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A Physical Approach to Wind Speed Prediction for Wind Energy Forecasting

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ABSTRACT: In this study mesoscale meteorological model and CFD model was used to downscale the numerical weather prediction (NWP) data and verified at Hachijo Jima wind power plant. To reduce the computational cost of mesoscale model, coefficient matrix method was proposed. Following results were obtained. The root mean square error (RMSE) was reduced to 3.1m/s and 2.8m/s by mesoscale and CFD model respectively from 5.7m/s of original NWP. The coefficient matrix method reduced the computational time to a few seconds by one PC from two hours by parallel computers with 8CPUs without increasing the prediction error.

KEYWORDS: Physical model, Wind speed Prediction, Wind energy forecasting, Mesoscale model, CFD

1 INTRODUCTION

For electric power supply system, good agreement between demand and supply is essential. But in case of wind energy it is difficult to know the power output fluctuation in advance as it fluctuates with wind speed. This uncertainty causes problem in demand and supply planning for electric power and in real time electricity supply operation everyday. In countries with high wind energy penetration like Denmark and Germany, the day ahead forecast and the daily forecast of wind energy output are carried out based on the numerical weather prediction data and online measurement of the wind energy output.[1)]

However, operational models use statistical methods somehow, which means the power prediction is based on the past experience on the relationship between the prediction and measurement. This approach is efficient when past measurement data is available. On the other hand, the needs for the wind power prediction exist at the beginning of the operation of a new wind farm or even before the construction of the wind farm. In such cases, physical approach is needed, in which wind speed is predicted by physical model without using any past measurement data.

In this study, a physical model based wind speed prediction system was developed for online power prediction and verified by the anemometer located at the nacelle of the wind turbine at the Tokyo Electric Power Company Hachijo Jima wind power station.

2 PHYSICAL DOWNSCALING MODEL

Local wind is strongly affected by local topography and roughness. In the statistical approach, which is widely used in the operational forecast models in Europe, this local effect is taken into account by using measurement data at the site. On the other hand, in the field of wind resource assessment, where no onsite measurement data is available, downscaling of wind using mesoscale model and CFD based micro scale model was widely used. In this case, these mesoscale model and CFD based micro scale model is applied to downscale numerical weather prediction data.

2.1 *Downscaling using mesoscale meteorological model*

In this study, Japan Meteorological Agency Regional Scale Model (JMA-RSM) was used as the numerical weather prediction. JMA-RSM has the forecast horizon of 51 hours and can be used for the day-ahead forecast. However, its spatial resolution is 20km, which is too coarse to take the effect of local topography and

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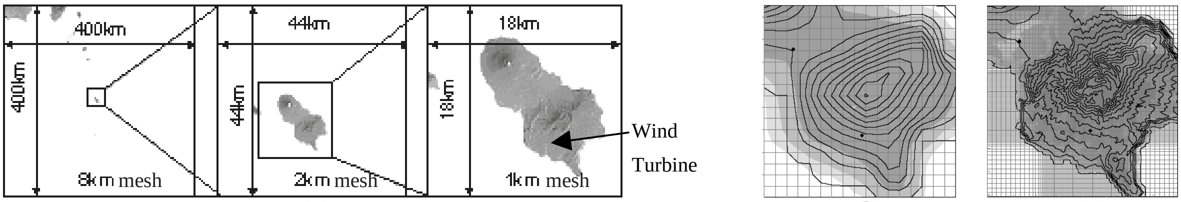
roughness into account. To take the effect of local terrain into account, mesoscale model RAMS[2)] was used. Figure 1(a) shows the computational domain for the model. Three step nesting grids are used and horizontal resolution of 1km was used as the finest grid. This computation takes approximately two hours using 8 CPUs.



(a) (b) (c)

Figure 1 (a) Nested grids used in mesoscale meteorological model RAMS. (b) Course terrain and computational grids used in MASCOT. (c) Fine terrain and computational grids used in MASCOT

2.2 *Downscaling using CFD based model*

The terrain in Japan is generally very complex and it is mentioned that 10m spatial resolution is needed to accurately take the effect of local terrain into account. Usually, downscaling of local wind up to 10m is carried out by CFD based Model. In this study, CFD based non-linear model MASCOT[3)] (Microclimate Analysis System fro COmplex Terrain) was used.

Mascot calculates the speed up and the change in wind direction relative to upstream virtual region, where topography is flat and roughness is constant, for 16 wind direction sectors. In this study Idealizing and Realizing Approach (IRA) [3] was used to downscale the predicted wind speed by mesoscale model. In this method local wind speed was estimated by correcting the difference between the effects of course terrain used in the mesoscale model and real terrain. First a simulation by MASCOT was performed with the course terrain and roughness (figure 1b) used in mesoscale simulation and speed up $C^c(\theta^I)$ and the change in the wind direction relative to the upwind virtual terrain as functions of upwind wind direction θ^I are calculated. From these, wind speed at upwind virtual region was estimated by:

$$u^I = u^R / C^c(\theta^I) \tag{1}$$

where, u^R is the predicted wind speed by mesoscale model. Then, another MASCOT simulation with real terrain and roughness (figure 1c) was performed and resulting speed up $C^F(\theta^I)$ and the change in wind direction were determined. Then local wind speed is estimated by:

$$u^L = u^I C^F(\theta^I) \tag{2}$$

2.3 *Results*

Figure 2 shows the root mean square error (rmse), defined by equation (3), of the prediction of wind speed at the wind turbine for JMA-RSM, RAMS and MASCOT.

$$\mathrm{rmse} = \sqrt{\overline{\left(u^{\mathrm{Pred}} - u^{\mathrm{Meas}}\right)^2}} \tag{3}$$

where, u^{Pred} and u^{Meas} denotes predicted and measured wind speed respectively. Obviously, by using RAMS root mean square error was reduced for all the season compared to original numerical weather prediction by JMA-RSM. For all the four seasons, by using RAMS the rmse was reduced to 3.1m/s from 5.7m/s. By using MASCOT, rmse is further reduced to 2.8m/s.

To investigate the source of these errors, RMSE can be split into three parts, i.e. bias, bias of standard deviation (sdbias) and dispersion (disp).

$$\mathrm{rmse}^2 = \mathrm{bias}^2 + \mathrm{sdbias}^2 + \mathrm{disp}^2 \tag{4}$$

$$\mathrm{bias} = \overline{u^{\mathrm{Pred}} - u^{\mathrm{Meas}}} \tag{5}$$

$$\mathrm{sdbias} = \sigma\left(u^{\mathrm{Pred}}\right) - \sigma\left(u^{\mathrm{Meas}}\right) \tag{6}$$

$$\mathrm{disp} = \sqrt{2\sigma\left(u^{\mathrm{Pred}}\right)\sigma\left(u^{\mathrm{Meas}}\right)\left(1-r\left(u^{\mathrm{Pred}},u^{\mathrm{Meas}}\right)\right)} \tag{7}$$

Here, $\sigma\left(u^{\mathrm{Pred}}\right)$ and $\sigma\left(u^{\mathrm{Meas}}\right)$ denotes standard deviation of predicted and measured wind speed and $r\left(u^{\mathrm{Pred}},u^{\mathrm{Meas}}\right)$ denotes the cross-correlation coefficient between the measured and predicted wind speed. The bias accounts for the difference between the mean values of prediction and measurement, bias of standard deviation shows the accuracy of prediction of the variability and dispersion accounts for the contribution of phase error.

Table 1 shows the rmse, bias, sdbias and disp for wind speed by JMA-RSM, RAMS and MASCOT. It was clear that the main contribution of reduction of error by RAMS and MASCOT is bias. By the prediction of MASCOT, the bias is reduced to almost 0, i.e. mean wind speed is very well predicted by MASCOT. On the other hand dispersion, which accounts for the phase error, is only slightly reduced by RAMS and MASCOT, implying the difficulty of reduction of phase error.

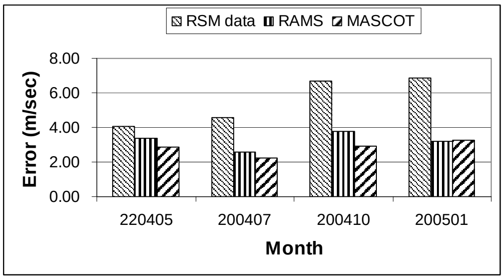


Figure 2 Root mean square error of predicted wind speed by JMA-RSM, RAMS and MASCOT.

Table 1 Root mean square error and its components of predicted wind speed by JMA-RSM, RAMS and MASCOT

Forecast Type	Month	RMSE	Bias	SD_bias	DISP	Month	RMSE	Bias	SD_bias	DISP
RSM Data	2004/05	4.06	2.62	1.06	2.91	2004/10	6.70	5.26	2.78	3.08
RAMS		3.35	1.67	0.53	2.86		3.77	2.39	1.35	2.59
MASCOT		2.84	0.73	0.23	2.81		2.90	0.17	0.89	2.75
RSM Data	2004/07	4.59	3.29	1.82	2.63	2005/01	6.88	5.49	2.62	3.22
RAMS		2.56	1.69	-0.18	1.92		3.19	1.12	0.78	2.88
MASCOT		2.25	0.14	-0.93	2.05		3.28	-1.74	-0.25	2.77

3 THE COEFFICIENT MATRIX METHOD

Downscaling by mesoscale meteorological model RAMS requires significant computational effort and time. For online applications, computational time is an important factor. To reduce the computational time, a coefficient matrix method is developed.

3.1 *Basic idea*

The basic idea of coefficient matrix method is that the relationship between wind speed predicted by rams and original JMA-RSM model can be expressed as a simple function of some parameters. In this study the relationship shown in equation (8) is assumed.

$$u^{RAMS} = k(\theta)\times u^{RSM} + \varepsilon \tag{8}$$

Here, u^{RAMS} and u^{RMS} denote wind speed predicted by RAMS and JMA-RSM respectively, $k(\theta)$ denotes coefficient matrix as a function of predicted wind direction θ by JMA-RSM and ε denotes error term. This assumption is based on the idea that the speed up by local terrain is only the function of wind direction. Figure 3 (a) shows the relationship between u^{RAMS} and u^{RMS} for SSW wind. It can be seen that the assumption in equation (8) is adequate. In this study, $k(\theta)$ is estimated using the past data of predicted wind speed by RAMS and JMA-RSM so that the square of the error ε become minimum. Figure 3 (b) shows the estimated coefficient matrix.

(a) (b)

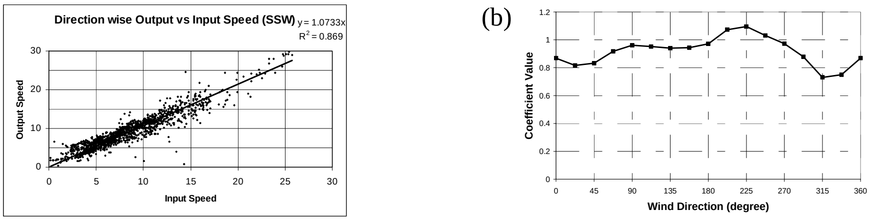


Figure 3 (a) The relationship between wind speed predicted by JMA-RSM (*x*-axis) and RAMS (*y*-axis) for SSW wind. (b) Estimated coefficient matrix at Hachijo Jima wind pwer plant.

3.2 *Results*

Coefficient matrix method is applied to the prediction of the wind speed at Hachijo Jima wind power plant. Figure 4 shows the predicted wind speed at May 2005 by coefficient matrix method and RAMS. Obviously both prediction shows similar wind speed. Table 2 shows the rmse and its components discussed in last section. There is no significant difference between those predictions.

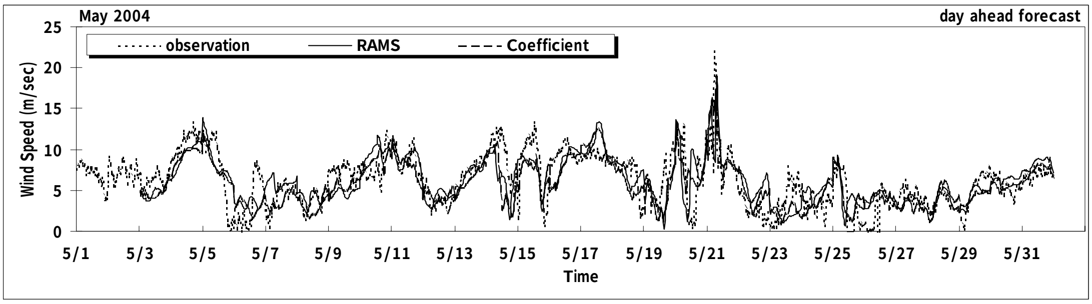


Figure 4 Measured and predicted wind speed by RAMS and coefficient matrix method in May 2004

Table 2 Root mean square error and its components of predicted wind speed by RAMS and coefficient matrix method

Forecast Type	Month	RMSE	Bias	SD_bias	DISP	Month	RMSE	Bias	SD_bias	DISP
RAMS	2004/05	3.35	1.67	0.53	2.86	2004/10	3.77	2.39	1.35	2.59
Transfer Coefficient		2.90	0.94	0.47	2.70		3.74	2.26	1.45	2.61
RAMS	2004/07	2.56	1.69	-0.18	1.92	2005/01	3.19	1.12	0.78	2.88
Transfer Coefficient		2.37	1.00	0.30	2.13		3.31	1.47	1.09	2.76

Although there is no significant difference in accuracy, the reduction of computational cost is significant. The computational time was reduced to a few seconds by 1 PC from two hours by parallel computer with 8CPUs.

4 CONCLUSION

In this study mesoscale meteorological model and CFD model was used to downscale the numerical weather prediction (NWP) data and verified at Hachijo Jima wind power plant. To reduce the computational cost of mesoscale model, coefficient matrix method was proposed. Following results were obtained.

1) The root mean square error (RMSE) was reduced to 3.1m/s and 2.8m/s by mesoscale and CFD model respectively from 5.7m/s of original NWP.
2) The coefficient matrix method reduced the computational time to a few seconds by one PC from two hours by parallel computers with 8CPUs without increasing the prediction error.

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