Optimal Bidding Strategies for Wind Power Producers with Meteorological Forecasts

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Abstract

In recent years, the interest in clean renewable energy resources, such as wind and photovoltaic, has grown rapidly. It is well known that the inherent variability in wind power generation and the related difficulty in predicting future generation profiles, raise major challenges to wind power integration into the electricity grid. In this work we study the problem of optimizing energy bids for an independent Wind Power Producer (WPP) taking part into a competitive electricity market. It is assumed that the WPP is subject to financial penalties for generation shortfall and surplus. This means that, if the energy delivered over a given time slot is different from that subscribed in the bid, the WPP will be penalized, the monetary entity of the penalty depending on the wholesale market behavior, the day of the year and the time slot involved. An optimization procedure is devised to minimize this risk and maximize the expected profit of the seller. Specifically, each energy bid is computed by exploiting the forecast energy price for the day ahead market, the historical wind statistics at the plant site and the day-ahead wind speed forecasts provided by a meteorological service. We also examine and quantify the strategic role of an energy storage device in increasing reliability of bids and mitigating the financial risks of the WPP.

1 Introduction

Energy generation from renewable sources is one of the main targets for the development of the grid of the future. The expected advantages are cheaper energy, the reduction of CO_2 emissions, and also the reduction of transmission costs and losses, since energy is generated closer to where it is used. On the other hand, integration of Renewable Energy Sources (RES) in the grid causes serious problems to transmission and distribution system operators. In order to cope with the intrinsic RES intermittency and variability, system operators need to procure large quantities of reserve power, thus incurring in increased costs in the final price applied to consumers. One possible way to mitigate the uncertainty of RES generation is to require that producers provide day-ahead generation profiles, and to apply penalties if the actual generation profile differs from the schedule. For example, the Italian Authority for Electricity and Gas (AEEG) has set this regulatory framework since January 1, 2013. In a first phase, 20% tolerance is allowed, while in a second phase the tolerance will be reduced to 10%. On the producers' side, this calls for the development of suitable bidding strategies to offer the right amount of energy without incurring in penalties. In this paper, we address the above problem in the case of Wind Power Producers (WPPs).

Wind is an inherently intermittent source of energy and is difficult to predict. For this reason, forecasting of wind power generation has recently attracted the attention of researchers, and several different approaches can be found in the literature. The interested reader is referred to the survey paper [1], where a categorization into physical, statistical, spatial correlation and artificial intelligence models is proposed. In many cases, the focus is on wind speed forecasts, which are then converted to power through the power curve of a wind turbine. Forecasts of wind power generation can be directly used for bidding. However, since for a given model structure forecasting models are typically optimized with respect to the prediction performance, bids based on wind power forecasts may not be the best one can do, if the objective is to maximize the profit in a framework with penalties.

The problem of designing optimal WPP bidding strategies has been addressed in [2, 3, 4], and very recently in [5], where the authors derive explicit formulae for optimal contract bids based on a given stochastic model for wind power generation. The optimal offer at a certain time of the day turns out to be a suitable percentile of the wind power probability distribution at the same time. The result is a generation profile which is the same every day. This is obvious because no additional prior knowledge about the next day is assumed to be available. In this paper we investigate how ad-

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ditional prior knowledge can be used to derive better suited day-ahead schedules. In particular, we assume that day-ahead wind speed forecasts provided by a meteorological service are available. These forecasts may be inaccurate for wind power prediction, but can give a rough indication to classify the next day (e.g. high or low wind, turning out in high or low wind power generation). This makes it possible to offer the optimal profile for the next day computed as in [5], but using the conditional wind power probability distribution of the corresponding class. For the classification step, many different types of linear and nonlinear classifiers can be applied (see, e.g., [6]). In this paper, we adopt the Multicategory Robust Linear Programming (MRLP) approach described in [7].

Also the use of energy storage can help improve the expected profit and mitigate the financial risk associated with the variability of wind power generation. Under the same framework as in [5], it is shown in [8] that the problem of determining optimal contract offerings for a WPP with co-located energy storage can be tackled using convex programming. However, the optimal bid cannot be analytically determined anymore. In this paper, we propose a suboptimal solution to the problem, which can be computed based on the historical data of the wind power plant.

The paper is organized as follows. Section 2 provides the problem formulation both in the case with and without storage. Section 3 reviews the optimal bidding strategies reported in [5] and [8], and describes the proposed suboptimal solution in the case with storage. The use of wind speed forecasts and the related classification strategy are addressed in Section 4. Section 5 reports the experimental results obtained under different pricing scenarios using experimental data from a real Italian wind farm composed of 34 wind turbines. Finally, conclusions are drawn in Section 6.

2 Problem formulation

In this section the problem of finding the optimal energy bids for an electricity market is formulated in a setting mainly adapted from [8]. Let w_n be a discrete-time random process denoting the active power generated by the wind plant, averaged over the n-th sampling interval of the day, with h being the sampling time. Let $C^{(m)}$, $m = 1, \ldots, M$ denote the bid of active power for the m-th interval of the day, as per contract. To ease the notation, let us assume that length k of the contract interval is an integer multiple N of the sampling time of the average power, i.e. $k = Nh$. For instance, if actual power was averaged over 10 minutes and the WPP should make a bid for the power generated during each hour of the day, then $h = 10$ min, $k = 1$ hour, $M = 24$, $N = 6$. Given a sample w_n of the generated power, the corresponding bid is $C^{(m)}$, where $m = \lceil n/N \rceil$ and $\lceil x \rceil$ denotes the smallest integer greater than or equal to x. Finally, let $C = [C^{(1)}, \ldots, C^{(M)}]^T \in \mathbb{R}_+^M$.

2.1 Scenario without energy storage. It is assumed that the WPP is remunerated according to the bid C and its deviation from the actual power w in the following way. Let p denote the unitary price of offered energy, q denote the unitary penalty for energy shortfall and λ be the unitary price for energy surplus. The WPP receives p units of money for each unit of offered energy $hC^{(m)}$. In case the actual generated energy hw_n is smaller than the corresponding bid $hC^{(m)}$, the WPP is penalized by q units of money for each unit of short energy $h(C^{(m)} - w_n)$. On the contrary, if the actual generated energy hw_n is greater than the corresponding bid $hC^{(m)}$, the energy surplus $h(w_n - C^{(m)})$ is remunerated at unitary price λ. Hence, the net daily profit amounts to

$$\begin{aligned} \Pi(C, w) = & h \sum_{m=1}^{M} \sum_{n=(m-1)N+1}^{mN} \Big(pC^{(m)} \\ & - q[C^{(m)} - w_n]^+ + \lambda [w_n - C^{(m)}]^+ \Big), \end{aligned} \tag{2.1}$$

where $[x]^+ = \max\{0,\ x\}$. Throughout the paper the prices p, q and λ are supposed to be constant and known beforehand. Moreover, in order to rule out meaningless scenarios, it is assumed that $0 < p < q$ and $0 \leq \lambda < p$. Notice that $\lambda < 0$ means that the WPP would incur in a monetary penalty if its generation exceeds the corresponding bid. While such a scenario could be of interest, in general, one can assume $\lambda \geq 0$ without loss of generality, if the WPP has curtailment capabilities.

Since the profit $\Pi(C, w)$ is a stochastic quantity due to the uncertainty on the generated wind power w, the optimal bidding problem consists in determining the bid C^* maximizing the expected profit $J(C) = \mathbf{E}[\Pi(C, w)]$

$$C^* = \arg\max_C J(C). \tag{2.2}$$

2.2 Scenario with energy storage. When an energy storage system is available, it can be exploited to mitigate the volatility of the generated energy and be more compliant with the bids put on the market. Before formulating the optimal bidding problem, let us introduce a simplified model of energy storage system. The energy e_n stored in the device at time n evolves according to the difference equation

$$e_{n+1} = e_n + h\Big[\eta_i P_{n,i} - \frac{1}{\eta_e} P_{n,e}\Big]. \tag{2.3}$$

In (2.3), $P_{n,i} \geq 0$ and $P_{n,e} \geq 0$ are the power injected into and extracted from the device at time n, respectively. The parameters defining the storage system are the energy capacity $\bar{e}$, the charging power capacity $\bar{P}_i$ and discharging power capacity $\bar{P}_e$, the charging efficiency $\eta_i \in (0,1)$ and discharging efficiency $\eta_e \in (0,1)$. The time evolution (2.3) holds as long as it satisfies some constraints. The stored energy cannot be negative nor it can exceed the energy capacity, i.e.

$$0 \leq e_n \leq \bar{e}. \tag{2.4}$$

The in/out power flow cannot exceed the corresponding power capacity

$$0 \leq P_{n,i} \leq \bar{P}_i, \tag{2.5}$$

$$0 \leq P_{n,e} \leq \bar{P}_e. \tag{2.6}$$

At a given sampling time n, the WPP selects the power $P_{n,i}$ and $P_{n,e}$ according to a suitable policy g aiming at maximizing the matching between the bid and the power actually delivered. In general, the policy g computes the in/out power flow on the basis of the current storage state e_n, the generated wind power w_n and the corresponding bid $C^{(m)}$ (with $m = \lceil n/N \rceil$) [8]:

$$g\left(e_n, w_n, C^{(m)}\right) = \begin{bmatrix} P_{n,e} \\ P_{n,i} \end{bmatrix}, \tag{2.7}$$

subject to the constraints (2.3)-(2.6). This additional degree of freedom allows the WPP to modulate to some extent the energy injected into the grid, and consequently the net daily profit (2.1) in the presence of a storage system becomes

$$\Pi(C,w,g) = h \sum_{m=1}^{M} \sum_{n=(m-1)N+1}^{mN} \Big(pC^{(m)} - q[C^{(m)} - w_n + P^g_{n,i} - P^g_{n,e}]^+ + \lambda[w_n - C^{(m)} + P^g_{n,e} - P^g_{n,i}]^+\Big), \tag{2.8}$$

where the superscript g emphasizes the dependence of the in/out storage power flow on the policy g. In this setting, the optimal bidding problem consists in determining the bid C^* and the policy g^* maximizing the expected profit

$$J(C,g) = \mathbf{E}[\Pi(C,w,g)], \tag{2.9}$$

while satisfying the storage constraints (2.3)-(2.6)

$$\begin{aligned} (C^*, g^*) = \arg\max_{C,\ g} & J(C,g) \\ \text{s. t. } & e_{n+1} = e_n + h\Big[\eta_i P^g_{n,i} - \frac{1}{\eta_e} P^g_{n,e}\Big],\ n = 1,\dots,NM, \\ & 0 \leq e_n \leq \bar{e}, \\ & 0 \leq P^g_{n,i} \leq \bar{P}_i, \\ & 0 \leq P^g_{n,e} \leq \bar{P}_e. \end{aligned} \tag{2.10}$$

3 Optimal bidding strategies

This section describes possible solutions to the optimal bidding problems described so far. First, the exact solution when no storage devices are installed at the WPP premises (problem (2.2)) is recalled. Then, an approximate solution for suitably exploiting the storage capabilities (problem (2.10)) is proposed.

3.1 Scenario without energy storage. When no storage systems are available, the bid $C^{(m)}$ that the WPP offers for the m-th time interval depends only on the expected energy generated during the same period. Hence, two bids $C^{(i)}$ and $C^{(j)}$, $i \neq j$, related to different intervals are independent from each other. As a result, the optimization problem (2.2), involving an M-dimensional optimization variable C, boils down to M scalar optimization problems

$$C^{(m)*} = \arg\max_{C^{(m)}} J_m\left(C^{(m)}\right), \qquad m = 1,\dots,M, \tag{3.11}$$

where

$$J_m\left(C^{(m)}\right) = \mathbf{E}\Bigg[\sum_{n=(m-1)N+1}^{mN} \Big(pC^{(m)} - q[C^{(m)} - w_n]^+ + \lambda[w_n - C^{(m)}]^+\Big)\Bigg].$$

The optimal solution to (3.11) depends on the wind power statistics over the considered interval. Let

$$F(w;n) = \Pr(w_n \leq w)$$

denote the cumulative distribution function (CDF) of the random variable w_n. Then the time-averaged CDF

$$F_m(w) = \frac{1}{N} \sum_{n=(m-1)N+1}^{mN} F(w;n) \tag{3.12}$$

plays a key role in the computation of the optimal bid $C^{(m)*}$. As a matter of fact, in [5] it has been shown that

$$C^{(m)*} = F_m^{-1}(\gamma), \tag{3.13}$$

where $\gamma = \dfrac{p-\lambda}{q-\lambda}$ and $F^{-1}(x) = \inf\{y \in [0,1] : F(y) \geq x\}$, is the quantile function.

3.2 Scenario with energy storage. Let us focus on the optimal policy g^* solution of the optimization problem (2.10) first. When $\lambda = 0$, i.e. the energy surplus is not remunerated at all, the optimal policy is as follows [8]. Since p and q are constant, there is no possibility of price arbitrage. Then, in case of positive imbalance, the best choice is to inject the power surplus $w_n - C^{(m)}$ into the storage device as long as it is not full. Similarly, in case of negative imbalance, the power shortfall $C^{(m)} - w_n$ can be extracted from the storage device as long as it is not empty. Letting $m = \lceil n/N \rceil$, the optimal policy at sampling time n can be summarized as

$$g_n^* = \begin{bmatrix} \min\left\{C^{(m)} - w_n,\ \dfrac{\eta_e}{h}e_n,\ \bar{P}_e\right\} \\ 0 \end{bmatrix} \tag{3.14}$$

if $C^{(m)} - w_n > 0$, or

$$g_n^* = \begin{bmatrix} 0 \\ \min\left\{w_n - C^{(m)},\ \dfrac{1}{\eta_i h}(\bar{e} - e_n),\ \bar{P}_i\right\} \end{bmatrix} \tag{3.15}$$

if $C^{(m)} - w_n \leq 0$. The $\min\{\cdot\}$ function is used to guarantee that the limitations on the energy capacity, power capacity and charging efficiency are satisfied. In general, the policy (3.14)-(3.15) is still optimal when $\lambda \neq 0$, provided that it is smaller than a critical value. In fact, when an energy surplus $h(w_n - C^{(m)})$ is available, the corresponding profit is $\lambda h(w_n - C^{(m)})$ if it is immediately injected into the grid. On the contrary, if the surplus is stored in the battery and subsequently extracted for compensating an energy shortfall, the saving amounts to $q\eta_i\eta_e h(w_n - C^{(m)})$. The total efficiency $\eta_i\eta_e$ of the storage system accounts for energy loss when injecting into and extracting energy from the device. Hence, if $\lambda < \eta_i\eta_e q$ it is still preferable to store energy surplus rather than immediately selling it. Clearly, if $\lambda \geq \eta_i\eta_e p$ the optimal policy is to sell energy surplus at a price λ rather then storing it. In this case the storage device does not bring any benefit to the WPP. In the remaining of the paper we will assume $\lambda < \eta_i\eta_e p$.

Since the policy g^* in (3.14)-(3.15) is optimal irrespective of the bids C, the optimization problem (2.10) simplifies to

$$\begin{aligned} C^* &= \arg\max_C J(C, g^*) \\ \text{s. t. } e_{n+1} &= e_n + h\Big[\eta_i P_{n,i}^{g^*} - \frac{1}{\eta_e}P_{n,e}^{g^*}\Big],\ n = 1, \ldots, NM, \\ 0 &\leq e_n \leq \bar{e}, \\ 0 &\leq P_{n,i}^{g^*} \leq \bar{P}_i, \\ 0 &\leq P_{n,e}^{g^*} \leq \bar{P}_e. \end{aligned} \tag{3.16}$$

Notice that the bids related to different time intervals are now no longer independent due to the presence of the storage device. Consequently, problem (3.16) has to be solved for the whole bid portfolio $C \in \mathbb{R}^M$. Moreover, the equality constraints related to the evolution of the storage system state e_n involve the actual wind power w_n which is unknown at the time of the contract sizing. As a result, the optimal bid C^* cannot be analytically determined anymore.

A suboptimal ("sample") solution to the problem (3.16) can be found by analyzing the historical data of the wind power plant. The basic idea is to approximate the expected profit (2.9) with its sample mean

$$\begin{aligned} \bar{J}(C, g) = \frac{1}{D}\sum_{d=1}^{D}\Bigg[h\sum_{m=1}^{M}\sum_{n=(m-1)N}^{mN}\Big(pC^{(m)} &- q[C^{(m)} - w_n^{(d)} + P_{n,i}^{g,(d)} - P_{n,e}^{g,(d)}]^+ \\ &+ \lambda[w_n^{(d)} - C^{(m)} + P_{n,e}^{g,(d)} - P_{n,i}^{g,(d)}]^+\Big)\Bigg] \end{aligned} \tag{3.17}$$

where the superscript $\cdot^{(d)}$ denotes the realization taken by the corresponding quantity on the d-th day of the time series, and D is the total number of days available. The optimal bids C^* are then computed by numerically solving the problem

$$\begin{aligned} \bar{C*}^* &= \arg\max_C \bar{J}(C, g^*) \\ \text{s. t. } e_{n+1}^{(d)} &= e_n^{(d)} + h\Big[\eta_i P_{n,i}^{g^*,(d)} - \frac{1}{\eta_e}P_{n,e}^{g^*,(d)}\Big],\ n = 1, \ldots, NM, \\ 0 &\leq e_n^{(d)} \leq \bar{e}, \qquad d = 1, \ldots, D, \\ 0 &\leq P_{n,i}^{g^*,(d)} \leq \bar{P}_i, \\ 0 &\leq P_{n,e}^{g^*,(d)} \leq \bar{P}_e. \end{aligned} \tag{3.18}$$

In the next section, we show how to suitably exploit meteorological forecasts to compute the suboptimal bidding solution.

4 Exploiting wind forecasts

Since the generated power is highly dependent on the wind speed, meteorological forecasts for the day the bids refer to (typically, the next day) can help guess the generated power, and hence refine the amount of energy to offer. Assuming that the power curve of the wind plant is available (e.g. from wind turbine data sheet or estimated from data), one could simply substitute the wind speed forecasts into the equation of the power curve, and be tempted to build the bids based on the forecasts of generated power thus obtained. However, such a naive approach has a number of drawbacks. First, inaccurate wind speed forecasts may lead to unacceptable errors when predicting wind power. Second, and more importantly, forecasts of generated power do not take into account the price p and the penalties q and λ. This implies that bidding these forecasts may not be the best one can do. For instance, let us consider the limit case $q = p$, i.e. energy shortfall is not penalized. Clearly, under this assumption the optimal strategy is to offer the maximum allowable amount of energy, since this results in having all the generated energy be remunerated at price p . Similarly, should $\lambda = p$, i.e. energy surplus is remunerated at the same price of the bids, then the optimal strategy is to bid zero contracts. As shown in Section 3.1, the optimal bidding strategy has to take into account the relative weight of p, q and λ, besides the wind power statistics.

In this paper we pursue a different idea to exploit effectively wind speed forecasts for bidding of wind power. The idea is that even inaccurate wind speed forecasts may give a qualitative information about the meteorological conditions which can be expected for the next day, e.g. whether the next day will be a windy one or not. The proposed approach consists in classifying the days for which the bids are planned on the basis of the expected energy generated by the wind plant, and then determine an optimal bidding strategy for each of such classes. Let us group the M bidding time intervals of one day into g sets $S_i = \{a_i, a_i+1, \ldots, a_{i+1}-1, a_{i+1}\}$, $i = 0, \ldots, g-1$, where the integers $a_i \in \mathbb{N}$ are such that

$$1 = a_0 < a_i < \cdots < a_g = M.$$

To ease the notation let us assume that the sets S_i have the same cardinality, i.e. they contain an equal number of bidding intervals. Denote by $\bar{E}$ an upper bound on the amount of energy that the power plant can produce during the intervals associated to any set S_i. The energy interval $[0,\ \bar{E})$ is then partitioned into s contiguous, non overlapping intervals $[E_i,\ E_{i+1})$, $i = 0, \ldots, s-1$, such that

$$0 = E_0 < E_1 < \cdots < E_{s-1} < E_s = \bar{E}.$$

Now, each day can be classified according to the amount of energy generated during each period S_i. For example, let us suppose hourly bids ($M = 24$) and consider the energy generated during "day" and "night" hours ($g = 2,\ a_1 = 12$). If we consider only two levels of generated energy ($s = 2$), e.g. "high" (H) and "low" (L) generation, then each day belongs to one of four possible classes $\{(L, L), (L, H), (H, L), (H, H)\}$ where the pair (X, Y) denotes the class of days having a X generation level during the first 12 hours and a Y generation level during the last 12 hours. In general, given g sets of bidding intervals and s levels of energy generation, it is possible to define a family of s^g classes $\mathcal{C} = \{\mathcal{D}_{i_1,\ldots,i_g},\ i_j = 1, \ldots, s,\ j = 1, \ldots, g\}$ such that a day d belongs to the class $\mathcal{D}_{i_1,\ldots,i_g}$, $d \in \mathcal{D}_{i_1,\ldots,i_g}$, if

(4.19)
$$h \sum_{m=a_{j-1}}^{a_j} \sum_{n=(m-1)N}^{mN} w_n^{(d)} \in [E_{i_j},\ E_{i_{j+1}}), \quad j = 1, \ldots, g,$$

where $w_n^{(d)}$ denotes the n-th sample of power generated in the d-th day.

The next step is to train an automatic classifier which takes as inputs the wind speed forecasts and returns the class the next day will belong to. To this purpose, a training set is created from past data of generated power and wind speed forecasts. First, each day of the data set is assigned to the corresponding class on the basis of the actual generated energy. Then, a g-dimensional feature vector representative of the considered day is built from wind speed forecasts. Features have been selected as a function of the cube of the wind speed forecasts. Specifically, given the wind speed forecasts $\hat{v}_m^{(d)}$, $m = 1, \ldots, M$, for each bidding interval of the day d, the corresponding features are stacked in a vector $f^{(d)} = [f_1^{(d)}, \ldots, f_g^{(d)}]^T \in \mathcal{F} \subseteq \mathbb{R}^g$, where

$$f_j^{(d)} = Nh \sum_{m=a_{j-1}}^{a_j} \left(\hat{v}_m^{(d)}\right)^3, \quad j = 1, \ldots, g. \tag{4.20}$$

At this point, the training set

$$\mathcal{T} = \left\{ \left(\mathcal{D}_{i_1,\ldots,i_g}^{(d)},\ f^{(d)}\right),\ d = 1, \ldots, D \right\} \tag{4.21}$$

contains the pairs class/features for each day d, where $\mathcal{D}_{i_1,\ldots,i_g}^{(d)}$ denotes the class the day d belongs to according to the definition (4.19) and D is the cardinality of the training set. The set $\mathcal{T}$ is used to train a classifier $H : \mathcal{F} \to \mathcal{C}$ which, given a feature $f \in \mathcal{F}$, returns a class $H(f) \in \mathcal{C}$. Several approaches can be adopted to identify the function H [6]. In this paper, we adopt the Multicategory Robust Linear Programming (MRLP) approach described in [7].

Having a classifier available, the last step is to determine the optimal bidding strategy for each of the classes which have been defined. When no storage devices are available, this boils down to estimating a CDF $F^{(i_1,\dots,i_g)}(w;n)$ for each class $\mathcal{D}_{(i_1,\dots,i_g)}$, and then using the time averaged distributions

$$F_m^{(i_1,\dots,i_g)}(w) = \frac{1}{N} \sum_{n=(m-1)N+1}^{mN} F^{(i_1,\dots,i_g)}(w;n), \tag{4.22}$$

in place of (3.12) when computing the optimal bid. When a storage system is available, an optimization problem like (3.18) has to be solved for each class, by including in the cost function (3.17) only the days belonging to the corresponding class.

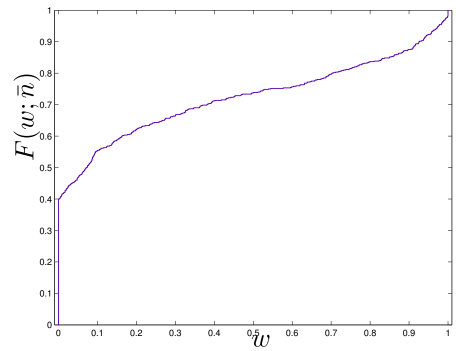

Figure 1: Empirical CDF for random variable $w_{\bar{n}}$ (normalized with respect to the maximum power).

5 Experimental results

In this section, the bidding strategies previously introduced are validated on experimental data taken from a real Italian wind farm composed of 34 wind turbines, having a nominal power of 2 MW. For each turbine, the following data are available:

- actual generated power $w_n^{(d)}$, $n = 1,\dots,NM$, $d = 1,\dots,D_T$;
- actual wind speed $v_n^{(d)}$, $n = 1,\dots,NM$, $d = 1,\dots,D_T$;
- wind speed forecasts $\hat{v}_m^{(d)}$, $m = 1,\dots,M$, $d = 1,\dots,D_T$;

where $D_T = 150$ is the number of days spanned by the data set (about 5 months of recordings), the measurements of generated power and wind speed are taken every $h = 10$ minutes, whereas hourly bids are assumed. This results in $M = 24$ bids per day and $N = 6$ power samples per bid interval. Notice that the wind speed forecasts have a coarser temporal resolution, i.e. the meteorological service provides hourly forecasts of the average wind speed for the area where the plant is located. The data set is split in a training set composed of the data of the first 100 days ($D = 100$ in (3.18) and (4.21)) and a validation set containing the data of the remaining 50 days.

The optimal bidding strategy when no storage is available requires the knowledge of the CDF $F(w;n)$ in (3.12) (or, equivalently, the per-class CDF $F^{(i_1,\dots,i_g)}(w;n)$ in (4.22) when exploiting weather forecasts). The function $F(w;n)$ can be estimated from the power measurements $w_n^{(d)}$, $d = 1,\dots,D$ contained in the training set according to one of the many CDF approximation methods available [9]. Figure 1 shows the empirical CDF of the random variable w_n (normalized with respect to the nominal power of a wind turbine) for a given sampling time $n = \bar{n}$. This solution has been used to compute the optimal bids from the inverse quantile function as in (3.13).

In order to exploit the wind speed forecasts, a classifier like that described in Section 4 has been trained. Days are classified on the basis of the energy generated during the first and the second 12 hours of the day. For each period, two levels of generation have been defined, with the threshold set at 25% of the maximum amount of producible energy. With the notation of Section 4, we have $g = 2$, $a_1 = 12$, $s = 2$, $E_1 = 0.25\bar{E}$, where $\bar{E} = 24$ MWh is the maximum energy which a 2MW wind turbine can produce in 12 hours. This choice results in a family of four classes $\mathcal{C} = \{\mathcal{D}_{11}, \mathcal{D}_{12}, \mathcal{D}_{21}, \mathcal{D}_{22}\}$. For each day d in the training set, the feature vector $f^{(d)} = [\ f_1^{(d)}\ f_2^{(d)}\ ]^T \in \mathcal{F} \subseteq \mathbb{R}^2$ is computed as in (4.20). A Multicategory Robust Linear Programming (MRLP) classifier has been trained using the data set (4.21), by solving a linear program to minimize the number of misclassifications [7]. Figure 2 shows the final regions in the feature space associated to each of the four classes for one of the considered wind turbines.

The training phase ends with the computation of the optimal bids with or without storage devices. When no weather forecasts are assumed to be available, C^* is computed according to (3.13) (where a single CDF $F(w;n)$ is estimated from all the days belonging to the training set) or (3.18) (where the cost function contains all the days in the training set). On the contrary, when wind forecasts are available, a CDF $F^{(i_1,i_2)}(w;n)$ is estimated for each of the four classes (without storage) and one problem of the form (3.18) is solved for each of the four classes (with storage). The performance of such bidding strategies has been evaluated using the data

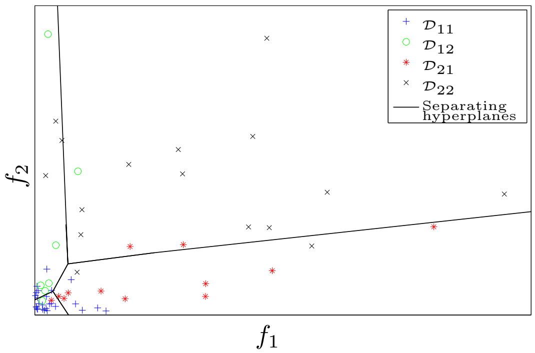

Figure 2: Regions resulting from the training of the MRLP classifier for one of the wind turbines.

$\bar{e}$ (KWh)	$\Pi_{S\bar{C}}$(€)	Π_{SC}(€)
10	352.48	492,50
25	353.05	493,18
50	353.96	494,11
100	355.67	496,12
200	360.66	501,81
500	368.05	509,46
1000	380.43	520,91

Table 1: Market scenario I: Average daily profit with different energy capacity.

contained in the validation data set under two possible market scenarios.

5.1 Market scenario I. In the first scenario, the energy surplus is supposed to be not remunerated at all, i.e. $\lambda = 0$. The following market parameters are assumed: $p = 72$ €/MWh and $q = 88$ €/MWh. When neither meteorological forecasts nor energy storage are available (situation denoted by the subscript $\bar{S}\bar{C}$), the optimal bids computed as in (3.13) result in an average daily profit $\Pi_{\bar{S}\bar{C}} = 352.42$ € per wind turbine. Table 1 reports the average daily profit $\Pi_{S\bar{C}}$ in the case with energy storage and without meteorological forecasts, and the average daily profit Π_{SC} in the case with both energy storage and meteorological forecasts.

For computation of $\Pi_{S\bar{C}}$, the bids are determined according to (3.18) and evaluated on a plant equipped with the same storage system. In the validation phase, storage systems featuring different energy capacity have been taken into account in order to evaluate the impact of such a parameter on the expected profit (corresponding to different rows of Table 1). The remaining storage parameters have been set to $\eta_i = \eta_e = 0.85$, $\bar{P}_i = \bar{P}_e = \bar{e}/4$ corresponding to a recharging time of 4 hours. All the results are averaged over all the days of the validation set and all the turbines of the wind farm. Depending on the capacity of the storage device, a profit increase up to 8% with respect to $\Pi_{\bar{S}\bar{C}}$ can be expected (first column of Table 1).

When exploiting the weather forecasts, the optimal bids computed and validated assuming no storage device result in an average daily profit $\Pi_{\bar{S}C} = 491.72$ € per wind turbine. This result shows the huge impact that the wind speed forecasts can have on the expected profit (40% higher than $\Pi_{\bar{S}\bar{C}}$). It is worth remarking that these results have been achieved using very rough forecasts provided by a meteorological service.

For computation of Π_{SC}, the bids are determined according to (3.18) for each class and evaluated on a plant equipped with the same storage system. Corresponding results are reported in the second column of Table 1. It has to be noted that the success rate of the classifier has a major impact on the performance of the bidding strategy. As a matter of fact, it turns out that the classifier has very different classification performance depending on the true class a day belongs to (85 % of correct day classification for classes $\mathcal{D}_{11}$ and $\mathcal{D}_{22}$ vs. 50 % of hit rate for the remaining classes).

$\bar{e}$ (KWh)	$\Pi_{S\bar{C}}$(€)	Π_{SC}(€)
10	457.74	545,03
25	458.03	545,33
50	458.66	545,95
100	459.85	547,22
200	462.98	550,44
500	467.61	555,23
1000	474.91	560,62

Table 2: Market scenario II: Average daily profit with different energy capacity.

5.2 Market scenario II. In this scenario, the energy surplus is remunerated at $\lambda = 30$ €/MWh. All the other market parameters and storage system characteristics are the same as before.

In this case, the average daily profit $\Pi_{\bar{S}\bar{C}}$ is 457.67 € . Now the benefits introduced by the storage system and strategy (3.18) when meteorological forecasts are not assumed to be available, are less evident than before ($\Pi_{S\bar{C}}$ in the first column of Table 2), since positive imbalances are now remunerated to some extent and consequently the role played by the storage device is less significant. This phenomenon is also confirmed when exploiting the wind speed forecasts in the bidding strategy. In this case, when the bidding strategy and validation are carried out by neglecting the storage system, the average daily profit is $\Pi_{\bar{S}C} = 545.02$ €. While the improvement provided by the meteorological forecasts is still relevant (about 19% with respect to $\Pi_{\bar{S}\bar{C}}$), the presence of a storage system yields only a little increase (Π_{SC} in the second column of Table 2).

6 Conclusions

In this paper, optimal bidding for wind power producers has been addressed. By starting from a dynamic stochastic optimization problem formulation, we introduced a statistical approach based on classification for fully exploiting the information contained in meteorological forecasts. Information in historical wind power data and wind speed forecasts is used to train a classifier which allows for using the wind power conditional probability distribution function in place of the unconditional distribution in the optimization problem. The approach improves consistently the quality of the bidding strategy, both with respect to the unconditional case and to the case in which the bidding plan is computed simply by offering the wind power corresponding to the wind speed forecasts.

The approach has been exploited in both the case when a storage device is available or not. The derived algorithm has been tested on historical real data of wind and generated power gathered in a wind farm over a period covering almost five months. The obtained quantitative results confirm the effectiveness of the newly proposed procedure, showing the roles of classification and storage in different scenarios.

Ongoing research is concerned with extensions of the proposed approach to the case where additional meteorological information is available, e.g., wind direction and speed at different heights, instead of wind speed at regional level only.

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