Assessment of the Cost Associated With Wind Generation Prediction Errors in a Liberalized Electricity Market

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***Abstract*—In this paper, a probabilistic methodology for estimating the energy costs in the market for wind generators associated with wind prediction errors is proposed. Generators must buy or sell energy production deviations due to prediction errors when they bid in day-ahead or hour-ahead energy markets. The prediction error is modeled through a probability density function that represents the accuracy of the prediction model. Production hourly energy deviations and their associated trading costs are then calculated. Three study cases based on real wind power installations in Spain are analyzed. The three study cases show that the error prediction costs can reach as much as 10% of the total generator energy incomes.**

***Index Terms*—Ancillary services, electricity markets, short-term wind forecast, wind power.**

I. Introduction

IN DECEMBER 1999, the Spanish government approved the Renewable Energies Promotion Plan, which followed the European Union (EU) guidelines set out in the 1997 White Paper on renewable energies and was then legislated in the EU Directive 2001/77/EC [1]. Its goal is to increase the contribution of renewable energy sources (RESs) in gross domestic energy consumption in the EU from the present 6% to 12% by 2010. Under this target, the problem of the integration of wind power, the RES with the most promising future, into the new deregulated energy framework is of great importance.

Since January 1998, in fact, the Spanish Electricity System has been deregulated by Electricity Law 54/1997, which introduced wholesale and retail competition and replaced the old model based on a Central Purchasing Agent. Regulated activities, i.e., transmission and distribution, have been separated from nonregulated businesses, i.e., generation and retail [2], [3].

In Spain, RES have been regulated through several royal decrees. RES and cogeneration facilities are not obliged to sell their production in the market but receive a remuneration based on an administrative premium scheme. This measure was adopted to allow for the development of RES technologies, often still at a prototype level, whose production costs are still too high to withstand competition in a liberalized energy market. Nevertheless, the last changes in the Spanish legislation aim to also integrate RES facilities into the pool market [4].

Wind energy is the RES with the lowest cost of electricity production and, in Spain, is greatly available. This explains the impressive growth of the installed wind capacity over the last years: from the around 800 MW installed in 1998 to the almost 6000 MW at the end of 2003, with the objective of reaching 13 000 MW by 2011 [5].

Large-scale integration of wind power (WP) in the electricity system presents some planning and operational difficulties, due mainly to the intermittent and difficult-to-predict nature of wind, which is, therefore, considered an unreliable energy source. For example, in a large-scale WP penetration scenario, wind intermittency could oblige the system operator to allocate a greater spinning and supplemental energy reserves[1], in order to balance possible errors between programmed and actually produced wind energy in a certain time period. This would increase total operation costs and, consequently, final energy prices. Since the accuracy of WP prediction is fundamental in order to reduce energy production uncertainty, the development of WP forecasting models is widely recognized as a major contribution for increasing wind penetration.

This paper is focused on the assessment of energy costs that wind generators should bear due to energy generation errors when they bid hourly energy production in day-ahead or hour-ahead energy markets. Therefore, a production interval of one hour is considered. Other costs associated with the schedule of regulating and spinning reserves to compensate power fluctuations over shorter periods (minutes) are not explicitly considered in this paper. In the presented study cases, based on the Spanish electricity market, hourly energy production errors in the day-ahead and intraday-ahead energy markets are valued at the tertiary reserve energy price[2]. This price is obtained through a dedicated market managed by the system operator [6].

In this paper, a probabilistic methodology for estimating the energy costs in the market for wind generators associated with wind prediction errors is developed. The hypothesis that hourly energy production errors in day-ahead or intraday-ahead energy markets are compensated by using supplemental reserve

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[1]As defined by FERC

[2]Spanish legislation defines tertiary reserve energy as the supplemental-reserve energy hourly dispatched to replace the actual spinning-reserve energy used to correct the generation/load imbalances occurred in the system.

energy is assumed. WP generators should pay the costs associated with those energy deviations valued at the supplemental energy market prices.

The performance of any prediction model is characterized by the probability density function (pdf) of the associated WP prediction error. Therefore, the proposed method does not depend on any particular WP prediction model.

In Section II, the probabilistic model used to characterize WP prediction errors is presented. In Section III, taking into account the developed prediction error model, a method to determine the associated supplemental reserve energy cost is presented. Finally, Sections IV and V analyze three study cases: a single wind farm, an ensemble of 15 wind farms, and the simulated total production of peninsular Spain (Balearic and Canary Islands excluded). In these three cases, the proposed methodology is tested, and error prediction energy costs are obtained and expressed as a percentage of total generator energy incomes. Section VI presents the conclusions of this study.

II. Probabilistic Analysis of WP Prediction Error

A. *Definition of WP Prediction Error*

Knowing that no prediction model forecasts perfectly, the quality of a model can be measured by the mean absolute error (MAE) [7]

$$\mathrm{MAE} = \frac{1}{N}\sum_{i}^{N} \left|p_{\mathrm{pred}} - p_{\mathrm{meas}}\right|_i = \frac{1}{N}\sum_{i}^{N} e_i \qquad (1)$$

where N is the number of measurements, p_{pred} is the predicted power for the time period i, p_{meas} is the actual power value measured in the same period, and $e_i = \left|p_{\mathrm{pred}} - p_{\mathrm{meas}}\right|_i$ is the WP prediction error (for the same time period). In the following, in this paper, the time period is one hour, and predicted and measured values correspond to WP energy production at that hour. For time series of prediction and measured power, the quantity e can be modeled as a random variable defined by its mean value (the MAE) and its standard deviation (*std*).

B. *WP Prediction Error Standard Deviation*

In general, the *std* parameter of a particular WP prediction model depends on the quality of the model, prediction time horizons, and some other physical variables related to local conditions of WP installations. For instance, in [8], a wind-power model to schedule daily operation of wind and hydro power plants, based on [9], is used to characterize the uncertainty in WP generation. Error prediction standard deviations increase with the prediction time horizon from 1–48 h. In [10], an ARMA time-series prediction method is proposed to predict WP energy production from 1–6 h ahead. Prediction errors are compared for two different sites in Iowa and Minnesota, for different seasonal periods, and for different prediction horizons.

References [11] and [12] analyze experimental time series of predicted and measured wind power for 30 wind farms located in Northern Germany. A weather forecast model in combination with actual wind speed and power measurements was used. It was proved that, for forecasts up to 48 h, the standard deviation of the dataset was a function of the normalized predicted power

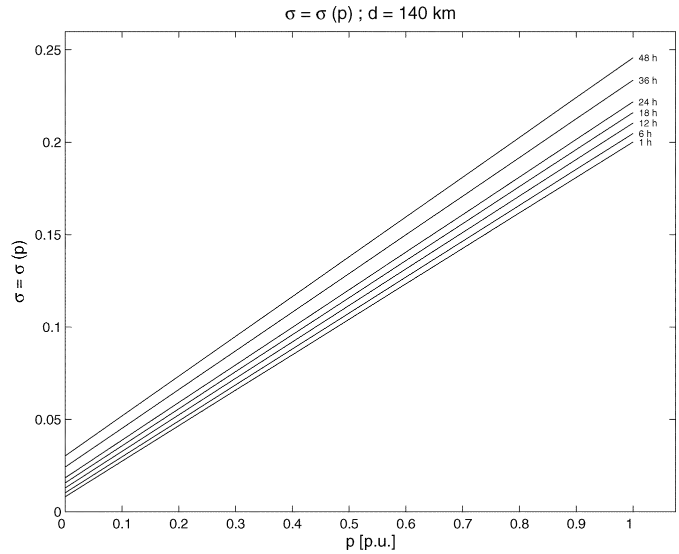

Fig. 1. Standard deviation of a WP forecast model as a function of the normalized predicted power.

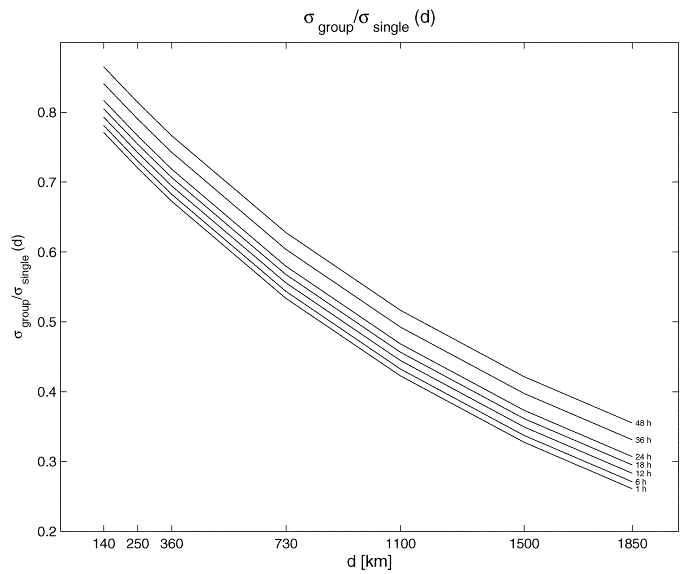

Fig. 2. Standard deviation of a WP forecast model as a function of the size of the region where the wind farms are located.

($p = p_{pred}/p_{\mathrm{inst}}$), where p_{inst} is the WP installed capacity, the forecast horizon (t_{pred}), and the size of the region where the wind farm installations are located (d) (it was observed that the dependency from the number of sites within each region was not significant).

In Fig. 1, the dependency of *std* parameter from these variables, found in [11] and [12], has been represented. A generalized linear equation has been obtained by interpolation of experimental curves.

In Fig. 2, the dependency of the *std* parameter with respect to the region size is represented. The *std* decreases as the size of the region increases. This behavior over an extended region is explained by the statistical smoothing effects. Errors underlying measurement and forecast at single sites cancel out partly by integrating energy production over a more extended region.

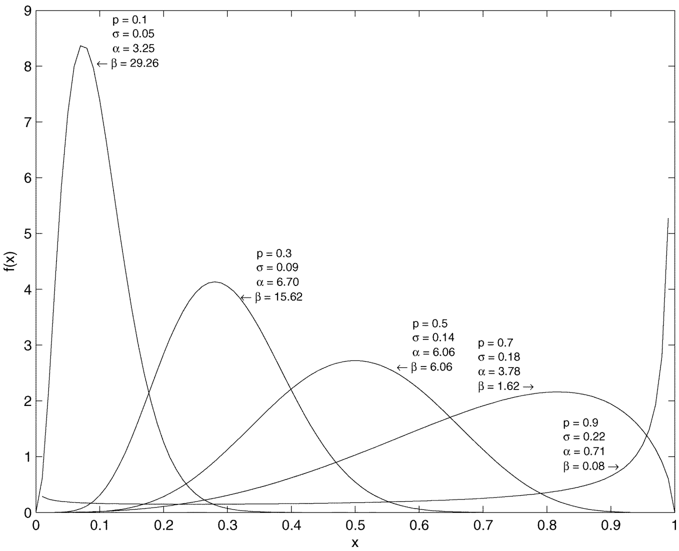

Fig. 3. Beta pdf for $p = 0.1$, 0.3, 0.5, 0.7, 0.9., and $t_{\rm pred} = 48$ h.

C. PDF of the WP Prediction Error

Despite the fact that most of the revised works on wind power forecast [7]–[10] assume a normal distribution function to represent the pdf of the prediction error, in [12], a more comprehensive proposal modeling that pdf as a Beta function is justified. Because the normalized produced power p must be within the interval [0,1], the beta function is more appropriate than standard normal distribution functions. The Beta function defined by the two parameters α and β allows for the representation of the prediction error for a predicted power p, with a mean value, which is the predicted power, and a standard deviation that varies with p. That variation is explained by the nonlinear characteristic of the turbine wind speed-power produced curve.

Therefore, the Beta function that models the occurrence of real power values x if a certain prediction value p has been forecasted is given by

$$f_p(x) = x^{\alpha-1} \cdot (1-x)^{\beta-1} \cdot n \tag{2}$$

where p is the normalized predicted power ($p = p_{\rm pred}/p_{\rm inst}$, $p \in [0,1]$), α, β are distribution function shape parameters, and n is the normalization factor.

Parameters α, β of a Beta function are related with the mean value and the variance of that distribution function by the following equations:

$$\text{Mean} = p = \frac{p_{\rm pred}}{p_{\rm inst}} = \frac{\alpha}{\alpha+\beta} \tag{3}$$

$$\text{Variance} = \sigma^2 = std^2 = \frac{\alpha \cdot \beta}{(\alpha+\beta)^2(\alpha+\beta+1)}. \tag{4}$$

The mean value is the predicted power (forecast models are centered in the mean value), and the variance refers to the variance of the prediction error for that predicted power. Therefore, a couple of predicted power and variance values univocally defines a probability distribution Beta function by solving (3) and (4).

For illustrative purposes, in Fig. 3, different Beta functions have been represented corresponding to different values of predicted power according to values of standard deviations from Fig. 1.

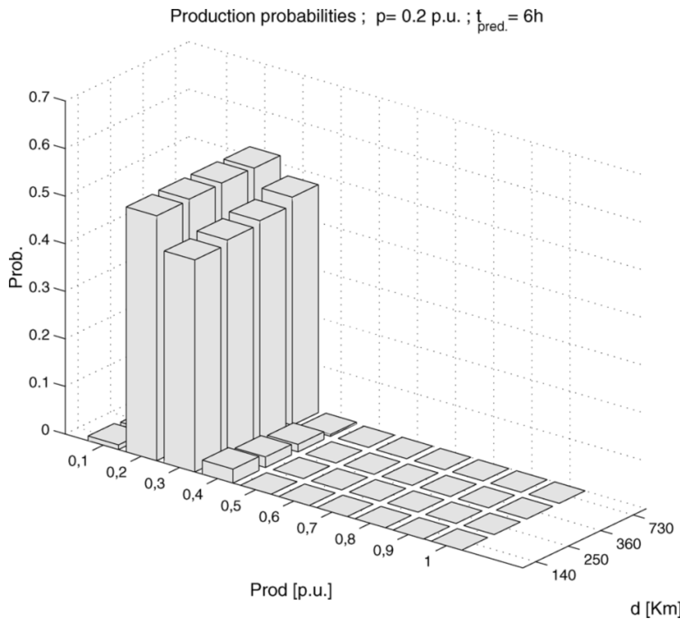

Fig. 4. WP production probabilities for a predicted power $p = 0.2$ p.u. and a forecast horizon $t_{\rm pred} = 6$ h.

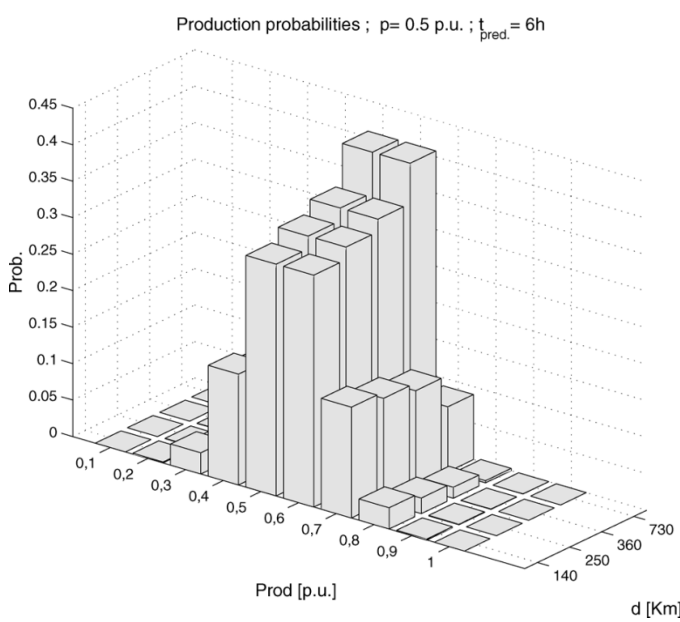

Fig. 5. WP production probabilities for a predicted power $p = 0.5$ p.u. and a forecast horizon $t_{\rm pred} = 6$ h.

D. Calculation of the WP Prediction Error Probability

Knowing the Beta function for a particular predicted power (p), the probability that the actual power will be within a specific interval [*prod1*, *prod2*] can be calculated by integrating the pdf between both interval bounds

$$prob_p(prod1, prod2) = \int_{x=prod1}^{x=prod2} f_p(x) \cdot dx. \tag{5}$$

Figs. 4–6 represent the probability of overproduction or underproduction with respect to the predicted value for p equal to 0.2, 0.5, and 0.7, respectively. These probabilities have been drawn for intervals of overproduction or underproduction of 0.1 p.u.

As can be observed from these figures, for every given prediction value, the probability to obtain a real power 0.1 p.u. greater

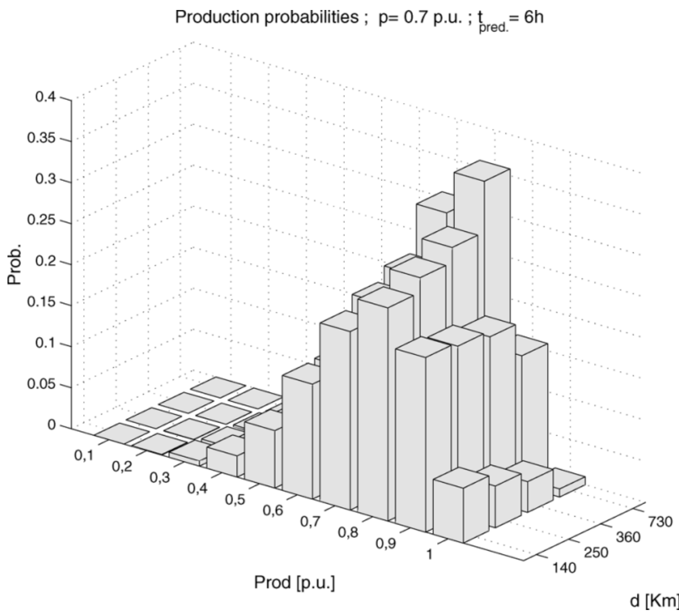

Fig. 6. WP production probabilities for a predicted power $p = 0.7$ p.u. and a forecast horizon $t_{\rm pred} = 6$ h.

or smaller than the predicted one, i.e., a 0.1 p.u., or smaller prediction error, upward or downward, is higher for the two adjacent intervals to the prediction value than for the rest of the intervals. This tendency increases (the prediction is more precise) when the forecast horizon is shorter and the region size is larger, i.e., when the prediction error probabilities "squeeze" near the predicted power.

III. Calculation of Costs Associated With the WP Prediction Error

A. Total Probabilistic Prediction Error (TPPE)

In the previous section, the method of how to compute the probability of overproduction or underproduction, within a specific interval, given a predicted power, has been shown.

The TPPE for a predicted power p can be calculated upward (TPPE_u) and downward (TPPE_d).

For a given value of overproduction ($x > p$), the amount of expected energy deviated in 1 h can be calculated as

$$(x - p) \cdot prob_p(x, x + dx) \cdot p_{\rm inst}. \tag{6}$$

Therefore, the $\mathrm{TPPE}_u(p)$ defined as the expected value of the volume of wind energy over generated with respect to the predicted value p, in 1 h, and measured in megawatthours, can be calculated as

$$\mathrm{TPPE}_u(p) = \int_{x=p}^{x=1} (x - p) \cdot f_p(x) \cdot p_{\rm inst} \cdot dx. \tag{7}$$

Similarly, $\mathrm{TPPE}_d(p)$ defined as the expected value of the volume of wind energy under generated with respect to the predicted production, in 1 h, can be calculated as

$$\mathrm{TPPE}_d(p) = \int_{x=0}^{x=p} (p - x) \cdot f_p(x) \cdot p_{\rm inst} \cdot dx. \tag{8}$$

B. Total Prediction Error Costs

The total cost associated with WP prediction errors (TCPE), for a certain period of time T, can be calculated as follows:

$$\mathrm{TCPE} = \sum_{h=1}^{T} \left\{ \mathrm{TPPE}_u(\overline{p_h}) \cdot EPd_h + \mathrm{TPPE}_d(\overline{p}_h) EPu_h \right\} \tag{9}$$

where $\overline{p}_h$ is the predicted power in hour h, EPu_h is the supplemental-up reserve energy price minus the daily market energy price in hour h, and EPd_h is the daily energy price minus the supplemental-down reserve energy price in hour h.

It is assumed that WP prediction errors are balanced by using supplemental reserve energy. In reality, spinning reserve energy would be used to correct real-time generation errors, and then, supplemental reserve energy would be dispatched to replace the actual spinning reserve used to correct the generation/load imbalances. In addition, it is assumed that WP generators are "price-takers" in all of the energy markets they participate in; therefore, they do not affect market prices.

For comparison purposes between different WP installations or different operational conditions at the same installation, the TCPE can be expressed as a relative cost per megawatt of installed generation capacity or as a percentage of the total gross income from selling the produced WP energy. In the first case, the error prediction cost per megawatt of installed capacity is calculated as

$$\frac{\mathrm{TCPE}}{\mathrm{MW}} = \frac{\mathrm{TCPE}}{p_{\rm inst}} \left(\frac{\mathrm{Euro}}{\mathrm{MW}} \right). \tag{10}$$

In the second case, the relative error prediction cost is calculated as

$$\mathrm{TCPE}\% = \frac{\mathrm{TCPE}}{\mathrm{AGI}} 100\% \tag{11}$$

where the annual gross income (AGI) from selling WP energy is obtained as

$$\mathrm{AGI} = \sum_{h=1}^{T} \overline{p_h} \cdot SP_h \cdot p_{\rm inst}. \tag{12}$$

SP_h is the selling price of the WP predicted power at hour h in the energy market. In Spain, wind power integrated into the energy market is sold at the hourly energy price plus a regulated "premium." In 2003, this premium was set at 2.66 cEuro/kWh.

IV. Study Cases

Three study cases have been analyzed: a single wind farm, a group of 15 wind farms, and the simulated total production of peninsular Spain. Historical hourly energy time series in 2003 for the production of the single wind farm and the group of the 15 wind farms were provided by the owner. A series for hourly wind energy production in Spain was obtained through a simulation model that considered geographical differences in wind speed. Table I summarizes the main characteristics of the three study cases. Table II shows the computed AGI for the three cases.

TABLE I
SIGNIFICANT PARAMETERS FOR THE STUDY CASES

	Installed Capacity (MW)	Annual average power output (MW)		Annual equivalent hours*	Annual produced energy (GWh)
1 wind farm	24.6	7.1	(28.8%)	2,521	62
15 wind farms	301.7	88.9	(29.5%)	2,582	778
Simulated Spanish production.	5,000	1,170.8	(23%)	2,051	10,256

*) Number of hours generating at full capacity to produce the total annual energy, calculated as the annual produced energy divided by the installed capacity.

TABLE II
INSTALLED CAPACITY AND AGI FOR THE THREE STUDY CASES

	Installed power (MW)	AGI (€)
1 wind farm	24.6	3,945,079.-
15 wind farms	301.7	49,845,664.-
Simulated Spanish production	5000.	661,047,253.-

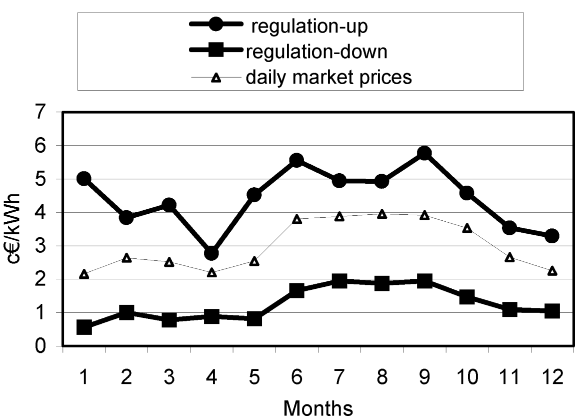

Fig. 7. Monthly mean supplemental reserve energy prices [13].

In order to apply the proposed methodology to quantify the WP prediction error costs, the supplemental reserve energy prices in 2003 in Spain are analyzed.

In Fig. 7, monthly mean supplemental reserve energy up and down prices are shown. These prices are compared to the mean value of prices in the energy market.

The monthly variation of reserve energy prices follows the same evolution as daily market energy prices. Maximum values are in June and September, but prices are high during all summer months, due to an increase of electricity consumption for air conditioning. Regulation-up energy is more expensive, because the deployment of more expensive units is required in the system.

Moreover, the monthly evolution of reserve energy prices has a negative correlation with the level of hydroelectric reservoirs, as shown in Fig. 8. During rainy months (from January to May), when hydroelectric production is greater, reserve energy prices are lower; in dry summer months (especially July, August, and September), prices increase appreciably.

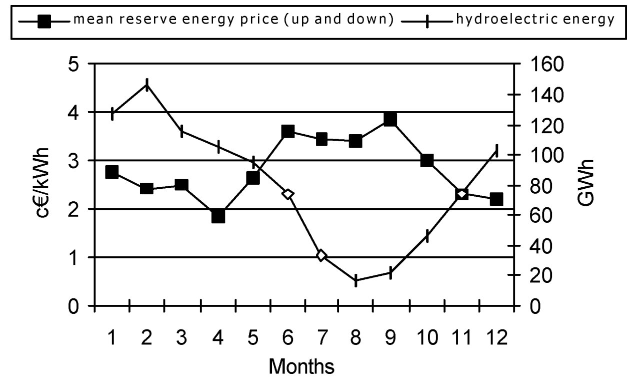

Fig. 8. Mean reserve energy price and hydroelectric energy levels, 2003 [13], [14].

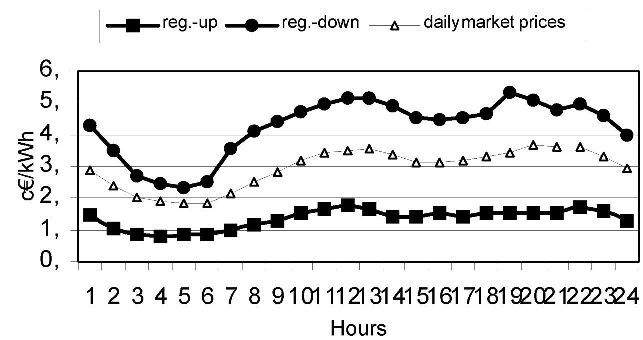

Fig. 9. Mean hourly supplemental reserve energy prices and daily market energy prices, 2003 [13].

TABLE III
TPPE (IN P.U.) AS A FUNCTION OF PREDICTION TIMES FOR THE THREE STUDY CASES

	TPPEu			TPPEd		
	1 h	6 h	48 h	1 h	6 h	48 h
1 wind farm	0.3757	0.3857	0.4674	0.4901	0.4996	0.5601
15 wind farms	0.2982	0.3052	0.3657	0.3971	0.4061	0.4756
Simulated Spanish production.	0.2448	0.2471	0.2680	0.3197	0.3233	0.3534

In Fig. 9, the mean hourly supplemental reserve energy prices are compared with the ones of the daily energy market. Energy hourly prices decrease during low-consumption hours and increase in peak-consumption hours. Hourly reserve energy prices follow the same trend, more sharply for regulation-up energy.

V. RESULTS

Based on the methodology presented in the previous sections, the monthly and annual WP prediction error costs for the three study cases are calculated.

Table III shows total probabilistic WP prediction errors $TPPE_u$ and $TPPE_d$, in p.u., obtained by applying (7) and (8), respectively, for different prediction horizon times: 1, 6, and 48 h. Better prediction conditions, i.e., shorter prediction times

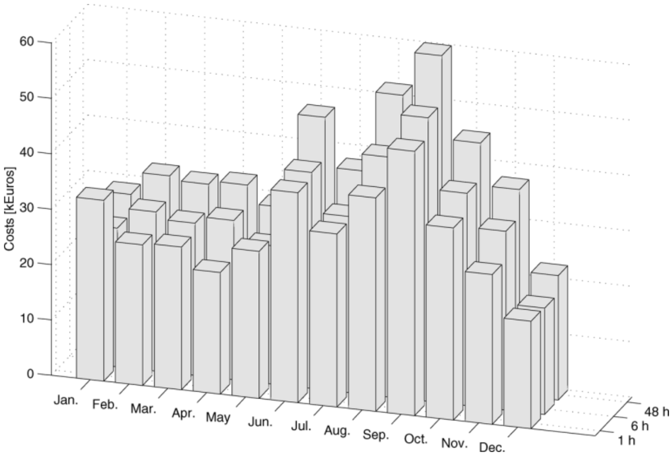

Fig. 10. Monthly costs (thousands of Euros) for supplemental reserve energy use for the single wind farm case ($\mathrm{t_{pred}} = 1$, 6, and 48 h).

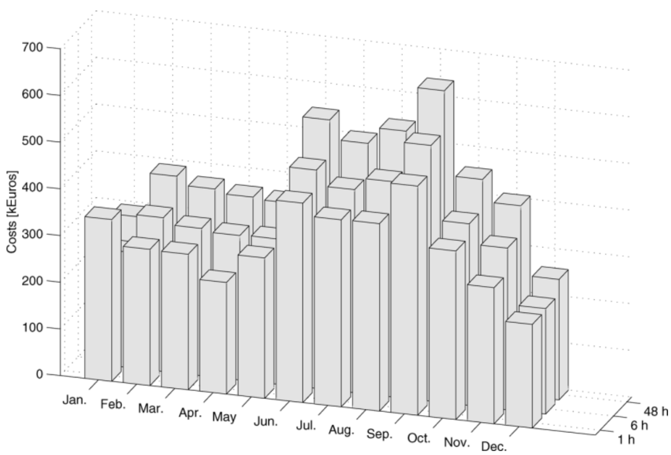

Fig. 11. Monthly costs (thousands of Euros) for supplemental reserve energy use for the 15 wind farms case ($\mathrm{t_{pred}} = 1$, 6, and 48 h).

and larger regions, where the wind farms are located, lead to smaller TPPE.

Error prediction monthly costs are calculated by applying (9) where supplemental up and down reserve energy prices presented in the previous section have been considered. These results are shown in Figs. 10–12, for the single wind farm, for 15 wind farms, and for the total production, respectively.

For experimental data (1–15 wind farms), the monthly cost evolution is similar: September and December are the months in which prediction costs are, respectively, bigger and smaller. This is due in part to the supplemental reserve energy prices—September is the most expensive month, and December the second cheapest—and in part to the annual wind speed profile. In fact, in September, wind energy production is quite high, and so, for the hypothesis, the prediction error is made bigger. December is a low-production month; therefore, the prediction error is less important.

For Spanish WP generation simulated data, the influence of reserve energy prices over the final cost is even greater because monthly generation differences are smaller and centered around the annual average value. In this case, September is still the month with the highest costs, whereas April is the one with the lowest costs.

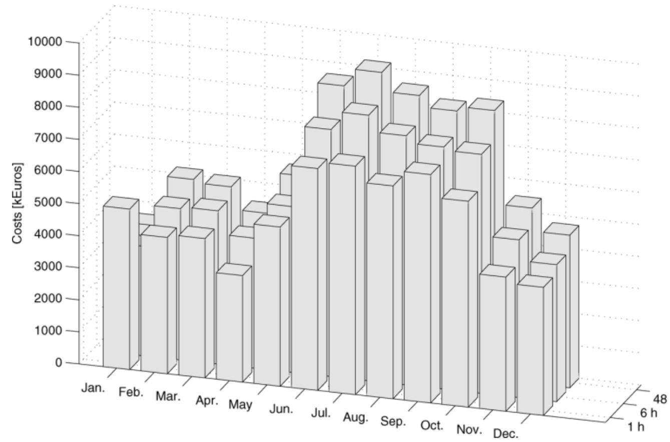

Fig. 12. Monthly costs (thousands of Euros) for supplemental reserve energy use for the total production case ($\mathrm{t_{pred}} = 1$, 6, and 48 h).

TABLE IV
ANNUAL COSTS RELATED TO INSTALLED POWER AND AGI, FOR THE THREE STUDY CASES, FOR $\mathrm{t_{pred}} = 1$, 6, AND 48 h

	Annual Costs (1 h) related to	
	Installed power (€/MW)	AGI (%)
1 wind farm	15,037	9.4
15 wind farms	13,464 (- 10.5%)	8.1 (- 1.3%)
Simulated Spanish production	12,845 (- 14.6%)	9.7 (+0.3%)

	Annual Costs (6 h) related to	
	Installed power (€/MW)	AGI (%)
1 wind farm	15,355	9.6
15 wind farms	13,709 (- 10.7%)	8.3 (-1.3%)
Simulated Spanish production	12,984 (- 15.4%)	9.8 (+ 0.2%)

	Annual Costs (48 h) related to	
	Installed power (€/MW)	AGI (%)
1 wind farm	18,363	11.5
15 wind farms	15,990 (- 12.9%)	9.7 (- 1.8%)
Simulated Spanish production	14,296 (- 22.1%)	10.8 (- 0.7%)

Table IV shows WP error prediction annual costs for prediction times of 1, 6, and 48 h. These are relative costs TCPE/MW and TCPE%, as defined in (10) and (11).

With the prediction model considered in this study, there are no important cost differences between prediction horizon times. The annual costs associated with the WP prediction error, as calculated in this paper, would represent a significant fraction (around 10%) of a wind farm's annual income in the electricity market.

Aggregation of energy production from different wind farms located in an extended region, in general, would decrease the overall prediction error as well as the relative prediction costs.

It is important to emphasize that the results obtained in this paper are a consequence of the probabilistic characterization of a particular forecast model. This paper has developed a general probabilistic method to calculate the WP error prediction costs, once the probability distribution function of the error associated with the forecast model is known. Different forecast models can lead to different results; for instance, a more accurate wind forecast model will produce lower relative prediction costs than the ones presented in Table IV.

VI. Conclusion

In this paper, a general probabilistic methodology for calculating the WP error prediction costs has been presented.

The WP forecast models are becoming a key tool used to facilitate the integration of wind power plants in energy markets. Deviations between predicted and real WP generation should be settled using a supplemental energy reserve at the price of this market. This involves a cost for the WP generator.

The developed method computes the WP error prediction costs by multiplying expected energy generation deviations in each hour by hourly supplemental energy reserve prices. Expected energy deviations are obtained by applying a probabilistic prediction error model, which characterizes the WP forecast method, to historical or simulated WP generation data.

The three study cases show that the error prediction costs can reach as much as 10% of the total WP incomes from selling energy. Error prediction costs will decrease when aggregating energy productions from wind plants spread over large areas, by decreasing the time horizon making the prediction closer to the real-time market, and definitively, by improving the accuracy of the WP forecast model.

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