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An Advanced On-Line Wind Resource Prediction System for the Optimal Management of Wind Parks

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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 on a real wind farm using HIRLAM numerical weather predictions as input.

Keywords: Wind power, time-series forecasting, numerical weather predictions, on-line software, adaptive fuzzy-neural networks.

I. INTRODUCTION

Nowadays, wind park installations in Europe exceed 12.000 MW, while the motivated by Kyoto protocol objective for 12% electricity generation by year 2010, is translated to a wind capacity of 60.000 MW. Such a large-scale integration of wind power emerges the development of appropriate tools to assist the wind farm operators on their management task.

Of major importance are tools that forecast wind parks production for the next 24-48 hours. In a liberalised market environment, prediction tools enhance the competitiveness of wind power, since they reduce the penalties resulting from the wind resource intermittence.

Research on wind speed forecasting and, correspondingly the forecast of power output from a wind park, is actively pursued by several research centres in Europe.

Actually there are two main state-of-the art approaches; one based on physical modelling and a second one based on timeseries modelling.

The "physical" approach for wind power forecasting is based on a detailed description of the site (orography, roughness, obstacles), a description of the wind turbines (hub height, power curve, thrust curve) and a description of the wind plant. The main input is numerical weather predictions (NWP). Model output statistics are developed to account for systematic errors [1]. 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 "timeseries", or statistical, approach includes typical linear models (ARMA, ARX etc) [2] and non-linear ones (i.e. neural networks, conditional parametric models, etc) [3,4]. These models aim to predict the future by capturing temporal and spatial dependencies in the data. The input to these models can be on-line SCADA data and numerical weather predictions (NWP). For look-ahead times more than ~10 hours, 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, timeseries 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 timeseries approach. In previous work, several types of models have been benchmarked on the wind power prediction problem [5,6,7]. Linear autoregressive models, radial basis functions, wavelet networks, feedforward and recurrent neural networks, and finally adaptive fuzzy-neural network models were compared for the task of short-term prediction. Fuzzy neural networks, originally used here for wind forecasting, were found to outperform the other approaches in both short-term and long-term wind prediction.

This paper presents an advanced wind power forecasting tool developed at Ecole des Mines de Paris. This tool has been integrated in the MORE-CARE Energy Management System (EMS) developed in the frame of a EU project. MORE-CARE is installed at the islands of Crete and Madeira, where it optimizes the operation of these power systems, and also in

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Ireland, where it operates as a stand-alone wind-forecasting platform for 11 wind farms. The system provides optimal forecasts for a horizon up to 48-72 hours ahead.

II. DESCRIPTION OF THE PREDICTION MODEL.

Adaptive fuzzy-neural networks (F-NN) are applied here for both short-term and long-term 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 NWP.

The core FNN model is generic and 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.

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:

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

The generic fuzzy-neural function $f(\cdot)$ is described in Section III. 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 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 can be useful for horizons up to ~10 hours. They are found to outperform persistence up to 20% according to the time-step [4,5,6]. Such predictions are adequate for small applications, for which NWPs are not available, e.g. in the case of islands [9]. In larger systems, timeseries models based on meteorological information, as the one presented below, outperform short-term models (improvement up to 40% w.r.t. persistence for horizons up to 10 hours).

B. Models based on meteorological information.

For “long-term” horizons up to 24-48 hours ahead, it is necessary to include numerical weather forecasts as

explanatory input to the model in order to have an acceptable performance. NWPs include usually wind speed, direction and temperature at 10 m, as well as at several levels related to levels of atmospheric pressure. They 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 this study it was tested and gave satisfactory results with input from the SKIRON system for the case-study of Crete, and also from HIRLAM for the case of Ireland. SKIRON forecasts were provided for a grid of 15x15 km (System B in Figure 1), while HIRLAM predictions were provided at the level of the wind farm (System A in Figure 1).

Forecasts are generated every hour for the next 2 days. At the moment of update, the most recent available NWPs are used as input to the model together with measurements of wind power. Eventually measurements of wind speed or direction can be used as input. Model configurations that do not include such online information as input were found to perform worse than persistence in look-ahead times up to 6 hours ahead. 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 general scheme of the model is shown in Figure 1.

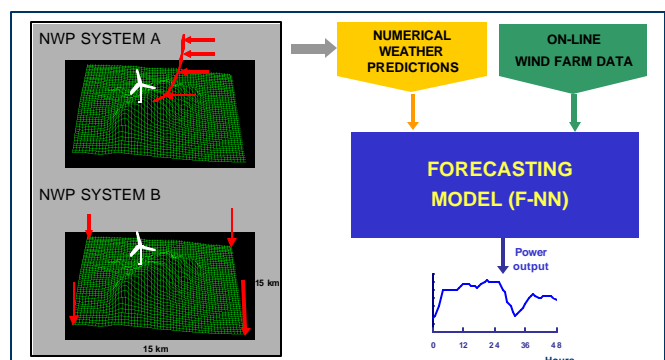


Figure 1 : General scheme of the “long-term” prediction model with examples of two configurations of NWP systems used as input (SKIRON,HIRLAM).

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.

- Spatial projection of the meteorological wind speed forecasts from the NWP grid points (eg. 15x15 km) to the level of the wind farm.
- 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 like fuzzy neural networks compared to a physical one 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.

The above mapping relations introduce inaccuracy in the modeling procedure. Among the difficulties, one should add the error of weather forecasts, without neglecting the intermittent nature of wind itself. Wind speed is a non-stationary process both in the mean and in the 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.

III. MODEL DEVELOPMENT AND GENERALIZATION.

A. General description of the fuzzy-neural network model.

The fuzzy model can be expressed in the form of rules of the type:

"IF \underline{x} is A THEN y is B "

where \underline{x} , y are linguistic variables and A , B are fuzzy sets. In the case of time-series prediction rules may have the form:

R : IF x_1 is A_1 , and ..., and x_n is A_n THEN $y = g(x_1, \dots, x_n)$

where:

x_1, \dots, x_n are real-valued variables representing input variables of the system defined in the universes of discourse X_1, \dots, X_n respectively.

A_1, \dots, A_n are fuzzy sets.

y is variable of the consequence whose value is inferred. In the specific problem it represents future wind power ($\hat{P}(t+1), \hat{P}(t+2), \dots$).

$g(\cdot)$ is a function that implies the value of y when x_1, \dots, x_n satisfy the premise. The function $g(\cdot)$ in the consequent part of the rules may be a linear or a non-linear one or even a constant. In the case of a linear function the fuzzy rule-base takes the form:

R^1 : IF x_1 is A_1^1, \dots , and x_n is A_n^1 THEN $y^1 = p_0^1 + p_1^1 x_1 + \dots + p_n^1 x_n$
 \vdots
 R^m : IF x_1 is A_1^m, \dots , and x_n is A_n^m THEN $y^m = p_0^m + p_1^m x_1 + \dots + p_n^m x_n$

Each rule gives an estimation of the output y_i according to the conditions defined by the fuzzy sets in the premises. In the context of timeseries prediction, each variable x_i in the premise corresponds to a past value of the process (i.e. power: $P(t), P(t-1), \dots$), or past values of explanatory input (i.e.

wind speed: $WS(t), WS(t-1), \dots$) or meteorological forecasts ($WS_m(t+1), WS_m(t+2), \dots$).

A linear function in the consequence is indeed an ARX (autoregressive with exogenous variables) model. It is clear that with the above definitions, the rule-base consists of an ensemble of "local" models. Local modeling is a desired property of the model, especially in the case of a non-stationary process such as wind generation.

Fuzzy sets in the premises are modeled here using Gaussian functions:

$$m_{A_j}(x_j) = \exp\left(-\left(\frac{x_j - a_j}{b_j}\right)^2\right)$$

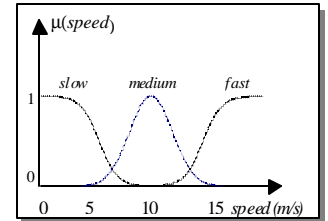


Figure 2: Representation of fuzzy wind speeds. "Speed" is a linguistic variable with three terms "slow", "medium", and "fast" represented as fuzzy sets with the membership functions shown in the Figure.

In the case of a linear function in the consequence, the model may be written analytically as following:

$$\hat{y} = \frac{\sum_{i=1}^r \left(p_0^i + \sum_{j=1}^m p_j^i x_j \right) \prod_{j=1}^m m_{A_j^i}(x_j)}{\sum_{i=1}^r \prod_{j=1}^m m_{A_j^i}(x_j)} \hat{=} \sum_{i=1}^r w^i \hat{y}^i$$

B. Learning and Generalization.

Model building is characterized by two phases: optimization of the model architecture and tuning of the model internal parameters (learning).

These two phases are driven by the requirement for good "generalization". Generalization is the capacity of the model to perform well when it predicts new data (data not used during the two phases of model development). It is a primary requirement for the on-line use of a model.

The tuning of the model parameters is performed taking into account [8]:

- *Learning rules* based on stochastic gradient for tuning the parameters a, b, p of the model.
- Learning rules are appropriately developed to minimize simultaneously prediction error and the Information content of the model (max entropy). This acts as a *self-regularization* process that permits to avoid overfitting of the data.
- *Simulated annealing* is performed for controlling the evolution of the learning process through appropriate adaptation of the learning rate.
- *Early-stopping* is applied to the learning process is early- to avoid overfitting.
- *Cross-validation* is applied to terminate learning. For this purpose, a subset of the data (validation set) is reserved.
- The cross-validation criterion is expressed as a weighted function of the performance of the model over the whole

prediction horizon. By this way, generalization is optimized for multi-step ahead prediction.

The above process permits to tune optimally a model with a specific architecture. The architecture of a model is defined by the types of input variables and the number of fuzzy sets associated to each one. For each type of measured data it is needed to decide the number of past values to be used as input. When NWP are considered (“past values” have no sense), it is necessary to select the relevant information (forecasts of wind speed, direction, etc) for the model.

This selection procedure, which is also similar to other types of models like neural networks, is a time consuming one due to the infinite number of combinations that can be tested. Often it is performed by trial-and-error, where several candidate configurations are tested. It is noted that the evaluation of each candidate model requires carrying out the above-described learning process.

In this work, the trial-and-error has been replaced by a fully automated process for model architecture optimization. The constrained nonlinear simplex (“Complex”) optimization algorithm is used for this purpose. The algorithm has been modified for handling both discrete and continuous decision variables. The optimization process is based on the evaluation of the surface of the generalization function (defined as the performance of a model on the validation set) using a complex of points. Each point corresponds to a candidate model. The computational cost is high due to the necessity of the algorithm to tune each candidate model. However, in global, the automatic nature of the process permits to save considerable engineering time compared to the trial-and-error.

An alternative genetic algorithm approach did not present any advantages with respect to the simpler “Complex” algorithm. Genetic algorithms appeared to be less parsimonious w.r.t the number of models they need to test in order to converge compared to the Complex algorithm

Each decision variable in Complex represents the number of fuzzy sets associated to each type of input data. In the special case, when the algorithm converges to zero-number of fuzzy sets for a specific type of data, then this input is excluded

from the model as non-significant. By this way the algorithm performs input selection. When the number of fuzzy sets is converging to one, then the variable does not participate in the premises, but appears only in the function of the consequent part. Parsimony in the selection of input is critical to avoid overfitting from overparametrized models.

Figure 3 shows an example of a run of the Complex algorithm. 115 candidate models are totally examined. The input selection is performed among past values of wind power and Hirlam wind speed, direction and temperature forecasts. The upper left figure shows the evolution of the Complex objective function. Each point in the figure corresponds to the “generalization” performance of a candidate model on the validation set. The rest of Figures show the number of fuzzy sets associated by the algorithm to each input type of data.

When the number of fuzzy sets for all variables is either one or zero then a single “rule” is obtained. The premise has no significance and the model corresponds to a simple linear function of the input variables. This limit case corresponds to the ARX class of models. Consequently, the optimization process can indeed exclude the use of a nonlinear fuzzy model and lead to a classical linear one. In this way, a selection between linear and nonlinear models is performed.

IV. RESULTS

The case study of a real wind farm in Ireland is presented. This farm contains 20 wind turbines of 300 kW each and 1 turbine of 450 kW. Online data and Hirlam forecasts have been used covering the period between 5th February 2001 to 31st March 2002.

On-line data of the wind park power, given as 15-min values, are averaged to produce hourly values. Hirlam forecasts of speed, direction and temperature are provided as interpolated values for the wind farm site for 10 m and for the model levels 22, 23 and 24. They are provided 4 times per day and cover 48 hours ahead with hourly time-step. The horizon considered here is 43 hours; this is the max horizon covered by Hirlam every hour of the day.

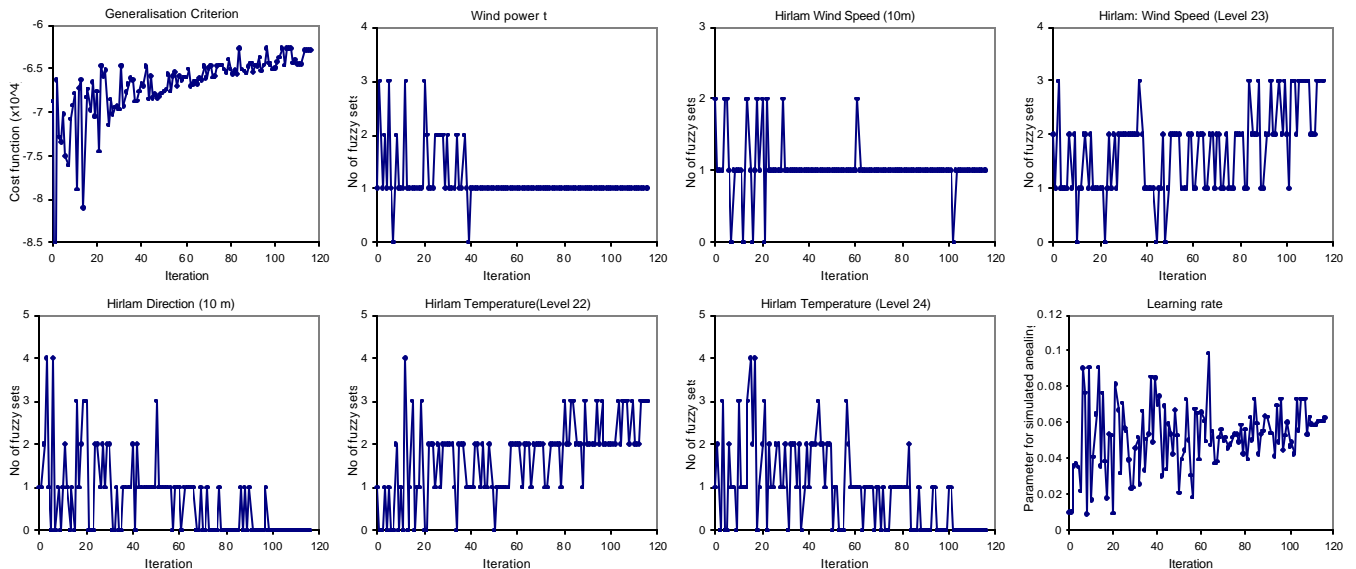


Figure 3: Evolution of the algorithm for the model architecture optimization.

The time series cover a period of 10000 hours from which 6600 were used for training (learning set), 1000 for cross-validation and 2400 (100 days) for testing the performance of the model. The results presented here are on the testing set.

Figure 5 shows the behavior of the model over a period of 4 days. In the 2nd day, an abrupt decrease of wind production takes place. The model updates predictions every hour. Here, 6 sets of predicted profiles are presented; they constitute an ensemble in which the event is persistently predicted.

In Figure 4, the model predicts the same level of power (5 MW) for the look-ahead times 1-3 and 37-43 although wind speed in the second case is higher. On the other hand, for look-ahead times 6-13, the predicted power decreases despite the speed increase. This means that during the two periods of 7-13 and 37-43, the model predicts less power than what would be expected by a direct consideration of Hirlam speed. This is in fact due to the influence of wind direction on the park production (in both cases is around 120 degrees).

Figure 6 shows a comparison between the performance of the fuzzy model and a simple model based on the conversion of the Hirlam wind speed at 10 m to the hub height and then to power using the machine power curve. The simple model under-predicts significantly power during the first hours. In contrast the fuzzy model predicts a higher power for the first lower peak of the Hirlam wind speed and captures the shape of the real curve.

Figure 7 compares the performance of the fuzzy model with that of persistence (“what you see is what you get”) on the testing and the validation sets. The mean absolute error is given both in terms of MW and as a percentage of the maximal wind park power. The difference in the performance in the two sets is due the difference at the levels of average wind park production during the two periods (Validation set: mean power: 1.59 MW, st. deviation: 1.91 MW. Testing set: mean power 2.53 MW, st. deviation.: 2.23 MW).

In Figure 8 the improvement w.r.t. persistence is given. It rises up to 54% according to the time-step. It is important that this improvement is always positive and especially in the

period up to 6-10 hours ahead. Moreover, for this period the inclusion of meteorological forecasts contributes to have twice as better performance as the one of short-term models (without meteorological forecasts). In this sense, it becomes evident that the long-term model can replace also short-term models when NWP is available.

V. CONCLUSIONS

The paper presents an adaptive fuzzy-neural network model developed for the prediction of the power output of a wind farm. The architecture of the model is optimized using the

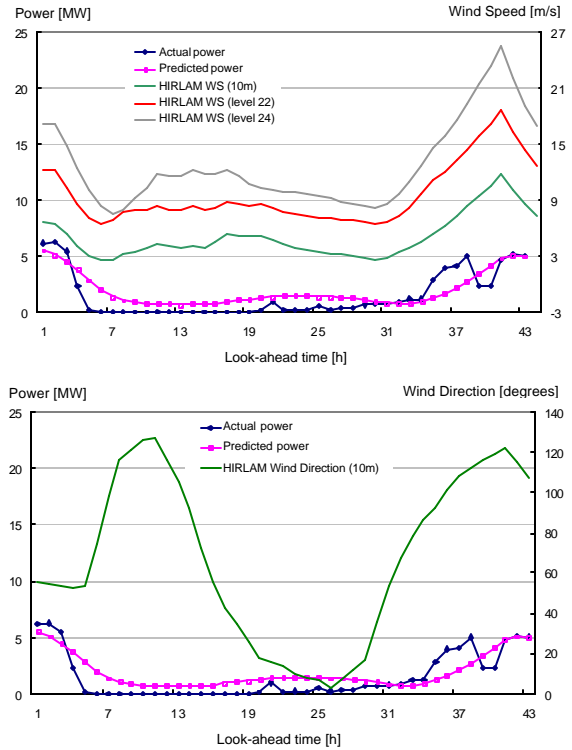


Figure 4: Role of wind direction for adapting predictions.

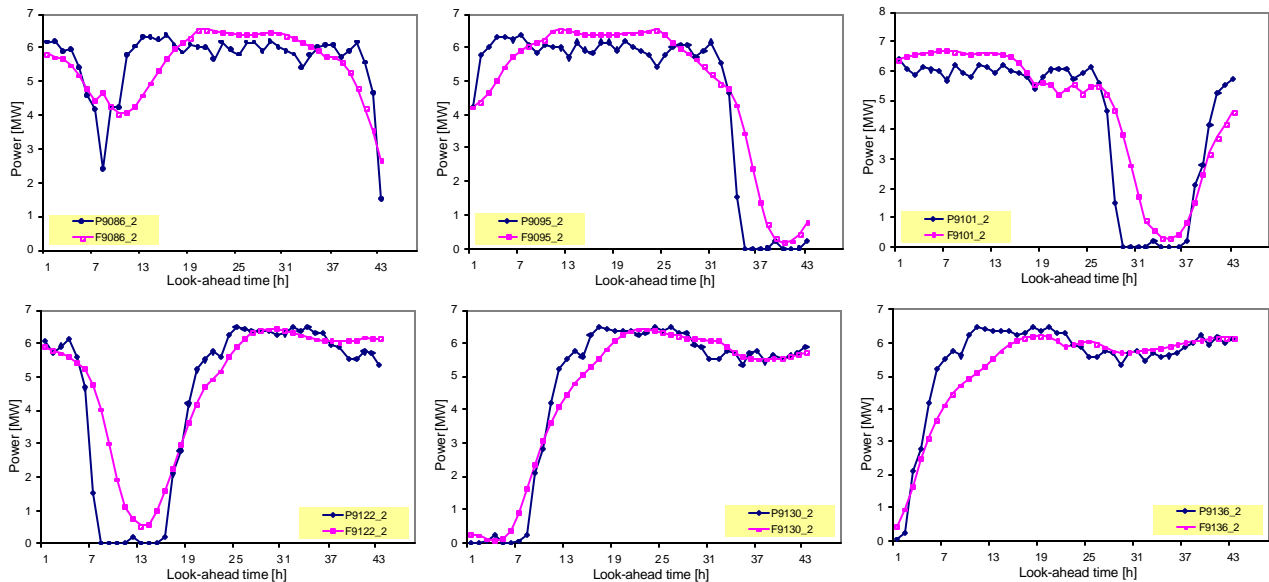


Figure 5: Performance of the model on a period of 4 days.

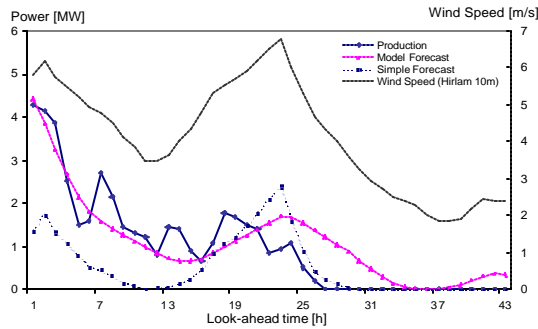


Figure 6: Comparison with a simple model.

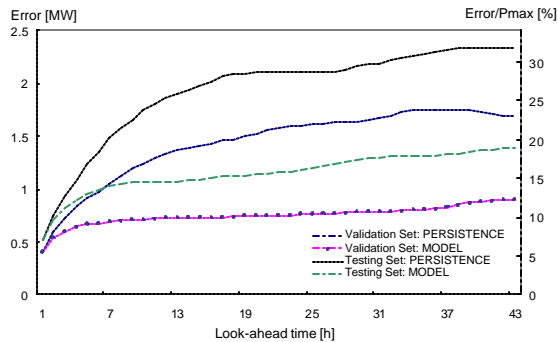


Figure 7 : Performance on the validation and testing sets.

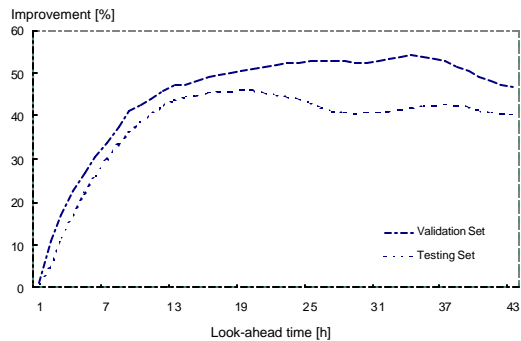


Figure 8: Improvement w.r.t. persistence.

nonlinear simplex algorithm. The case of a real wind farm in Ireland was presented using online and Hirlam data of one year. The performance of the model is found to outperform both persistence as well as simple methods. An online module was developed in C++ using ODBC and SQL functionalities and integrated in the More-Care EMS software. The software is installed for on-line operation at the islands of Crete and Madeira, where its performance is currently under evaluation. It has been run in historical mode and tested extensively for the case of 11 wind farms in Ireland with a view to implementing in October 2002. Figure 9 shows a display of the MORE-CARE on-line platform as configured to run as a stand-alone wind forecasting application.

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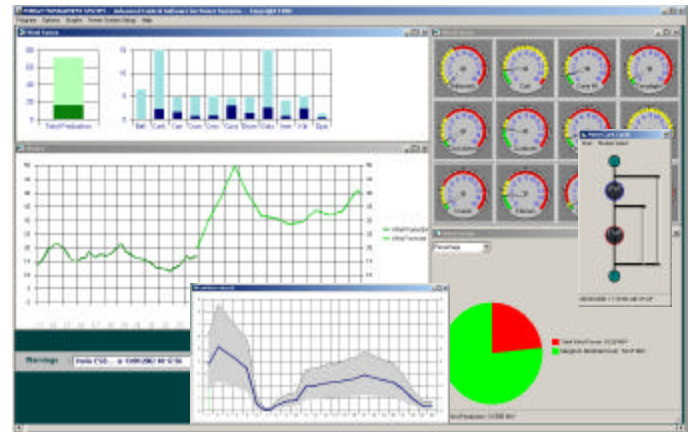


Figure 9: The user interface of the More-Care forecasting platform.

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BIOGRAPHIES

Georges Kariniotakis was born in Athens, Greece. He received his production and management engineering and MSc degrees from the Technical University of Crete, Greece and his PhD degree from Ecole des Mines de Paris in 1996. He is currently with the Center of Energy Studies of Ecole des Mines de Paris as a scientific project manager. He is a member of IEEE. His research interests include renewable energies, distributed generation and artificial intelligence.

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