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Improvements in Wind Speed Forecasting Using Multi-Layered Perceptrons .

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Abstract—**the use of wind energy has developed significantly worldwide. Wind power is the strongest growing form of renewable energy, ideal for a future with pollution-free electric power. But the intermittent nature of wind makes it difficult to forecast. The researchers have embarked on use of the Multi-Layered Perceptrons (MLP) neural networks and other architectures of neural networks for predicting the actual wind speed from the previous values of the same variable. Several algorithms are then supplied with the data to establish the relationship between the inputs and the output. The obtained results indicate that the identified model can successfully be used, but with a poor accuracy prediction of the wind speed and the Forecasting error increases as we go far dates (hours or minutes) of learning data. In this work a new neural networks approach is developed for predicting the actual wind speed from the previous values of the same variable. Model parameters are estimated from a set of past available data, and they are regularly updated during online operation by accounting for any newly available information. The learning involves physical changes of the connections between neurons. The association between several neural structures, with a specific function, allows the emergence of a higher-order function for all. If the neural network can not monitor the physical changes over time we opt for a dynamic learning over time. Finally, we present a mathematical foundation for our approach.**

Keywords-Artificial Neural Network (ANN); Forecasting; Learning;Wind data.

I. INTRODUCTION

When dealing with renewable industry, the performance analysis of the conceived power system needs to take into account the predicted variations of meteorological parameters, such as wind speed [1]. The wind forecast problem aims to find an estimate f (t + k) of the wind vector y (t + k) based on the previous n measurements y (t), y (t − 1), …, y (t − n + 1). In order to have accurate wind speed forecast, k is chosen to be small and this is called short-term wind speed forecast. For instance, long-term wind speed prediction is vital for the sitting and sizing of wind power applications [2], whereas short-term forecasting of wind speed is important for improving the efficiency of a wind power generation systems [3] and [4] as well as for the integration of wind energy into the power system [5], [6] and [7].

It is well-known that neural networks represent a valuable tool for this kind of analysis [9–11]. Namely, neural networks are nonlinear processing systems composed of interconnected units (called neurons) that cooperate to perform complex tasks as well as to solve ill-defined problems. Specifically, neural networks are useful when it is necessary to build a model from the existing data, when it is necessary to simulate the behaviour of systems characterized by noisy and incomplete data [12–19]. For which there is an abundance of examples. As time series prediction is conventionally performed entirely by inference of future behaviour from examples of past behaviour, it is a suitable application for a neural network predictor.

Recently, some new methods based on artificial intelligence techniques have been developed, including the Artificial Neural Network (ANN) of Multi-Layer Perceptrons (MLP)[20] and [21], Radial Basis Function [22] and Recurrent Neural Networks [23] and [24], and FuzzyLogic [25] and [26].

In [27] comprehensive comparison study on the application of different artificial neural networks in 1-h-ahead wind speed forecasting is presented. Three types of typical neural networks, namely, adaptive linear element, backpropagation, and radial basis function, are investigated. The wind data used are the hourly mean wind speed. The results show that even for the same wind dataset, no single neural network model outperforms others universally in terms of all evaluation metrics. Moreover, the selection of the type of neural networks for best performance is also dependent upon the data sources. Among the optimal models obtained, the relative difference in terms of one particular evaluation metric can be as much as 20%.

This indicates the need of generating a single robust and reliable forecast by applying a post-processing method [27]. Different network structures, learning rates, and inputs are believed to result in different forecast accuracies. However, a two-hidden layer neural network in combination with a backpropagation learning algorithm and characterized by the hyperbolic tangent transfer function in the first hidden layer and the logarithmic sigmoid transfer function in the second hidden layer has been represented in [28] as useful tool to carefully predict the wind energy output. Three input neurons, representing the monthly average wind speed, the monthly average relative humidity are used in [28].The proposed

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approach in [29] considers five inputs, with two additional inputs given by the air temperature and the monthly maintenance hours. The more accurate energy prediction is confirmed [29]. Major developments of statistical approaches to wind speed prediction is concentrate on the use of the artificial-intelligence-based models such as Neural-Networks (NNs). However, there will be always an inherent and irreducible uncertainty in every prediction. This epistemic uncertainty corresponds to the incomplete knowledge one has of the processes that influence future events. Therefore, in complement to point forecasts of wind speeds, a major importance is to provide means for assessing online the accuracy of these predictions. A major part of the research efforts on wind power forecasting still focuses on a significant decrease of the level of prediction error. In order to generate a robust and reliable forecast method by applying a new learning algorithm, in this work our objectives are:

•A use of a simple MLP (Multi Layer Perceptron) models for hourly wind speeds

forecasting with simple and a fast network training method, and a minimum of inputs.

•A significant decrease of the level of prediction error.

In this paper, first we investigate the suitability of a two-hidden layer neural network with a back propagation learning algorithm used in [28−29]. We used just one input, the hourly average wind speed, so as to avoid facing such lack of measuring of other changeable landmarks (such as temperature, atmosphere stability, roughness ...) or at least one of them. So we notice that different inputs used as learning rate directly influence the forecast accuracy. To bridge this gap we have introduced (developed) a new algorithm of learning for neural networks. This new method allows a renewal learning data in time.

II. MODEL AND ALGORITHM

Our problem can be classified as input –output model assumes that the new system output can be predicted by the past inputs. So, our system is supposed single-input-single-output (SISO). Inputs are series of wind speed. So the input-output mapping function $f(.)$ of a system can be represented as the sum of a linear function $l(.)$ and a nonlinear function $n(.)$:

$$y(k) = l(y(k-1), y(k-2),.....) + n(y(k-1), y(k-2),.......) \quad (1)$$

The output of a hybrid network will be:

$$y_{yet} = W_{2a}[W_{1a}U] + W_{2b}F[W_{1b}U] \quad (2)$$

Where the input vector of a neural network is $\boldsymbol{U}$, the scalar output of a network is y_{yet}, the nonlinear vector is $\boldsymbol{F}$, and the weight matrices of the linear, nonlinear, and hybrid net works are respectively W_{1a}, W_{1b}, W_{2a} and $\boldsymbol{W_{2b}}$. In this work, we developed a new method of learning for neural networks. This new method allows a renewal learning data in time:

- So to predict Y_n we use $Y_{n-1}, Y_{n-2}, Y_{n-3}$ ….. Y_1 as learning data,
- and to predict Y_{n+1} we use $Y_n, Y_{n-1}, Y_n Y_{n-2}, Y_{n-3}$ ….. Y_2 as learning data .
- $Y_{n+1}, Y_n, Y_{n-1}, Y_n\ Y_{n-2}, Y_{n-3}$….. Y_3 Will be learning data to predict Y_{n+2}.

III. RESULTS

In this work two forms of representation are adopted: Figure 1 illustrated a typical plot of real wind speed (time series) at 10m.Figure 2 illustrated a plot of dependence structure between wind speed at t and wind speed at t+1, without time.The tool used for the creation, manipulation and visualization of the results obtained by the networks of neurons is MatLab, version 7.

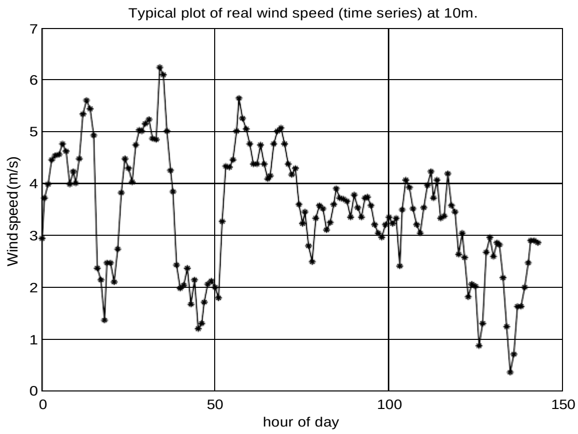

Fig. 1. measured data day changes of hour average wind speeds at a height of 10m.

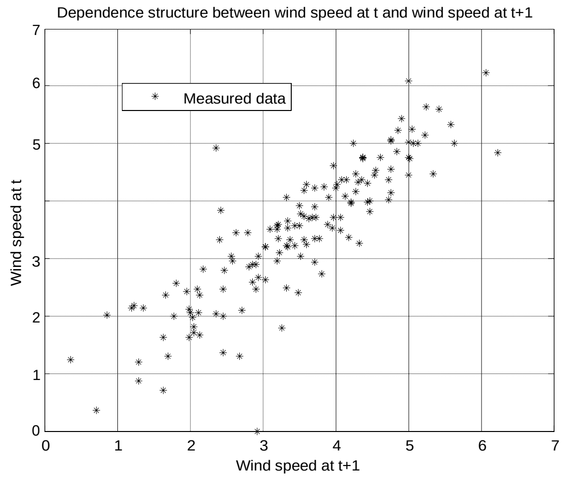

Fig. 2. Dependence structure between wind speed at 't ' and wind speed at 't+1'.

In this work we performed experiments with a step time of one hour. The input network is a sequence of hourly mean values prior. The target output is made of future values.

In figure 3,4,5,& 6 we have shown that the choice of learning area helps to achieve better results for figures 3 and 4 the neural network can not explore or predicts the speed below 2.5m / s because during the learning from 0 to 10 such probabilities are not shown .So figure 5&6 give better results for learning between 10 and 30

In figure 7,8& 9 we have shown that ,if the speed to predict goes away from the last sample (used during the learning), prediction error increases.

In table 1 a correlation analysis was shown that only 8 past values of wind speed (as learning period) had acceptable correlation with future value of wind speed. And more than 15 past values do not improve accuracy.

Our new 03 types of learning approach are:

- Keep a constant distance between predicted data and learning zone,
- By an algorithm that cycles through learning after each validation figure 7, 8&9.
- By increasing learning data.

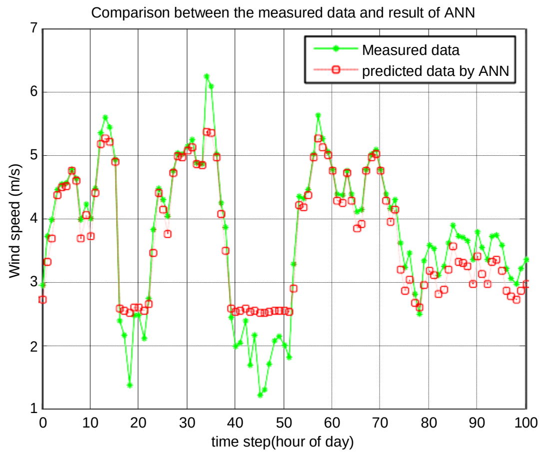

Fig. 3. Measured values versus predicted values of the wind speed (learning between 0 and 10

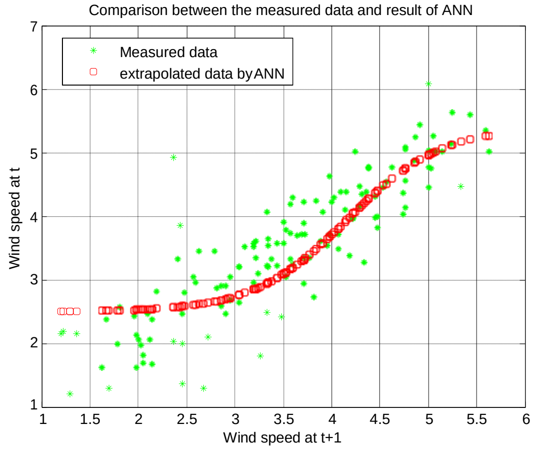

Fig. 4. Dependence structure between wind speed at 't ' and wind speed at 't+1(learning between 0 and 10)

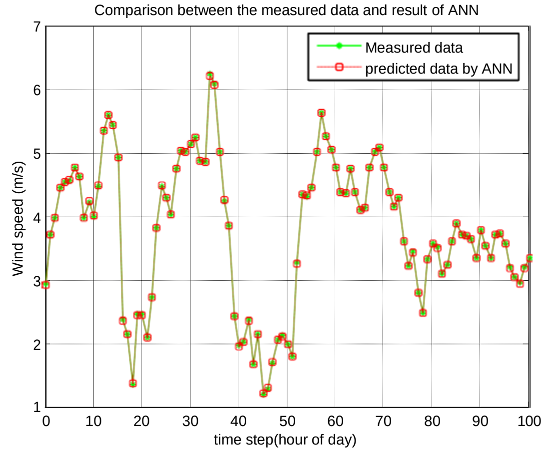

Fig. 5. Measured values versus predicted values of the wind speed (learning between 10 and 30)

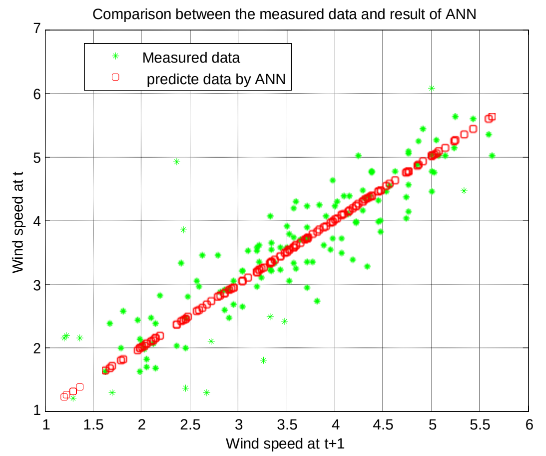

Fig. 6. Dependence structure between wind speed at 't ' and wind speed at 't+1(learning between 10 and 30) '.

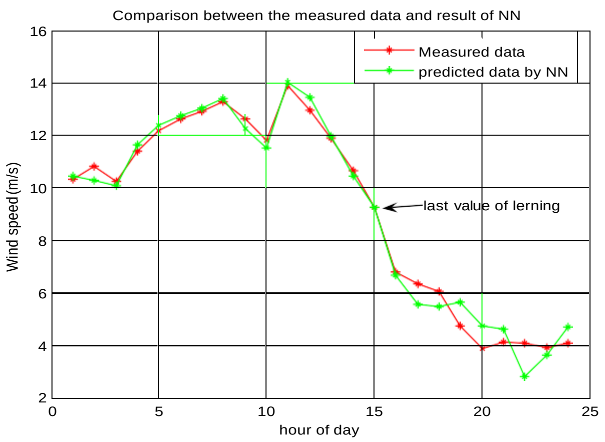

Fig. 7. Comparison between the two outputs: obtained and desired with with period of learning from 2 to 15 as learning data.

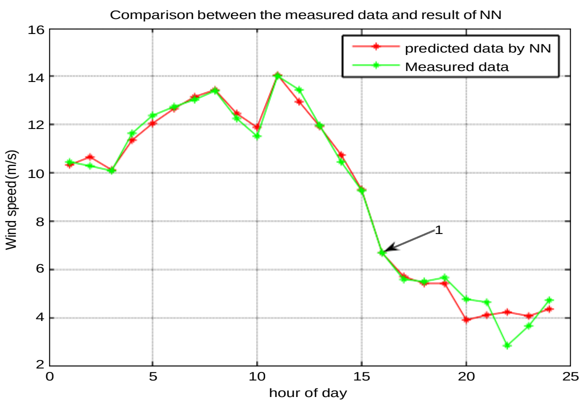

Fig. 8. Comparison between the two outputs: obtained and desired with period of learning from 4 to 16 as learning data.

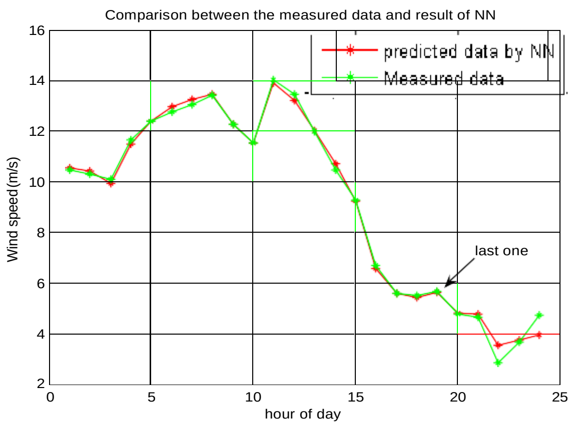

Fig. 9. Comparison between the two outputs: obtained and desired with period of learning from 4 to 19 as learning data.

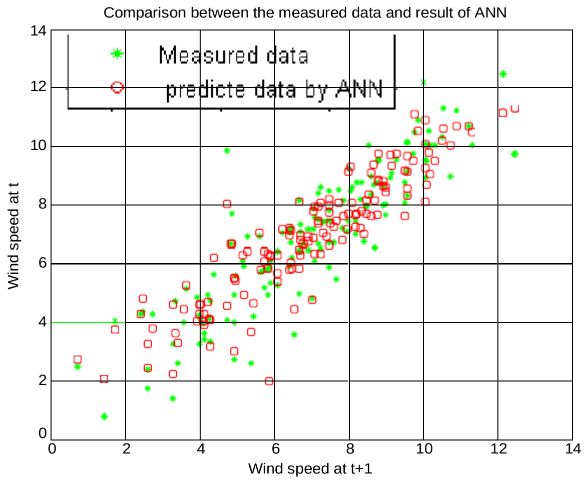

Fig. 10. Dependence structure between wind speed at 't ' and wind speed at 't+1' for our approach.

So we can clearly note that our approach allows predicting hidden variables. These Properties give it better prediction accuracy for wind speeds.

Root Mean Square the Error (RMS) differences between observed and estimated values, by chosen models, were used to valuate the performance of models RMSE were computed by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_t - \hat{y}_t)^2} \quad (3)$$

Where yt is the original time series, $y\hat{}t$ is the computed

The RMS error and Mean relative error has been calculated for the different estimation of the wind speeds compared at real measured data wind speed. The resultants are given in table 1.

TABLE I. ACCURACY (FOR DIFFERENT PERIODS OF LEARNING) FOR A DAY

D	***from 0 to 4***	***from 0 to 6***	***from 0 to 8***	***from 0 to 10***	***from 0 to 12***	***from 0 to 15***	***from 0 to 20***	***from 0 to 24***
RMSE	***3.631***	***0.319***	***0.062***	***0.015***	***0.014***	***0.016***	***0.018***	***0.018***
E (%)	***43***	***2***	***00.4***	***00.14***	***00.13***	***00.13***	***00.14***	***00.13***

D:Learning time in hours
RMSE: Root-mean-square error
E:Mean relative error in %

IV. MATHEMATICAL FOUNDATION

When wind speeds of successive four days are plotted against local time they show a periodic behavior (figure 11). From the figure it is clear that the wind speeds show some periodic/oscillatory behaviors. It is therefore appropriate that an empirical formula containing periodic function, like sine can be used for prediction of wind speed. Accordingly an empirical formula of wind speed at

an instant of time t is,

$$y(t) = A + B.y(t-1) + \frac{\sin(ct+n)}{ct+n} \qquad (4)$$

Where Y(t−1) is the wind speed of previous hour and

A, B, c and n are constants.

To get the constants in equation (4)), the usual numerical method of least square for curve fitting has been used. But the partial derivatives of constructed function are nonlinear in nature. So it becomes very difficult to obtain the values of constants, numerically. The equation (4) can be simplified by using power series approximation of sine function in t. The approximated formula is as follows:

$$y(t) = a_0 + a_1 y(t-1)t + a_2 y(t-1)t^2 + \dots + a_n y(t-1)t^n \qquad (5)$$

The coefficients a0, a1, a2, . . . , an can be easily obtained by using Least Square method**.**

Fig. 13, presents the fencing or enclosure of the wind potential for a year by a shift between two sine function.

If we grouped the new presentation the new approach we can calculate the wind potential c fencing or enclosure by just one month observation, in figure 14

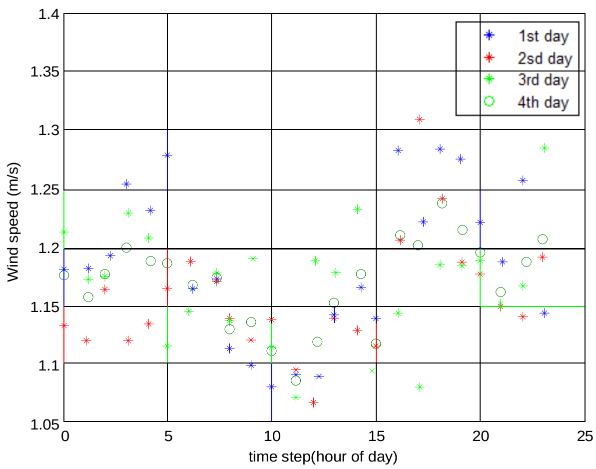

Fig. 11. Plot of wind speeds of successive four days as function of time.

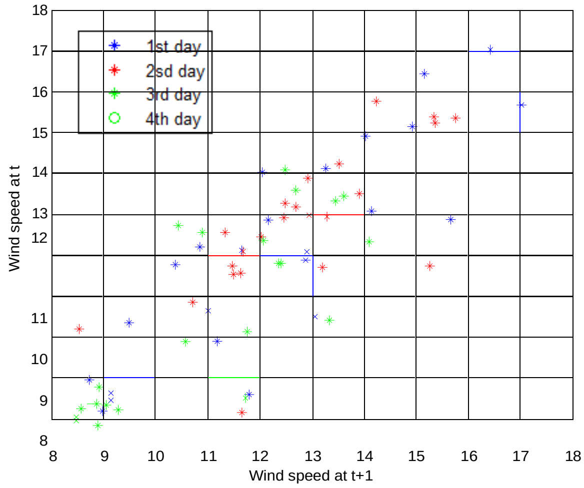

Fig. 12. Dependence structure between wind speed at 't ' and wind speed at 't+1' for our approach of wind speeds of successive four days.

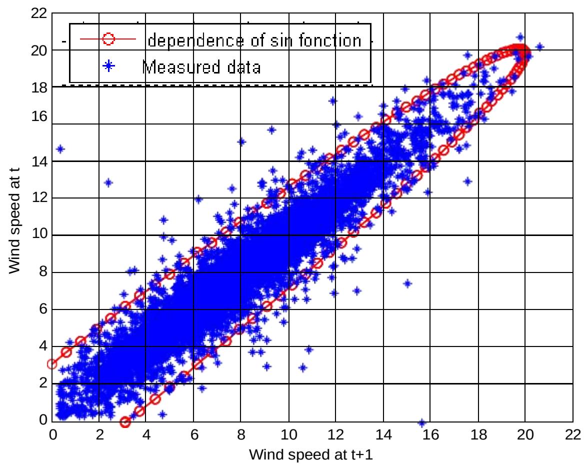

Fig. 13. Enclosure.of measured values of the wind speed for our approach for one year.

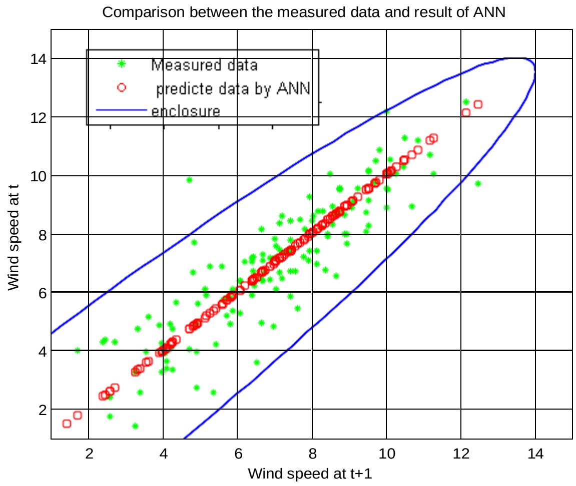

Fig. 14. Enclosure.of measured values of the wind speed for our approach for one month.

V. CONCLUSION

The learning involves physical changes of the connections between neurons. The association between several neural structures, with a specific function, allows the emergence of a higher-order function for all. If the neural network can not monitor the physical changes over time we opt for a dynamic learning over time.

This paper compares the results obtained with a simple MLP models for hourly wind speeds forecasting and measured speeds in a real sit. The results show a significant improvement of Accuracy if measurements weather data are used as online input data learning.Wind power forecasting plays a very important role to improve the economical and technical integration of a large share of wind energy into an existing electricity grid.

The wind power forecasting accuracy is directly related to new weather changes. The model developed on the basis of neural networks approach fits well wind speed time series and can be used for forecasting purpose.

The plot of dependence structure between wind speed at t and wind speed at t+1, without time ,help us better to understand and even the problems and dependency of wind speeds in time.In this first fesibility study only one site was investigated. Therefore the results have to be verified in a study, where we use other sites to show the full benefit of this approach. A longer data period will also be beneficial in order to verify the results of this study.

Work is validated on several sites in the paper we have presented the results of two sites. In the near future we can consider developing some aspects concerning this work we propose to predict a wind direction.

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