Renewable Energy 34 (2009) 1848–1854

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Comparison of two new short-term wind-power forecasting systems

Ignacio J. Ramirez-Rosado [a,*], L. Alfredo Fernandez-Jimenez [b], Cláudio Monteiro [c,d], João Sousa [c,d], Ricardo Bessa [c,d]

[a] Department of Electrical Engineering, University of Zaragoza, Zaragoza, Spain
[b] Department of Electrical Engineering, University of La Rioja, Logroño, Spain
[c] FEUP, Fac. Engenharia Univ. Porto, Portugal
[d] INESC – Instituto de Engenharia de Sistemas e Computadores do Porto, Porto, Portugal

ARTICLE INFO

Article history:
Received 22 July 2008
Accepted 16 November 2008
Available online 25 December 2008

Keywords:
Forecasting
Neural networks
Wind-power forecasting

ABSTRACT

This paper presents a comparison of two new advanced statistical short-term wind-power forecasting systems developed by two independent research teams. The input variables used in both systems were the same: forecasted meteorological variable values obtained from a numerical weather prediction model; and electric power-generation registers from the SCADA system of the wind farm. Both systems are described in detail and the forecasting results compared, revealing great similarities, although the proposed structures of the two systems are different. The forecast horizon for both systems is 72 h, allowing the use of the forecasted values in electric market operations, as diary and intra-diary power generation bid offers, and in wind-farm maintenance planning.

1. Introduction

The significant increase worldwide in power plants based on renewable energy sources is mainly due to their important environmental advantages. Most industrialized countries have adopted policies to increase installed power with renewable energy power plants in order to comply with international environmental agreements. In recent years, wind power has become the most promising renewable energy source with a total global capacity of almost 94 GW at the end of 2007 [1].

One of the most essential tasks in power system operation and control is short-term load forecasting. In countries with a high integration of wind farms, the short-term forecasting of electric power production at wind farms is also essential because it allows power production schedules at conventional power plants to be established and power reserves to be determined. Accurate forecasts of electric power production at wind farms have direct implications on the economic operation of power systems [2].

In recent years, different short-term wind-power forecasting models have been developed using physical or statistical approaches: the physical approach attempts to estimate local wind speed using the physical laws governing atmospheric behaviour, and then the corresponding power generated at the wind farm; the statistical approach aims to determine the relationship between a set of explanatory variables and the power generated at the wind farm using historical data.

Forecasting models can be divided into two groups: a first group that only employ time series data and predict future values taking into account past history; and a second group that uses forecasted values from a Numerical Weather Prediction (NWP) model. The models in the first group use the statistical approach to forecast mean hourly wind speed at wind farms (using that data to predict electric power production) or to directly forecast electric power production. The statistical relationship may be modelled using different methods ranging from classical time series analysis to soft-computing techniques with the time series (mean wind speed or mean electric power) from the wind farm [3–7] or with data from near reference locations [8,9].

The models in the second group use, as additional input data, the values forecasted by a NWP model, corresponding to weather variables, mainly hourly mean wind speed and direction [10,11]. The forecasting horizon can be of very few days, since the period of predictability with a NWP model is of the order of 2–5 days [12]. The forecasted values for wind speed by the NWP model can be used directly for electric market applications, with interesting simulation results [13,14]. But wind-power forecasts can be improved using physical or statistical approaches, or even a combination of both approaches. The published results obtained with these models using these approaches reveal significant improvements with respect to results obtained with models in the first group, only when the forecast horizon is over a few hours. Different research groups have developed wind-power forecasting systems using as input values forecasted by a NWP model such as the Danish Prediktor model [15] and WPPT model [16], the Spanish Sipreolico model [17] and CENER's LocalPred model [18], the

* Corresponding author. Tel.: +34 976761929.
E-mail address: ignacio.ramirez@unizar.es (I.J. Ramirez-Rosado).

0960-1481/$ – see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.renene.2008.11.014

German Previento model [19] and ISET's WPMS model [20], the French Armines AWPPS model [21], the Greek National Technical University of Athens (NTUA) model [11] and the Aristotle University of Thessaloniki (AUTH) model [22], and the North American eWind model [23]. An interesting review about the development of wind-power short-term predictions tools can be found in Ref. [24].

Short-term wind-power forecasting employs mathematical models to predict the power produced by a wind farm during a look-ahead time. With models of the first group, the forecasted value is based on the last known data for power production, wind speed or wind direction. With models of the second group, the wind-power forecasted value can also be based on the forecasted mean values of wind speed, wind direction and other meteorological variables (pressure, temperature, etc.).

This paper presents two new advanced short-term wind-power forecasting systems, based on artificial neural networks for short-term forecasting, and on a combination of forecasting models for very short-term forecasting. Two independent research groups developed these systems using the same data. Both systems had a forecast horizon of 72 h, enabling their use for electricity market bid offers and wind-farm maintenance tasks.

Section 2 describes the NWP tool used to provide forecasts of meteorological variables for the wind-power forecast systems. Sections 3 and 4 describe the two short-term wind-power forecasting systems. Section 5 presents a case study comparing the performance of both forecasting systems, using the same input variables, with forecast horizons from 0.5 to 72 h, in steps of 0.5 h. Section 6 includes the final conclusions.

2. Numerical weather prediction models

The development of powerful computers has enabled the implementation of reliable NWP models. These models, which are usually developed and maintained by meteorological institutes, can be classified according to their space-temporal scale. Each NWP model tries to monitor the evolution of the atmosphere for its specific scale, even though high spatial resolution cannot be combined with high temporal resolution. In general, a NWP model with high spatial resolution (small spatial scale) will have a low temporal validity for its predictions (small temporal scale). A NWP model with a low spatial resolution (great spatial scale) will have a much greater temporal validity. The NWP models with great spatial and temporal scales are known as macro-scale models; they usually make predictions for the whole world (they are also known as global models) valid over one week. The NWP models with high spatial resolution, but with limited temporal resolution (validity) of a number of hours, are known as mesoscale models.

Short-term wind-power forecasting needs predictions from a NWP model with high spatial resolution. At least mean wind speed and direction are required to serve as a reference point for the wind-power forecast. In this paper, the MM5 model has been used as the NWP tool. The MM5 (Fifth-Generation Mesoscale Model) is a limited-area, terrain-following sigma-coordinate model designed to simulate or predict mesoscale and regional-scale atmospheric circulation [25]. It was developed at Pennsylvania State University and the National Center for Atmospheric Research (NCAR), both in USA. The MM5 is the last model in a series initiated in the 1970s that has been improved through contributions from users at several universities and government laboratories.

In this paper, the MM5 model produces weather forecasts for a reference geographical point of the wind farm for the next 72 h at half-hour intervals. The forecasts for mean wind speed and direction, temperature and pressure were interpolated, from the lowest levels from the MM5, to a height of 60 m, the hub height of the wind turbines. The MM5 model was initialized every day with the predictions of the GFS model (global model) corresponding to the assimilation of atmospheric data at 00:00 GMT. The MM5 forecasts were available at about 07:00 GMT.

3. FORECAS system

FORECAS is a short-term wind-power forecasting system that combines inputs of the most recent measurements of wind-farm production from SCADA with information on wind speed and wind direction, forecasted by a NWP model. The output produced by the FORECAS system is the forecast of electric wind-power production for the 3 days (72 h) corresponding to the forecast horizon of the NWP model. Fig. 1 shows the structure of the FORECAS system.

The meteorological forecast of the NWP model used (MM5 model) was provided specifically for a geographical reference point inside the area of the wind farm. The Power Curve Model, PCM(i), used by the FORECAS system is a transfer function between the forecasted values of mean wind speed and mean wind direction from the NWP model and the electric power production of the ith wind turbine. The FORECAS system uses one PCM for each wind turbine that is represented by a multi-layer perceptron (MLP) neural network. This MLP approach enabled each wind turbine transfer function to be correctly represented, modelling the pattern differences of electric power production due to terrain characteristics, wake effect and power curve characteristics of each power-generation machine. In the present study, this representation

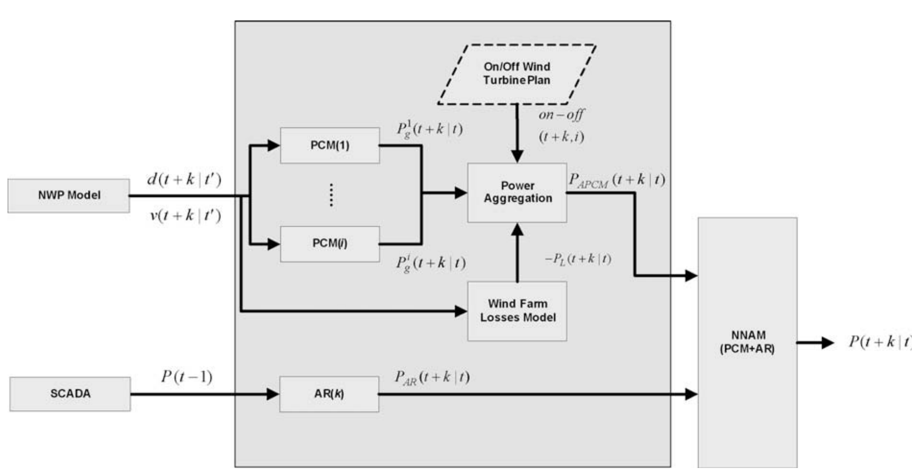

Fig. 1. Structure of FORECAS forecasting system.

(PCM) is purely statistical; however this FORECAS structure allows physical models (e.g. Computed Fluid Dynamics models) to be integrated to adjust wind forecasts for each wind turbine geographical location using NWP forecasts from a reference point.

The abovementioned MLP neural network, used for each wind turbine, was trained with the back-propagation learning algorithm, had one hidden layer with 13 neurons, and used the hyperbolic tangent activation function. Input selection, among the available variables, and the topology were adopted on a trial and error basis.

As shown in Fig. 1, the inputs of the PCM models (of the wind turbines) are NWP meteorological forecasted values: forecasted mean wind speed values $v(t+k|t')$, lagged forecasted mean wind speed values $v(t+k-1|t')$, forecasted mean wind direction values $d(t+k|t')$ and lagged forecasted mean wind direction values $d(t+k-1|t')$, where t' represents the forecast instant value for NWP model and t represents the forecast instant value for the FORECAS system. The wind direction variable comprised two components, i.e. the sine and cosine components. The model totalled 6 input variables. The output of each MLP neural network (representing each PCM model) was the electric power production forecast for each wind turbine. The same MLP neural network structural characteristics were used for all forecast horizon values k, but obviously each MLP was different for each wind turbine.

All the individual electric wind-power production forecasts indicated above, $P_g^i(t+k|t)$, were aggregated (by the "Power Aggregation" module in Fig. 1) to obtain the aggregated electric power production forecast $P_{APCM}(t+k|t)$. Wind-farm losses were also included in the aforementioned aggregation by another neural network module ("Wind Farm Losses Model" in Fig. 1) that used mean wind speed values $v(t+k|t')$ and mean wind direction values $d(t+k|t')$ as inputs, and that provided the forecasted wind-farm active power loss values $P_L(t+k|t)$ as outputs. Thus

$$P_{APCM}(t+k|t) = \sum_i P_g^i(t+k|t) - P_L(t+k|t) \quad (1)$$

where $P_{APCM}(t+k|t)$ represents the electric wind-farm power production forecasted by the "Power Aggregation" module.

For the described electric power production aggregation, a schedule of the availability of each wind turbine can be used (on–off plan, indicated in the "On/Off Wind Turbine Plan" module of Fig. 1). The schedule is defined by the wind farm operator, based on expected times for forced or programmed outages. This capacity is an important added value for the real operation of the forecast system. However, in the case study of this paper, the availability of all wind turbines was considered.

Note that the instant value represented by t', corresponding to the forecast instant for the NWP model, was greater than the forecast instant value represented by t for the FORECAS system forecast. Thus, in the case study (Section 5) $t' = 00{:}00$ h and $t = 08{:}00$ h.

In Fig. 1, another branch (module AR(k) in Fig. 1) of the FORECAS system used dynamic information values of measures of wind-farm electric power production in the previous instant $P(t-1)$, received from SCADA, and the system produced the wind-farm electric power forecast values $P_{AR}(t+k|t)$ for the future instant value $(t+k)$.

This module AR(k), based on a simple first-order autoregressive AR model, was determined by linear regression between wind-farm electric power production values $P(t)$ and the corresponding electric power production values $P(t-k)$ lagged k steps.

A neural network assembling module (NNAM module) was used for weighted aggregation of the electric power forecast of the dynamic AR module and the electric power forecast of the "Power Aggregation" module (i.e. a static electric power PCM aggregation). Thus, this neural network used the following as inputs: the wind-farm electric power forecast values $P_{AR}(t+k|t)$ from the AR module; the wind-farm electric power forecast $P_{APCM}(t+k|t)$ from the "Power Aggregation" module; the mean error observed in the last three days (for forecast horizon value k) of the AR module, $\varepsilon_{AR}(k)$; and the mean error of the "Power Aggregation" module $\varepsilon_{APCM}(k)$. Both mean errors are not shown in Fig. 1 (for the purpose of simplicity). This NNAM module used higher weight values for the AR model for the first hours of the forecast horizon (lower k values) and then comparatively lower weight values for the "Power Aggregation" module. But for the remaining hours of the forecast horizon (higher values of k), the NNAM module used higher weight values for the "Power Aggregation" module, and then comparatively lower weight values for the AR module.

This AR module significantly improved electric power forecast accuracy for the initial forecasting hours ($k < 4$ h). The neural network used for the NNAM module was a MLP using back-propagation learning algorithm with only one hidden layer with 9 neurons, using a hyperbolic tangent activation function.

4. SGP system

The proposed global SGP forecast system comprised a set of forecast models, covering the whole range of considered forecast horizons. There were specific models for very short-term forecasts, specialized forecast models for the next day, etc. The best models were chosen (according to the moment when the forecasts are made and the horizon of these forecasts) to ensure that forecast error was minimal. Fig. 2 shows the structure of the proposed global SGP forecast system.

Fig. 2 shows 11 very short-term specific models (with forecast horizons from 0.5 to 4.5 h). Three models were selected for each

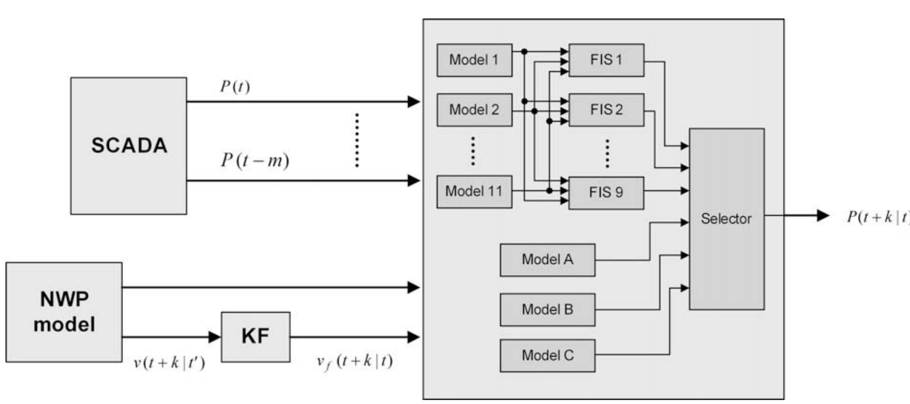

Fig. 2. Structure of the SGP forecasting system.

forecast horizon so that their outputs were the inputs of a fuzzy inference system that provided the forecasted value as a non-linear combination of the outputs of the three selected models. There were nine fuzzy inference systems, one for each forecast horizon (0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4 and 4.5 h).

Fig. 2 also shows three other models, models A, B and C, specialized in short-term forecasts (model C specialized in horizons from 48.5 to 72 h, model B specialized in horizons from 24.5 to 48 h, and model A specialized in horizons from the end of the very short-term forecast model to 24 h).

The input variables for the global forecast system were the six last known values of mean electric power from the wind farm (i.e. measured from SCADA at its electric power substation) and the forecasted values for the meteorological variables (mean wind speed and wind direction, temperature and pressure) obtained with the NWP model. A Kalman filter (KF) was used to improve the system performance in the very short-term period and thus reduce bias in forecasted mean wind speed provided by the NWP model.

4.1. Very short-term forecast models

The 11 very short-term forecast models included one ARMA(1,1) model, the new-reference model [26], and 9 artificial neural network models; each model was specific to each forecast horizon (from 0.5 to 4.5 h). The models based on artificial neural networks were selected from three different types of neural networks: MLP neural networks, generalized feed-forward neural networks (FFBPs), and modular neural networks. The selected model was the one with the minimum forecast error with the validation set of the three models. These neural networks models were developed as is described in the following paragraphs.

Mean power forecasts in the very short-term were obtained from 9 first-order Takagi–Sugeno–Kang (TSK) fuzzy inference systems [27]. The TSK fuzzy inference systems were chosen because of their ability to model non-linear relationships between inputs and output. The inputs for these fuzzy inference systems were the forecasted values obtained with the following models: ARMA(1,1), new-reference and the neural network model specific for the corresponding forecast horizon. The results obtained with these three types of models were the best ones obtained from intensive and systematic tests of results selected from a large number of possible combinations of models. The output of each TSK fuzzy inference system represented the wind-power forecasted value for the corresponding horizon (0.5–4.5 h).

A Kalman filter (KF) was used for forecast horizons from 0.5 to 1 h to improve the forecasted values for the mean wind speed provided by the MM5 model. In this filter, measured wind speed was not used; an estimated value was used instead. This estimated value was obtained from the wind-farm power curve (without taking into account wind direction), using electric power generated at the wind farm as an input.

The implemented Kalman filter estimated the bias in the forecasted value for the mean wind speed supplied by the MM5 model. This bias was modelled as an n-1 grade polynomial, using the forecasted value as a variable [28]. In tests, polynomial grades from 0 to 3 were tested, and the best results were obtained with a 0 grade polynomial, i.e. an independent value (the bias was independent from the forecasted value for the mean wind speed).

The use of these forecast models in the very short-term significantly improved the forecast results compared with the persistence model, as shown in the case study section.

4.2. Short-term forecast models

Forecasts in the short-term were obtained using three other forecast models, based on neural networks. A first model, model A, provided the forecasted values for horizons between the end of the very short-term and 24 h; the second model, model B, provided the forecasted values for horizons between 24.5 and 48 h; the third model, model C, provided the forecasted values for horizons between 48.5 and 72 h. These models only used the forecasted values supplied by the NWP model as inputs.

These three models, A, B and C, based on artificial neural networks, were developed after selection from different types of neural network models. The following types were studied: MLPs, FFBPs, modular neural networks, Elman neural networks, radial basis function (RBF) neural networks, principal components analysis (PCA) neural networks, time-lagged neural networks (with TDNN, Gamma and Laguerre memory structures) and recurrent neural networks.

4.3. Neural network models development

The neural network models were developed using the data defined in the next section. The following process was used:

1. All the neural network models were developed in an optimization process controlled by a genetic algorithm. This process enabled the selection of inputs (last known values of mean electric power measured at the power station of the wind farm; and forecasted mean wind speed and direction, temperature and pressure obtained from the MM5 model); the number of neurons in hidden layers; the learning and momentum factors of the back-propagation algorithm used in the training phase; the number of centers for RBF neural networks; the number of principal components for PCA neural networks; and the number of taps in time-lagged neural networks. The fitness function used in the optimization process was the mean square error with the data of the validation set. Over-fitting was avoided with the interruption of the training phase when the error with the validation data did not decrease after 100 epochs. The number of generations and individuals per generation was 50.
2. Once the optimization process had selected the optimal structure for the neural network, forecast error was calculated for the training and validation data sets. The model offering the minimum forecast error was selected. Table 1 shows the inputs used by the neural network models with the minimum forecast error in the very short-term; and Table 2 shows the inputs used by the neural network models with the minimum forecast error in the short-term. In both tables, $v_f(t+k)$ represents forecasted mean wind speed for the future instant $t+k$, supplied by the Kalman filter; $v(t+k|t')$, $d(t+k|t')$ and $\mathrm{tem}(t+k|t')$ represent the forecasted values, for future instant $t+k$, mean wind speed, mean wind direction and mean temperature,

Table 1
Very short-term neural network forecast models.

	Horizon (h)	Type	Inputs
Model 1	0.5	FFBP	$v_f(t+k\|t)$, $\sin(d(t+k\|t'))$, $\cos(d(t+k\|t')), P(t), P(t-0.5)$
Model 2	1	FFBP	$v_f(t+k\|t)$, $\sin(d(t+k\|t'))$, $\cos(d(t+k\|t')), P(t)$
Model 3	1.5	Modular	$P(t)$, $P(t-0.5)$, $P(t-1)$, $P(t-1.5)$
Model 4	2	Modular	$P(t)$, $P(t-0.5)$, $P(t-1)$, $P(t-1.5)$
Model 5	2.5	MLP	$P(t)$, $P(t-0.5)$, $P(t-1)$, $P(t-2)$
Model 6	3	MLP	$P(t)$, $P(t-0.5)$, $P(t-1)$, $P(t-1.5)$
Model 7	3.5	MLP	$P(t)$, $P(t-0.5)$, $P(t-1.5)$
Model 8	4	Modular	$P(t)$, $P(t-0.5)$, $P(t-1)$
Model 9	4.5	FFBP	$P(t)$, $P(t-0.5)$, $P(t-1.5)$

Table 2
Short-term neural network forecast models.

	Horizon (h)	Type	Inputs
Model A	5–24	Elman	$v(t+k\|t')$, $\sin(d(t+k\|t'))$, $\cos(d(t+k\|t'))$, $\mathrm{tem}(d(t+k\|t'))$
Model B	24.5–48	Elman	$v(t+k\|t')$, $\sin(d(t+k\|t')$, $\cos(d(t+k\|t')$, $\mathrm{tem}(t+k\|t')$, $a(t+k\|t')$
Model C	48.5–72	Modular	$v(t+k\|t')$, $\sin(d(t+k\|t'))$, $\cos(d(t+k\|t'))$, $\mathrm{tem}(t+k\|t')$, $a(t+k\|t')$

respectively, supplied by the MM5 model; $P(t)$ represents the last known value for mean electric power measured in the power substation; $P(t-x)$ represents the value of mean electric power measured in the power substation x hours before instant t; $a(t+k|t')$ represents the number of past half hours of the forecasted values $P(t+k|t)$ from the forecast instant value for the MM5 model.

4.4. Forecast model selection

Depending on the forecast horizon and the instant when the forecasts were made, the models were selected to forecast mean electric power generated by the wind farm. The selected forecast models changed in the very short-term depending on which model offered the best forecast results: for example, if the forecasts were made at 19:00 then the very short-term forecast models were used for the next 2 h (forecast horizons of 0.5, 1, 1.5 and 2 h); if the forecasts were made at 04:00, then the very short-term forecast models were used for the next 4.5 h (forecast horizons from 0.5 to 4.5 h). The forecasts for the following horizons to complete the day were obtained with model A. The forecasts for the 48 half-hour periods for the next day were obtained with model B. The forecasts for the 48 half-hour periods for two days later were obtained with model C.

5. Case study

This section presents the computer results obtained with the two proposed forecasting systems, FORECAS and SGP, when forecasting the mean hourly electric power delivered to the electric network by a real wind farm.

5.1. Wind-farm characteristics

The wind farm has a rated power of 21,600 kW and comprises 12 equal wind turbines of 1.8 MW. The wind farm is situated in the north of Portugal, in a complex mountainous region 65 km far from the Atlantic Ocean.

5.2. Data characteristics

The data collected from the wind farm included SCADA registers with mean electric power delivered by the wind farm into the substation connecting it to the electric power network and the mean wind speed and wind direction measured at the wind farm. Other forecasts included mean wind speed, wind direction, temperature and atmospheric pressure, obtained with the NWP model (MM5 model), for a reference point in the wind farm with forecasting horizons ranging from 0 to 72 h. The first forecasted values corresponded to 00:00 (instant t') of the present day and the last forecasts to 00:00 three days later. All the data had an interleave period of 0.5 h.

To develop the forecasting systems, the available data were divided into three sets: the first set, with 60% of the data, was used as a training set; the second set, with 20% of data, was used as a validation set; and the third set, with the last 20%, was used as a testing set for comparing the forecasting systems. Table 3 shows the statistical characteristics of the mean electric power series data. A negative value indicates electric power consumption of the wind farm.

Table 3
Characteristics of the data available.

	Training	Validation	Test
Mean (kW)	5706.65	3080.97	4177.11
Variance (kW)	6069.97	4220.26	4740.32
Range (kW)	21686.83	21225.67	21329.01
Minimum (kW)	−73.5	−68.17	−77.67
Maximum (kW)	21613.33	21157.5	21251.33
Number	4356	1400	1400

5.3. Simulation characteristics

This section contains a description of several time intervals of wind-farm power-generation forecasting basically for common daily market and intra-daily market applications, defining different forecast horizons and thus the corresponding target horizons of both the FORECAS and SGP systems.

Fig. 3 shows the scheduling time periods for a known daily electric power market (Spanish market), which can give us an idea of certain common characteristics for typical electric market rules for electric energy generation. The main objective of the daily market is to schedule hourly electric energy trading actions for the next day (day D + 1 in Fig. 3). For an electric power-generation producer, such as a wind-farm owner, electric energy sale bids must be presented to the Market Operator before a specified hour (10:00) on the day (day D in Fig. 3) prior to the day corresponding to the power generation and electric demands schedule to be established. Thus, hourly bids must be presented before the specified hour, covering the 24 h of the following day (day D + 1 in Fig. 3). To adjust deviations of generated electric power and/or demands that may occur after the establishment of the diary schedule, a given number of sessions of the intra-daily market (6 sessions) take place (on days D and D + 1). Participation in these sessions is open to agents (producers, distributors, qualified customers, etc.) who have participated in the diary market session. Fig. 3 shows the closing hour of a specific session (5th session) of the intra-daily market (08:45), when the scheduled generation and the electric energy marginal price are obtained for each hour from 12:00 to 23:00.

Wind farms not participating in the electric power market must submit forecasted electric production values for each scheduling period (for each hour) of the electric power market to the Electric Power System Operator at least 30 h before the beginning of the day corresponding to the forecasted values, i.e. the forecasted values for the day D + 2 (hours from 48 to 71 in Fig. 3) must be submitted before the 18th hour on day D in Fig. 3.

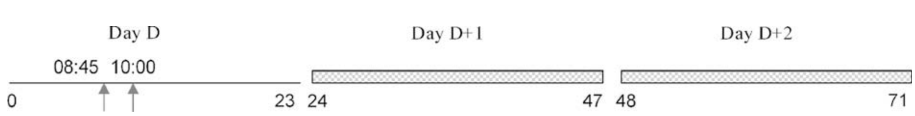

Fig. 3. Different time intervals for applications of wind-power forecasting.

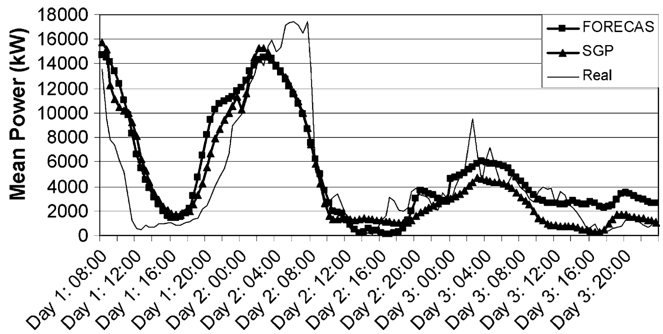

Fig. 4. Forecasted and real electric power production values.

5.4. Analysis of computer results

This section presents the computer results obtained for the real-life case study described here, as well as the corresponding analysis and discussion. The RMS power-generation forecast errors in the different forecast horizons from 0.5 until 72 h are also shown, as well as common applications of this forecast: daily market offers, intra-daily market offers, operation and maintenance applications, etc.

Fig. 4 shows the forecasted values for mean electric power from the wind farm obtained with both the FORECAS and SGP forecasting systems and the real mean power production (real). Fig. 4 shows the wind-farm forecast made at 08:00 for one of the days in the test data set, with a forecast step of half hour, until 00:00 three days later. In this case, both forecasting systems followed the real mean electric power values measured from SCADA reasonably well.

Fig. 5 shows the RMS errors for both forecasting systems and the persistence model for each hour through the forecast horizons. The RMS persistence model error increased relatively quickly in the first four hours from 11% to 30%. After these first four hours, error stabilized between 30% and 40%. The persistence model error in this formulation reflects the mean variation with respect to the 08:00 reference values.

RMS errors in both forecasting systems followed a similar pattern because both systems used the same wind forecast from the MM5 model. In the first hours, the forecasting systems achieved better electric power forecast errors since they used information from the dynamic models (with SCADA data) instead of the MM5 model forecasts.

RMS errors for both forecasting systems ranged between 10% and 25%, with a mean value of 17% over the three forecast days. Over the forecast days, moving average error increased gradually from 10%, for the first forecast hour to about 20% for final forecast hours. With respect to the persistence model, both forecasting systems presented positive error improvements over the entire forecast days. The improvement in RMS error, computed by (2), ranged from a minimum of 7% for the first hour to a maximum of 65%, with a mean value of 48%.

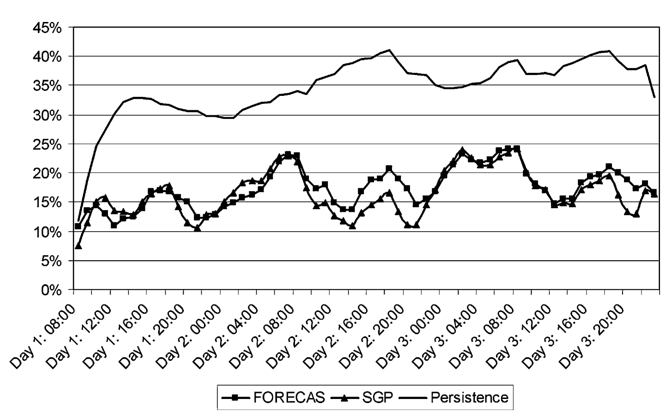

Fig. 5. RMS errors from the FORECAS and SGP forecasting systems and the persistence model.

Table 4
Average RMS errors in the three time intervals.

Period	FORECAS	SGP	Persistence
12–24 h	14.0%	14.1%	31.2%
24–48 h	17.6%	16.2%	35.5%
48–72 h	19.7%	18.8%	37.5%

$$\text{Improvement} = \frac{\text{RMS}_{\text{Persistence}}(k) - \text{RMS}_{\text{System}}(k)}{\text{RMS}_{\text{Persistence}}(k)} 100\% \qquad (2)$$

As discussed in sub-section C, the forecasts for this case study, carried out at 08:00 on day D, could be used for applications of different time intervals:

(a) intra-daily market between 12:00 and 23:00 on day D.
(b) daily market for day D + 1.
(c) wind-farm maintenance and electric power system operation from day D to day D + 2.

The mean hourly RMS error for each application and for each forecasting system is presented in Table 4.

For the intra-daily market session, the error was lower than the error of the daily market session in both forecasting systems. This difference justified the refreshment of forecasts to be used in intra-daily sessions. In some countries, the Electric Power System Operator requires information about wind-farm production plans for the third day (48 h to 72 h). This forecast RMS error on the third day increased 17% with respect to the forecast for the second day.

6. Conclusions

This paper describes the performance of two new and sophisticated forecasting systems. Both systems are complex integrated structures of models, which can be adapted to all wind-farm characteristics and to the use of upstream forecasts from different NWP models.

The two wind-power forecasting systems are based on a combination of power curve models and dynamic models. The power curve models are stationary transfer functions between the NWP wind forecasts, for a reference geographical point in the wind-farm area, and the corresponding electric power production. The dynamic models use the last values corresponding to wind-farm power-generation measurements to obtain the forecasts in the first hours. The difference between the two forecasting systems is the way they represent the power curve: different techniques, a set of different forecasting modules, different ways of module selection and module combination, as well as differences in the representation of the wind farm or each wind turbine. The dynamic models are also different: the FORECAS system uses a simple MLP neural network and the SGP system uses a combination of the Kalman filter, ARMA model and several neural network models, selecting the best combination of the models in a fuzzy inference system. To summarize, the FORECAS system presents a more complex and detailed representation of the power curve of each wind turbine and the SGP system offers a more complex and detailed selection of forecasting modules from a larger variety of soft-computing based models. Both the FORECAS and the SGP systems obtained good results and improved very significantly the persistence model forecasts.

The two forecasting systems created independently by two different research groups were applied to the same real-life case study using the same train, validation and test data sets. However, the two forecasting systems were free to select the variables that achieved the best forecasting system performance. Both forecasting systems used the same forecasts from the NWP model (MM5 model). This approach allowed us to draw conclusions about the performance comparison of the forecasting systems.

In this case study, the forecasting systems issued daily predictions and produced electric power forecasts until the last hour of the day after tomorrow. This allowed forecast errors for applications of three different time intervals to be evaluated: the most short-term application corresponded to intraday power-generation market bids for the present day; the second application related to power-generation market bids for the daily market on the next day; and the third application referred to electric power system operation tasks for the third day (as well as to the other two previous days), and also wind-farm maintenance tasks. The paper offers an idea of the usefulness of the two system forecasts for all three applications, but with different error levels for each application.

Acknowledgements

The authors would like to thank the "Ministerio de Educación y Ciencia" of the Spanish Government for supporting this research under the Project DPI2005-07494 and by the ERDF funds of the European Union.

References

[1] World Wind Energy Association. Wind turbines generate more than 1% of the global electricity. Available from: <http://www.wwindea.org/home/images/stories/pr_statistics2007_210208_red.pdf>; 2008.
[2] Parsons B, Milligan M, Zavadil B, Brooks D, Kirby B, Dragoon K, Caldwell J. Grid impacts of wind power: a summary of recent studies in the United States. Wind Energy 2005;7:87–108.
[3] Kariniotakis GN, Stavrakakis GS, Nogaret EF. Wind power forecasting using advanced neural networks models. IEEE Transactions on Energy Conversion 1996;11:762–7.
[4] Sfetsos A. A novel approach for the forecasting of mean hourly wind speed time series. Renewable Energy 2002;27:163–74.
[5] Potter CW, Negnevitsky M. Very short-term wind forecasting for Tasmanian power generation. IEEE Transactions on Power Systems 2006;21:965–72.
[6] El-Fouly THM, El-Saadany EF, Salama MMA. Grey predictor for wind energy conversion systems output power prediction. IEEE Transactions on Power Systems 2006;21:1450–2.
[7] Gog SL, Chen M, Popovic DH, Aihara K, Obradovic D, Mandic DP. Complex-valued forecasting of wind profile. Renewable Energy 2006;31:1733–50.
[8] Bilgili M, Sahin B, Yasar A. Application of artificial neural networks for the wind speed prediction of target station using referente stations data. Renewable Energy 2007;32:2350–60.
[9] Damousis IG, Alexiadis MC, Theocharis JB, Dokopoulos PS. A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. IEEE Transactions on Energy Conversion 2004;19:352–61.
[10] Larson KA, Westrick K. Short-term wind forecasting using off-site observations. Wind Energy 2006;9:55–62.
[11] Sideratos G, Hatziargyriou ND. An advanced statistical method for wind power forecasting. IEEE Transactions on Power Systems 2007;22:258–65.
[12] Sørensen B. Renewable energy. 3rd ed. Burlington, USA: Elsevier Academic Press; 2004.
[13] Meibom P, Svendsen T, Sørensen B. Trading wind in a hydro-dominated power pool system. International Journal of Sustainable Development 1999;2:458–83.
[14] Roulston MS, Kaplan DT, Hardenberg J, Smith LA. Using medium-range weather forecasts to improve the value of wind energy production. Renewable Energy 2003;28:585–602.
[15] Landberg L. Short-term prediction of local wind conditions. Journal of Wind Engineering and Industrial Aerodynamics 2001;89:235–45.
[16] Nielsen TS, Madsen H. WPPT – a tool for wind power prediction. In: Wind power for the 21st Century, Kassel, Germany; 2000. p. 25–7.
[17] Sánchez I. Short-term prediction of wind energy production. International Journal of Forecasting 2006;22:43–56.
[18] Marti I, San Isidro MJ, Cabezón D, Loureiro Y, Villanueva J, Cantero E, et al. Wind power prediction in complex Terrain: from the synoptic scale to the local scale. In: the science of making torque from wind, Delft, The Netherlands; 2004.
[19] Focken U, Lange M, Mönnich K, Waldl HP, Beyer HG, Luig A. Short-term prediction of the aggregated power output of wind farms - a statistical analysis of the reduction of the prediction error by spatial smoothing effects. Journal of Wind Engineering and Industrial Aerodynamics 2002;90:231–46.
[20] Rohrig K, Hoppe-Kilpper M, Ernst B, Schlögl F. Online-monitoring and prediction of wind power in German transmission system operation centres. In: World wind energy conference, Cape Town, South Africa; 2003.
[21] Pinson P, Ranchin T, Kariniotakis G. Short-term wind power prediction for offshore wind farms – Evaluation of fuzzy-neural network based models. In: Global wind power conference, Chicago, Illinois, USA; 2004.
[22] Barbounis TG, Theocharis JB, Alexiadis MC, Dokopoulos PS. Long-term wind speed and power forecasting using local recurrent neural network models. In: IEEE Transactions on Energy Conversion, 21; 2006. 273–284.
[23] Bailey B, Brower MC, Zack J. Short-term wind forecasting – Development and application of a mesoscale model. In: European wind energy conference, Nice, France; 1999. p.1062–5.
[24] Costa A, Crespo A, Navarro J, Lizcano G, Madsen H, Feitosa E. A review on the young history of the wind power short-term prediction. Renewable and Sustainable Energy Reviews 2008;12:1725–44.
[25] Grell GA, Dudhia J, Stauffer DR. A description of the fifth-generation Penn State/NCAR mesoscale model (MM5). NCAR Technical Note-398, 1995. Available from: <http://www.mmm.ucar.edu/mm5/documents/mm5-desc-doc.html>.
[26] Nielsen TS, Joensen A, Madsen H. A new reference for wind power forecasting. Wind Energy 1998;1:29–34.
[27] Sugeno M, Kang GT. Structure identification of fuzzy model. Fuzzy Sets and Systems 1988;28:15–33.
[28] Galanis G, Louka P, Katsafados P, Pytharoulis I, Kallos G. Applications of Kalman filters based on non-linear functions to numerical weather predictions. Annales Geophysicae 2006;24:2451–60.