Oil Shale, 2009, Vol. 26, No. 3 Special, pp. 208–219
doi: 10.3176/oil.2009.3S.04 ISSN 0208-189X

ESTIMATION OF WIND POWER PRODUCTION THROUGH SHORT-TERM FORECAST

H. AGABUS*, H. TAMMOJA

Department of Electrical Power Engineering
Tallinn University of Technology
5, Ehitajate Rd., 19086 Tallinn, Estonia

Characteristics of wind power are different and therefore its integration leads to some important challenges concerning the electricity system. Due to weather dependence, the availability of the energy generated from wind power differs fundamentally from that generated conventionally from fossil fuels.

In an electricity system with an important share of wind power, new methods for balancing supply and demand are needed. Wind power forecasting plays a key role in tackling this challenge. Good wind power predictions increase the value of the wind power making it more competitive.

Introduction

Wind energy is the energy source that contributes most to the new renewable energy mix of European countries.

While there are good wind resources throughout Europe, the uncertainty of the wind represents a major challenge to the deployment of wind energy in electricity networks [1].

Nevertheless, wind power has been undergoing a rapid development in recent years. Several countries such as Germany, Spain, Denmark, have already reached a high level of installed wind power capacity, while others follow with high rates of development.

It is technically possible to integrate very large amounts of wind capacity into power systems, the limits arising from how much can be integrated at socially and economically acceptable costs [2].

Wind is a variable resource that is difficult to predict wherefore the variability of wind energy presents a special challenge for TSO-s and wind park operators. While conventional power plants produce a near constant output, the output of a wind power plant fluctuates. As far as the fluctuations

* Corresponding author: e-mail *Hannes@4energia.ee*

cannot be predicted, they create costs for the electricity system (balance power purchase etc.) and consumers as well as potential risks to the reliability of electricity supply.

In general, a high degree of reliability and accuracy is required by wind park operators and utility systems for wind park forecasts. The performance requirements for a forecasting service are dictated by the needs of both the grid owners and the wind generators' operators. The priority is to minimize the deviation between forecasted and actual output of the plant.

A number of methods based physics and statistical techniques incorporating artificial intelligence are available to deal with the problems on all-time scales. The current paper introduces different methods for forecasting wind energy generation, presents short-term forecast/actual characteristics of a single wind park and the results of preliminary experiments using a neural network to predict wind power production. The predictions are compared with those of a simple physical model. The results showed useful performance of the neural network model, but also clearly indicate that further experimenting is needed before the model can reach its full potential.

Forecasting methods

The problem of forecasting wind energy generation is closely linked to the problem of forecasting the variation of specific atmospheric variables (wind speed and direction, air density) over short time intervals and small spatial scales for a small volume of the atmosphere for a variety of time horizons.

Due to the wide range of spatial and temporal scales that determine the variations in generation of the wind energy power, it is necessary to use a diverse mix of data sources and types to achieve the best possible forecast performance. For wind energy forecasting, the most fundamental type of data is the time series of meteorological forecast for entities (like wind speed, etc.) and power generation from the wind plant itself [3].

Forecasting tools and models

There are two fundamental types of tools used in the forecasting process: 1) data gathering and 2) data processing.

The data gathering tools include a wide range of measuring devices that provide data to the forecast process. These include measurements made at the wind power plant itself as well as those made in the local-area, regional and even global meteorological weather systems as inputs to regional models.

The data processing tools serve to transform the measurement data into the forecast for a desired period of time. The data processing tools include physical and statistical atmospheric models as well as models of the relationship between meteorological conditions within the wind plant volume and the plant output (usually referred to as a plant output model) [3].

There are two basic types of wind power prediction models used in the wind energy forecasting process: 1) physical models, 2) statistical models. There are many types of models within each of these major categories.

Physical models are based upon the fundamental physical principles of conservation of mass, momentum and energy and the equation of state for air. These models are actually models specially adapted to simulate the atmosphere. These models consist of a set of differential equations that are numerically solved on a three-dimensional data grid with a finite resolution.

Statistical models use statistical techniques to arrive at the connection between predicted weather parameters and power output. A large number of such techniques exist, some very complex.

All statistical models require information about the true output of wind power for calibrating the model parameters to a particular site or collection of turbines. Some models are tuned on a set of historical measurement data before being put into operation. Others can take in measurements in the real time or near real time and continuously adjust the model parameters to improve the predictions.

In general most of the forecast models have the three following steps in common [4]:

- numerical weather prediction (NWP);
- wind-to power model;
- regional upscaling.

Precisely, the NWP models are invaluable tools for wind forecasting. These models predict the evolution and movement of weather systems in three dimensions using the physical laws that govern atmospheric motion starting from the current known state of the atmosphere.

A variety of techniques can be applied in conjunction with numerical forecast models to help to reduce error in wind energy predictions. Artificial Intelligence (AI) software (such as neural networks), which are among the newest signal-processing technologies in the engineer's toolbox, can be applied to reduce systematic model forecast error at a given plant location.

These self-adaptive models learn continuously from past experience and are thus able to adjust to changing circumstances, such as seasonal changes, small changes in weather model set-up, or even changes to the numbers or types of wind turbines. Self-adaption means that the system parameters are changed during operation, normally called the training phase. After the training phase the neural network parameters are fixed and the system is deployed to solve the problem at hand (the testing phase). The input/output training data are fundamental in neural network technology, because they convey the necessary information to discover the optimal operating point. The nonlinear nature of processing elements of the neural network provides the system with lots of flexibility to achieve practically any desired input/ output.

The main drawback of the neural network model and other self-adaptive models is that they need measured values of the power output in the real or near-real time in order to perform the ongoing adjustments. When such measurements are not available, the physically based models can still do a very good job.

Wind power variability and uncertainty

The output of a wind power plant exhibits greater variability and uncertainty than that of conventional sources of power generation. Wind plant output forecasting helps to manage this variability and uncertainty on all time scales. Utilities are also modifying operating procedures, acquiring flexible operational generation units and drawing upon their previous experience with variability and uncertainty in the system load.

Wind plant power varies rapidly and frequently in a wide range, as output power of those plants is a function of the wind speed in the third power, their production is hard to forecast, and they cause various technical problems and additional investments in the system. For large-scale wind power production coming from different locations, the variability is smoothed and predictability is improved as there are more turbines and wind power plants distributed over the area.

A way of reducing the uncertainty associated to wind power production is to use forecasting tools and models.

There are probabilistic models available for wind power forecasting concentrating on the prediction of specific quintiles or intervals. Probabilistic forecasting consists in providing the future probability of one or more events. In this sense, it is generally opposed to deterministic forecasting, where a single predicted value is provided for each considered horizon [5]. Probabilistic forecasts can be provided under different forms depending on the nature of the variable being forecast.

The accuracy requirements for wind speed forecasts from today's NWP models can only be met at certain times. This means that the uncertainty of the forecast becomes a parameter that is as important as the wind speed and wind power itself. To quantify the uncertainty of a forecast valid for tomorrow requires an ensemble of forecasts [6].

Among the challenges of uncertainty estimation one can consider the problem of regional forecasting. In applications with several wind farms, the uncertainty metric cannot be combined by simple adding individual wind farms. The quantiles of the prediction have to be calculated specifically for the new aggregate.

It is noted that when ensemble predictions are provided as forecasting product, it is necessary to have appropriate methods to calibrate and convert ensemble power predictions to predictive distributions that can be then used to produce prediction intervals or other quantities expressing uncertainty.

In addition to conventional approaches for uncertainty estimation, new complementary tools are proposed today for predicting the level of uncertainty in the form of prediction risk indices. Such indices may indicate what is the expected predictability for the future period considered based on ensemble forecasting [6].

When considering uncertainty it is important to take into account the possibility of learning, because this can change the nature of the problem. If there is uncertainty and learning together in the forecasting process, learning will reduce or resolve the uncertainty. It is best to take account of this in the decision problem, because if more insight can be obtained after a number of periods, using this additional information in the model will improve the decision process (forecast output) [7]. Learning is a continuous process, but modeling it as such leads to a very complicated model.

Nevertheless, the input/output training data are fundamental in all statistical models, because they convey the necessary information to learn and discover the optimal operating point. There are many algorithms for training neural networks through learning. Most of them can be viewed as a straightforward application of optimization theory and statistical estimation. For advanced wind power forecast systems, the learning sources through training are the wind park online measurements (wind park SCADA data).

Even more different variability and uncertainty factors related to wind power forecasting are reviewed in [8].

Short-term forecasting

Predicting the wind power production on time horizons from hours to weeks ahead is simple in principle. What you need is a general-purpose weather model, which predicts the wind and other weather parameters at the site or sites in question, and a wind power model, which converts the predicted weather parameters into power.

In the day-ahead time frame, in a market area with a security-constrained unit commitment, the market operator will want to know how much wind energy is expected to be produced next day on an hourly basis so that the thermal generation is not over-committed, which leads to inefficient market operation.

Short-term ("day-ahead") forecast methods use essentially the same tools as very short-term forecast ("next-hour") techniques. However, there are two important differences: 1) the importance of real-time data from the wind plant and its immediate environment is significantly reduced when horizon is larger; 2) regional and sub-regional simulations with a physics-based atmospheric model play a much more significant role in the forecast process.

On the side of the actual short-term prediction model, typical error sources are the wind speed forecast error, power curve modeling and taking into account the stability of the atmosphere.

In a typical short-term prediction model, the largest source of error is still the NWP input. Within the weather forecast, the largest error possibilities are due to the (limited) horizontal and vertical resolution of the model, the number of weather observations used (especially upstream) and the quality of the data assimilation, plus the actual model physics as well. The limited horizontal resolution is especially important in complex terrain, which is why wind farms in mountains and, to some extent, near-shore conditions show typically higher errors than wind farms in easy terrain [6].

Practice patterns of short-term wind generation forecast

Description of wind park forecasting models

As a reference forecast, power predictions generated with a very simple physical model was used. This physical model[*] converts the predictions of regional numerical weather model[†] what gives out a weather model predictions of wind speed at the 10 m level adjusted to hub height using a logarithmic wind profile, and the wind speed thus obtained was then converted into power using the nominal power curve.

The forecasted wind park output power could be described as

$$P(t) = P\left(v(t), t\right) + a_1 \cdot D_v(t) + a_2 \cdot \beta; \quad t = 1,...,24, \tag{1}$$

where $P(v)$ – generator power curve; v – wind speed, D_v – wind direction, β – site singularity (roughness, etc.), a_1, a_2 – multipliers.

The second wind forecast model based on Artificial Neural Network (ANN)[‡] uses online power measurements from the wind turbine SCADA system as input combined with highly accurate wind (direction and speed) and weather forecasts (pressure, precipitation and temperature). The program is based on AI (neural network) [9] in order to make the best power predictions through learning.

The weather forecasts for ANN are based on very accurate NWP models, with additional input from all available satellite and radar information, as well as conventional real-time observations. The data flow in the forecast system is depicted in Fig. 1.

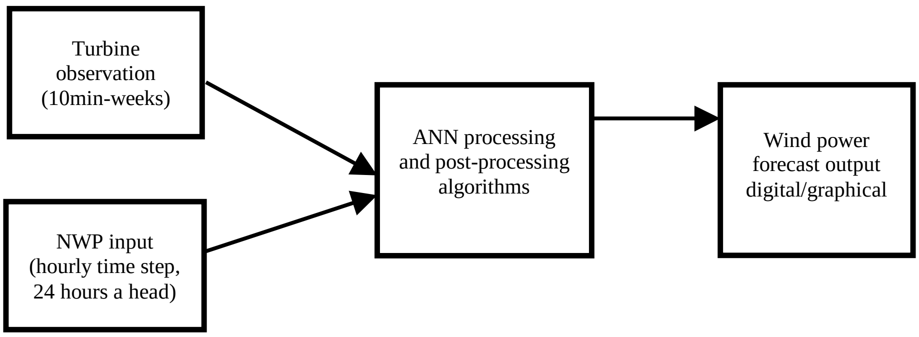

Fig 1. Graphical illustration of data flow in Advance Forecast System

[*] EMD International A/S
[†] Estonian Meteorological and Hydrological Institute (EMHI)
[‡] Wind Power-Forecast Program (WP-FP) by Vejr2-Frontweather A/S

The forecasted power with ANN could be described as

$$P(t) = a_1 \cdot P_p(D_v(t), v(t), C_w(t), t) + a_2 P_m(t); \quad t = 1, ..., 24 \tag{2}$$

where P_p – predicted power, D_v – wind direction, v – wind speed, C_w – coefficient witch takes into account weather forecasts (air pressure, precipitation, temperature), P_m – the measured power from wind farms and a_1, a_2 – multipliers.

In order to establish a system with the highest performance, data from the turbines are required. With the optimal turbine information, both historical and online, the day-ahead wind power forecast will have around one percent-point lower mean absolute percentage error (MAPE) on a monthly basis compared to our physical models. This information is used for training the network with respect to historical NWPs. On a daily basis, online power and meteorological input will result in a higher performance of the system forecasts. Turbine data in ten minutes resolution will result in the best possible wind power forecasts.

The ANN model is trained with the historical series of predicted meteorological parameters and measured wind power data. By performing the training session, the system learns the correlations between each meteorological time series and the historical wind power output, and therefore, by applying these correlations to the weather forecast time series, it will provide the wind power prediction output. The training is done for every turbine, one by one.

Previous training finds the local variation with respect to specific weather situations and local surroundings, and systematic deviations in the numeral weather predictions are detected. After the learning period the operational system is programmed to learn from all data input, and new turbines can also be included. The system has several post-processing algorithms, taking care of for example cut-off effects in connection with storm and freezing rain. New turbines with no historical data are set up with a physical model in the first phase. The forecast system is trained for every 15 degrees wind direction, giving 24 training directions for each turbine.

When looking ahead, the neural model should more effectively manage the daily forecast challenges and decrease the cost of imbalance and also makes available very short-term (“next hour” or 2 hours ahead) forecasting. As the MAPE of very short-term forecasts is typically in the range of 5% to 15% [2], therefore such prognosis implementation in the near future has large impact for accurate forecasting.

Evaluation of wind power forecasting

As test case we used data from an onshore wind power plant in Paldiski, at the tip of the Pakri peninsula, having a total capacity of 18,4 MW. The study period was one year beginning form June 2007 and during different time periods, one physics based forecast model and one ANN forecast model were introduced. Power output data and information about wind turbine availability were available in 1-hour resolution.

Illustrative wind park production forecast/actual comparison is shown in Fig, 2.

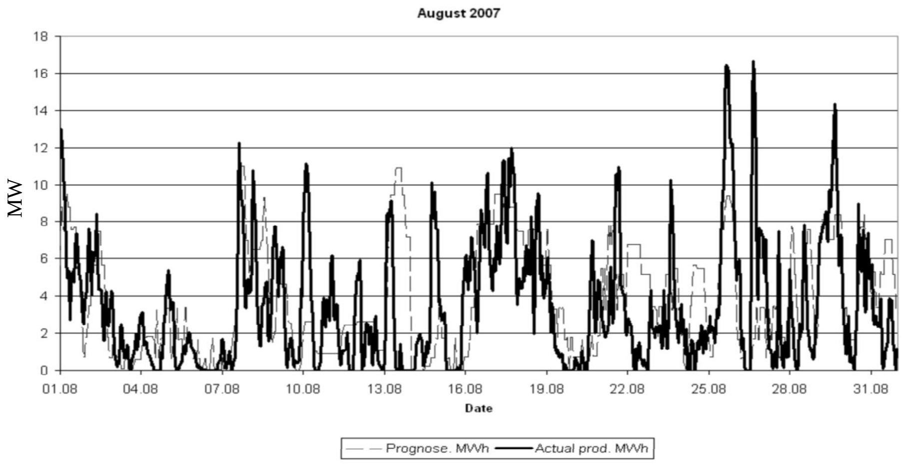

Fig. 2 Wind power predictions and actual production for Pakri wind park, August 2007. Time series plot, 0–24 hours.

From the whole test period, some reference days where chosen to calculate different prediction characteristics. The primary results are presented in Table 1.

Table 1. **Different prediction characteristics for the selected days**

Day	Average predicted wind E(v)	Wind. pred. stand. deviation σ(v)	Wind predic-tion vari-ation E(Δv)	Actual wind stand. deviation σ(Δv)	Prod. pred. error E(ΔP)	Prod. pred. error σ(ΔP)	Correlation forecast/actual		Correlation wind/prod.	
							prod.	wind	forecast	actual*
18.10.2007	5.50	1.18	–0.54	1.46	–1.45	4.94	0.34	0.84	1.00	0.65
8.11.2007	5.58	1.21	1.63	0.88	0.29	2.22	0.61	0.69	0.99	0.88
23.12.2007	6.00	1.41	2.18	1.17	3.09	1.62	0.73	0.62	0.99	0.55
14.01.2008	7.50	0.72	2.48	1.29	–3.73	3.32	0.63	0.47	0.74	0.61
20.01.2008	11.92	2.36	1.30	1.04	2.17	3.09	0.76	0.93	0.69	0.89
28.02.2008	10.00	1.41	–2.23	1.88	–1.01	1.82	0.63	0.47	0.91	0.74
13.03.2008	4.21	0.98	2.31	1.19	0.88	0.82	0.94	0.39	0.20	0.86

* Independent characteristic from the nature of forecasting model and human behavior

It is notable that presented characteristics involve uncertainty on a large scale. There are many different factors what could cause the inaccurate forecast. Therefore, it is very hard to link each variation with a certain factor.

Still, it could be pointed out that weather forecast accuracy holds a key factor in short-time forecasting. As wind generator output power is basically cube root reliance from the wind speed, then even a slight difference in wind prognosis could cause wide production difference. For example, if there was hourly forecasted wind speed 5 m/s but actual speed was 2.5 m/s, the production bias was already 1 MWh, which had to be covered by expensive balance power.

In brief, the general forecasting errors could caused by: 1) inaccurate wind prognosis; 2) insufficiently calibrated power forecast model; 3) human factor (forecaster); 4) insufficient planning of wind park maintenance.

A summary of the results of one-year forecast performance is presented in the following table. Table 2 gives monthly values of the mean absolute error as percentages of the total installed power for the first 24 hours in hourly resolution.

Table 2. **Wind power forecast performance results with simple physical model, June 2007 – February 2008**

Parameter	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Veb
MAPE, %	16	15	14	19	12	18	21	29	17

It is noticeable that two-month MAPE values are above reasonable. Commonly, it is acceptable, if MAPE is 20% at the maximum [8], while some errors in high wind might be as large as 35% or more [10, 11]. Level of accuracy should be improved when combining predictions for larger areas.

The results of wind power forecast performance with ANN model were: the average MAPE 16%, the minimum MAPE was 14% and maximum MAPE 18% (results of spring 2008).

Apparently, here the errors are generally smaller than those shown in Table 2. The neural network engine is in average 3% better than the ordinary forecast model/approach.

Neural network system has currently its own weaknesses. Namely, the information on the real-time wind turbine availability is not yet fully available for Pakri wind park. The algorithm is currently in development and testing and was not used in the results reported in this paper. The current limitations introduce obvious sources of error in the forecast (and the training data for the learning system), so the results are expected to continue to improve as this limitation is addressed.

More solid reviews and analysis related to the wind power short-term forecasting/wind energy trading could be found in [12–15].

Conclusions

As the amount of wind energy production grows in proportion to the electric load and other resources in the generation portfolio, operations become very sensitive to errors in wind generation forecasting.

The accuracy of wind power forecast is directly connected with the need for balancing energy and hence with the cost of wind power integration. For a time scale from some hours to two days additional conventional reserves have to be kept ready to replace the wind energy share in case wind speed decreases. Consequently, a large amount of research has been directed toward the development of good and reliable forecasts of wind power in recent years, and many different forecasting systems with different approaches have been developed.

There is a large and diverse pool of tools that can be used to generate wind energy forecasts. The future challenge is to use the optimal set of tools and configurations for a specific forecast application.

The majority of operational prediction models were initially designed to provide deterministic forecasts, in the form of a unique value for each hour of the prediction horizon. As the wind penetration increases, end-users would require complementary information on the uncertainty of such forecasts.

Generally, however, for time horizons beyond a few hours it is the quality of the input data from the weather models that limits the quality of the wind power predictions. Therefore any error made by meterology is critical for wind power prediction, and when wind data input is not accurate, there will be forecast errors which lead to an inaccurate generation prediction. Same principles stand for wind power model accuracy.

The dynamics of meteorological processes is strongly influenced by the available energy. The accuracy of a specific power prediction can be described quantitatively in terms of the power curve and the mean error of the underlying wind speed prediction.

From the two model performance results shown, the following conclusions can be drawn:

- The physical model performs below average;
- The neural network model performs slightly better than a simple reference forecast, demonstrating the superiority of the ensemble and learning system approach over a single-model forecast;
- Good-quality training data, including availability data, are essential. As for the moment, the access to real-time data on wind plant output, including curtailments and outages, is limited, it will directly dictate the accuracy of the forecasts;
- Further experiments are needed in order to obtain good setup of neural network and good forecast. The biggest potential for further improvements will be in the very short term prediction up to a few hours ahead.

Acknowledgements

Authors thank Nordic Energy Research (NER) project “Model Development for Power System Analysis” for financial support of this study.

REFERENCES

1. *Möhrlen, C.* Uncertainty in Wind Energy Forecasting. Thesis (PhD) Department of Civil and Environmental Engineering, University College Cork, Ireland, DP2004MOHR, May 2004.
2. *Holttinen, H., Lemström, B., Meibom, P., Ensslin, C., Tuohy, A.,. Tande, J. O., Estanqueiro, A., Gomez, E., Söder, L., Shakoor, A., Smith, J. C., Parsons, B., Hulle, F.* State-of-the-art of design and operation of power systems with large amounts of wind power, summary of IEA Wind collaboration // CD-Rom Proceedings of the Nordic Wind Power Conference 2007, Roskilde, Denmark, 1–2 November 2007.
3. *Zack, J.* Overview of Wind Energy Generation Forecasting. Draft report for NY State Energy Research and Development Authority and for NY ISO, True Wind Solutions LLC, Albany, NY, USA, 17 December 2003.
4. *Lange, B., Rohrig, K., Ernst, B., Schlögl, F., Cali, Ü., Jursa, R., Moradi, J.* Wind power prediction in Germany – Recent advances and future challenges// Proc. European Wind Energy Conference 2006, Athens, Greece, 27/2-2/3 2006.
5. *Juban, J., Fugon, L., Kariniotakis, G.* Probabilistic short-term wind power forecasting based on kernel density estimators // Proc. European Wind Energy Conference 2007, Milan, Italy, 7–10 May 2007.
6. *Giebel, G., Kariniotakis, G.* Best practice in short-term forecasting. A Users Guide // CD-Rom Proceedings European Wind Energy Conference 2007, Milan, Italy, 7–10 May 2007.
7. *Agabus, H., Landsberg, M., Liik, O*. Optimal investment strategies for energy sector under uncertainty // Publications of the 3rd International Symposium “Topical problems of education in the field of electrical and power engineering. Doctoral school of energy and geotechnology” / R. Lahtmets (ed.). Tallinn University of Technology, Kuressaare, 2006 (ISBN 9985-69-036-2). P. 120–123.
8. *Nielsen, T. S. et al.* Advanced statistical modelling and uncertainty assessment for wind power forecasting // Proc. European Wind Energy Conference 2006, Athens, Greece, 27/2-2/3 2006.
9. *Pinson, P., Nielsen, H. Aa, Madsen, H., Kariniotakis, G. N.* Skill forecasting from different wind power ensemble prediction methods // CD-Rom Proceedings of the 2nd Conference on: 'The Science of Making Torque from Wind', Lyngby, Denmark, 2007.
10. *Ahlstrom, M. L. and Zavadil, R. M.* The role of wind forecasting in grid operations // Proc. Reliability, Transmission and Distribution Conference and Exhibition: *Asia and Pacific*. Dalian, China, 2005. IEEE/PES, 2005.
11. *Zack, J.* Overview of Wind Energy Generation Forecasting. Draft report, December 17, 2003.
12. *Sideratos, G., Hatziargyriou, N. D.* Application of radial basis function networks for wind power forecasting // Proc. Artificial Neural Networks – ICANN,

16th International Conference, Athens, Greece, Part II, September 10-14, 2006. Lecture Notes in Computer Science 4132, Springer, 2006. P. 726–735.

13. *Parkers, J., Wasley, J., Tindal, A., Munoz, L.* Wind energy trading benefits through short term forecasting // Proc. European Wind Energy Conference 2006, Athens, Greece, 27/2-2/3 2006.
14. *Kariniotakis, G. et al.* The ANEMOS Project: next generation forecasting of wind power // CD-Rom Proc. 2004 German Wind Energy Conference DEWEC'04. Wilhelmshaven, Germany, 20–21 October 2004.
15. *Tambke, J., von Bremen, L., Barthelmie, R., Palomares, A. M., Ranchin, T., Juban, J., Kariniotakis, G., Brownsword, R. A., Waldl, I.* Short-term forecasting of offshore wind farms production – developments of the ANEMOS Project // Proc. European Wind Energy Conference 2006, Athens, Greece, 27/2-2/3 2006.

Received March 2, 2009