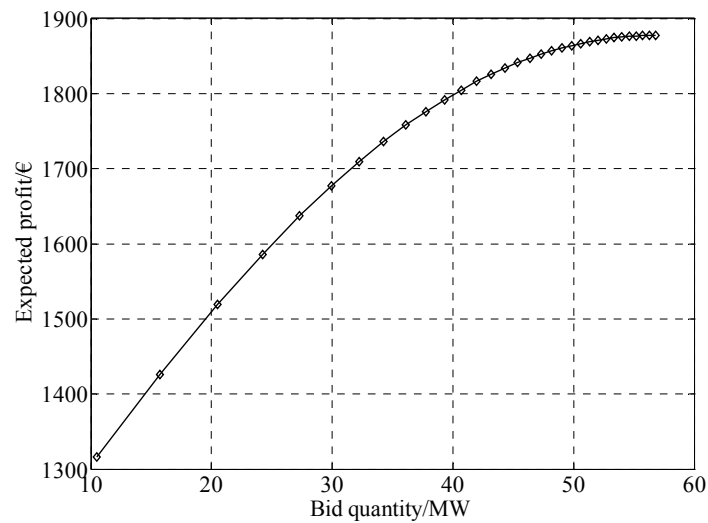
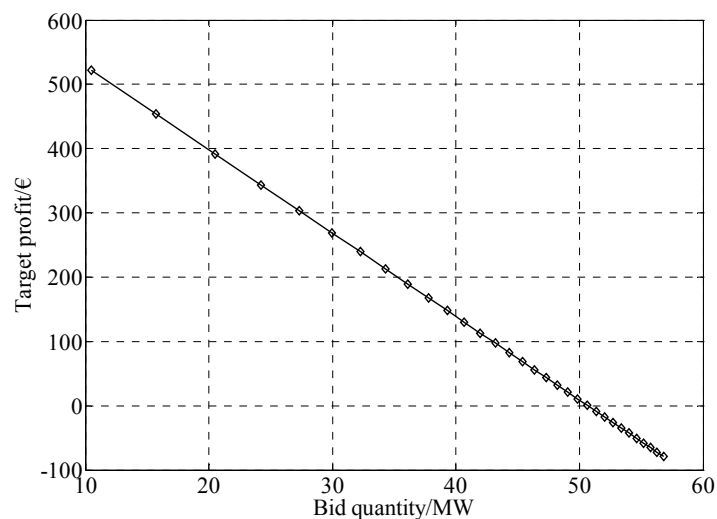
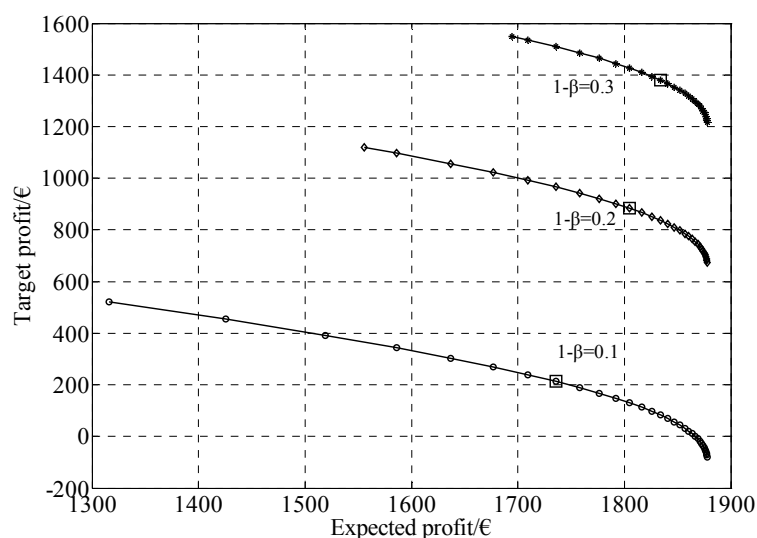
Figure 6. Expected profit *versus* bid quantity under EPCS with $1 - \beta = 0.1$.**Figure 7.** Target profit *versus* bid quantity under EPCS with $1 - \beta = 0.1$.

Figure 8 gives the Pareto optimal front *versus* different $1 - \beta$ in the EPCS. The values shown in the square boxes are the optimal values of each objective. The optimal bid quantities (*i.e.*, the best compromise solutions) are 44.31 MW ($1 - \beta = 0.3$), 40.68 MW, and 34.28 MW, respectively. The maximal and minimal values of F_i used here to calculate the membership function are listed in Table 4. Based on these calculations, it can also be expected that the higher risk the WPPs face, the more profit they will obtain.

Figure 8. Pareto optimal front *versus* different $1 - \beta$ under the ECPS.**Table 4.** Maximal and minimal values of single objectives and best compromise values of F_1 and F_2 .

$1 - \beta$	F_1^{min} (€)	F_1^{max} (€)	F_2^{min} (€)	F_2^{max} (€)	F_1 in square box (€)	F_2 in square box (€)
0.1	1316	1877.7	-79.11	521.46	1747.4	200.72
0.2	1555.9	1877.7	674.35	1119	1798.6	892.1
0.3	1694.8	1877.7	1217.7	1549.9	1839.9	1379.5

Figure 9 shows a comparison of the bid quantity *versus* risk between the CPS and the ECPS. In both strategies, the bid quantity increases when the risk increases. The CPS takes into account only the risk, while the ECPS considers both the expected profit and risk; thus, the variation range of bids under the CPS is larger than that under the ECPS and is similarly more sensitive to risk than the ECPS.

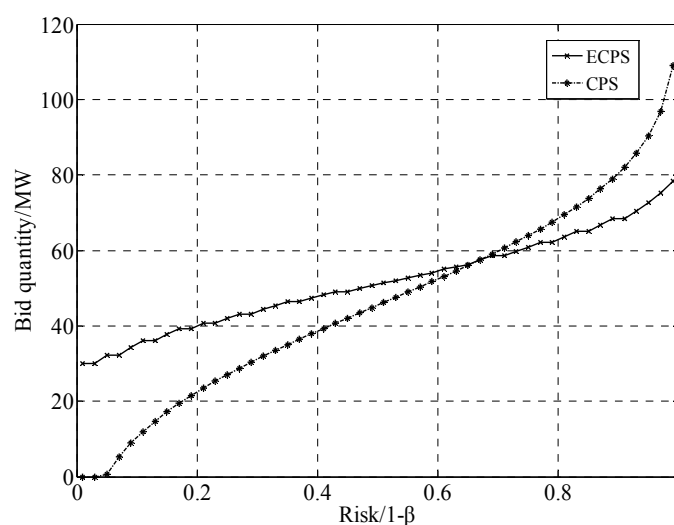
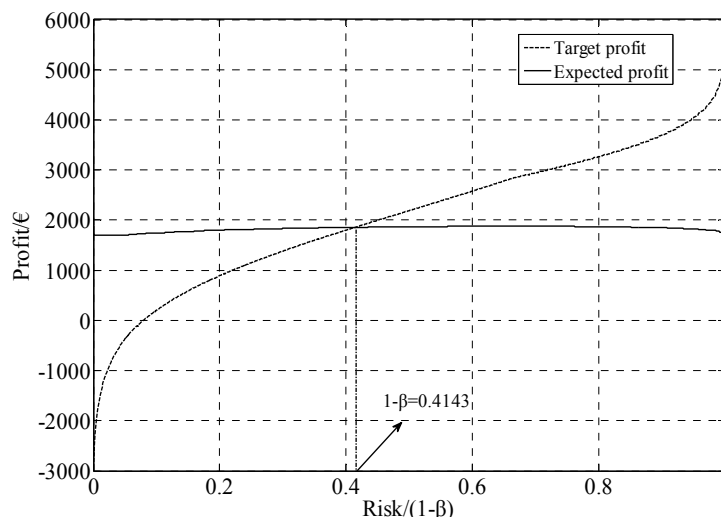
Figure 9. Comparison of bid quantity *versus* $1 - \beta$ between the CPS and ECPS.

Figure 10 gives how the expected profit and target profit change as a function of the risk parameter under the CPS and ECPS. The value of risk at the cross point is 0.4143. When the risk is larger than

0.4143, the target profit is greater than the expected profit; this implies that WPPs face a high risk to realize the target profit. When the risk is smaller than 0.4143, the target profit is less than the expected profit, implying that WPPs face a low risk to realize the target profit. WPPs are usually assumed to be risk-averse; the EPCS can help to manage the risk and provide guidelines to set the risk parameter.

Figure 10. Change trend of target profit and expected profit *versus* risk under the ECPS.



Period 2 can serve as an example; here, assume $1 - \beta = 0.1$, with other parameters unchanged, the impact of the standard deviation on bidding results can be obtained by varying the standard and is shown in Table 5. The accuracy of the wind power forecast has a significant effect on the three tested strategies. Under the EPS and CPS ($1 - \beta = 0.1$), the smaller deviation (*i.e.*, increased accuracy of the wind power forecast) will bring greater expected profit and target profit. The objectives under the EPS and CPS have a monotonic relation with the standard deviation. However, under the ECPS, the objective F_1 has a monotonic relation with the standard deviation, while F_2 does not, as discussed in Section 3.3.2. The values of F_1 and F_2 are calculated by the best compromise criteria.

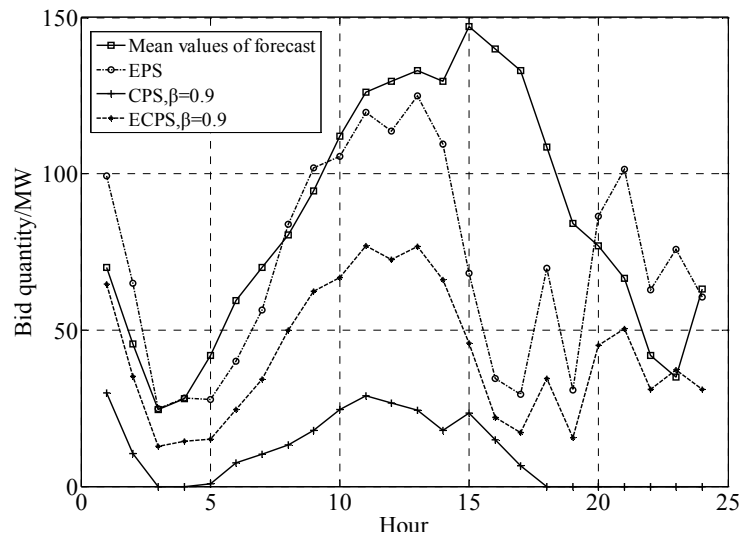
Table 5. Comparisons of the impact of the standard deviation on bidding results.

Standard deviation	EPS		CPS ($1 - \beta = 0.1$)		ECPS ($1 - \beta = 0.1$)		
	p_b	F_1	p_b	F_2	p_b	F_1	F_2
4.32	47.33	2201.5	39.96	1987	43.87	2180.9	1936.3
14.18	51.49	2062.7	27.33	1358.7	0	2062.7	1974
24.04	55.66	1923.9	14.69	730.46	0	1923.9	1773.6
33.90	59.83	1785.1	2.055	102.19	0	1785.1	1573.1
43.76	63.99	1646.3	0	-663.30	33.11	1483.8	-1092.8

We now discuss the optimal bidding strategy for the entire day. Figure 11 shows that the bid quantity under the EPS is the greatest among three strategies, and also the closest to the mean value of the forecast. The EPS is mainly driven by the standard deviation of the wind power forecast and the relationship among the MCP, the price for positive energy, and the price for negative energy. Under the CPS, aside from the relationship among the prices and the standard deviation, the bid quantity is also strongly correlated to the risk. The bid quantity under the CPS with $1 - \beta = 0.1$ is the lowest, as

shown in Figure 11. The ECPS is the compromise of EPS and CPS, and takes into account both the expected profit and target profit. WPPs tend to bid a higher quantity than that under the CPS and less than that under the EPS.

Figure 11. Bid quantity with 24 hours.



5. Conclusions

Due to the stochastic nature of wind resources, wind power producers are sometimes required to pay for imbalance costs caused by deviations between bids in the day-ahead market and the real power generated in the real-time market. This article has developed three different bidding strategies for wind power producers to use when participating in the day-ahead market. The EPS aims to maximize the expected profit, and the CPS calculates the target profit considering the risk which is defined as the probability that target profit cannot be realized. The ECPS is formulated as a multi-objective model. In the test case, we have discussed the optimal bids in the day-ahead market under three strategies. The following conclusions are reached: (1) The bid quantity under the EPS is highly dependent on the mean value and standard deviation of wind forecast, and also the MCP, the price for positive energy, and the price for negative energy; it is also the closest to the mean values of wind forecast. The EPS is suitable for WPPs to use when WPPs are risk-neutral; (2) Besides the parameters mentioned above, the bid quantity under the CPS is strongly correlated to the risk, and is the farthest from the mean value of wind forecast. The ECPS, which combines both the EPS and CPS, tends to bid a higher quantity than that under the CPS and less than that under the EPS; (3) Both the CPS and ECPS consider the risk and provide an alternative method for risk management; (4) The ECPS acknowledges the significance of the relationship between expected profit and target profit, and can help to set appropriate risk parameters for WPPs.

Finally, it should be pointed out that our article does not discuss the prediction techniques for prices and wind power in detail. However, high accurate prediction techniques are more helpful for WPPs to make better bidding strategies. The state-of-the-art prediction tools enable WPPs to bid to the market, but of course further research is conducted to further improve the accuracy.

Acknowledgments

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