Wind Power Forecast Methods and Very Short-term Steady-State Analysis of an Electrical Distribution System

Antonio Bracale
Parthenope University of Naples

Guido Carpinelli
University of Naples Federico II

Daniela Proto
University of Naples Federico II

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A. Bracale[*], G. Carpinelli[**], M. Mangoni[**] and D. Proto[**]

[*]Dept. for Technologies – University of Naples Parthenope (ITALY), antonio.bracale@uniparthenope.it

[**]Dept. of Electrical Engineering – University of Naples Federico II (ITALY), guido.carpinelli@unina.it, danproto@unina.it, marzia.mangoni@unina.it

Abstract—Dispersed Generation (DG) has impacts on power system planning and operation, and these impacts must be taken into consideration. This paper deals with the very short-term (VST) steady state analysis of a distribution system with wind farms. Several forecasting methods of wind power are taken into account in order to obtain reliable input data for the VST steady-state analysis. Numerical applications are presented and discussed with reference to an actual medium voltage 109-bus distribution system in the presence of wind farms connected at different busbars.

Keywords—Power Systems, wind farm, wind power forecast methods, steady-state analysis.

1 Introduction

In recent years, the characteristics of electrical distribution systems have been significantly modified due to the presence of more and more dispersed generation (DG) units. Distribution systems have become active, rather than passive, generating many new technical considerations that must be addressed, such as distribution network planning and operation.

Even though DG units can be sourced from different types of primary energy sources, the presence of wind generators in medium-voltage distribution systems is increasing, and wind power is now producing a significant fraction of the energy produced by renewable energy sources.

However, as is well known, wind energy production is characterized by high uncertainty due to the random nature of wind speed, which is weather dependent [1, 2]. Thus, in distribution systems with a significant penetration of wind generators, the problem of studying the impact of wind farms on the performance of these systems has to be deeply considered and requires the availability of accurate wind-power forecast methods. For example, an accurate method for wind-power forecasting can be useful for different applications, such as optimizing scheduling for power plants, reducing the need for balancing energy and reserve power, and analyzing system steady-state conditions. In addition, the time horizons to be taken into account as references for such studies are becoming more and more variable (from a few hours to days) due to the needs of liberalized markets [3-5].

In the relevant literature that has been published recently, many research projects have been conducted for the purpose of developing reliable wind-forecasting methods, and these efforts have produced methods with different levels of accuracy for different applications. In general, the methods can be classified as physical methods, statistical methods, methods based on artificial neural networks and hybrid approaches [5–14].

The physical methods use the physical information involved, e.g., wind conditions at the height of turbine hubs, turbine power curves, and weather conditions, to obtain an estimation of the wind power; these methods can also use meteorological information provided by complex numerical weather-prediction models.

The statistical methods forecast either a wind-speed/power value (“point-forecast” methods) or a wind-speed/power-probability density function (“pdf-forecast” methods), and both are obtained from statistical analyses of time series from past data.

The artificial-neural-networks methods try to determine the relationship between wind power and the time series from past data.

Finally, hybrid approaches are combinations of different methods, e.g., physical and statistical approaches or alternative statistical methods.

In general, physical methods are characterized by significant computational complexity and guarantee good performance mainly for long-term wind-power forecasting (intra-day or days ahead). On the other hand, with reference to very short-time (VST) wind-power forecasting (a few hours ahead), statistical methods can furnish accurate results with reduced computational efforts [5]. Then, the choice of a wind-power forecasting method should be made taking into account the considered application and the related time horizon that is needed.

In this paper, a comparison of some statistical approaches for VST wind-power forecasting (a few hours ahead) is provided. Both “point-forecast” and “pdf-forecast” methods are considered. The “point-forecast” methods are the Persistence Method, the Generalized Persistence Method, and the Nielsen Method [6, 14]. The “pdf-forecast” method is derived from the Bayesian wind-speed prediction method proposed in [15,16].

Among the technical problems to be solved in an active distribution system with wind farms, the wind-power prediction is used for the very short-term steady-state analysis of a distribution system, which consists of forecasting the steady-state conditions of the system at hour t+k (with k = 1 or 2, or few hours), using input data available at hour t. In particular, when the "point-forecast" methods are applied, the predicted value is used to perform a deterministic load flow; on the other hand, when the "pdf-forecast" method is applied, the predicted probability density function is used to perform a probabilistic load flow [16-18].

In this way, the steady-state analysis is predictive, i.e., it utilizes statistical wind prediction methods to assess the future hourly steady-state behavior of the active distribution system. The prediction of the state of the distribution system is based on recent information and allows VST forecasting, which is useful for solving intra-day problems [16].

This paper is organized such that the statistical wind forecast methods (Persistence Method, Generalized Persistence Method, Nielsen Method, and Bayesian Method) are presented first. Then, the deterministic and probabilistic load flows are discussed briefly. Finally, numerical applications and comparison of all the methods described are presented, using an actual, medium-voltage distribution system.

2 Very Short-term steady state analysis of a distribution system with wind farms

In this paper, the impact of the wind-distributed power generation on the distribution network's performance is considered, since wind farms are one of the most frequent source employed in distribution systems. In particular, the analysis was conducted with wind farms that use several induction generators directly connected to the electrical supply system by estimating the hourly steady-state operating condition of the distribution system.

The method for estimating "at hour t" the steady-state operating condition of an electrical distribution system "at hour t+k" (k = 1, 2,..) is based on the three-step procedure shown in Fig. 1, which consists of:

(i) Step 1: forecast "at hour t" the wind-turbine powers "at hour t+k" at the sites where the wind farms are installed;

(ii) Step 2: calculate the active and reactive powers of the induction generators of the wind farms on the basis of the Step 1 forecast; and

(iii) Step 3: perform the very short-term, steady-state analysis of the electrial distribution system.

As shown in Fig. 1, the wind-turbine power-forecast methods considered in this paper use a certain number N of hourly measurements obtained from monitoring instrumentation located where the wind turbine is installed. These measurements can be wind-speed values or turbine power values. These values are the input data for the VST wind-speed or turbine-power forecast methods that furnish the prediction at a generic hour with different time horizons (from one hour to few hours), starting from knowledge of the hourly wind speed/power measurements at the sites where the wind farms are installed. It is obvious that when the prediction refers to wind speed, the turbine-power production is obtained successively using the well-known wind-turbine power curve, which determines the power output of the conversion devices as a function of wind-speed data.

In the case of a wind farm composed of more than one wind turbine, the outputs of the wind turbines that are associated with the same wind farm are properly aggregated [5].

Once the wind-turbine power production is known, the active and reactive powers of the induction generators can be calculated, and, then, these values can be included among the input data for the very short-term, steady-state analysis of the electrical distribution system using deterministic or probabilistic load flows.

In the following subsections a description of the aforementioned three steps is presented in more detail.

2.1 Wind Turbine Power Forecast

In the relevant literature, several techniques have been proposed for wind-speed/power forecasting. As mentioned before, the majority of techniques can be classified into physical methods, statistical methods, methods based on artificial-neural-networks and hybrid approaches. The different approaches can use different input data.

Usually, physical methods take into consideration both physical information about the site (such as local terrain roughness and wind-farm layout) and information from numeric weather-prediction (NWP) systems, which provide wind forecasts by using complex meteorological models.

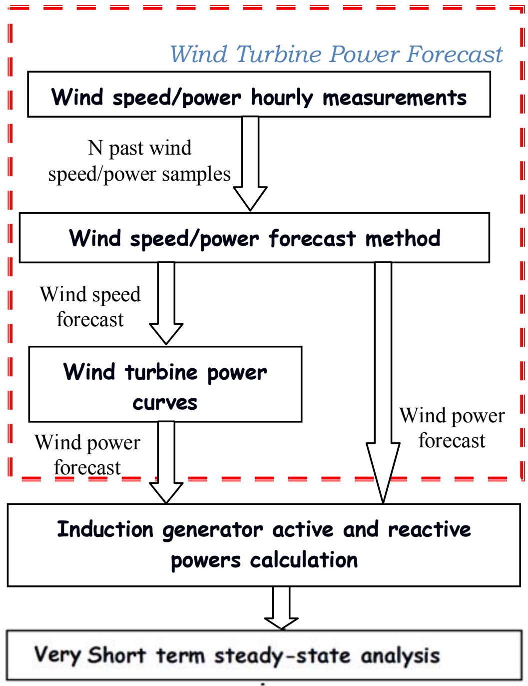

Fig. 1. Flow chart of the steps for a very short-term steady-state analysis

Physical methods generally furnish accurate predictions for long-term time horizons (more than six hours). On the other hand, they may not be the ideal tool for short-term time horizons, because the use of NWP systems leads to complex mathematical models characterized by high computational efforts. In addition, another main difficulty in implementing these methods is that a detailed description of the wind-farm site is needed [8].

Statistical and artificial-neural-networks methods can use historical wind-speed/power time series and wind-speed/power online measurements. Usually, these methods are accurate for very short-term time horizons; in particular, they produce acceptable results in this case because these models give a high weight to the more recent measurements with respect to the historical wind-time series. In particular, artificial-neural-networks methods are used to attempt to determine the connection between the input wind-speed data and the output wind forecast using algorithms that are able to describe complex, non-linear relationships; appropriate methods are designed to determine this connection by means of adequate time-series models [5].

Finally, hybrid methods are based on combinations of the aforementioned approaches and are designed to use the advantages of each approach in order to obtain an optimal forecasting performance.

In this paper, the statistical approaches are taken into account to provide the very short-term forecasts (a few hours ahead); these methods can forecast either a wind- speed/power value ("point-forecast" methods) or a wind-speed/power probability density function ("pdf-forecast" methods). In particular, the "point-forecast" methods considered here are the Persistence Method (PM), the Generalized Persistence Method (GPM), and the Nielsen Method (NM) [6, 14]. The "pdf-forecast" method (BM) considered here is derived from the Bayesian wind-speed prediction method proposed in [15,16].

A. "Point-forecast" methods

All the considered "point-forecast" methods are based on the use of the hourly online measurements of wind-turbine power. The PM is the simplest method for making a prediction; in fact, it is based on the assumption that the wind power to predict in a future hour is highly correlated with the last observed values.

Let us assume that we want to predict the wind power at hour t+k; the PM provides forecasting using the following relationship:

$$\hat{P}_{t+k} = P_t \, , \tag{1}$$

where meaning of the symbols is obvious.

The PM was developed and used by meteorologists as a comparison tool. In general, it guarantees accurate results only for very short-term time horizons (a few hours ahead).

The GPM is an extended version of the PM to a certain number of last wind-power observations. It uses the average of the last N hourly observed values of wind power to make predictions. In fact, the GPM provides forecasting using the following relationship:

$$\hat{P}_{t+k} = \frac{1}{N}\sum_{i=0}^{N-1} P_{t-i} \, . \tag{2}$$

The GPM provides useful results only in case of observations of stable wind power. Thus, the accuracy of the predictions provided by the GPM is highly dependent on the particular site and, once again, the time horizon considered.

In [14], Nielsen et al. proposed a method that combines relationships (1) and (2) in order to obtain the best of their two performances. In particular, NM is based on a forecast model that is a weighting between the PM given by (1) and the mean given by (2); in fact NM provides forecasting using the following relationship:

$$\hat{P}_{t+k} = c_k P_t + (1-c_k)\frac{1}{N}\sum_{i=0}^{N-1} P_{t-i} \, , \tag{3}$$

where c_k is defined as the correlation coefficient between P_t and P_{t+k} [14]; in fact it is calculated using the following relationship:

$$c_k = \frac{\sum_{m=k}^{N-1}\left(P^{v}_{t-m} P^{v}_{t-m+k}\right)}{\sum_{m=k}^{N-1}\left(P^{v}_{t-m}\right)^2} \, , \tag{4}$$

with $P^{v}_t = P_t - \frac{1}{N}\sum_{i=0}^{N-1} P_{t-i}$. From relationships (3) and (4) it is evident that when k is small, the correlation coefficient c_k is close to one and the NM predictions are close to those obtained from PM; on the other hand, when k is large, c_k decreases and the NM predictions are close to those obtained from GPM.

B. "Pdf-forecast" method

In [16], the N hourly observed wind-speed samples measured until the hour t are used in a Bayesian time series model to obtain the predictive pdf $f_{v^{t+k}}$ characterizing the random variable representing the wind speed ν at hour t+k.

The random variable representing wind speed is modeled using the Weibull probability density function:

$$f_V(\nu \mid \eta\ \beta) = \frac{\beta}{\eta}\left(\frac{\nu}{\eta}\right)^{\beta-1} e^{-\left(\frac{\nu}{\eta}\right)^{\beta}} \, , \tag{5}$$

where η is the scale parameter and β is the shape parameter.

In order to apply the Bayesian approach, the prior random variables have to be fixed. To accomplish this, let us express the scale parameter η in terms of the mean value of wind speed μ by using the following relationship:

$$\eta = \frac{\mu}{\Gamma\left(1+\frac{1}{\beta}\right)}, \tag{6}$$

where $\Gamma(z)$ is the gamma function. Then, we can apply the Auto Regressive (AR) model of the first order to link the mean value of wind speed at hour t (μ^t) to the value of wind speed at hour t-1 v^{t-1}. This first-order AR model uses the following relationship:

$$log(\mu^t) = \alpha_1 + \alpha_0 \, log(v^{t-1}), \tag{7}$$

where α_0 and α_1 are the coefficients of the model.

From relationships (5), (6), and (7), the prior random variables required to apply the Bayesian approach can be selected; they are the shape parameter β, and the coefficients α_0, and α_1.

In order to obtain an approximation of the posterior distributions of parameters α_0, α_1, and β, a Markov Chain Monte Carlo (MCMC) approach that uses the Metropolis-Hasting (MH) algorithm was applied. Once the samples from the posterior distributions of α_0 and α_1 are known, we can use these samples and the wind value v^{t-1} to calculate the pdf of the mean value of wind speed at "hour t+k." The pdf of the scale parameter distribution η^{t+k} is calculated from the knowledge of the μ^{t+k} pdf and the posterior distribution of β. Finally, using the posterior distribution of β and the η^{t+k} pdf, the predictive distribution of the wind speed v^{t+k} can be obtained.

Eventually, the applied methodology for "pdf forecast" furnishes a probability density function of the wind speed at hour t+k; thus, in order to obtain a probability density function of the wind power, the wind-turbine power characteristics must be used.

It should be noted that, since the predictions are in terms of wind speed, a systematic amplification of the prediction error is added due to the relationship between the wind speed and the wind power.

2.2 Calculation of induction generators' active and reactive powers

When a wind farm with induction generators has to be included in a load flow, the PQ and RX models are the most commonly used [19]. In this paper, the PQ model shown in [19] is used.

In particular, neglecting the losses, the active power is assumed to be coincident with the turbine power.

With reference to the reactive power, the following approximated expression is applied:

$$Q \approx -\left(V^2 \frac{X_c - X_m}{X_c X_m} + P^2 \frac{X}{V^2}\right), \tag{8}$$

where V is the voltage, P is the active power, X is the sum of the stator and rotor leakage reactances, X_m is the magnetizing reactance and X_c is the reactance of the bank of capacitors for power factor improvement.

As clearly evidenced by relationship (8), the reactive power depends on the active power and the bus voltage. Since the active power has a specified value for an assigned machine, the only variable is the bus voltage. There are two possibilities for taking the voltage into account in (8):

(i) the voltage is approximated with its rated value, and, then, the active and reactive powers of the induction generators both have specified values;

(ii) the reactive power is considered as a function of the voltage, and, then, relationship (8) must be included in the load flow equations to be solved.

In [19], it has been shown that the error due to approximation (i) is not significant, so this model is used in this paper. In any case, more accurate models, such as the one proposed in [16], can be easily included in the load flow equation system to be solved.

It should be noted that when one of the "point-forecast" methods is applied (subsection 2.1.A), only one predicted value of turbine power is used to calculate one value of the active and reactive powers injected by the induction machine. When the "pdf-forecast" method (subsection 2.1.B) is applied, the predicted value of the turbine power pdf is used to calculate the probability density functions of the active and reactive powers injected by the induction machine (e.g., using a Monte Carlo simulation).

2.3 Distribution system steady-state analysis

When one of the "point forecast" methods is applied, the subsequent value of the active and reactive powers injected by the induction machine can be assumed as specified input data of a deterministic load flow equation system:

$$\begin{aligned} \mathbf{P}^{sp} &= \mathbf{P}(\mathbf{V},\boldsymbol{\delta}) \\ \mathbf{Q}^{sp} &= \mathbf{Q}(\mathbf{V},\boldsymbol{\delta}) \end{aligned} . \tag{9}$$

In (9) $\mathbf{P}^{sp}, \mathbf{Q}^{sp}$ are the input vectors of the specified active and reactive powers (including the induction generator powers), and $\mathbf{V}, \boldsymbol{\delta}$ are the state vectors of voltage magnitudes and arguments.

When the "pdf-forecast" method is applied, the subsequent probability density functions of the active and reactive powers injected by the induction machine can be assumed as input data of a probabilistic load flow to be performed in order to obtain the statistical figures of the state variables (voltage magnitude and argument at all busbars) characterizing the power system's operating condition at hour t+k.

In this paper, the probabilistic load flow is performed by a Monte Carlo Simulation Method (MCSM). The MCSM procedure consists of solving non-linear equation system (9) several times, each time assuming one set of the input random variables generated according to their assigned probability density functions as input vector elements. The process is repeated a sufficient number of times to obtain an accurate estimate of the state variables.

The random nature of the input random variables other than the active and reactive induction generator powers (e.g., the active and reactive load powers) can be specified as shown in [17]. Moreover, we can use directly the wind speed as input random variable in the Monte Carlo simulation; once generated a value of wind speed according to its probability density function, the wind-turbine power and, then, the induction generators powers can be calculated.

3 Numerical applications

A comparison of the proposed forecasting methods was conducted with reference to a medium-voltage distribution system (Fig. 2) characterized by two Wind Farms connected at buses #37 and #93 and constituted by 2x330 kW asynchronous generators, whose data can be found in [19].

The distribution system is a part of an actual distribution system with 109 system nodes and a voltage level of 20 kV [20]. The only substation on the network is located above node #2 with the 150/20 kV transformer with $V_{cc}\%$ = 8%; all the other nodes are just joints of branches.

The daily load variation shown in Fig. 3 was considered at each node. The load variation is expressed in p.u. of the rated load powers given in the Appendix. In the probabilistic load flow application, the hourly loads have been considered characterized by non-correlated Gaussian pdfs whose mean values correspond to the rated powers given in Appendix (and taking into account the daily load variation in Fig. 3); the standard deviations are assumed to be 10% of the mean values.

The hourly steady-state analysis of the distribution system was conducted with reference to a winter day.

The hourly power generated by wind farms has been obtained for PM, GPM and NM directly by historical data at the site at which wind farms are installed.

With reference to the BM method, the pdfs of the hourly wind speed were obtained by applying the procedure shown in Sec. 2.1.B. In particular, the prediction of the t+k hour's wind-speed pdf was obtained using the observed wind-speed samples of six days before (N = 144 hours).

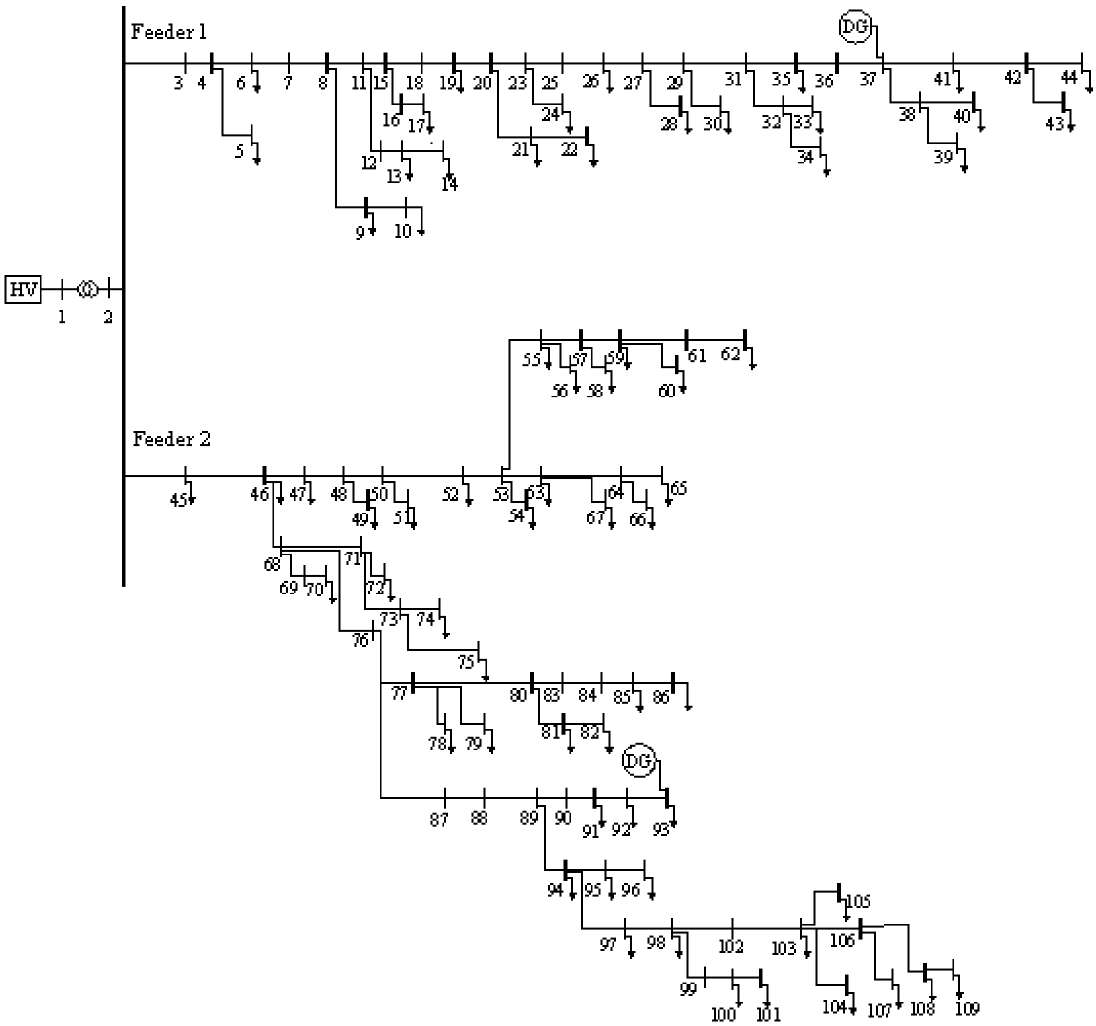

Fig. 2. Test distribution network

Starting from the wind-speed prediction, the power generated by the wind farms is obtained by applying the procedure of Sec. 2.2. To consider a real case, wind-speed samples were obtained from the Royal Netherlands Meteorological Institute (http://www.knmi.nl/samenw/hydra/index.html). These data refer to the measured data at wind stations Texelhors and De Kooy.

With reference to the GPM and NM methods, the hourly wind power values were obtained by applying the procedure illustrated in Sec. 2.1.A. The prediction of the power generated by wind farms was based on the observed generated power samples; in particular, in order to compare the methods with BM, the same number N of observed samples have been used.

The analysis of the steady-state operating conditions of the distribution system was conducted considering three different time horizons of prediction, i.e., one, two, and three hours ahead (corresponding to t+k with k = 1, 2, 3).

As an intermediate result of the BM method, Fig. 4 compares (in case of k = 1) the hourly forecasted mean value of the wind speed with the actual wind-speed value at busbar #93 (also the spread between minimum and maximum values of the pdf is shown in Figure); good predictive behaviour is clearly evident. (The same happens for the wind station at the other busbar.)

Fig. 5 compares the BM mean value of the hourly forecasted wind power with the actual wind power value at bus #93. In the same Figure, the hourly forecasted wind power values obtained by applying the other methods are also reported.

The results of Fig. 5 show that PM furnishes a simple shifted curve of actual powers. Moreover, GPM, NM and BM predictions generally assume values lower than the ones obtained by PM. In particular, GPM predictions, as expected, were slightly variable due to the significant influence of the mean value of the last N measured powers in the application of relationship (2).

Figures 6–8 show, in the case of k = 1, k = 2, and k = 3, respectively, the voltage profile of the network obtained by means of the considered forecasting methods in the “critical hour.” The voltage profile in case of BM refers to the voltage mean values. The “critical hour” of the considered day is the hour when the difference between the nominal voltage and the actual voltage magnitude, calculated on all network busbars, reaches its maximum value.

In case of k=1 (Fig. 6) and k=2 (Fig. 7), all methods perform very well for busbars of feeder 2 while only the GPM method furnishes results that are not strictly closed to the real results for busbars of the feeder 1. This is mainly due to the fact that the last N power samples used in relationship (2) for the GPM prediction of the generated power of the DG at busbar #37 in the critical hours are greater than the actual power values. Moreover, the DG at bus #37 influences the voltage profile of feeder 1 more than the DG at bus #93 influences the voltage profile of feeder 2, so that an error in the wind farm power at bus #37 has more significant influence than an error in the wind farm power at bus #93.

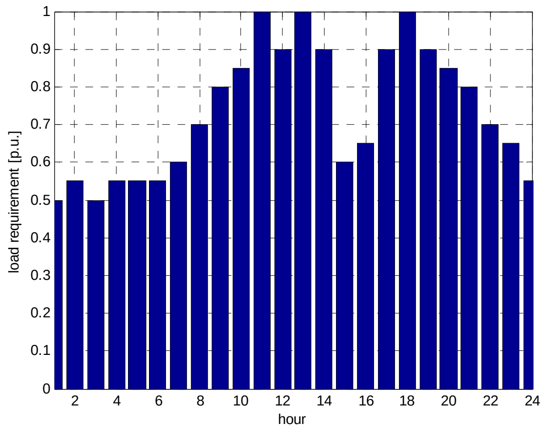

Fig. 3. Daily load variation

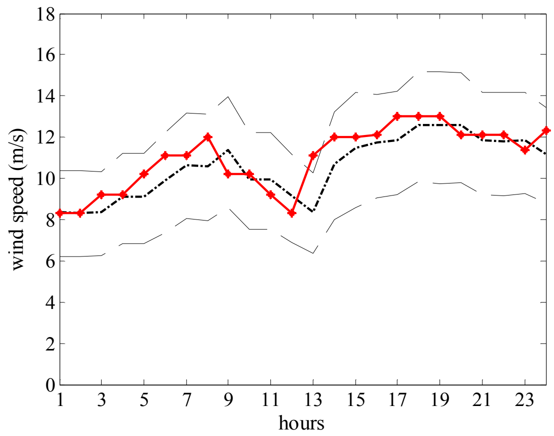

Fig. 4. BM predicted value (--) and measured value (-*) of the hourly wind speed at site of wind farm connected to busbar #93 (k=1)

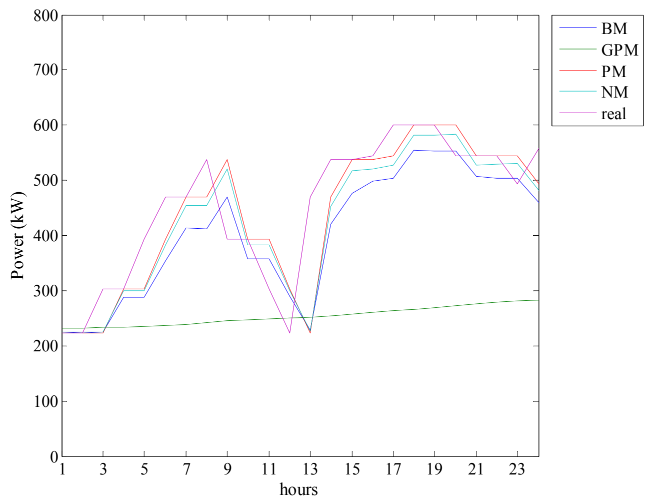

Fig. 5. BM mean values, GPM, PM, NM predicted values and measured value of the hourly wind farm power at busbar #93 (k=1)

In case of k=3 (Fig. 8), PM furnishes the worst results for the busbars of feeder 1; differently from the cases k=1 and k=2, all methods furnish results that are slightly different from the real results for busbars of feeder 1.

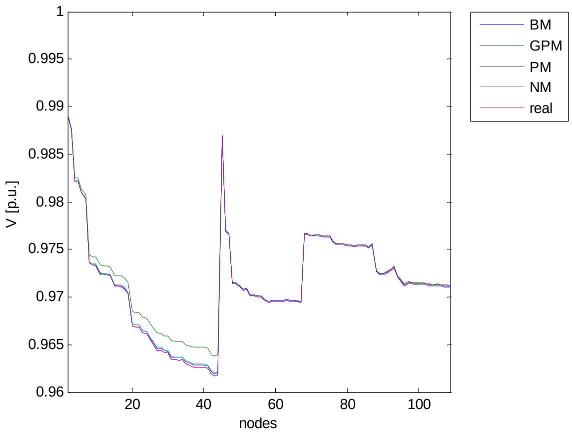

Fig. 6. Voltage profile of network in the critical hour (k=1)

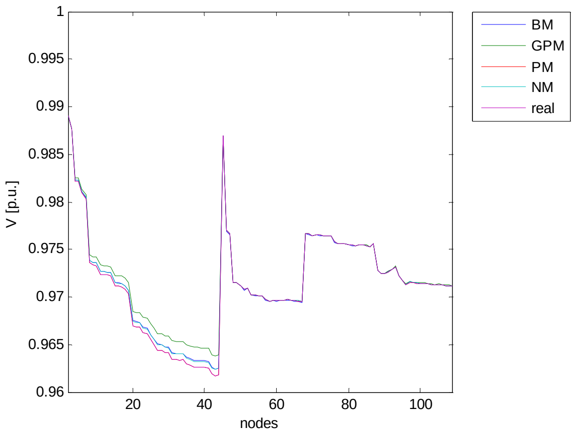

Fig. 7. Voltage profile of network in the critical hour (k=2)

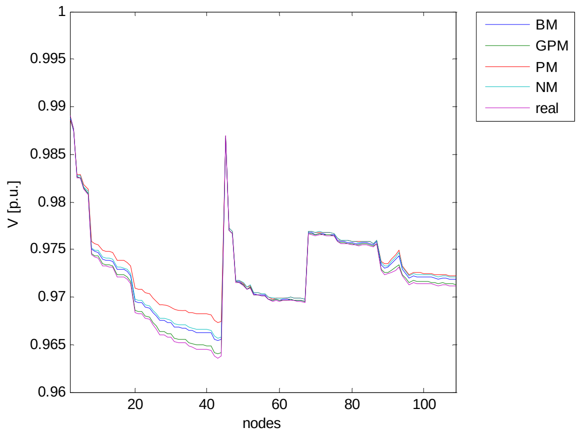

Fig. 8. Voltage profile of network in the critical hour (k=3)

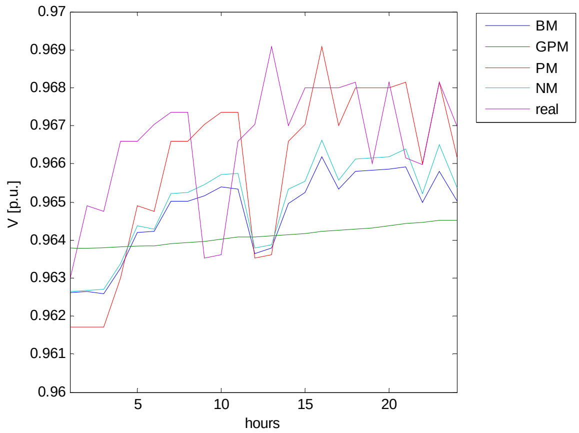

Fig. 9. Voltage magnitudes during 24 hours at critical busbar #44 (k=3)

As a further example of the obtainable results, Fig. 9 show the values (expressed in p.u.) of the voltage magnitudes during 24 hours at busbars #44 in cases of k=3. The voltage in case of BM refers to the voltage mean value. Busbar #44 is the "critical busbar" of the network; in this busbar, in fact, the difference between the nominal voltage and the daily mean value of the voltage magnitude is at its maximum value.

All of the methods, except the GPM, furnish very good results for the pre-selected time horizon. Similar results were obtained for all of the time horizons. It should be noted that, as obvious, the voltage errors for all of the methods were significantly lower than the errors in the wind farm power values. This is clearly due to the fact that the Wind Farm power values are a not significant fraction of the power required by the distribution system's loads, so that the prediction errors in the wind power values have a reduced effect on the voltage value predictions.

4 Conclusions

A very short-time steady-state analysis of an active distribution system with asynchronous generators was performed using some statistical forecasting methods for wind power.

These methods forecast either a wind-speed/power value or a wind-speed/power-probability density function so that the steady-state analysis used deterministic and probabilistic load flows.

The main conclusion of this paper is that even though the Persistence Method, the Nielsen Method, and the Bayesian Method are more accurate than the Generalized Persistence Method in the forecasting of wind power values, all of these statistical methods furnish similar acceptable results in the steady-state prediction of a distribution system. This is due to the fact that the prediction errors for the wind power values have a reduced effect on the voltage prediction since, in the examined cases, the distributed generation power is a not significant fraction of the total distribution load. When the impact of distributed generation becomes more significant, a greater influence from wind errors can be forecasted.

Nevertheless, it is important to evidence that the use of the Bayesian Method makes it possible to apply a probabilistic steady state analysis and then to consider the unavoidable uncertainties of both wind generation and loads.

In order to reduce the prediction errors of the Bayesian method, further works will regard the application of this method directly to wind power generation forecasting.

5 List of principal symbols

c_k	correlation coefficient between P_t and P_{t+k}
f_v	probability density function of wind speed ν
N	number of hourly observed values of wind power
P_t	wind power at hour t
$\hat{P}_{t+k}$	estimation of wind power at hour t+k
$\mathbf{P}^{sp}$	input vector of the specified active powers
Q	induction generator reactive power
$\mathbf{Q}^{sp}$	input vector of the specified reactive powers
X	sum of the stator and rotor leakage reactances
X_c	reactance of capacitors for power factor improvement
X_m	magnetizing reactance
V	state vectors of voltage magnitudes
α_0, α_1	coefficients of the Auto Regressive model
β	shape parameter
δ	state vectors of voltage arguments
η	scale parameter
μ	mean value
ν	wind speed

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Appendix

Table I shows the rated powers of the distribution system loads.

Table I. Rated Load Powers

bus	P (kW)	Q (kVAr)	bus	P (kW)	Q (kVAr)
5	25.5	15.8	**60**	25.5	15.8
6	74.5	23.0	**62**	25.5	15.8
9	124.0	40.0	**63**	113.6	37.3
10	61.5	33.2	**65**	25.5	15.8
13	40.0	13.0	**66**	25.5	15.8
14	90.0	43.5	**67**	284.5	108.4
17	71.3	25.6	**70**	71.3	25.6
19	25.5	15.8	**72**	84.0	33.5
21	25.5	15.8	**74**	25.5	15.8
22	25.5	15.8	**75**	25.5	15.8
24	96.0	31.5	**78**	25.5	15.8
26	25.5	15.8	**79**	25.5	15.8
28	25.5	15.8	**81**	25.5	15.8
30	63.7	39.5	**82**	25.5	15.8
33	25.5	15.8	**85**	25.5	15.8
34	25.5	15.8	**86**	51.0	31.6
35	25.5	15.8	**91**	25.5	15.8
39	25.5	15.8	**92**	25.5	15.8
40	12.7	7.9	**93**	25.5	15.8
41	25.5	15.8	**94**	59.9	27.1
43	351.0	122.0	**95**	71.3	25.6
44	25.5	15.8	**96**	324.0	113.6
45	25.5	15.8	**97**	12.7	7.9
46	25.5	15.8	**98**	71.3	25.6
47	25.5	15.8	**100**	25.5	15.8
49	25.5	15.8	**101**	25.5	15.8
51	364.0	174.6	**103**	51.0	31.6
52	25.5	15.8	**104**	25.5	15.8
54	25.5	15.8	**105**	25.5	15.8
55	25.5	15.8	**107**	25.5	15.8
56	25.5	15.8	**108**	25.5	15.8
58	25.5	15.8	**109**	25.5	15.8
59	25.5	15.8			

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