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Probabilistic Wind Power Prediction Based on Ensemble Weather Forecasting

Daisuke Nohara*, Masamichi Ohba*, Takeshi Watanabe*, and Shinji Kadokura*

*Central Research Institute of Electric Power Industry, 1646 Abiko, 270-1194, Chiba, Japan
(e-mail: nohara@criepi.denken.or.jp, oba-m@criepi.denken.or.jp, watatake@criepi.denken.or.jp, kdkr@criepi.denken.or.jp).

Abstract: Despite the growing popularity of the use of renewable (e.g., wind and solar) energy, the volatility of the corresponding sources, partially due to the natural variability of weather conditions, hinders their further commercialization and necessitates the development of cost-effective and easily implementable predictive models such as those that simulate power generation. Despite the recent increase in the accuracy of numerical weather prediction models, most of them still face problems such as the poor predictability of wind ramp event intensity, location, and timing. However, these challenges can be addressed through the use of probabilistic modeling. Herein, we present a probabilistic wind power prediction method based on a numerical weather prediction model, using a power curve empirically estimated from the relationship between area-averaged wind speed and area-integrated wind power generation to project wind power while accounting for the inherent uncertainty associated with the power curve. The established probabilistic prediction method exhibits high statistical consistency and reliably captures the confidence interval of wind power variability; thus, it is well suited for ramp event prediction.

Keywords: Probabilistic prediction, Numerical weather model, Ensemble prediction, Wind power prediction, Ramp events, Power curve, Monte Carlo

1. INTRODUCTION

Wind power generation is becoming increasingly popular, with the total wind generation capacity in Japan currently (end of 2018) amounting to approximately 3.7 GW. As wind power generation features a certain volatility partly due to the natural variability of weather conditions, the management of wind power variability is essential to minimizing the cost of integrating wind power generators into electric grid systems. Wind power prediction is one of the most cost-effective and easy to implement tools for this purpose; however, many system operators require relatively more accurate prediction of events characterized by large changes in wind power production over short periods. These events, called wind ramp events (Marquis et al., 2011), are mainly caused by large weather fluctuations such as the passing of extratropical cyclones (Yoshida et al., 2016; Ohba et al., 2016) and increase power grid instability, thus requiring the use of other power sources for balance. Hence, the accurate prediction of ramp event magnitude and timing can significantly help system operators to conservatively schedule wind power output and eliminate the need to balance unexpected power supply changes.

Although the prediction accuracy of numerical weather models has recently increased, predictions of the intensity, location, and timing of ramp events are still challenging because of the poor performance of current models and the inherently low predictability of ramp events, which occur under unstable atmospheric conditions. Probabilistic prediction can effectively model the behavior of such events and commonly relies on ensemble prediction systems.

Area-averaged wind power generation can be simulated using predicted wind speed and a power curve. In general, this estimation is derived from the relationship between predicted area-averaged wind speed and wind power generation observed in the past, and is affected by the corresponding uncertainty in conversion.

This study aims to develop a probabilistic wind power prediction method based on dynamical ensemble prediction using the Weather Research and Forecasting (WRF) model and considering the error in converting wind speed to power.

2. METHOD

Figure 1 describes the procedure of wind power prediction and shows that it can be categorized into a prediction and power curve. Prior to prediction, the power curve is empirically estimated on the basis of the relationship between the predicted wind speed and the observed wind power generation. In the prediction, the obtained curve is applied in the conversion of the predicted wind speed to wind power.

2.1 Dynamical Ensemble Weather Prediction

The weekly ensemble prediction provided by the Japan Meteorological Agency (JMA-WEP), which uses a singular vector method in a global model for initial perturbation, has been used to establish initial and boundary conditions. Although perturbations gradually expand because of the

Table 1. Model configurations and physics options.

Prediction range	75 hours (12UTC)
Output interval	30 min
Prediction domain	Japan
Map projection	Lambert conformal
Horizontal grids	150 x 150
Grid spacing	15 km
Vertical layers	45
Ensemble size	6
Initial and boundary conditions	- JMA Global Spectral Model - One-week Ensemble Prediction - Daily sea surface temperature
Convection parameterization	Kain-Fritsch
Cloud process	Morrison 2-moment
Planetary boundary layer	Yonsei University
Land surface model	Noah land scheme model

nonlinear effect of atmospheric dynamics, ensemble members that the perturbation expands in the Japan region are limited because perturbations are distributed globally. Therefore, we selected six ensemble members from the 27 members of JMA-WEP based on cluster analysis (Nuissier et al., 2012) to achieve maximum ensemble spreading in the Japan region for 24-h-ahead prediction (Nohara et al., 2015). For regional-scale prediction, the WRF model (Skamarock et al., 2008) is employed, with model configurations and physics options listed in Table 1. For regional-scale ensemble prediction, six ensemble members are integrated using the initial and boundary conditions derived by simple dynamical downscaling based on the WRF model with a 15-km horizontal resolution and 45 vertical levels. The used domain covers most of Japan.

Figure 2 shows an example of dynamical ensemble prediction. On January 14, 2013, a developed cyclone passed off the southern coast of Japan, bringing heavy snow to some areas of the southern Kanto/Koshin region including the Tokyo metropolitan area. According to the previous day's forecast, rainfall was expected because of the weak development of the cyclone. This snowfall event was revisited, and regional ensemble prediction was applied. Under the initial conditions, the difference between both ensemble members (cyclone location and intensity) was small. After the 24-h-ahead, ensemble member 1 (2) indicated that the predicted cyclone developed strongly (normally). The central pressure of the cyclone for member 1 (2) decreased to 953 hPa (986 hPa). The growth of the ensemble spread between these members over time and space because of the nature of flow-dependent predictability. Therefore, this example indicates that ensemble prediction represents how cyclone intensity and location are affected by small initial condition differences.

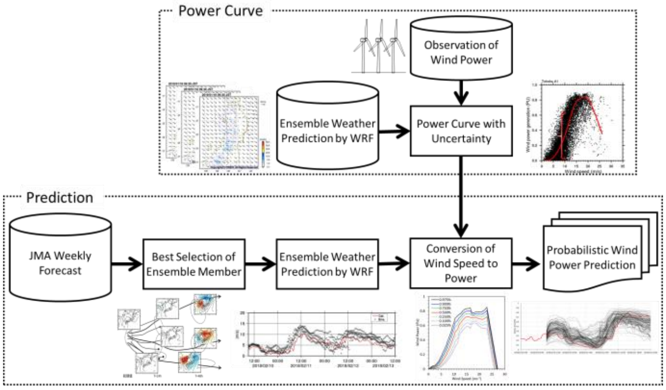

Fig. 1. Schematic procedure used for wind power prediction.

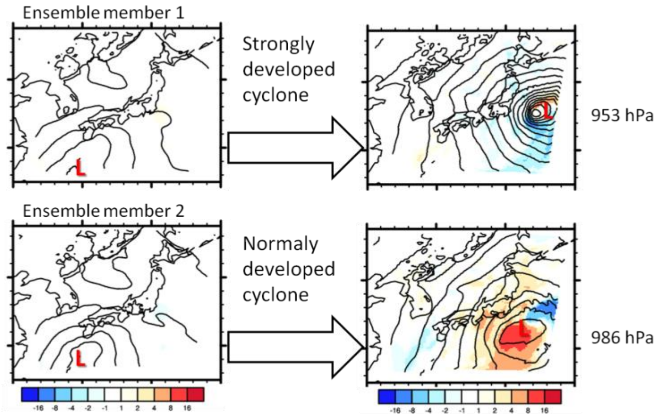

Fig. 2. Synoptic weather chart based on regional ensemble prediction for (left) the initial condition at 21 JST on 13 Jan. 2013 and (right) the 24-h-ahead prediction at 21 JST UTC. The upper (lower) ensemble member indicates that the predicted cyclone was strongly (normally) developed. Red (blue) shaded contours indicate relatively high (low) SLP compared with the control prediction.

2.2 Power Curve

This study focuses solely on area-integrated wind power generation in the Tohoku area, which comprises the north-eastern portion of Honshu (the largest island of Japan) and features numerous wind power plants locates along the coastline. As for wind power generation, we use area-integrated power generation data for one year (Jan. 2016 to Dec. 2016) corrected by the Tohoku Electric Power Company. The total wind power capacity equals 645.34 MW (generated by 33 wind power plants located in this area).

The power curve is fitted using the historical records of integrated wind power generation in the Tohoku area and predicted wind speed. For this fitting, we use 4 to 27 h ahead prediction data for area-averaged wind speed in that same period of the observation of the area-integrated power generation. Then, the best prediction is selected from six ensemble members to reduce the wind speed prediction error. The selection reduces the prediction error by 20% for the power curve.

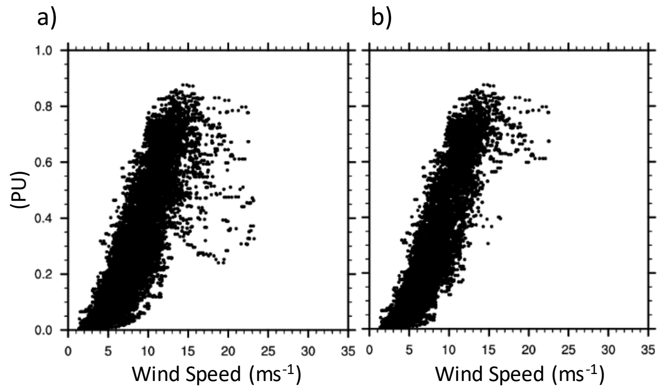

Fig. 3. a) Scatter diagram for prediction of area-averaged wind speed and area-integrated wind power generation. b) Same as a) but with the lower-skill wind predictions removed.

Figure 3a shows the scatter diagram for the prediction of area-averaged wind speed and wind power generation divided by rated power (per unit, hereafter PU), revealing a large uncertainty in every computed wind speed, mainly owing to the wind speed prediction error. To reduce this uncertainty, lower-skill wind predictions (~30%) are removed from the scatter diagram (Fig. 3b), thus reducing power uncertainty.

The diagram in Figure 3b is used for empirical power curve estimation. In this study, we hypothesize that the uncertainty of power is fitted by a beta distribution. Figure 4 shows a quantile plot of the diagram.

Multiple power curves obtained based on the cumulative distribution of power. Each power curve changes in proportion to the cube of the wind speed, up to speeds of ~10 m s^{-1} and then remains almost constant for wind speeds of 10–20 m s^{-1}. At speeds above 23 m s^{-1}, a rapid power decrease is assumed due to wind turbine cut-off. The 50% quantile curve is used as a basic power curve. The power curve and predicted wind speed obtained allow for easy estimation of wind power generation.

2.3 Probabilistic Wind Power Prediction

For wind power prediction, an empirically estimated power curve is created using the observed power generation and predicted wind speed from 2016. Based on this power curve, experiments of wind power prediction are conducted throughout 2017. In the first step, area averaged wind speed weighted by the rated capacity of wind farms is obtained from wind speed prediction. Then the averaged wind speed is converted to wind power using the empirical power curve. The power curve has a high uncertainty because plots of the generation are widely distributed in any of the wind speeds shown in Figure 4. To consider the uncertainty, we introduce an expanded ensemble method that comprises a random selection of any dynamical ensemble member and any percentile curve using Monte Carlo simulation. Then the total number of the ensemble members increases to 100. As the weight of one ensemble member accounts for 1%, probability prediction is easy when estimated as the count of the ensemble member.

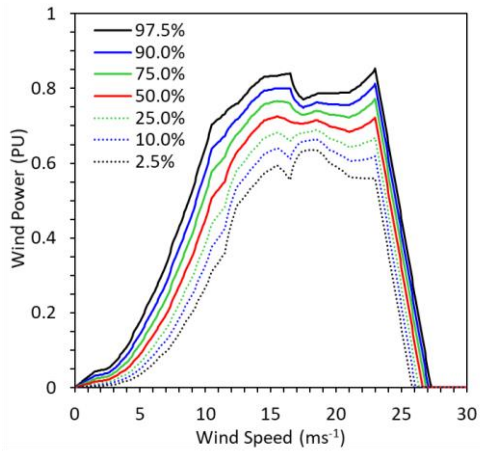

Fig. 4. Quantile plot of power curve.

In addition, a ramp event of area-integrated wind power generation is defined as a 30% change in generation within 6 h after the ramp start. The corresponding prediction considered each member of the expanded ensemble, and ramp prediction probability is obtained from the number of predicted ramp events by dividing the total number of ensemble members.

2.4 Verification metrics

To evaluate ramp forecasting, all forecasts and observations of significant wind ramps are grouped into four categories based on the accuracy of actual ramp prediction (Zhang et al. 2017). Table 2 is a generic contingency table summarizing the results of event prediction. True positive (TP) represents the number of forecast ramps (forecast YES) actually observed in the actual power output (observed YES); false positive (FP) is the number of forecast ramps not observed for actual wind power output (observed NO); false negative (FN) represents the number of observed ramps (observed YES) not predicted by the wind forecasting system (forecast NO); true negative (TN) is the number of non-occurring events for both observed and forecast results; and N is the total number of events.

Categorical statistics provide measures of accuracy and skill for forecasts of notable events such as ramps in power, detrimental temperatures, or rainfall. Based on the contingency table, a suite of metrics is derived for the evaluation of ramp forecasting performance as follows. Probability of detection (POD) is defined as

$$POD = TP / (TP + FN).$$

Success Ratio (SR) is defined as,

$$SR = TP / (TP + FP).$$

Critical success index (CSI) is used to measure the fraction of observed and/or forecast events that are correctly predicted, ranging between zero and unity (perfect prediction) and considering only observed and forecast ramps while excluding true negative events:

$$CSI = TP/ (TP + FN + FP).$$

The value of CSI is between 0 and 1, with 1 representing perfect prediction. The CSI considers only observed and forecasted ramps, excluding true negative events.

Table 2. Contingency table for ramp event.

	Observed YES	Observed NO	Total
Prediction YES	TP (hits)	FP (false alarm)	TP+FP
Prediction NO	FN (misses)	TN	FN+TN
Total	TP+FN	FP+TN	N=TP+FP+FN +TN

3. EXPERIMENTAL DESIGN

To confirm the effects of the uncertainty in the prediction, a comparative experiment of three methods is performed. The details of the experiment are described as follows.

3.1 Only Ensemble Prediction (E06P06)

In this case, only the uncertainty of ensemble prediction is considered for wind power prediction. The probabilistic prediction relies on six members from the ensemble prediction with the basic power curve as the 50% quantile of the power curve.

3.2 Only Conversion Error in Power Curve (E01P100)

In this case, only the uncertainty of the power curve is considered for wind power prediction. The probabilistic prediction relies on 100 members estimated by the random selection of any percentile curve using Monte Carlo simulation and only the control prediction.

3.3 Two Types of Prediction Uncertainty (E06P100)

For a probabilistic wind forecast, uncertainties in prediction and conversion are considered. The probabilistic prediction relies on 100 members estimated by the random selection of any dynamical ensemble member and any percentile curve using Monte Carlo simulation.

4. Results

4.1 Case study

On January 9, 2017, a developing cyclone passed Honshu island, bringing storm wind to some areas of the Tohoku region. Figure 5 shows the wind power generation and weather maps for this period, and reveals the occurrence of a strong ramp up event from 1500 JST to 2400 JST 9 Jan. 2017 due to the developing cyclone. After that, wind power generation gradually decreased, and a weak ramp down event due to cyclone departure occurred from 0600 JST to 0900 JST January 10, 2017. Another ramp up event, started at 1800 JST January 10, due to the strengthening of typical winter pressure patterns such as the high-pressure area to the west and the low-pressure area to the east.

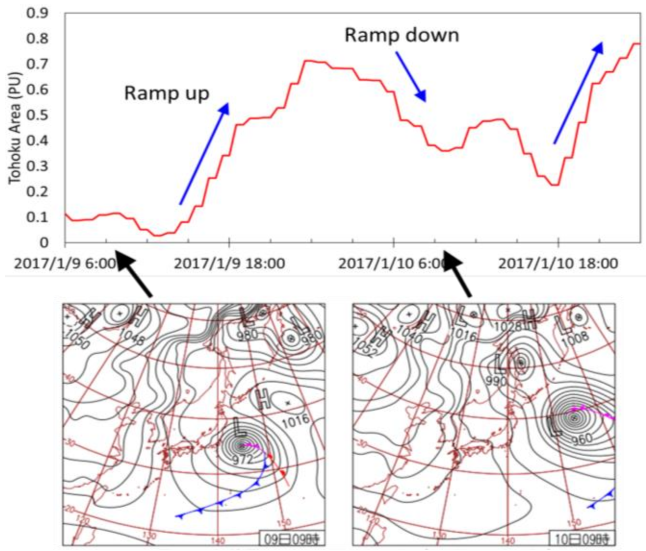

Fig. 5. Area-integrated wind power generation from 9 Jan. 2017 to 10 Jan. 2017 and the corresponding weather map. Power generation rapidly increased (ramp up) in the evening of 9 Jan., rapidly decreasing (ramp down) in the morning of 10 Jan.

Figure 6a shows wind power generation predicted by six members of the ensemble and the 50% quantile of the power curve (E06P06). The performance of dynamical ensemble prediction started from 0900 JST on January 9, 2017. All ensemble members predicted the ramp up event on January 9, although the timing of this event was different for each ensemble member. This difference indicated the uncertainty in prediction caused by the nature of atmospheric dynamics. In this case, the uncertainty of event timing was close to 3 h. After that, ramp down and up events occurred. Some ensemble members captured the ramp down events while other could not capture these events.

Figure 6b shows the results of 100-ensemble-member prediction considering only the uncertainty in the power curve (E01P100), revealing that the results were distributed around the 50% quantile of the power curve in a parallel fashion. In this case, all ensemble members could capture the first ramp up and down events but could not capture the second ramp up event, because the control weather prediction could not predict the strengthening of the winter pressure pattern on January 10.

Figure 6c shows the results of 100-ensemble-member prediction considering two types of uncertainty (E06P100).

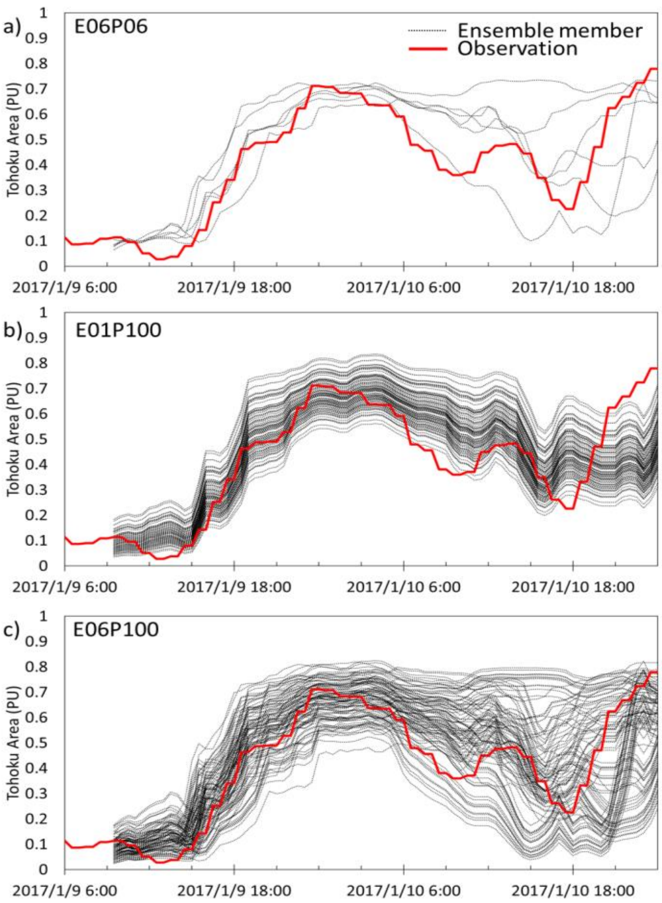

Fig. 6. Time series for a) E06P06, b) E01P100, and c) E06P100 predictions.

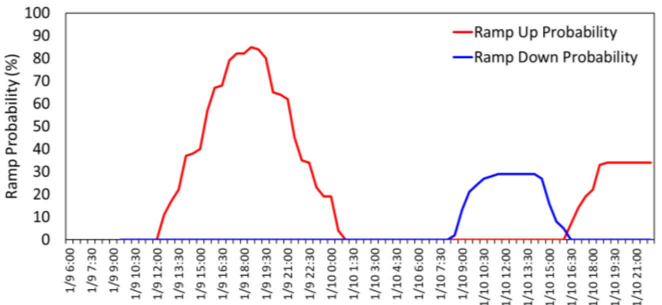

Fig. 7. Time series of probability prediction for ramp up and ramp down.

The ensemble prediction accounted for the uncertainty of atmospheric chaos and the error in the conversion of wind speed to power. Ensemble members were more widely distributed than dynamical ensemble members. Almost all ensemble members captured the ramp up event on January 9, and some members captured the ramp down event on January 10 and the second ramp up event on January 10.

Figure 7 shows the results of probabilistic ramp event prediction based on E06P100 and reveals that whereas the probability of ramp up prediction exceeded 90% in the evening of January 9, that of the ramp down on January 9 and of the ramp up on January 10was close to 30%.

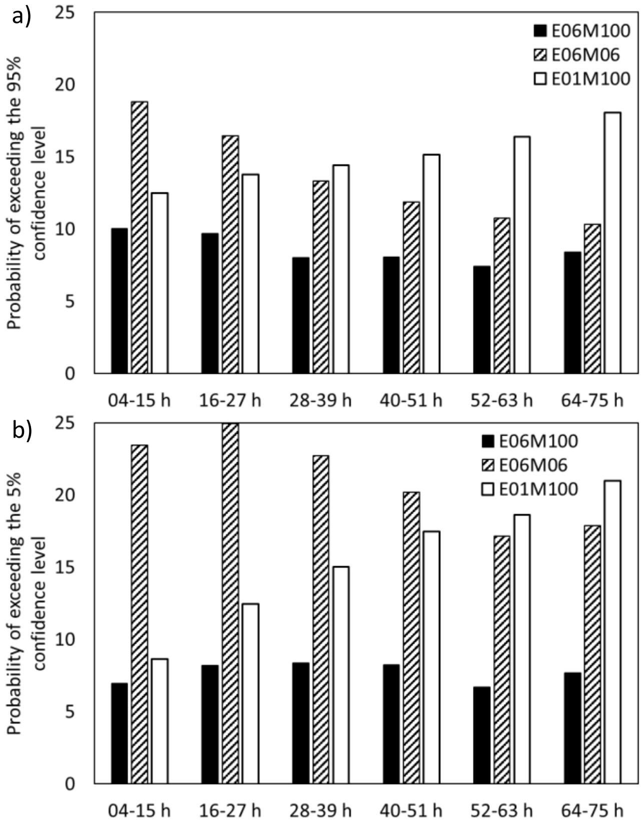

Fig. 8. probability of exceedance from confidential interval of a) 95% and b) 5% for different prediction time.

4.2 Verification

For the verification of wind power predictions, the empirical power curve was estimated using predictions for the year 2016. Predictions for verification were conducted twice a day throughout the year of 2017. Figure 8 shows the probability of exceeding the 5–95% confidence interval for different experiments and prediction times. As all experiments underestimated the confidence interval, the probabilities exceed the 5% level. In the case of E01P100, the probability gradually increases, because ensemble spread is constant and independent of prediction time. In the case of E06P06, the probability gradually decreases. These results indicate that prediction accuracy is increased with increasing prediction time because dynamical ensemble prediction represents the uncertainty of the prediction caused by atmospheric chaos. However, the probability exceeds the 5% level and is larger than that of E06P100. In the case of E06P100, probability remained almost constant even when the prediction time was extended, which is indicative of proper ensemble spread representation. These results indicate that uncertainties of prediction caused by weather prediction and other factors can be evaluated separately.

The accuracy of ramp event prediction is verified using the modeling of ramp alerts, which are issued when the predicted

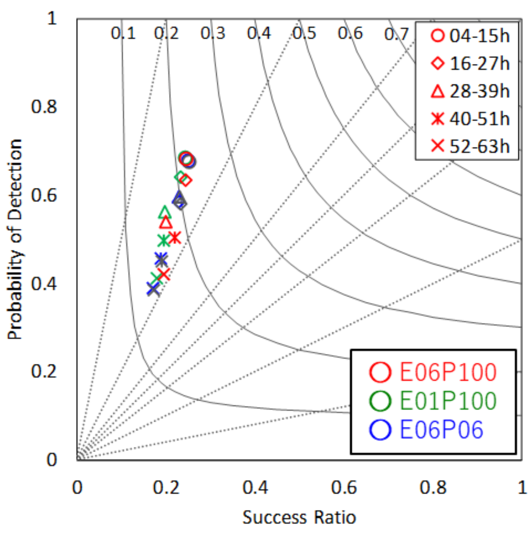

Fig. 9. Comparison of ramp prediction for different experiments (colours) and prediction time (shapes).

probability of ramp occurrence exceeds 40%. Figure 9 compares ramp predictions for different experiments and prediction periods, revealing that the frequency of ramp alert prediction exceeds that of observed ramp events. Although the accuracy of ramp prediction decreases with increasing prediction time, CSI exceeds 0.2 for 28–39-h predictions, and E06P100 is slightly superior to other methods.

4. CONCLUSIONS

An understanding of the impact of uncertainty on integrated wind power production and variability is important for ensuring energy security and operational grid management. In addition to the evaluation of wind power potential, the forecasting of the variability of wind power output is a significant challenge in wind power management. Meteorological forcing for the variability of wind speed and ramp events is complex and still unexplained for the most part. In this study, probabilistic predictions of wind power generation and ramp events were performed through a regional ensemble prediction method relying on the WRF and the uncertainty of conversion from wind speed to wind power in the power curve. The number of ensemble members was increased to one hundred using Monte Carlo simulation. As a result, probabilistic wind power prediction achieved high statistical consistency and reliably captured the confidence interval of wind power variability, compared to only dynamical ensemble prediction or only the conversion error consideration. The probabilistic prediction offers useful information for the electric system because it can be used as a preliminary assessment of uncertainty of the generation by wind power and as a risk hedge of the prediction error.

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