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Short-term Wind Power Prediction for Offshore Wind Farms - Evaluation of Fuzzy-Neural Network Based Models

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Abstract

Future major developments of wind power capacities are likely to take place offshore. As for onshore wind parks, short-term wind power prediction up to 48 hours ahead is expected to be of major importance for the management of offshore farms and their secure integration to the grid. Modeling the behavior of large wind farms of several tens or hundreds of MWs installed capacity and covering areas of several square kilometers is going to be a challenge. The adaptation of wind power forecasting methods to reach the specificities of the offshore case is not straightforward and very few results are available in the literature.

The paper presents the new considerations that have to be made when dealing with large offshore wind farms and therefore the necessary evolutions of prediction models. Then, a state-of-the-art fuzzy-neural network based wind power forecasting model is described. Its performance is assessed for offshore conditions and compared to its level of performance for typical onshore parks. A general methodology dedicated to large offshore wind farms is developed. In order to deal with the spread of the turbines in such cases, methods based on the division of large wind farms into clusters are proposed. Furthermore, the use of satellite images for mapping the wind flow behavior inside offshore parks is investigated.

Keywords: Wind power, short-term forecasting, offshore wind farms, satellite images, production clusters.

1 Introduction

NOWADAYS, wind farm installations in Europe exceed 28 GW. Motivated by the Kyoto Protocol, the European Commission has set the target of doubling the share of renewables in gross energy consumption from 6% in 1997 to 12% in 2010 [1]. This directive targets 22,1% indicative share of electricity produced from renewable energy sources in total Community electricity consumption by 2010. To achieve this share, installed wind power capacity in the Member States should increase to 45-60 GW. In 2003, the Eu-

ropean Renewable Energy Council (EREC) revised upwards the 2010 target to 75 GW [2]. Certain countries, such as Germany, Denmark and Spain, have managed to perform large-scale integration of wind generation on land. However, mainly due to the problem of local population acceptance, future major developments of wind power capacities are more likely to take place offshore. Higher and more regular wind speeds [3], as well as the possibility to install numerous and powerful (multi-megawatt) wind turbines, are the main advantages of going offshore to produce electricity. In addition, offshore wind energy could be sufficient to feed the local demand in countries like United Kingdom or Denmark [4]. For example the Horns Rev wind farm of 160 MW in Denmark (in operation since December 2002) consists a first technical achievement of that kind of large-scale offshore projects. This specific wind farm is able to supply alone up to 2% of the whole electricity consumption of Denmark [5]. Several other examples of very ambitious offshore projects are under study or development in some of the European countries.

At an operational level, large-scale integration of wind generation causes several difficulties in the management of a power system. Often, a high level of spinning reserve is allocated to account for the intermittent profile of wind production, thus reducing the benefits from the use of wind energy. Predictions of wind power production up to 48 hours ahead contribute to a secure and economic power system operation. Increasing the value of wind generation through the improvement of prediction systems' performance is one of the priorities in wind energy research needs for the coming years [6].

Several short-term prediction models are available for onshore wind farms: they usually give an estimation of the two-days ahead wind park output using on-line power production data and Numerical Weather Predictions (NWP) as input. Some of these models are operational and can be helpful for end-users such as utilities, transmission system operators, energy service

providers, energy traders for managing the intermittent wind generation, planning reserves, storage, or even the maintenance of wind farms, trading wind power in electricity markets etc. Although several results exist in the literature on the performance of prediction models for the onshore case, no models are described or results are reported for the offshore.

The paper presents initially a brief review of the state-of-the-art prediction methods as well as the requirements for their adaptation to the offshore case. We will refer to specific tasks of the European project ANEMOS that focus on the benchmarking of various models on several conditions (including offshore) and on a better understanding of the offshore specificities. Then, the prediction system AWPPS developed at École des Mines de Paris/ARMINES and based on adaptive fuzzy-neural networks will be described. Results obtained for an offshore park situated in Denmark will be given and compared to typical ones for onshore. A generic methodology appropriate for large offshore wind farms is then introduced. The contribution of information that can be extracted from satellite images in designing efficient prediction tools is investigated.

2 State of the art and offshore prediction

In general, forecasting models provide a guess of the future wind generation for the next 24-72 hours, on an hourly basis, by using NWP and eventually online wind power production data as input. They can be classified in two families: the physical and the statistical or time-series ones. The former uses physical considerations for the downscaling problem (by using the geostrophic drag law or computationally expensive CFD models), for modeling the park effects and the power curve, while the latter learns and reproduces the relationship between a wealth of explanatory variables and the resulting wind generation. Model output statistics (MOS) are applied to cope with the systematic errors. The parameters of the statistical models (parametric models, neural networks, etc.) are usually determined with estimation and optimization methods. Depending on the type of the model, expert knowledge on the physical process may be used to design the prediction model. For a thorough survey on the wind power prediction methods we refer to [7].

All state-of-the-art prediction models were originally designed for the onshore. For the case of offshore, special modeling considerations have to be made for adapt-

ing physical models. This fact has been recognized already for the problem of resource assessment [8]. The variable roughness of the sea surface needs to be modeled. Due to the spread of the wind turbines over a large area, wake effects and influence of the coast have to be studied [9].

The adaptation of physical prediction models is not straightforward since, as for resource assessment, a real understanding of the offshore wind speed profiles — and wind characteristics in general, is needed. Studies concerning those points are ongoing [10, 11] and will serve for the adaptation of physical models [12].

The statistical alternative, and more precisely the artificial intelligence based methods, does not need a very precise knowledge of offshore conditions for designing suitable prediction models. Indeed, these methods can be trained to give an estimation of the wind farm power output for given meteorological conditions, allowing one to avoid all the intermediate physical modeling steps.

It is however necessary to evaluate the performance of current approaches, based on a global modeling of a wind farm, against alternative approaches able to better consider the spatial and temporal characteristics of a large offshore wind farm.

In the frame of the ANEMOS project, emphasis is given to the development of appropriate prediction models for the offshore. In order to evaluate models, a benchmarking process is developed. Case studies representing various onshore conditions (flat/complex terrain, northern/southern Europe, near coast, etc.) have been set up. The aim is to characterize the performance of various models depending on these conditions and to propose solutions for a higher performance. A similar reasoning takes place for the offshore, where new methodologies are developed to cope with spatio-temporal characteristics of large offshore parks taking into account the impact of high-resolution meteorological forecasts, the contribution of information from satellite-radar images, etc.

3 Offshore prediction with fuzzy-neural networks

This section describes briefly the main features of the adaptive fuzzy-neural network (Fuzzy-NN) based prediction model. A detailed description is provided in [13]. The specific considerations made in the frame of this work are discussed and first results obtained for an offshore wind farm are presented and compared to typ-

ical results obtained for onshore sites.

3.1 Description of the prediction model

The "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. The input to these models can be numerical weather predictions (NWP) and on-line data if available by a SCADA (Supervisory Control and Data Acquisition) system. In case that NWPs are not available, as can be the case in small applications, prediction models can be based only on recent on-line data. Such models may have an acceptable performance for horizons up to around 6 hours ahead. However, even in such "short-term" horizons, the consideration of NWPs improves considerably the performance [13]. For "longer-term" horizons up to 48 hours ahead, horizons NWPs are indispensable for an acceptable performance, since they represent weather dynamics that cannot be modeled using only recent on-line data. In the frame of this work, only model configurations that consider NWPs as input are considered.

The adaptivity property of the Fuzzy-NN 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, or changes in the configuration of the model used to produce the NWPs.

The NWPs used as input include usually wind speed (\hat{u}), direction ($\hat{\theta}$) and temperature (\hat{t}) at 10 m, as well as at several levels related to atmospheric pressures. They are computed on a grid surrounding the farm, but they can alternatively be provided at the geographical coordinates of the wind farm as interpolated values. 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 wind power

forecasting system is able to operate with input from different NWP systems. Typically, the wind power forecasts are generated every hour for the next 2 days (sliding window scheme). At the moment of update, the most recent available NWPs are used as input to the model together with measurements of wind power. 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 form of the model can be formulated as follows

$$\hat{p}(t+1) = f(p(t), \hat{u}(t+1), \hat{\theta}(t+1), \hat{t}(t+1), \dots). \quad (1)$$

The generic fuzzy-neural function $f(\cdot)$ is described in [13]. 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 has been found to outperform alternative ones such as multi-output models or approaches based on different models for each time step. A minor drawback of the iterative approach is that it does not allow iteration of explanatory input, since no forecasts can be available for such quantities.

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 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 allows one to avoid inaccuracies when modeling explicitly each one of the above intermediate steps. This is particularly important for the offshore where modeling the variable roughness of the sea or weak effects can be difficult.

Furthermore, in contrast to neural networks, fuzzy-neural networks have the desired property for local modeling that permits to represent efficiently special

conditions related to the non-stationary wind prediction problem such as cut-off situations.

In the context of fuzzy-neural networks, off-line model building is characterized by two phases :

- the model architecture selection: an optimization procedure is used to select the most relevant input to the prediction model among all the available types of data. This procedure provides also the optimal model architecture (i.e. number of rules) in terms of accuracy and robustness. Robustness proves to be a very important property for wind power forecasting. Being automated, this procedure is objective, while it permits to avoid trial-and-error procedures for selecting the model structure.
- the training (or learning) of the network, for a given architecture: this consists in tuning the model parameters in order to obtain a model that both minimizes the prediction error and maximizes its generalization ability. 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.

In an online environment, the models uses self-adaptation schemes for fine-tuning its parameters to account for variations in the environment of the application, changes in the NWP model, etc.

3.2 Application to an offshore wind farm

In this paper, we consider the Danish experimental wind farm located in Tunø Knob. This farm, installed in 1995, has a rated capacity (P_n) of 5MW. It is situated six kilometers from the coast, and consists in two rows of five turbines each. This test case presents several challenges; the small installed capacity yields less smoothing of the power output while its location close to the shore may lead to complex sea-coast interactions and difficult to predict diurnal cycles.

The available time-series cover a period of 13 months. They include hourly wind generation data for the whole park, as well as Hirlam NWPs of wind speed and direction at 10 meters and at model level 30. The NWPs have a spatial resolution of around 0.15° . They are provided 4 times per day and at the level of the wind farm as interpolated values.

The prediction model is the fuzzy-neural network described above. It provides forecasts for the next

43 hours with hourly time-steps. Forecasts are updated every hour using SCADA data as input. Regarding the tuning of the model, the first 6 months are used for learning and the following 2 months for cross-validation. The evaluation results presented here are on the remaining 5 months testing set of data.

In order to illustrate the Fuzzy-NN skills, and following the evaluation protocol described in [14], we consider the Normalized Mean Absolute Error (NMAE) and the Normalized Root Mean Square Error (NRMSE), for both Persistence (considered as the reference forecasting model) and the fuzzy-neural network. The model performance for the whole testing set is given by Figure 1. The improvement with respect to Persistence, defined as the gain of using an advanced model instead of the naive predictor, is defined as follows

$$Imp_{EC}^k = 100 \cdot \frac{EC_{pers}^k - EC_{model}^k}{EC_{pers}^k} (\%), \quad (2)$$

where k is the lead time and EC the considered evaluation criterion (which can be either NMAE or NRMSE). This improvement is shown in Figure 2.

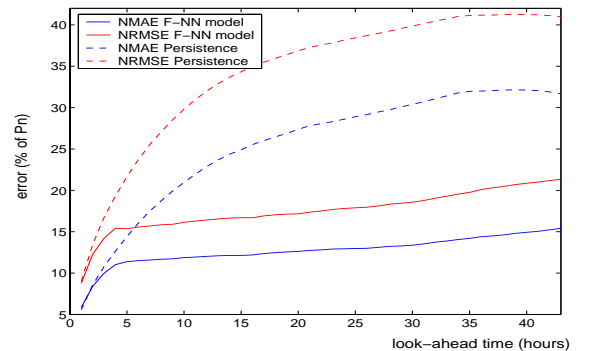


FIGURE 1: Comparison of Persistence and Fuzzy-NN model performance.

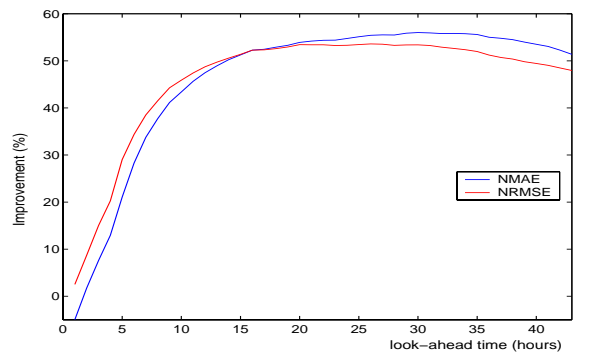


FIGURE 2: Fuzzy-NN model achieved improvement over Persistence.

The Fuzzy-NN model outperforms Persistence whatever the prediction horizon, in terms of NRMSE, while it

is slightly worse for the first horizon in terms of NMAE. This is because the model optimisation is based on a NRMSE based error measures. The skill of the model for the first 3-4 look-ahead times comes from the use of SCADA data as input to the model. The NMAE of Persistence ranges from 5.5% up to 32% of the nominal power, while that of the advanced model varies from 5.5% to 15.5%. The improvement the Fuzzy-NN model achieves with respect to Persistence is depicted in Figure 2 for both evaluation criteria and as a function of the lead time. Table 1 gives the NMAE) values together with the improvement for selected prediction horizons. The error reduction as obtained by the use of the advanced model reaches 30% for 6-hours ahead and 50% or more for horizons between 12 and 43 hours ahead (the maximum improvement being 56% for lead time 30).

TABLE 1: Performance of the Fuzzy-NN model compared to the one of Persistence (NMAE).

| Horizon | Pers. (% of P_n) | F-NN (% of P_n) | Improvement (%) |
|---------|---------------------|--------------------|-----------------|
| 1 | 5.58 | 5.85 | -4.80 |
| 2 | 8.57 | 8.42 | 1.75 |
| 6 | 16.05 | 11.51 | 28.29 |
| 12 | 22.89 | 12.02 | 47.49 |
| 18 | 26.47 | 12.46 | 52.93 |
| 24 | 28.60 | 12.94 | 54.76 |
| 36 | 32.01 | 14.39 | 55.04 |

Since the evaluation of the prediction model is done over a period of several months, it is of particular interest to visualize the monthly performance. Figure 3 gives the NRMSE of Persistence and the Fuzzy-NN for the 18-hour ahead horizon. Their performance vary from a month to another: for instance the Fuzzy-NN prediction error ranges from 15% of the nominal power in February, up to 22% in April. The resulting improvement w.r.t. Persistence varies as well, and is always very significant.

Typical performance results of the fuzzy-neural network model for onshore wind farms in Ireland are detailed in [15]. This evaluation concerns five parks spread on the western side of Ireland for a total installed capacity of a few tens of MW. In terms of NRMSE, the Fuzzy-NN performance for the offshore site compares with the one for the onshore: in both cases, the NRMSE criterion ranges from around 9% for the first lead time, to around 22% for the 43-hour ahead one. Indeed, the improvement with respect to Persistence is even better, since the naive predictor performs worse for Tunø Knob (this constitutes a sign of the higher wind variability for this site). When for the five Irish wind farms,

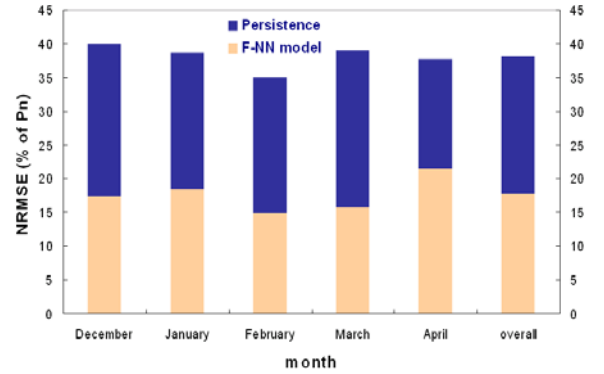


FIGURE 3: Monthly Performance of both the Fuzzy-NN model and Persistence for the 18-hour ahead horizon.

the maximum improvement is between 40% and 50% (in terms of NRMSE) depending on the farm, this one reaches 53% for the offshore park. It seems that despite the complexity of the offshore case study, the performance of the advanced model is of a high standard, and this shows the operational status of the statistical approach for offshore applications.

Wind power forecasts cannot be exact. A part of the uncertainty is due to the inaccuracy of the numerical weather forecasts used as input. An uncertainty estimation related to each individual forecast has to be given to end-users, so that they can decide on the risk they should undertake (i.e. level of allocated reserves, trading strategy, etc). An advanced methodology for estimating uncertainty and prediction risk, based on the past skill of the model and the expected weather stability, is described in [16]. This methodology provides confidence intervals around the spot forecast, with a requested confidence level. The techniques involved in the design of the confidence bounds are detailed in [17].

For the test case of this study, confidence intervals were estimated over the whole evaluation period, with a requested confidence level of 85%. Figure 4 gives an example of a 43-hours ahead wind power prediction with associated confidence bounds. The observed confidence was checked at the end of the 5-month testing set and was equal to 86.04%. This means that 86.04% of the times the real power values were lying inside the proposed intervals.

4 The case of large-scale offshore wind farms

The results presented in the previous Section concern a relatively small offshore wind farm, whose size is com-

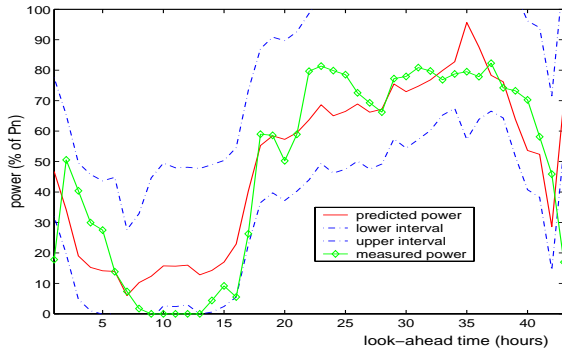


FIGURE 4: 43-hours ahead wind power prediction for Tunø Knob. The forecast is enhanced with 85% confidence intervals for uncertainty estimation.

parable to the one of classic onshore parks. The trend for the future is to develop larger and larger offshore wind farms, with arrays of turbines that can spread over several square kilometers.

The prediction approach presented above consists a base-line statistical model, which can be straightforwardly applicable to the case of large wind farms. However, as mentioned in Section 2, this approach has to be evaluated against model configurations able to take into account the spatio-temporal characteristics of a large wind farm. A prediction model for such a farm is required to be efficient in critical situations. For example in modeling gradients resulting from coming fronts crossing the wind park or switch off behavior of turbines due to high wind speeds. The high installed capacities in offshore projects imply that this behavior must be accurately modeled. The knowledge of spatio-temporal characteristics inside the farms will also help to estimate the impacts and propagations of switch-offs.

The clustering approach proposed here consists in dividing the wind farm into a limited number of power production clusters and developing a separate model for predicting the output of each cluster. As cluster is defined a group of turbines with a similar behavior for specific leading weather regimes. Apart from NWP for wind speed, predictions for wind direction are of major importance and are considered as input. The total power of the wind farm is obtained as a function of the predictions of the clusters. In the simplest case, this can be the sum of the cluster productions or a specific model can be applied in cascade for this purpose to weight the cluster productions using as input wind direction NWP. Figure 5 illustrates the configuration of such a prediction methodology.

A critical decision remains however on the way that the clusters will be defined. This can be done either

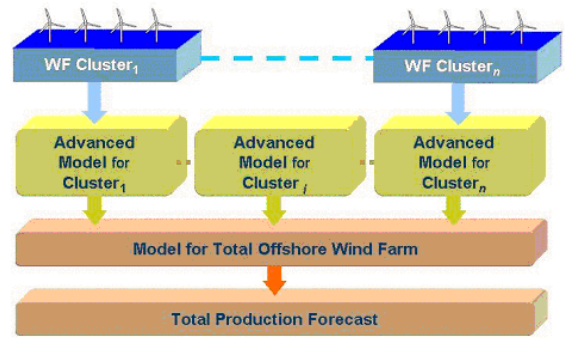


FIGURE 5: Prediction of large-scale offshore wind parks by the use of production clusters.

by considering physical existence of clusters (groups of wind turbines separated geographically from each other), or as a function of the available SCADA measurements or based on correlation and statistical analysis of the data and the available NWP. An alternative source of information coming from satellite radar images can be exploited for the design of either statistical or physical models. This is feasible by merging scatterometer data and SAR images, as described in the next paragraph.

The clustering approach is expected to be of significant help for offshore wind farm operators, since it will enable them to follow the evolution of the power production inside the park, to spot areas with higher and lower wind generation, and to better understand the propagation of switch-offs.

4.1 Mapping the wind flow behavior

Since 1991, radar satellite sensors provide, in an operational way, measurements of wind parameters over open ocean with a spatial resolution of 50km or better [18]. More recently, several works have been achieved on the production of wind maps at high spatial resolution (less than 1 km) from Synthetic Aperture Radar (SAR) [19–21]. This latest sensor allows one to map wind parameters over large areas (100 km x 100 km), even on coastal environments. The developed algorithms give values of wind parameters at 10m height for speed ranging between 4 to 30m.s⁻¹ with an accuracy of 2m.s⁻¹, and for the whole range of directions with an accuracy of 20°. These tools are very well adapted for rendering local wind conditions and for the mapping of wind patterns over offshore wind farms. They permit to produce maps for the area of interest with statistics of wind parameters [22,23] and to relate such maps to meteorological conditions in order to propose spatial dis-

tributions of the wind patterns for prediction. In the scope of this work, we will show how satellite data can be used for the design of wind power prediction tools devoted to offshore conditions.

4.1.1 Extraction of wind maps from satellite SAR images

In order to extract both wind speed and direction from radar images, two main C-band models exist. They have been calibrated for scatterometer data [18], and shown to be efficient when used on SAR data [24, 25]. These main models are the CMOD4 algorithm (from ESA) and the CMOD-ifr2 (from the Ifremer organization). These CMOD models provide a backscattering coefficient from given wind speed, wind direction and incidence angle. To obtain wind speed and direction, the model has to be inverted. As the incidence angle and backscattering coefficient are known at each point of the SAR image, one of the parameter (speed or direction) must be known to obtain the other one [26]. In Reference [24], it is indicated that, if the wind direction is well known, it is possible to extract wind speed from SAR images with 500-meter accuracy.

Currently, a running project from the European Space Agency, called EO-WINDFARM, focuses on the creation of services and products for the development and the operation of wind farms. This project will establish an operational service for the delivery of wind data over any offshore area of interest (<http://www.eo-windfarm.org>).

Figure 6 is a SAR image acquired over the Gulf of Lion (France) by the ERS-2 satellite operated by the European Space Agency (ESA) in 1998. In a very simple way, the lighter the image the faster the wind speed. Hence from Figure 6, it is easy to understand that the wind field is not homogeneous in the area of interest.

From this kind of image it is possible to extract a wind field with a cell size between 400m and several kilometers. The cell dimensions are appropriate for the proposed application: taking the example of the Horns Rev wind farm, the distance between turbines is about 560m [27]. More generally, given the size of wind turbines installed offshore, the distance between turbines will be of that order of magnitude.

Figure 7 presents such a wind field computed with a cell size of 1.6 km.

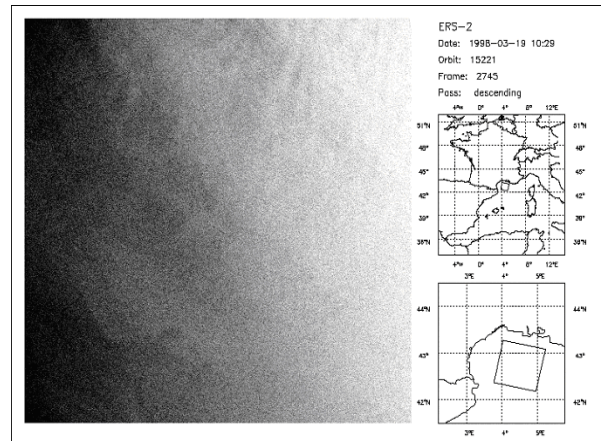


FIGURE 6: Example of ERS-2 SAR image over the Gulf of Lion.

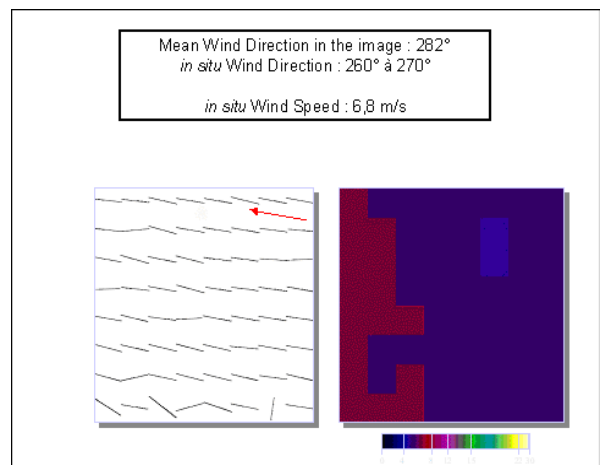


FIGURE 7: Wind field derived from a SAR image. The left image presents the wind direction with a cell size of 1.6 km, the right image presents the wind speed with the same cell size. The red arrow is the local wind measured at the buoy which is located just outside this extract. The in-situ value presented in this figure are measured at the buoy.

4.1.2 From satellite measurements to prediction

Figure 8 illustrates the product that will be derived from satellite data. This product will consist in a catalogue of wind patterns over the area of interest linked with the Numerical Weather Predictions. For a given NWP, the distribution of wind patterns for the specific wind farm will be proposed.

If enough wind data extracted from SAR images is available, the probability of apparition of the wind situation can be added to the information proposed to the user with a confidence level. Of course such a product is dedicated to a specific wind farm, and will be valuable for the operation, maintenance and monitoring of the wind farm.

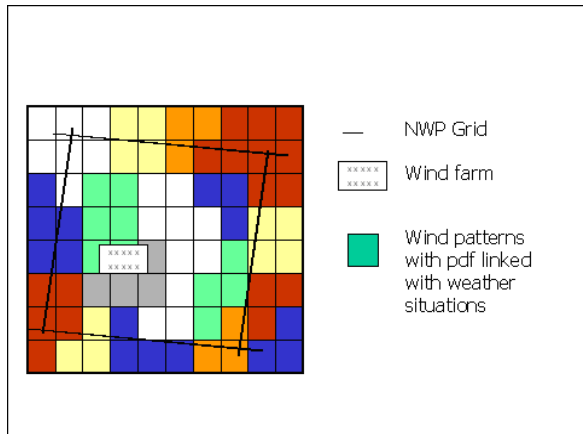


FIGURE 8: Example of a specific wind pattern derived from merging of scatterometer data and SAR images.

5 Conclusions

Dealing with large-scale offshore wind farms is one of the actual challenges for wind power forecasting technology. While the adaptation of physical-type forecasting models is not straightforward, the statistical alternative (including the artificial intelligence one) has already an operational status, since it has the ability to learn and reproduce the relation between explanatory inputs (on-line production data, NWP, etc.) and the resulting wind generation, without a complete understanding of the physical mechanisms. To highlight that point, the fuzzy-neural network based model of ARMINES Wind Power Prediction System (AWPPS) was described, and evaluated for the case of an offshore wind farm located in Denmark. It was shown that the level of performance of this model for this offshore wind farm was similar or even better than its standard level of performance for onshore conditions. Moreover, predictions from the Fuzzy-NN are enhanced with confidence intervals for giving an estimation of the uncertainty of each individual forecast.

Research in the field of marine meteorology is very active nowadays for a better understanding and forecasting ability of offshore wind profiles. Regarding the evolution of the prediction model itself, an advantage of the Fuzzy-NN is that it will be rather easy to consider various kinds of new input variables in the future, such as forecasts of wave height or vertical temperature gradient for instance, that are supposed to have an effect on offshore wind profiles.

The case of large-scale offshore projects was envisaged in the second part of the study. Given the surface covered by such wind parks, their spatio-temporal characteristics are of particular importance. Indeed, the

way wind fields may evolve inside the farms have to be taken into account when designing prediction models devoted to those specific conditions. For this particular problem, we have introduced a methodology, which is based on the division of offshore wind parks into production clusters for better capturing the local effects. The joint use of scatterometer and satellite data permits to map the wind fields inside the farms, and allows one to highlight specific wind patterns linked to the leading weather regimes. It is therefore a way to gain understanding about the behavior of a given large-scale offshore park. Production clusters can be defined consequently.

Ongoing developments for offshore wind power forecasting based on approaches such as clustering together with tools for evaluating uncertainty and prediction risk on-line are under implementation in the next generation forecasting platform development in the frame of ANEMOS project.

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