Wind Speed and Direction Prediction for Wind Farms Using Support Vector Regression

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***Abstract*—Predicting wind speed and direction is one of the most important and critic tasks in a wind farm, since wind turbine blades motion and thus energy production is closely related to wind behaviour. Machine learning techniques are often used to predict the non-linear wind evolution. In this context, this paper proposes a short term wind data prediction model based on support vector machines in their regression mode, which have the advantage of being simple, fast and well adapted for the short term. This research tries also to prove how wind direction may influence power generation, and why it is important to predict it. A real data set of wind speed and direction historical values is used, from Sidi Daoud wind farm, north-eastern Tunisia, in order to evaluate the proposed model. This forecasting system predicts wind speed and direction for the short term, from one to 10 hours in advance, using a set of past samples.**

Keywords—component; wind speed and direction forecasting; wind farm; support vector machines; regression

I. INTRODUCTION

Renewable energy is nowadays one of the most important energy resources, due to conventional energy related problems; like fossil fuel crisis, pollution and CO2 emissions. And wind energy is one of the most used worldwide, thanks to its availability in most Earth regions. However, intermittence of wind is the major problem encountered, which makes predicting wind data a necessity. Unlike conventional energy resources that are available at any time, wind energy should be forecasted in advance in order to estimate production and then plan its contribution in the national grid. An accurate forecast allows to minimize energy waste and costs, and equilibrate in real time the crucial equation production = demand.

Many researches were achieved in order to predict wind behaviour. However, it is still one of the most difficult quantities to forecast [1], namely due its stochastic nature. The actual state of the art includes two main families of methods; statistical approaches like autoregressive moving average ARMA, and artificial intelligence methods e.g. artificial neural networks ANN and support vector machines SVM. A review of intelligent methods of weather forecasting may be found in [2], and of specific wind speed forecasting and generated power in [3]. Some researchers combine two methods like in [4] which use the ensemble empirical mode decomposition and the support vector machine to estimate monthly wind speed. The wind power forecasting system of [5] includes high resolution and ensemble modelling capabilities, data assimilation, now-casting, and statistical post-processing technologies for the short and medium term. Some researchers use classic statistical models, like autoregressive moving average ARMA in [6] and [7], or probabilistic methods, like in [8] and [9]. These methods achieve good results in general, but only for the short term. Some rare methods were also used, like grey systems, in [10]. Many recent researches use numerical weather prediction NWP, like in [1] who used the Eta model. The major problem of NWP models is that they are time and resources consuming. Kalman filtering is also used to predict wind, either alone like in [11] or combined with neural networks, like in [12]. Neural networks may be combined also with wavelet transformation and this was done in [13]. ANN is the most used method in the literature, and this is justified by its capability of modelling non-linear systems, and good results achieved using it in many cases. However, it has some drawbacks, e.g. it is impossible until now to determine an optimal neural architecture, and its local minima don't always provide the optimal solution. To avoid these problems, some solutions were proposed, like FIR filters in [14]. Another solution consists of using SVM, like in [15] and [16], in order to predict hourly or daily wind speed. But this solution isn't well exploited yet, because there are some regression modes and kernels not used, and this may entail non-optimal results. For this purpose, this paper proposes a wind forecasting model based on SVM, aiming to avoid complicated numerical weather prediction models, heavy data and long simulation time. The main goal is to provide a simple and fast method to forecast wind data and then predict power generation. Using support vector machines, there is a lot of parameters to adjust in order to have maximum accuracy, according to the type of variable to be forecasted, and this is the main interest of this paper. Speaking about wind direction, only few papers tried to forecast it, like in [7] which uses ARMA model. This is justified by the fact that wind generation is closely related to wind speed [1]. However, this paper tried to give its contribution in wind direction forecast, to take into account the case of wind farms with auto-adjustable blades orientation, although this is till now quite difficult. The short term is chosen here, for both speed and direction predicting, and this justified by its necessity for network stability, and also for managing (turning on or off) wind turbines. For a large scale, the short term prediction is needed for load dispatch planning

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and load increment or decrement decisions [10]. Once wind forecast is done, predicting power generation is the following task, and this was done in [17] and [18] for example.

This introduction tried to justify the choice of using SVM for wind speed and direction forecast in the short term. The rest of the paper is organised as follows: section II presents the principle of SVM, and their regression mode, section III develops the model used for prediction, section IV shows results and comparisons with other researches and section V concludes the paper.

II. Mathematic Preliminaries

A. Support Vector Machines Development

Support vector machine is a calculus method used for classification and regression. Based on artificial intelligence and precisely on supervised learning, this technique is one of the last developments for energy prediction [19].

SVM is based on two main principles: finding the best separating hyper plan between two (or more) different classes of samples, which means maximize margin between nearest samples, and mapping the samples to another dimension if it isn't possible to classify, using a kernel function.

In a binary classification problem [20], we want to separate a set of vectors D:

$$D = \{(x_1, y_1), \dots, (x_m, y_m)\}, x \in \mathbb{R}^n, y \in \{-1,1\} \quad (1)$$

With the hyper plan:

$$< w, x > +b = 0 \quad (2)$$

Where w is the weight vector, b a scalar (bias) and $< w, x >$ the dot product. $f(x) =< w, x > +b$ is the equation of a linear classifier. But in general, samples aren't linearly separable, and this entails use of non linear classifier:

$$< w, \phi(x) > +b \quad (3)$$

Here, ϕ is a function used to map x to a higher dimensional space.

The SVM tries to resolve the following optimisation problem [21]:

$$\min_{w,b,\xi} \left(\frac{1}{2} < w, w > +C \sum_{i=1}^{m} \xi_i\right) \quad (4)$$

$$subject\ to \begin{Bmatrix} y_i(< w, \phi(x_i) > +b) \geq 1 - \xi_i \\ \xi_i \geq 0 \end{Bmatrix}$$

Where C is the penalty parameter of the error term, also called regularisation parameter ($C > 0$), ξ_i a variable measuring the misclassification of x_i, and ϕ is the mapping function. ϕ is defined in a function K called kernel:

$$K(x_i, x_j) =< \phi(x_i), \phi(x_j) > \quad (5)$$

There are four basic kernels [22]:

Linear	$K(x_i, x_j) =< x_i, x_j >$	(6)
Polynomial	$K(x_i, x_j) = (\gamma < x_i, x_j > +r)^d, \gamma > 0$	(7)
Radial basis	$K(x_i, x_j) = \exp\left(-\gamma \lVert x_i - x_j \rVert^2\right), \gamma > 0$	(8)
Sigmoid	$K(x_i, x_j) = \tanh(\gamma < x_i, x_j > +r)$	(9)

Here, γ, r and d are kernel parameters.

It is proven [23] that the resolution of the previous optimisation problem is equivalent to the resolution of the dual problem, defined as:

$$\min_{\alpha} \left(\frac{1}{2} \alpha^T Q \alpha - e^T \alpha\right) \quad (10)$$

$$subject\ to \begin{Bmatrix} < y, \alpha > = 0 \\ 0 \leq \alpha_i \leq C \end{Bmatrix}$$

Here, $\alpha = (\alpha_1, \dots, \alpha_m)^T$ are Lagrange multipliers, $e = (1, \dots, 1)^T$ is the vector of all ones (of size m) and Q is an m by m positive semi-definite matrix, $Q_{ij} = y_i y_j K(x_i, x_j)$. This model is much easier to resolve.

When this problem is solved, w satisfies:

$$w = \sum_{i=1}^{m} y_i \alpha_i \phi(x_i) \quad (11)$$

And the classifier is:

$$f(x) =< w, \phi(x) > +b = \sum_{i=1}^{m} y_i \alpha_i K(x_i, x) + b \quad (12)$$

Hence, any new vector x can be classified, using $sign(f(x))$ which predicts its class.

B. Regression Mode of SVM

Now in the regression mode, the value of y can be any real number, and it is not necessarily in the set $\{-1,1\}$.

$$D = \{(x_1, y_1), \dots, (x_l, y_l)\}, x \in \mathbb{R}^n, y \in \mathbb{R} \quad (13)$$

We want to approximate the set D with a non linear function:

$$f(x) =< w, \phi(x) > +b \quad (14)$$

And this was used in this paper. In this case, the optimisation problem becomes [23]:

$$\min_{w,b,\xi,\xi^*} \left(\frac{1}{2} < w, w > +C \sum_{i=1}^{m} \xi_i + \xi_i^*\right) \quad (15)$$

$$subject\ to \begin{Bmatrix} y_i - < w, \phi(x_i) > -b \leq \varepsilon + \xi_i \\ < w, \phi(x_i) > +b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0 \end{Bmatrix}$$

Here, ξ_i and ξ_i^* are slack variables representing lower and upper constraints, and ε is the error term ($\varepsilon > 0$). The dual problem is:

$$\min_{\alpha,\alpha^*} \frac{1}{2} (\alpha - \alpha^*)^T Q (\alpha - \alpha^*) + \varepsilon \sum_{i=1}^{m} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{m} y_i (\alpha_i - \alpha_i^*) \quad (16)$$

$$subject\ to \begin{Bmatrix} < e, (\alpha - \alpha^*) > = 0 \\ 0 \leq \alpha_i, \alpha_i^* \leq C \end{Bmatrix}$$

Here, α and α^* are Lagrange multipliers, e vector of all ones and $Q_{ij} = K(x_i, x_j)$.

The resolution of the problem gives the following regression function:

$$f(x) = \sum_{i=1}^{m} (-\alpha_i + \alpha_i^*) K(x_i, x) + b \quad (17)$$

This is called ε regression. There is another type, called ν regression, not detailed here, and it is a bit different, introducing a parameter ν to control the number of support vectors.

Anyway, this machine is used for regression, which means predicting the value y of an given variable x, knowing the m values y_i of a set of m variables x_i. The predicting function $f(x)$ is determined after resolution of the optimisation problem (16) described above, which is also called training process. Then, $f(x)$ is used to predict the value y of any given variable x, using equation (17) and this is called test process. This is used in our case to predict future wind data (speed and direction), knowing a set of past data.

III. Proposed Forecasting Model

Historical wind data, generally hourly sample, are divided into two sets, one for train process, and the other for test. In the training step, a pre-fixed number n of past samples, and a correspondent target (following sample n+1) are used to determine machine coefficients (optimization stage in the previous mathematical development). Then, the same number n of samples is taken from test set to predict the following sample n+1. This is called the static model, which is used to forecast one sample (thus one hour in advance). The dynamic model uses the static one iteratively to predict many hours in advance.

A. *First Step: Static Model*

Let's consider $v(h)$ the wind speed time series, where h is a discrete variable representing hour, the predictor model is shown in fig. 1.

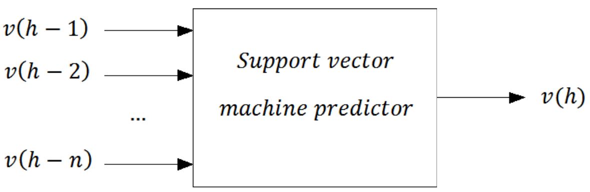

Fig. 1: Static model

In this case, all inputs are measured values. Using the regression function $f(x)$ described in the previous section, it is possible to consider $x = (v(h-1), \ldots, v(h-n))^T$ and $y = v(h) = f(x)$. The same thing is done for wind direction. This model is able to provide only data for one hour in advance.

B. *Second Step: Dynamic Model*

In the dynamic model, the previous static model is called iteratively. The number n of inputs (past samples) is the same. However, not all inputs are measured but there are some previously predicted values.

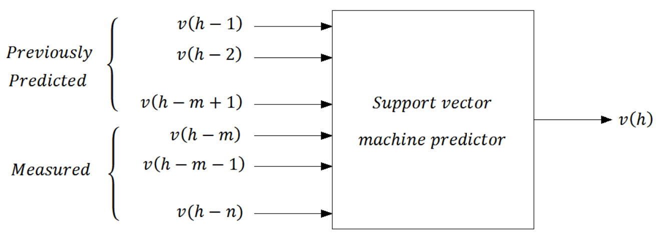

Fig. 2: Dynamic model

Hence, to predict $v(h)$ and referring to fig. 2, it is necessary to predict first $v(h-m+1), \ldots, v(h-2), v(h-1)$. In this case, m is the number of hours ahead. At each iteration, one predicted value is added and one measured value is removed, so the accuracy decreases as the forecast time horizon increases.

IV. Case of Study

A. *Data*

Data used in this paper are taken from Sidi Daoud wind farm, in north-eastern Tunisia, for the purpose of validating the proposed model. Wind speed and direction, 10 minutes sampled, are provided for 2010 and 2011. Then, data of January, February and March 2011 were sampled at one hour (by averaging every 6 consecutives values) and used to test the proposed model. There are no constraints on choosing test period, except avoiding long intervals of one fixed value, which is probably due to defective sensors. Wind speed is in m/s, and wind direction in degree, following fig. 3.

Cardinal Direction	Degree Direction
N	348.75 – 11.25
NNE	11.25 – 33.75
NE	33.75 – 56.25
ENE	56.25 – 78.75
E	78.75 – 101.25
ESE	101.25 – 123.75
SE	123.75 – 146.25
SSE	146.25 – 168.75
S	168.75 – 191.25
SSW	191.25 – 213.75
SW	213.75 – 236.25
WSW	236.25 – 258.75
W	258.75 – 281.25
WNW	281.25 – 303.75
NW	303.75 – 326.25
NNW	326.25 – 348.75

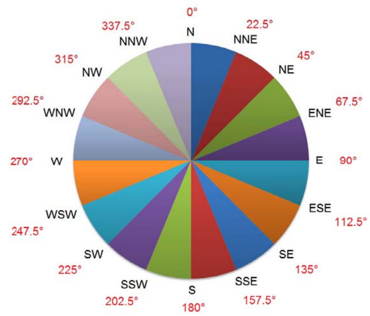

Fig. 3: Wind rose

B. *Results*

1) *Static Model*

First step is training the machine with January and February data, using 3 past wind speed samples (n=3) as inputs, and the following sample (fourth sample) as target. The number 3 is chosen because a bigger number of past samples doesn't really improve prediction accuracy (after simulation tests). From 1416 samples, 1413 vectors were created (3 first samples are used only to predict, and cannot be forecasted) and exposed to the machine, with the configuration of table I. The machine parameters were chosen manually according to simulation results, without parametric study.

TABLE I. Support Vector Machine Configuration

Regression Type	ε
Kernel	Radial
Coefficient γ	0.3
Penalty parameter C	10

The chosen SVM configuration is only valid for this case of study, and thus it may change in other cases. Then, test was performed with March data. Again, from 744 samples, 741 vectors were created and exposed to the SVM predictor. Wind speed prediction is given in fig. 4 (Only for the first 200 hours).

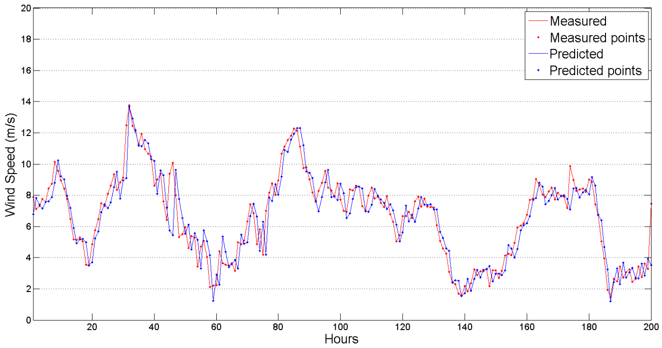

Fig. 4: Wind speed prediction, static model, one hour ahead

To predict every hour, three previous hours are used. Fig. 4 shows a slight shift between measured and predicted values of one hour (on average) because the predicted value tends to follow the last hour value given. Absolute mean error AME, for the entire test set is 0.8363 m/s and the root mean squared error RMSE is 1.1840 m/s. The linear regression coefficient LRC, which represents the slope of the regression line at fig. 5, is close to 1. It was not possible to calculate relative error, due to mathematical constraint of division by zero.

The AME is obtained by:

$$MAE = \frac{1}{m}\sum_{h=1}^{m}\left|v_{predicted}(h) - v_{measured}(h)\right| \qquad (18)$$

And the RMSE by:

$$RMSE = \sqrt{\frac{1}{m}\sum_{h=1}^{m}\left(v_{predicted}(h) - v_{measured}(h)\right)^2} \qquad (19)$$

Here, m is the samples number.

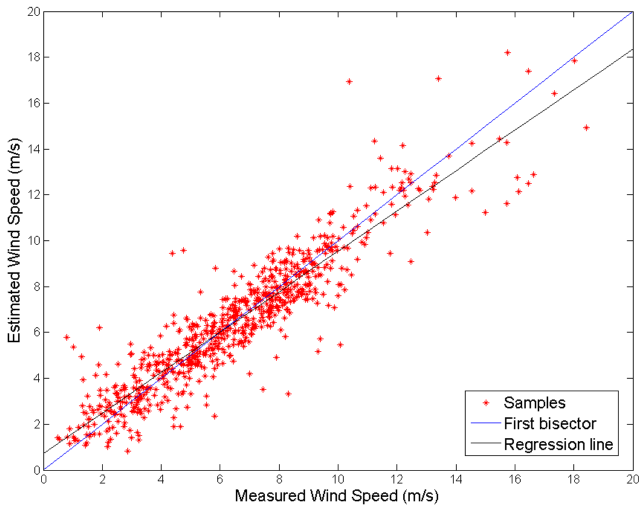

Fig. 5: Regression plot

Fig. 5 shows the regression line (line of correspondence between measured and predicted values, on average) and first bisector (ideal case). The distribution of samples on either side of the blue line reflects accuracy of the prediction. In this case, there are 741 samples (red stars) representing the entire test set.

Concerning wind direction, the exact same process was followed, the same train and test sets, except γ set to 0.005 and C set to 200. In fact, choosing parameters depends enormously on the type of data to forecast, and a parametric study may give the best parameters values to get the best possible results.

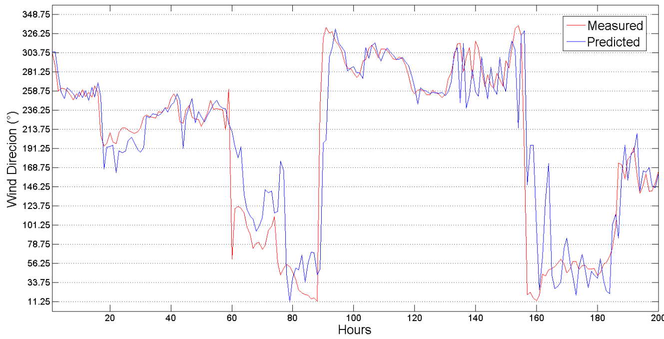

Fig. 6: Wind direction prediction, static model, one hour ahead

Fig. 6 illustrates the difference between measured and predicted wind direction, for the first 200 hours. However, unlike wind speed, hourly variation of direction is not very chaotic. The blue curve (predicted) has some peaks, especially after sudden variation of the red one. Speaking about evaluation criteria, the AME for the entire test set is 24.0416°, the RMSE is about 43.3013 °. But these values are not very representative, due to the circular direction coding (0°=360°). Fig.7 shows regression between samples, which are more scattered than wind speed case.

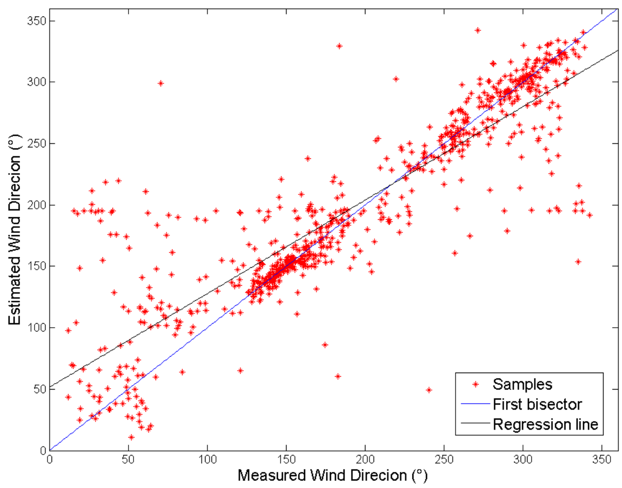

Fig. 7: Regression plot, wind direction prediction, static model

2) *Dynamic Model*

In the dynamic model, since the machine is confronted to many hours ahead to predict, it is necessary to take more past samples, for training as for test. Therefore, 10 past samples are considered, and the goal is to predict next 10 hours. The machine parameters to change are only γ and C, which are the most influent. However, test is done iteratively. Every hourly predicted datum is used to predict the next one, until the 10 hours are predicted. Again, the same data are used to evaluate this model. Wind speed prediction for 5 hours ahead is given in fig. 8 (beginning from sample n° 300).

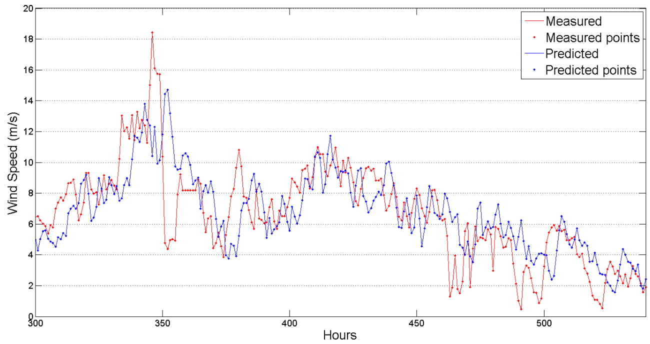

Fig. 8: Wind speed prediction, five hours ahead, dynamic model

To predict 5 hours in advance, it is necessary to predict first one hour (using static model) with 10 past samples, and then two hours ahead with 9 past samples and the previously predicted value, and then three hours etc until reaching five hours. This explains why the blue curve in fig. 8 (predicted) doesn't follow properly the red one (measured). In order to quantify error growth with the number of hours ahead, the MAE and RMSE are plotted in fig. 9.

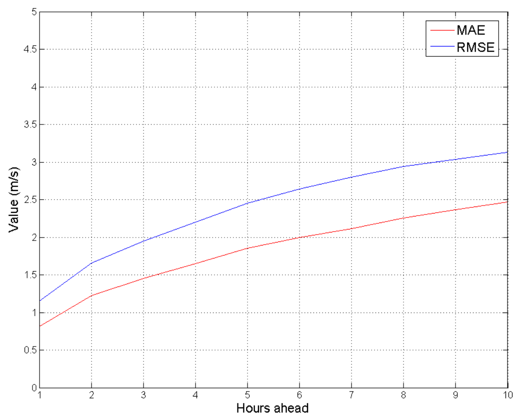

Fig. 9: Evolution of MAE and RMSE

In fig. 9, it is obvious that both MAE and RMSE increase with the number of hours ahead. Better or worse results may be found according to the number of past samples considered and hours to be predicted. However, increasing number of past samples doesn't improve accuracy in general.

Speaking about wind direction, simulation results are not very different from those of wind speed, as it is shown in fig. 10. The delay of 5 hours is more obvious in this case.

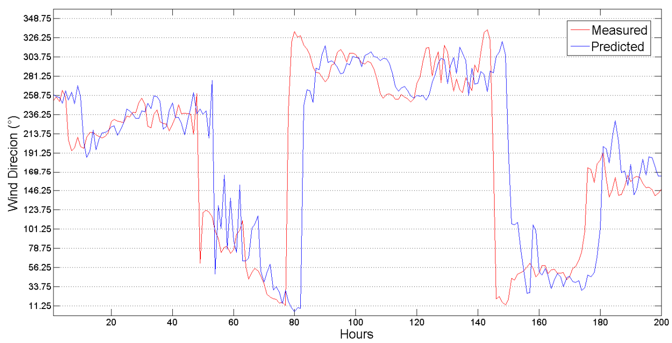

Fig. 10: Wind direction prediction, five hours ahead, dynamic model

C. *Wind Direction Influence on Power Generation*

In order to clarify relation between wind direction and output generation, some tests were performed with one 330 kW aerogenerator. For January and February 2011, all 10 minutes samples where wind speed is between 11 and 12 m/s are plotted in fig 11. Hence, when wind speed is fixed, it is possible to see wind direction effect. Production is very low (between 63 and 193 kW) when wind is WSW, moderate (211-335 kW) at NNE, and normal (297-364 kW) at WNW.

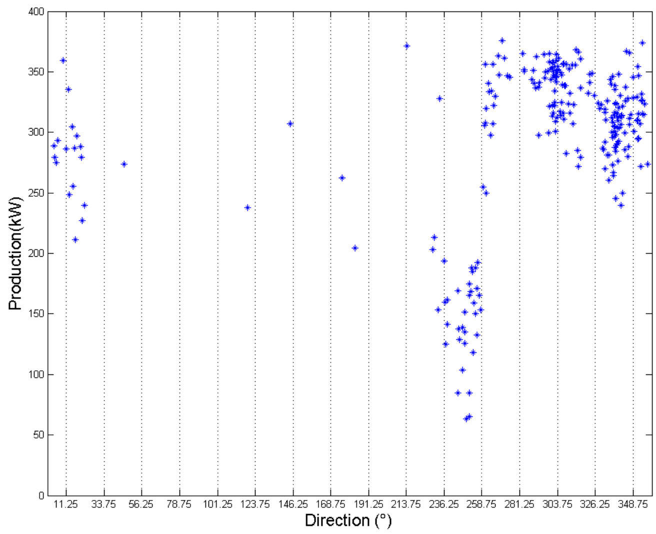

Fig. 11: Wind direction influence on power generation

Although wind speed is fixed (11-12 m/s), output generation is not the same for different directions, which justify the need for accurate wind direction prediction alongside wind speed forecast.

D. *Discussion*

The SVM model presented here achieves relatively good results for the short term. Similar results may be found in other publications. For example in [5], the RMSE is between 2 and 2.6 m/s for a lead time of 10 hours. In [6], it is between 1.2 and 3 m/s, and the MAE between 1 and 2.4 m/s. Use of SVM improves accuracy slightly for only few hours in advance, according to fig. 9, justifying again its well-adaptation for the short term. But its main advantage is simplicity and the reduced calculus time. In general, using NWP models requires extensive computational resources [8]; contrariwise, SVM needs about 2 seconds (depending on data) to run in any modern computer. In the other hand, wind direction may be predicted using the same machine and algorithms, which prevent user from executing other forecasting method, and this makes SVM a powerful and multi-task tool.

V. Conclusion

Support vector machine is a very powerful tool, which can be used for prediction by using its regression mode. This machine gives good accuracy in comparison with other time series methods, such as artificial neural networks. In this paper, SVM are used to predict wind data, which are speed and direction for the short term, and this is a necessity for wind farms.

The proposed method was applied using wind data taken from a real wind farm, and results achieved with are limited to 3 months. However, they are similar in terms of accuracy to those to found in the literature.

The next step will be then testing the SVM model for a period of one year at least; in order to take into account season effect, and possibly a model will be created for each calendar month. Also, it is possible to do a parametric study to set the optimal parameters for each type of prediction.

The main advantage of SVM is its simplicity and rapidity, and of course its ability to predict both speed and direction, without using complex numerical weather prediction models.

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