한국신·재생에너지학회 2008년도 추계학술대회논문집 pp.278~281

Error Analysis of Measure-Correlate-Predict Methods for Long-Term Correction of Wind Data

***Franz Vaas**, ****Hyun-Goo Kim**, *****Hyun-Soo Seo**, ****Seok-Woo Kim**

*Korea Institute of Energy Research, *leave from* Stuttgart University, Germany
**Korea Institute of Energy Research, ***Korea Wind Energy Development Organization

Abstract: In these days the installation of wind turbines or wind parks includes a high financial risk. So for the planning and the constructing of wind farms, long-term data of wind speed and wind direction is required. However, in most cases only few data are available at the designated places. Traditional Measure-Correlate-Predict (MCP) can extend this data by using data of nearby meteorological stations. But also Neural Networks can create such long-term predictions. The key issue of this paper is to demonstrate the possibility and the quality of predictions using Neural Networks. Thereto this paper compares the results of different MCP Models and Neural Networks for creating long-term data with various indexes.

Keywords: Long-Term Correction, Measure Correlate Predict, Neural Network

1. Introduction

Long-term data has been created using different MCP (measure-correlate-predict) methods as well as neural networks in order to study the results. These results are created for a 70 m met mast on Jeju Island near the potential location of an off-shore wind turbine. As long term reference data two nearby meteorological measurement stations were chosen. To compare the results various indexes like IOA, RMSE, BIAS, MAE and also the mean wind speed was used.

Chapter 2 gives some background about the used data, followed by creating a data background in chapter 3. In Chapter 4 the results are compared. At the end of this paper we find a short conclusion and a summary of the results.

2. Background

The reference data in the studied time period from the nearby meteorological stations (KMA184, AWS781) are almost complete. They are recorded as a 10 minutes average.

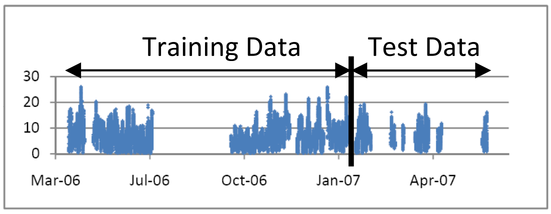

Figure 1. Data set from the met mast split into a training and a test period (8500 measuring points)

Figure 1 shows the local data for the 70 m met mast. This data is also recorded as a 10 minutes average, but the data is fragmentary and only available over short intervals. The data must be split into two datasets, a training dataset and a test dataset, to guarantee a validation with unused data. All in all there are over 34000 measuring points available. This is enough for training a Neural Network and also for testing.

3. Creating long-term data

Regression MCP

The Regression MCP is modeled as a linear or higher order function, whichever fits best to the available data.

In this case a linear regression method is used to create the long-term data. Because it is only possible to use one reference-dataset with the used software WindPRO, we created two different predictions, one for each reference-dataset. Thereto only wind speed data from the measurement stations with more than 1 m/s were used to generate the regression line for the different sectors.

Matrix MCP

Two different predictions were created with the Matrix MCP, too. The data is arranged in 10 degrees windows. Speeds under 1 m/s were skipped.

Neural Network

To create long-term data with a Neural Network Software Alyuda NeuroIntelligence is used. For making and training a Neural Network the input data is very important. The more input information the Neural Network gets, the better the result will be. But it is also necessary to exclude wrong data sets of the training set, like when one measurement station is out of order. To train the Neural Network, the data has to be sorted by time and date, WindPRO includes this function already. Contrary to WindPRO, it is possible to include more data sets for the input, so in this case the data of both measurement stations was considered.

In any case it is important to use the wind direction data as a trigonometric function like day time data (Both are circular). In addition the wind direction data is converted to a direction vector $\vec{V}$ = (sin α, cos α), like shown in Figure 3. A 4-6-1(or 6-6-1 because the direction data is split up in sin and cos) design was found to be the best solution for this kind of problem (Figure 2). In a second try day time data is used, too. So the network strukture becomes 5-6-1 (8-6-1).

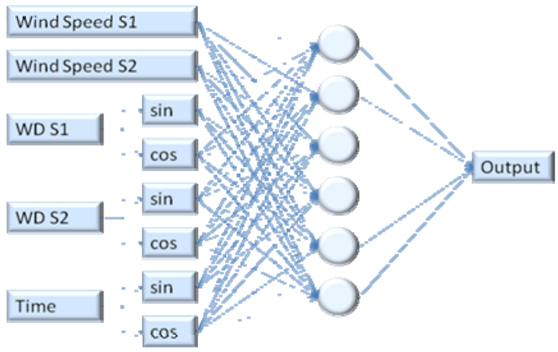

Figure 2. Used Neural Network design 5-6-1 (8-6-1). WD represent wind direction data, S stands for station.

4. Results

Table 1. RMSE, IOA, BIAS and MAE Indexes. The best value for the RMSE, BIAS and the MAE would be 0. The best IOA index is 1. The mean wind speed (MWS) should be 6.8 m/s like the real mean wind speed of the test data.

Method \ Index		RMSE	IOA	MWS [m/s]	BIAS [m/s]	MAE [m/s]
KMA 184	Reg.	4.138	0.691	6.58	-0.22	3.25
	Matrix	3.933	0.709	6.68	-0.12	3.03
AWS 781	Reg.	3.417	0.794	6.6	-0.2	2.61
	Matrix	3.177	0.818	6.72	-0.08	2.41
Neural Network (NN)		2.205	0.895	6.62	-0.18	1.64
NN + day time data as input		2.144	0.900	6.61	-0.19	1.58
NN using only AWS 781 data		2.452	0.864	6.49	-0.31	1.82

To contrast the results visually, the calculated wind speed is plotted over the real wind speed (Figure 3Figure , 4 and 6). The thick line shows the best possible result.

Regression and Matrix MCP

Comparing the indexes of the MCP methods in Table 1 the Matrix method gives in combination with the reference data from measurement station AWS781 the best result. The BIAS Index, representing the average deviation of the prediction from the wind speed, has even the best value of all methods.

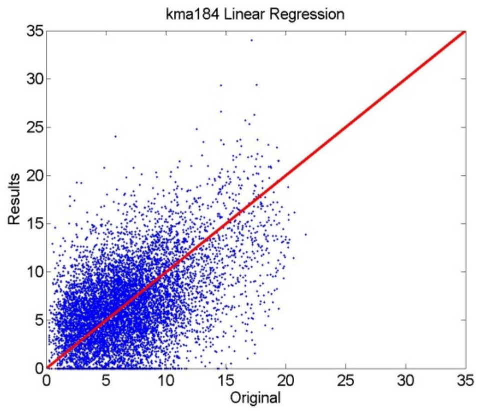

Figure 3. Result of the Linear Regression method using the data from the KMA184 measurement station.

Figure 3 shows the distribution of the result for the KMA184 Data in combination with a linear regression MCP. AS we can see there is a wide distribution of the results.

Neural Network

Several Neural Networks models were tested to create data. A 5-6-1 design with input data like wind speed and wind direction of both measurement stations combined with the time of the day offers the best result. Hereto Figure 4 shows the predicted wind speed above the desired one (Original).

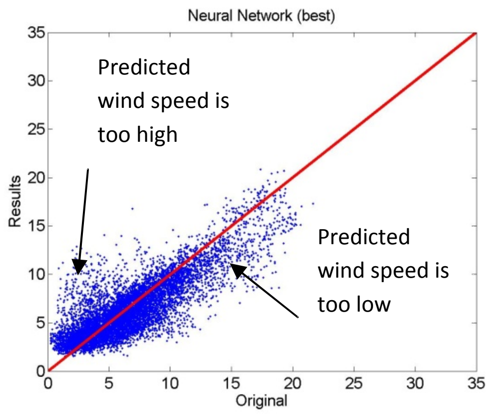

Figure 4. Results of the 5-6-1 Neural Network. As input data wind speed and wind direction of both measurement stations are used. Also the time of the day is used as an input.

Comparing the Indices in Table 1 the Neural Network seems to be the best choice for creating long term data in this case. However, the distribution of the results of the Neural Network (Figure 4) is much better than the one of the best MCP Model. By contrast a weakness of the Neural Network is that the quality of the results varies for different wind speeds. For low original wind speeds (less than 2 m /s) the predicted result is too high and for higher original speeds the prediction seems to be too low. This fact is important, in respect to the total energy production, as wind power is related to the wind speed like $P \sim v^3$. So in total the prediction of the produced energy will be undercharged because high wind speeds have more influence to the result. This deviation is also increased by the fact that the BIAS error is quite high.

To get an overview where the problems of this prediction are located Figure 5 shows the mean error (calculated like the MAE index) in dependence of the wind speed and the wind direction.

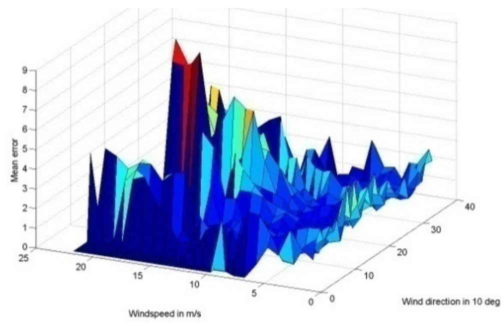

Figure 5: Prediction error depended of wind speed and wind direction.

The biggest error is located between wind speeds of 17 to 22 m/s. As we can see the error increases for higher wind speeds. We get good results with a mean error of 1 m/s for wind speeds between 3 and 10 m/s in all wind directions. For low wind speeds the mean error increases to 3 m/s for all wind directions.

In Table 2 the influence of the individual inputs on the outputs for the best network (Figure 4) is shown. Comparing the input influences we see that the wind speed at the AWS 781 measurement station is the most important for the result. But also wind directions of both measurement stations have some influence to the result file. The time of the day has only little influence to the result.

Table 2. Importance of the used data.

Name	Importance
Wind Speed KMA184	5%
Wind Speed AWS781	79 %
Wind Direction KMA184	9%
Wind Direction AWS781	5%
Time	2 %

To get a better idea of using a Neural Network instead of the traditional MCP models in WindPRO we created a Neural Network with the same input data like the MCP. So only data from one measurement station was included. Best results were achieved with a 3-11-1 (Input: Wind Direction, Speed, Time) design.

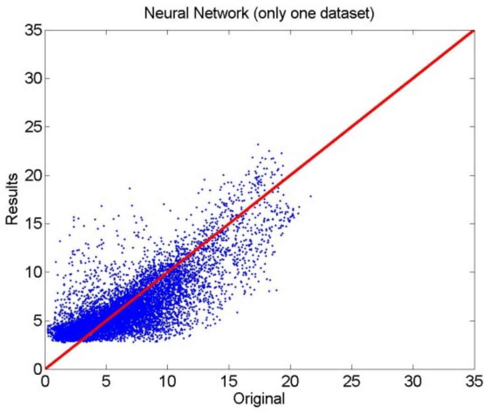

Figure 6: Result of the Neural Network using data of only one measurement station

Figure 6 shows the result of this Neural Network with data of only one measurement station. Comparing to the performance indices in Table 1 the results are better than the results from the WindPRO MCPs. However, there is again the problem with wind speeds less than 3 m/s.

5. Conclusion

Reliable and exact methods for creating long term data are highly needed. This paper shows that it is possible to use a Neural Network for creating long term data. The results of our researches demonstrate that the Neural Network is in the area of aberration very accurate, like shown in Table. The values of the RMSE, IOE and MAE are better than the values from the traditional MCP methods. In a comparison only the BIAS error is worse. A weakness of the Neural Network is the unbalanced distribution of the result wind speeds compared to the original wind speeds as displayed in Figure 4. This seems to be a problem in the point of calculating the total annual energy production. Further researches should be conducted about this topic. As good as the results of the Neural Network might look it is always necessary to verify the results.

Acknowledgements

This study was supported by KIER (Korea Institute of Energy Research) and IAESTE (International Association for the Exchange of Students for Technical Experience) Korea KU.

References

[1] Hyun-Goo Kim; Practical Application of Remote-Sensing Data for Wind Resource Assessment

[2] Morten Lybech Thøgersen, Maurizio Motta Thomas Sørensen & Per Nielsen; Measure-Correlate-Predict Methods, Case Studies and Software Implementation; EMD Int'l A/S

[3] H. Madson, G. Kariniotakis, H.Aa. Nielsen, T.S. Nielsen, P. Pinson; A Protocol for Standardizing the Performance Evaluation of Short-Term Wind Power Prediction Models; Technical University of Denmark; 2004

[4] Alyuda NeuroIntelligence: User Manual and Software

[5] WindPRO 2.5 User Guide; 2006