Evaluation of the MORE-CARE wind power prediction platform. Perfrmance of the fuzzy logic based models

Georges Kariniotakis, Pierre Pinson

Evaluation of the MORE-CARE Wind Power Prediction Platform. Performance of the Fuzzy Logic Based Models.

G. Kariniotakis, P. Pinson

Ecole des Mines de Paris,
Center for Energy Studies,
France.

georges.kariniotakis@ensmp.fr, tel: +33-493957501, Ecole des Mines de Paris, Centre d'Energétique, BP 207, 06904 Sophia-Antipolis, France.

Abstract- **The paper presents an advanced wind forecasting system that uses on-line SCADA measurements, as well as numerical weather predictions as input to predict the power production of wind parks 48 hours ahead. The prediction tool integrates models based on adaptive fuzzy-neural networks configured either for short-term or long-term forecasting. In each case, the model architecture is selected through non-linear optimization techniques. The forecasting system is integrated within the MORE-CARE EMS software developed in the frame of a European research project. Within this on-line platform, the forecasting module provides forecasts and confidence intervals for the wind farms in a power system, which can be directly used by economic dispatch and unit commitment functions. The platform can run also as a stand-alone application destined only for wind forecasting. Detailed results are presented on the performance of the developed models over a one-year evaluation period on five real wind farms in Ireland, using HIRLAM numerical weather prediction and SCADA data as input.**

Index Terms- **Wind power, time-series forecasting, numerical weather predictions, on-line software, adaptive fuzzy-neural networks.**

I. INTRODUCTION

The large-scale integration of wind power in interconnected or isolated power systems emerges the development of appropriate tools to assist the wind farm operators on their daily management task. Short-term forecasts of the wind farms production, up to 48 hours ahead, are necessary for a secure and economic large-scale wind power integration. Wind power prediction tools are useful for end-users such as Independent Power Producers, Transmission and Distribution System Operators, Energy Service Providers, Traders a.o. In a liberalised electricity market environment, such tools enhance the competitiveness of wind power, since they reduce the penalties resulting from the wind resource intermittence. Reduced operational and financial risk for the wind farm developers is a motivating factor for undertaking investments on wind farms.

Wind power forecasting is a far from trivial problem. Wind speed is a non-stationary process both in the mean and variance. Wind power is nonlinear w.r.t. speed with a major difficulty in the area of cut-off speed, where prediction intervals can extend from maximum to zero wind power.

Among the difficulties, one should add the error of numerical weather forecasts, which are often used as input to the models. Often, no adequate information is available online by a data acquisition system (SCADA) to assess the actual operational status of the wind farm (i.e. how many turbines are in operation). The available on-line data can be detailed (i.e. power, speed of each wind turbine) or not (i.e. only total power available). In some situations there is complete lack of data and information from neighbor wind farms has to be assessed.

Research on wind power forecasting is actively pursued by several research centres in Europe. Actually there are two main state-of-the-art approaches; one based on physical or deterministic modelling and a second one based on statistical or timeseries modelling.

The "physical" approach for wind power forecasting is based on a detailed description of the wind park site (orography, roughness, obstacles), the wind turbines (hub height, power curve, thrust curve) and the layout of the wind plant. In [1, 2], wind power forecasting platforms based on physical methods are described. The main input is numerical weather predictions (NWP). Model output statistics are developed to account for systematic errors. Weather predictions are however updated only a limited number of times per day by meteorological services. For this reason, the performance of these models is often satisfactory for rather longer (>6 hours ahead) than short-term horizons.

The alternative "time series", or statistical, approach includes typical linear models (ARMA, ARX etc) and non-linear ones (i.e. neural networks, conditional parametric models, etc). These models aim to predict the future by "capturing" temporal and spatial dependencies in the data [1], [3-6]. The input to these models can be on-line SCADA data and numerical weather predictions (NWP). For look-ahead times more than ~10 hours (mentioned hereafter as "long-term"), NWPs are indispensable for an acceptable performance, since they represent weather dynamics that cannot be modelled using only recent on-line data. For shorter horizons, up to ~10 hours ahead (mentioned hereafter as "short-term"), time series models can be based exclusively on recent measurements; however even in this case, NWPs as explanatory input improves results. It is noted that the threshold of 10 hours is mentioned as an example rather than a rule, since it depends on the characteristics of a specific wind profile.

The models presented in this paper belong to the time series approach. In previous work of the authors, linear autoregressive models, radial basis functions, wavelet networks, feed forward and recurrent neural networks and finally adaptive fuzzy-neural network models were compared for the task of short-term prediction [6-8]. Fuzzy neural networks, originally used here for wind forecasting, were found to outperform the other approaches in both tasks of short-term (0-10 hours) and longer-term (0-48 hours) wind prediction.

The developed models have been implemented in an online prediction module, which is the core of the Armines Wind Power Prediction System (AWPPS) developed by Ecole des Mines de Paris. The AWPPS platform integrates a relational database for data management and a Java Man-Machine Interface (MMI) for higher portability. Communication between the modules is performed using ODBC/JDBC.

The core prediction module of AWPPS has been integrated:

(i) in the More-Care Energy Management System (EMS) developed in the frame of a European project and installed for on-line operation in the islands of Crete, Madeira and in Ireland (see Figure 8);

(ii) in an industrial SCADA software (see Figure 9).

This paper presents results from the implementation of More-Care in Ireland where the aim is the prediction of the output of 11 wind farms of a total capacity of several tens of MWs.

II. THE AWPPS WIND PREDICTION SYSTEM.

The core prediction module of AWPPS provides forecasts for multiple wind farms. It integrates several functionalities such as:

1. short-term models considering only SCADA data as input based on adaptive fuzzy-neural networks (F-NN). Such models provide predictions for 1-10 hours ahead and are destined for small power systems.
2. Longer-term models based on adaptive F-NNs for 0-48 hours ahead using NWPs as input and on-line data if available.
3. Simple alternative models (persistence, moving average techniques, power curve models based on direct conversion of NWPs to power), which can be optionally activated as backup models.
4. Methods to estimate the uncertainty of the predictions.
5. A method to combine forecasts by different models.
6. Scheduled maintenance of the wind turbines, etc.

Adaptive fuzzy-neural networks have been used for both short-term and long-term wind power prediction. The adaptivity property stands for the capacity of the model to fine-tune its parameters during on-line operation. This is an important requirement for a non-stationary process like wind speed or power. Adaptivity of the model compensates changes in the environment of the application that may happen during the lifetime of a wind farm. Such changes can be changes in the number of wind turbines (extension of the wind farm, maintenance or availability of the machines that is usually not available through SCADA), in the performance of the wind turbines due to aging, changes in the surrounding of the wind park (i.e. vegetation), or changes in the configuration of the model used to produce the NWPs.

The generic F-NN model, described in [12], can be trained on appropriate input depending on the final use, which can be either short-term or long-term prediction.

A. Short-term models based on on-line data.

Short-term models receive historic values of wind power as input, as well as explanatory data, such as wind speed and direction, to predict wind power. The general form of a simple model with input only past values of power is:

$$\hat{P}(t+1) = f\left(P(t), P(t-1), \ldots, P(t-m)\right)$$

The function $f(.)$ stands for the generic fuzzy-neural function. Multi-step ahead forecasts are generated using the model in an iterative way. I.e., in order to produce a forecast for t+2, the forecast for t+1 is fed back as input to the model. This approach presents the drawback that does not permit to iterate explanatory input, since no forecasts can be available for such quantities. To handle this problem, models using the look-ahead time k as an input variable can be considered. An alternative approach is to develop multi-output models, or to tune a different model for each time-step. The implementation of this approach is complex and requires high development effort, which can be prohibitive in case of a large number of wind farms.

The short-term models based on fuzzy-neural networks are found to outperform Persistence up to 20% according to the time-step [7, 8]. Persistence is a simple approach used as reference to evaluate the performance of advanced models. It assumes that the "wind in the future will be the same as the wind now".

Short-term predictions are adequate for small applications, e.g. islands, for which NWPs are not available. However, in larger systems, where predictions up to 48 hours are required, timeseries models based on meteorological information, as the one presented below, are necessary. Such models, due to the fact that consider NWPs as input, manage to double the improvement w.r.t. Persistence for the first 10 hours (up to 40% versus 20% for short-term models).

B. Longer-term models based on meteorological information.

For "long-term" horizons up to 24-48 hours ahead, it is necessary to include numerical weather predictions (NWP) as explanatory input to the model in order to have an acceptable performance. NWPs include usually wind speed, direction and temperature at 10 m and at several levels defined by atmospheric pressure. NWPs can be provided for the geographical coordinates of the wind farm or for a grid of four points surrounding the farm. In the second case, the spatial resolution of the NWP model is of primary importance. Meteorological models with high resolution are often more accurate but require high computation time to produce forecasts, and as a consequence, they do not update frequently their output (i.e. 1-4 times per day). In contrast, forecasts from low-resolution NWP models are more frequently available.

The developed forecasting tool is able to operate with input from different NWP systems. In the frame of the More-Care project it was tested and gave satisfactory results with input from the SKIRON system for the case of Crete, and also from HIRLAM for the case of Ireland. SKIRON forecasts were provided for a grid of 15x15 km (System B in *Fig. 1*), while HIRLAM predictions were provided at the level of the wind farm as interpolated values but from a model resolution of 33 km (System A in *Fig. 1*).

The developed model receives on-line data as well as NWPs as input to predict the wind farms production for the next 48 hours. These forecasts are updated every hour based on the most recent wind power measurements. Wind power data are necessary for the on-line updating procedure, independently if they are used or not as input variables to the model. The updating procedure permits mainly a good performance of the model for the first hours (i.e. 1-6 hours) of the considered horizon. Model configurations that do not update

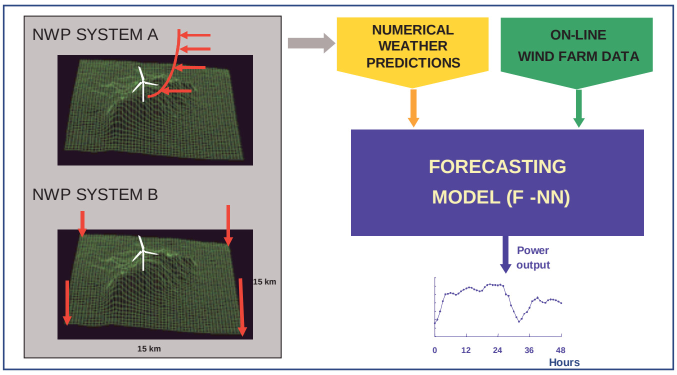

Fig. 1: *General scheme of the "long-term" prediction model with examples of two configurations of NWP systems used as input (SKIRON, HIRLAM).*

their forecasts based on recent wind power data were found to perform worse than Persistence in look-ahead times up to 6 hours ahead. Finally, the consideration of on-line information, other than wind power (i.e. wind speed or direction), was not found to contribute in the accuracy of the results. The general scheme of the model is shown in Fig. 1.

The aim of the prediction model is to capture the relations between input (meteorological information, on-line data) and output (future total wind park power). Such mapping includes the following implicit relations:

- Temporal correlations between past and future data of the process (autoregressive aspect of the model).
- Conversion of wind speed (meteorological predictions) from the height or the atmospheric level they are given to the hub height of the wind turbines.
- Spatial projection of the meteorological wind speed forecasts from the NWP grid points (e.g. 15x15 km) to the level of the wind farm ("downscaling").
- Correction of the wind park output for factors affecting the total production (i.e. array effects, effect of wind direction etc).

The advantage of a model such as the fuzzy neural network model, compared to models based on the "physical" approach, is that it permits to avoid all the above intermediate modeling steps. Moreover, its adaptive mode can compensate situations like the ones explained in the previous Section.

C. Integration in the More-Care Energy Management System.

The core prediction Module, with the above functionalities (1)-(6) has been integrated in the More-Care EMS. More-Care consists of a number of Modules for functions such as load, wind or hydro forecasting, economic dispatch, unit commitment, fast security assessment etc. The general architecture is shown in Figure 2. Numerical Weather Predictions are entered in the system via FTP connection, email etc. The short-term models, when activated, produce forecasts every 10-20 minutes for the next hours (sliding window scheme). The long-term models produce forecasts also with a sliding window scheme of one hour for the next 48 hours. The sliding window operation is a major difference from existing systems that produce forecasts only when new NWPs arrive (i.e. once or four times per day).

D. Off-line tuning of the prediction models.

Any wind power prediction software is not "*plug-and-play*" since it is always site-dependent. In order to run with acceptable accuracy when installed to a new site, it is always necessary to devote considerable effort for tuning off-line the prediction model on the characteristics of the local wind profile or for describing the environment of the wind farms. This task requires considerable expertise.

The outstanding problem in time series forecasting is to define the structure of the forecasting model for which optimal accuracy will be obtained. Optimal accuracy is required when predicting new data that is, data that have not been used during the model development. The capacity of the model to predict such "*out of sample*" data is called "*generalization*" and is a primary requirement during on-line operation.

Nowadays, models based on artificial intelligence are adopted in several prediction applications. This is because they permit to consider easily available explanatory input when this is available. In the case of wind power prediction, input can be past measurements of wind power, speed or direction, measurements from neighbor sites, numerical weather predictions of wind speed, direction, temperature etc for various levels of the NWP system and for grid points around the wind farm. A model however that uses excessive input will have a very high number of parameters and as a consequence will "learn" not only the useful information included in the data but also their noise ("*overfitting*"). Then, the capacity of that model to generalize will be low. As a conclusion: one should be cautious of models that use huge quantities of data as input. Models that use selectively and in an intelligent way the available input are expected to be more accurate. This is the well-known principle of "*parsimony*" in timeseries forecasting.

The off-line tuning of the prediction models considered here is based on an advanced methodology, which permits to select the optimal structure of a model and the most relevant input based on non-linear constrained optimization techniques. The estimation of the parameters is performed using learning algorithms that optimize simultaneously both the error response and the Information content of the model. The off-line methodology is presented in detail in [9, 12].

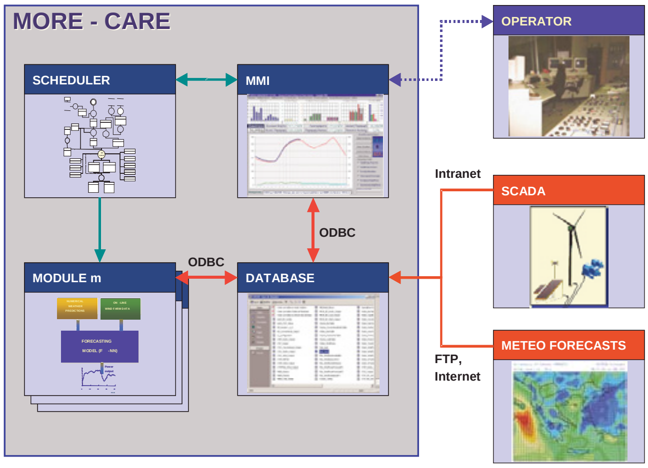

Fig. 2: *General architecture of the More-Care EMS system.*

III. EVALUATION RESULTS

Evaluation results are presented here for five wind farms in Ireland (WF-A to WF-E) with a total installed power of a few tens of MW. The available time series cover a period of almost two years from which 6600 hours were used for training (learning set), 1000 hours for cross-validation and one year for testing the performance of the models. Hirlam Numerical Weather Predictions (speed, direction and temperature at 10m or 2m and at model Levels 22, 23 and 24) are considered. Their resolution is 33 km. Only the total production of the wind farms is measured and used as input to the models.

The distribution of prediction errors varies as a function of the look-ahead time. As the prediction horizon increases, the standard deviation of the error distribution augments and the percentage of occurrence of low prediction errors diminishes significantly.

Figure 3 shows the error distribution of the F-NN model for WF-A and for different prediction horizons (1-hour ahead and 24-hour

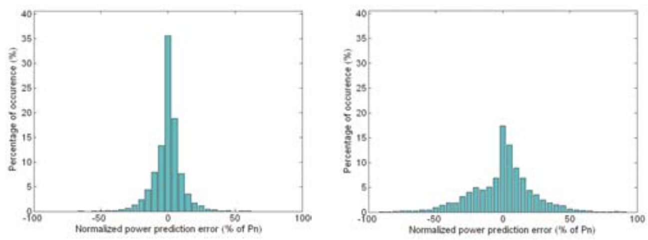

Fig. 3: *Distributions of prediction errors for two prediction horizons (left: 1-hour ahead prediction error distribution, right: 24-hour ahead prediction error distribution). Results are for WF-A.*

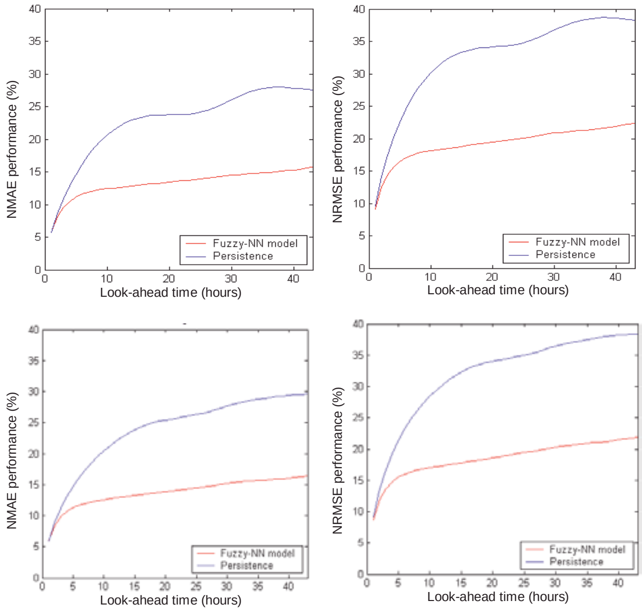

Fig. 4: *Error (NMAE, NRMSE) as a function of the look-ahead time for WF-A and WF-E as obtained by the F-NN model and persistence.*

ahead). The bar width represents 5% of the wind farm nominal power. These are representative error distributions for this advanced model. As one can notice, for the first look-ahead time, almost 70% of the prediction errors are lower than 7.5% of the wind farm nominal power, though for 24-hour ahead prediction, there are 38% of the prediction errors that are inferior to that threshold.

Figure 4 illustrates the performance of the advanced models versus that of Persistence for two wind farms (WF-A and WF-E).

The criteria used are the NMAE (Normalized Mean Absolute Error) and NRMSE (Normalized Root Mean Square Error). Normalization is based on the wind farm nominal capacity. The NRMSE criterion has higher values than the NMAE since larger errors weight more than small errors in contrast to the NMAE where all errors weight equally. In some situations, although NRMSE can provide some improvement w.r.t., Persistence this may not be the case for the NMAE criterion. Thus both criteria need to be used for a thorough evaluation.

The F-NN model always outperforms Persistence whatever the prediction horizon. This is also true for the first 3-4 look-ahead hours thanks to the use of SCADA data as input to the model. The NRMSE error of Persistence ranges between 9-39% of the nominal power, while that of the advanced model varies between 9-22%. The NMAE takes values between 5-16% according to the time step. A detailed analysis of the errors led to the conclusion that a major part of the uncertainty comes indeed from the Hirlam NWPs. Also given the fact

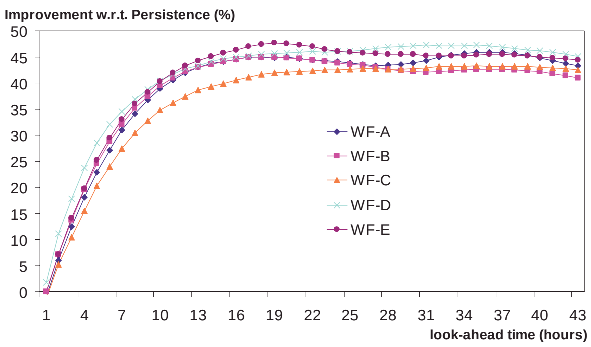

Fig. 5: *Performance of the Fuzzy-NN model: improvement w.r.t. Persistence for the 5 wind farms over a one-year evaluation period.*

that prediction of individual wind farms is performed, no spatial smoothing is present as would be the case in prediction of regional or national power. The level of accuracy increases when one considers the total number of wind farms. Then, average prediction error for the first 24 hours is inferior to 10%.

The improvement obtained by the Fuzzy-NN model w.r.t. to Persistence is depicted in Fig. 5 where the improvement is plotted for the five wind farms. In all cases the advanced model:

(i) is better than persistence, even for the first hours,

(ii) outperforms Persistence up to 50% depending on the time step.

Since the evaluation of the prediction model is done over a one-year period, it is of particular interest to visualize the monthly performance (Fig. 6). This performance is slightly variable from a month to another; for instance the prediction NMAE error ranges from 9.7% in July, up to 14.5% in May, for the 6-hour ahead horizon. In the results for each month of the year for all time steps the improvement obtained over persistence rises up to 60%. However, for several months, such as in August, this improvement is very low and this penalizes the overall result. This is because during this month low and relatively constant wind regimes are present. As a conclusion to this, further analysis could be based on a normalization of the criteria using average wind production as an alternative to nominal capacity.

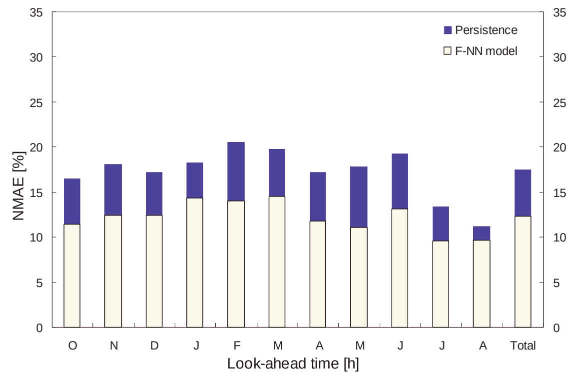

Fig. 6: *NMAE performance of the F-NN model and Persistence for WF-E for 6 hours ahead forecasts. Performance is given as a function of the month of the year (Oct. 2001-Aug. 2002).*

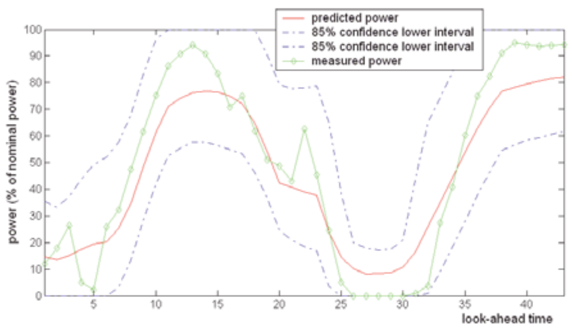

Fig. 7: *Example of wind power prediction by the Fuzzy-NN model with 85% confidence intervals (WF-E).*

Finally, Fig. 7 depicts an episode with the wind power predictions for the next 43 hours compared to the real values for WF-E. The 85% confidence intervals are built with the method described in [11].

IV. CONCLUSIONS

The paper presents results from the application of the fuzzy-neural network prediction model for the case study of Ireland. By using both SCADA data and Hirlam Numerical Weather Predictions, the F-NN model can provide high quality forecasts. The model presents a clear advantage for the first hours (1-6) where it outperforms Persistence. Emphasis is given in optimizing the model architecture using nonlinear constrained optimization techniques. By this way the most relevant input is automatically selected and the models obtained are parsimonious with optimal generalization capability.

The level of accuracy is satisfactory for single wind farm prediction. Part of the inaccuracy comes however from the NWP system and is mainly due to phase errors of the Hirlam predictions. On the other hand, the resolution of the available NWPs (33 km) was quite low. In the last months the resolution changed to 14 km and this is expected to improve accuracy in the future. When summing predictions for all wind farms, due to spatial smoothing effect of errors, the accuracy increases; the average error when predicting the total power reduces to less than 10% for the first 24 hours.

The developed methods have been implemented in operational software and installed for on line operation in Ireland as well as in Crete and Madeira in the frame of the European Project More-Care. Figure 8 shows a view of the Man-Machine interface of the More-Care implementation. Alternatively, the core prediction module has been also integrated in an industrial SCADA software (Figure 9) for predicting the output of individual wind farms connected in a power system.

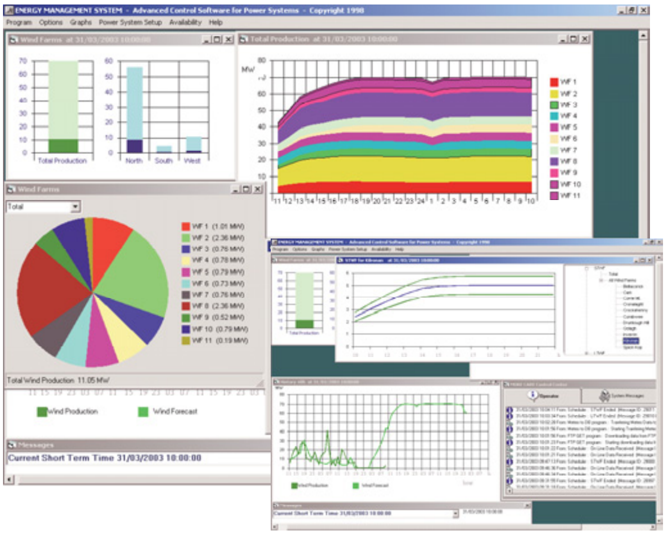

Fig. 8: *User interface of the wind power prediction module of More-Care.*

Fig. 9: *User interface of an industrial SCADA software integrating the wind power prediction module.*

V. ACKNOWLEDGMENTS

The authors gratefully acknowledge ESB National Grid for providing data for the realization of this work. This work was performed in the frame of the Project MORE-CARE (ERK-CT1999-00119) funded in part by the European Commission.

VI. REFERENCES

1. Giebel G., Landberg L., Kariniotakis G., Brownsword R., “State-of-the-Art on Methods and Software Tools for Short-Term Prediction of Wind Energy Production”, *Proc. of the 2003 European Wind Energy Association Conference*, EWEC’03, Madrid, Spain, 16-19 July 2003.
2. Focken, U., Matthias, L., Waldl, H.P., “Reduction of wind power prediction error by spatial smoothing effects”, *Proc. of the 2001 European Wind Energy Conference, EWEC’01*, Copenhagen, Denmark, July 2001, pp. 822-825.
3. Fukuda, H. et al., “The development of a wind velocity prediction method based on a Data-Mining type Auto-Regressive model”, in *Proc. of the 2001 European Wind Energy Conference, EWEC’01*, Copenhagen (Denmark), July 2001, pp. 741-744.
4. Nielsen, T.S., Madsen, H., Nielsen, H.A., Landberg., L., Giebel, G., “Prediction of regional wind power”, *Proc. of the 2002 Global Wind Power Conference*, Paris, France, April 2002, CD proceedings.
5. Kariniotakis G., Stavrakakis G.S. Nogaret E.F., “Wind power forecasting using advanced neural network models”, *IEEE Trans. on Energy Conversion*, Vol. 11, No. 4, Dec. 1996, pp. 762-767.
6. Kariniotakis, G., Nogaret, E., Stavrakakis, G., “Advanced Short-Term Forecasting of Wind Power Production”, in *Proc. of the 1997 European Wind Energy Association Conference, EWEC’97*, Dublin, Ireland, 1997, pp. 751-754.
7. Dutton A.G., Kariniotakis G., Halliday J.A., Nogaret E., “Load and Wind Power Forecasting Methods for the Optimal Management of Isolated Power Systems with High Wind Penetration”, *Wind Engineering*, Vol. 23, No 2, 2000.
8. Kariniotakis G., Nogaret E., Dutton A., Halliday J. Androutsos A., "Evaluation of advanced wind power and load forecasting methods for the optimal management of isolated power systems.” *In Proc. of the 1999 European Wind Energy Conference, EWEC’99*, Nice, France, 1-5 March 1999.
9. Kariniotakis G., *Contribution to the development of an advanced control system for the optimal management of autonomous wind-diesel systems*, PhD thesis, Ecole Nationale Supérieure des Mines de Paris, Centre d’Energétique, December 1996.
10. Hatziargyriou N. et al., “The "CARE" System Overview: Advanced Control Advice for Power Systems with Large-scale Integration of Renewable Energy Sources”, *Wind Engineering*, Vol. 23, No 2, 2000.
11. Pinson P., Kariniotakis G., “On-line assessment of prediction risk for wind power production forecasts”, *Proc. of the 2003 European Wind Energy Association Conference*, EWEC’03, Madrid, Spain, 16-19 July 2003.
12. Kariniotakis G., Mayer D., “An advanced on-line wind resource prediction system for the optimal management of wind parks”, in *Proc. of the 2002 IEEE/IEE MedPower Conference*, Athens, Greece, 4-6 Nov. 2002.