SHORT-TERM FORECASTING MODELS FOR PV SYSTEMS

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1. Introduction

Renewable energy has captured the attention of the authorities and public opinion over the last years. The incentives offered by renewable energy sources include many environmental advantages, including the fact that in most cases, it is pollution free energy and it is not dependent on foreign energy sources.

The installed power in wind farms all over the world has changed from 7.5 GW in 1997 to 94 GW at the end of 2007, becoming 1% of all the electric energy generated around the world [1]. Wind energy represents the renewable energy resource which has been developed the most in the last years. Initially, wind parks delivered the electrical energy generated into the electric networks, receiving an economic compensation regulated by tariff. In the last few years, authorities have forced wind parks to play into the national electricity markets, due to the fact that the installed power in a medium wind park has reached tens, even hundreds, of MW.

In order to be able to compete in the electricity market, wind farm managers must provide the market operator electric energy sale bids, covering 24 hours of the following day before a specified hour (10:00 in the Spanish electricity market). If the energy scheduling is not fulfilled, the wind farm manager is economically penalized according to the rules marked by authorities. So, wind farm managers are very interested in the development of wind power forecasting tools able to produce accurate predictions of energy production for the next day. This has been the cause of the development of short-term wind power forecasting models in the last few years, with several models used daily by electric utilities [2].

Grid-connected photovoltaic systems have grown in capacity in the last few years from small facilities with an installed power of some kWs, to great facilities with an installed power of tens of MWs. The installed power in these great photovoltaic plants reminds one of the average installed power in a wind farm 15 years ago. Therefore, it is not unthinkable that in a near future authorities will force the large photovoltaic facilities to participate in the electricity markets in the same way that wind parks are participating now. So, grid-connected photovoltaic systems managers, will need reliable prediction tools to forecast energy production in the power plant for the next two days. Several groups are working on the development of such tools, although published models try to forecast the solar radiation instead of electric energy production [3].

This paper presents the results obtained in the forecast of hourly electric energy generation in a real grid-connected photovoltaic plant for the following 48 hours time period. These models are based on the use of numerical weather prediction tools and neural networks. The best models offer forecasting values with average errors lower than 15% of the installed power, for the forecasting periods covering the 24 hours of the next day.

Keywords: short-term forecasting, photovoltaic systems, distributed generation, neural networks.

2. Description of the Forecasting Models

The goal of the research work described in this paper is the development of a short-term forecasting system for the prediction of the hourly electric energy generation in a real grid-connected photovoltaic plant for the following hours (forecasting horizons from 1 hour to 48 hours). The forecasting models predict future energy generation values, based on past values and forecasted values for weather variables obtained from a numerical weather prediction (NWP) model.

A. Input data for the Forecasting Models

The data used for the development of the forecasting models presented in this paper have been hourly electric energy generation values obtained from a real grid-connected photovoltaic plant sited in La Rioja and forecasted values for radiation and temperature for the location of the photovoltaic plant for the next two days. These last values were obtained with MM5 [4] NWP model for horizons from 0 to 48 hours at intervals of 15 minutes.

The photovoltaic plant studied is composed of panels with different technologies (fixed panels, tracking systems with one or two axles). The total power capacity of the plant is 36 kW peak. The time series data used included 362 days (from 02/06/2007 to 27/05/2008).

B. MM5 Model

The MM5 (Fifth-Generation Mesoscale Model), developed by PSU/NCAR (Pennsylvania University and the National Center for Atmosferic Research), is a limited-area, nonhydrostatic, terrain-following sigma-coordinate model designed to simulate or predict meso-scale and regional-scale atmospheric circulation. It has been developed with contributions from several research groups during past years. The MM5 model is implemented as a computer program with a high spatial resolution but with a limited temporal validity (low temporal scale). These kinds of NWP models are known as meso-scale models.

The MM5 has been implemented in several computers, with Linux operating system, in the University of La Rioja for the forecast of radiation and temperature values for the location of the photovoltaic plant. In order to increase the temporal validity of the forecasts (forecasting horizons up to 48 hours), the MM5 model used as input data the forecasted values for a set of meteorological variables obtained from a global NWP model, the GFS model (National Weather Services, USA), which provides forecasts covering the whole world in intervals of three hours with forecasting horizons from 0 to 180 hours. The input data from the GFS model were downloaded daily from governmental servers.

C. *Models Evaluation*

For general comparison among the results obtained with different candidate models in order to choose the model with the best results, the process was the following: the available data were divided into two groups, the first one, called training set in this paper, for fitting the parameters of the models, and the second, called testing set, for comparing the results among models. The criteria used to select the best model have been the minimum value of the root mean square error, RMSE, in its real value as expressed in (1), or in its standardized value with respect to the capacity power value of the plant (P_{inst}), as expressed in (2).

$$\mathrm{RMSE}(k) = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(e(t+k|\,t))^2} \qquad (1)$$

$$\mathrm{RMSE}_n(k) = \frac{1}{\mathrm{P_{inst}}}\sqrt{\frac{1}{N}\sum_{t=1}^{N}(e(t+k|\,t))^2} \qquad (2)$$

D. *Developed Models*

The chosen candidate models include the classic persistent model (forecasted value equal to the last known value), Box-Jenkins models, a model known as “k-nearest neighbors” model, models based on artificial neural networks and models based on fuzzy inference systems. All models were fitted or trained with the training data set. In the development of neural network based models, the architecture of the neural network was optimized by means of a genetic algorithm (number of neurons, training factors, etc.), trying to obtain the best model of each one of the considered types of neural networks.

Table I shows the results obtained with some of the studied models in the forecast of the values corresponding to the testing data set. These results represent the average *RMSE* for all the forecasting horizons. The best results were obtained with a neural network model (MLP 2), which achieves an average $RMSE_n$ value of 11.79% for the forecasting horizons corresponding to the next day (from 24 to 48 hours).

In Figure 1 is shown the forecasted values, with the MLP 2 model, of the electric energy production in the photovoltaic plant and the real values for the last 5 days of the testing set. The lower forecasting horizon is 24 hours (first hour in each day) and increases to 48 hours (last hour of each day).

Table I. Obtained results

Model	RMSE (Wh)	RMSE (%)
Persistent	7530.91	20.92
ARIMA(3,0,2)(1,0,0)$_{24}$	7609.12	21.14
10-Nearest neighbors	6041.25	16.78
MLP 2	**4243.01**	**11.79**
Modular 2	4377.83	12.16
Elman 1B	4964.37	13.79
RBF 2A	4429.43	12.30
TDNN	5315.29	14.76
ANFIS 2	4375.21	12.15

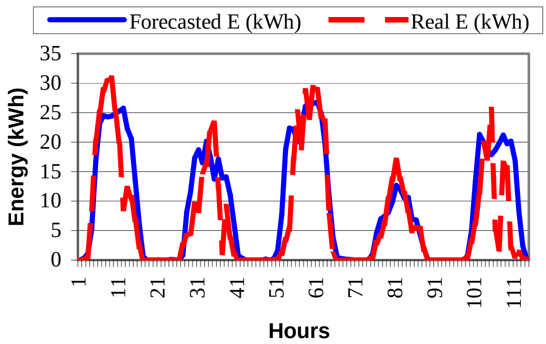

Figure 1. Comparison graph.

3. Conclusions

This paper presents the results obtained with a set of forecasting models based on different techniques, in the prediction of the hourly electric energy production in a grid-connected photovoltaic plant. These kinds of models can become useful in a near future not only for managers of large photovoltaic plants but also for managers of small hybrid plants. Further research is currently being performed by the research group to improve the forecasting models described in this paper.

References

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