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SHORT COMMUNICATION

Prediction of the extreme wind speed in the mixed climate region by using Monte Carlo simulation and measure-correlate-predict method

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ABSTRACT

The extreme wind speed at an offshore location was predicted using Monte Carlo simulation (MCS) and measure-correlate-predict (MCP) method. The Gumbel distribution could successfully express the annual maximum wind speed of extratropical cyclone. On the other hand, the estimated extreme wind speed of tropical cyclones by analytical probability distribution shows larger uncertainty. In the mixed climate like Japan, the extreme wind speed estimated from the combined probability distribution obtained by MCP and MCS methods agrees well with the observed data as compared with the combined probability distribution obtained by the MCP method only. The uncertainty of extreme wind speed due to limited observation period of wind speed and pressure was also evaluated by the Gumbel theory and Monte Carlo simulation. As a result, it was found that the uncertainty of 50 year recurrence wind speed obtained by MCS method is considerably smaller than that obtained by MCP method in the mixed climate. Copyright © 2014 John Wiley & Sons, Ltd.

KEYWORDS
Monte Carlo simulation; measure-correlate-predict method; mixed climate; extreme wind speed; prediction uncertainty; observation period

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1. INTRODUCTION

The assessment of the design wind speed of wind turbines requires the accurate estimation of the probability distribution of annual maximum wind speed. In those regions where strong wind event is dominated by only extratropical cyclones, measure-correlate-predict (MCP) method and Gumbel analysis can be used to assess the extreme wind speed as shown in IEC61400-1 Annex E.[4] However, in mixed climate regions where more than one significant wind-producing meteorological phenomena are observed, the examination of each phenomenon is required.[5,6]

Japan is one of those mixed climate regions, where both tropical and extratropical cyclones are the significant meteorological phenomenon, and the estimation of the probability distribution of annual maximum wind speed induced by tropical cyclones requires a special care. In Japan, for example, 26 typhoons are generated every year on average. However, in some years and in some locations, the strong wind event induced by tropical cyclones may not be observed, which results in the statistically unstable annual maximum wind speed induced by tropical cyclones.

To overcome this unstability, Monte Carlo simulation (MCS) of tropical cyclones[4] has been proposed and adopted in the Architectural Institute of Japan recommendation[5] and American Society of Civil Engineers standard.[6] This method is statistically more stable, and uncertainty would be smaller than the method based on measurement. However, very few studies have investigated the uncertainty of the extreme wind speed estimation on the basis of Monte Carlo simulations.

In this study, first, MCP method and Gumbel analysis is applied for the estimation of the probability distribution of strong wind events induced by both tropical and extratropical cyclones to investigate the applicability of MCP method. Then, the probability of annual maximum wind speed induced by tropical cyclone is estimated by using MCS to show the advantage of the Monte Carlo simulation. Next, the uncertainty of extreme wind speed related to the number of annual maximum wind speed for both tropical and extratropical cyclones are estimated theoretically. Lastly, the uncertainty related to the length of pressure measurement data used to identify the probability distribution of tropical cyclone parameters is investigated.

2. ESTIMATION OF EXTREME WIND SPEED ON THE BASIS OF WIND SPEED MEASUREMENT

Measure-correlate-predict method uses the short-term on-site measurement data and the long-term measurement data at nearby meteorological station, and on the basis of the correlation between those sites, the long-term wind speed and direction at the site of interest are estimated.[1] If on-site measurement is not available, numerical simulation can be used to estimate the correlation. In this study, a computational fluid dynamics based model, MASCOT,[7,8] is used to estimate the correlation and long-term wind speed and direction at the offshore site. In this section, the detail of this method is described and the extreme wind speed is estimated based on this method. Although, strictly speaking, this method is different from original MCP method, the distance between these two sites is a few kilometers, and a good correlation of wind speeds can be seen in measured wind speeds between these sites, this method is referred as MCP method in this paper.

2.1. The MCP method

In this study, the extreme wind speed is estimated at an offshore site, which is located offshore Choshi, on the East Coast of Japan, at 35°40′41′′N, 140°49′35.9′′E (Figure 1), at the hub height of 100 m.a.s.l. The 10 min average wind speed u_M and the direction θ_M measured at Choshi meteorological station from 1995 to 2007, are converted into the wind speed u_S and the direction θ_S at the offshore site using the following equations.

$$u_S = u_M \times S_S \tag{1}$$

$$\theta_S = \theta_M + D_S \tag{2}$$

where, S_S and D_S denote the wind speed ratio and the change in wind direction at the offshore site relative to the meteorological station, which are obtained from computational fluid dynamics based wind prediction model, MASCOT.[8] The wind direction measured at the meteorological station θ_M is used as the inflow.

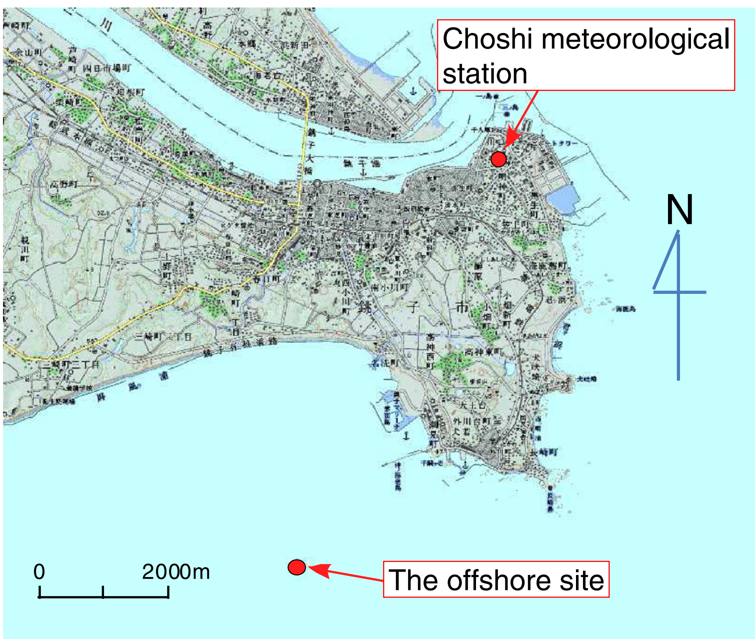

Figure 1. Location of the offshore wind power plan.

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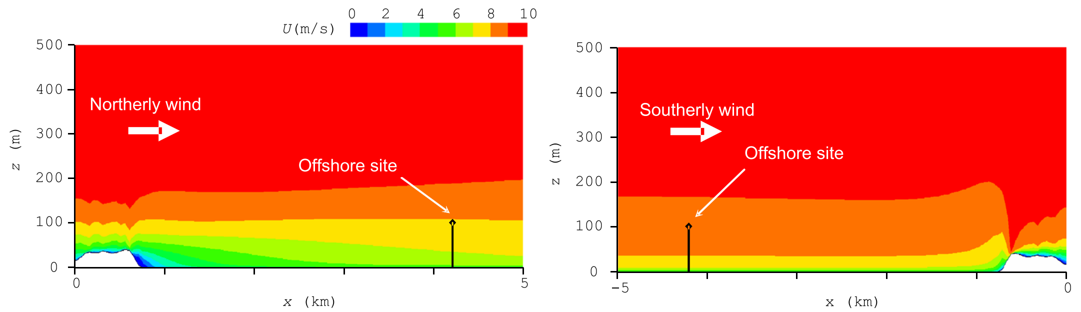

(a) Northerly wind (b) Southerly wind

Figure 2. Spatial distributions of wind speed at the offshore site for the northerly and southerly winds.

The spatial distributions of the wind speed at the site for northerly and southerly winds are shown in Figure 2. The northerly wind (Figure 2(a)) is affected by land, and the wind speed in the lower boundary layer decreases compared with the southerly wind (Figure 2(b)).

Figure 3 shows the speed-up ratio at the offshore sight relative to the Choshi meteorological station for each wind direction. Here, wind direction 0° denotes northerly wind, 90° easterly wind, etc. Because the anemometer at the Choshi meteorological station is located at 28 m.a.s.l., the speed up ratio shows larger than one for almost all the wind directions. For the wind direction between 135° (south easterly) and 270° (westerly), the speed up ratio is significantly larger than one. This is due to the wind speed decrease caused by local terrain at the Choshi meteorological station.

2.2. Estimation of extreme wind speed induced by extratropical cyclones

All of the strong wind events in which the center of tropical cyclone did not pass within 500 km from the site of interest are assumed to be caused by extratropical cyclones. Annual maximum wind speeds induced by extratropical cyclones are extracted and ranked in ascending order and named from u_1 to u_N. The probability distribution of annual maximum wind speed, i.e., non-exceedance probability of annual maximum wind speed can be written as equation (3).

$$F(u_i) = i/(N+1) \tag{3}$$

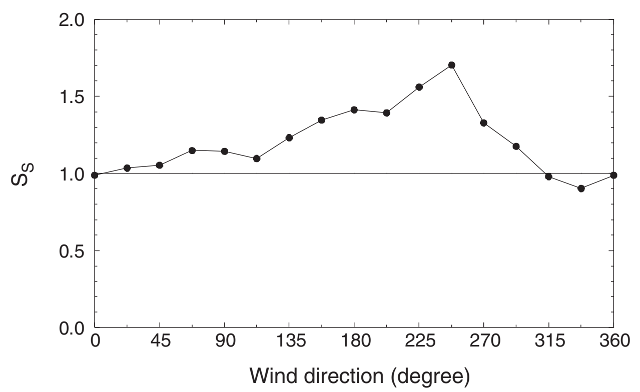

Figure 3. Variation of speed-up ratio of mean wind speed with wind direction.

Probability distribution of annual maximum wind speed induced by extratropical cyclones can be approximated by Gumbel distribution. In this case, the expected value u_E of annual maximum wind speed can be expressed as follows.[9]

$$u_E = V + \sigma_P(y - \gamma)/(\pi/6) \tag{4}$$

Here, V and σ_P are the average value and the standard deviation of annual maximum wind speed, γ is the Euler constant (=0.57722) and y is the reduced variate and can be calculated as

$$y_i = -\ln(-\ln(F(u_i))). \quad (5)$$

Figure 4 shows the comparison of estimated probability distribution based on the Gumbel distribution and the measurement. The uncertainty of the estimated probability distribution with the confidence interval of +/−1σ, is also calculated on the basis of the standard deviation shown in equation (31) and plotted in Figure 4. The relationship between the non-exceedance probability $F(u)$ of the annual maximum wind speed and the recurrence period R can be written as

$$F(u) = 1 - 1/R. \quad (6)$$

From the equations (5) and (6), the reduced variate that corresponds to 50 year recurrence period is calculated to be 3.9

2.3. Extreme wind speed induced by tropical cyclones

In some years, no tropical cyclone passes close to the site of interest, causing the annual maximum wind speed induced by tropical cyclone to be 0 m s^{-1}. In this case, the conventional Gumbel distribution cannot be applied directly. In this study, a mixed probability distribution F_{mod} is proposed for the annual maximum wind speed induced by tropical cyclones.

$$F_{\text{mod}} = F_{\text{zero}} + F_{\text{nonzero}} \quad (7)$$

F_{zero} is the probability distribution for the years when the annual maximum wind speed is 0 m s^{-1} and shown as follows.

$$F_{\text{zero}} = n_0/n \quad (8)$$

where n_0 is the number of years when the annual maximum wind speed is 0 m s^{-1} and n is the total number of years. F_{nonzero} is the probability distribution for the other years and assumed to follow the Gumbel distribution.

$$F_{\text{nonzero}}(u) = (n - n_0)/n \times G(u) \quad (9)$$

Assuming the mixed probability distribution, the annual maximum wind speed induced by tropical cyclones can be estimated by using equation (10) with the modified reduced variate $y^{'}$ as shown in equation (11)

$$u_T = V + \sigma_p\left(y^{'} - \gamma\right)/\left(\pi/\sqrt{6}\right) \quad (10)$$

$$y^{'} = -\ln(-\ln(F_{\text{nonzero}} \times n/(n - n_0))) \quad (11)$$

where V and σ_p are the mean value and the standard deviations of the annual maximum wind speeds for the years when the annual maximum wind speed is not 0 m s^{-1}. When $n_0 = 0$, proposed model is identical to the Gumbel distribution.

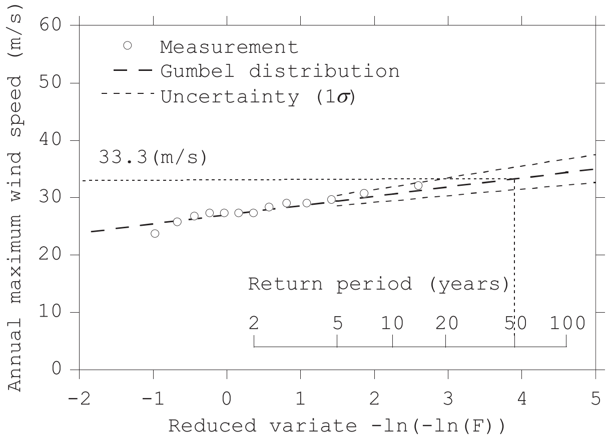

Figure 4. Comparison of predicted and observed extreme wind speeds induced by extratropical cyclones.

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Figure 5 shows the probability distribution of the annual maximum wind speed induced by tropical cyclones. The white circles denote the measured annual maximum wind speed induced by tropical cyclones for 13 years, and the dashed line denotes the proposed model. The uncertainty of the estimated probability distribution is also calculated as in Figure 4 and shown in Figure 5. Proposed model shows good agreement with the measurement for the recurrence period shorter than 5 years, whereas large uncertainty is found for recurrence period longer than 5 years. This is due to the large uncertainty in the estimation of the probability distribution.

2.4. Extreme wind speed in mixed climate

In mixed climate region, examination of each significant wind-producing meteorological phenomena is carried out followed by synthesis of the individual mechanisms into a combined extreme wind speed distribution.[2] When $F_E(u_E)$ and $F_T(u_T)$ are the probability distribution of annual maximum wind speed induced by extratropical and tropical cyclones, respectively, the combined probability distribution $F_C(u_C)$ can be written as

$$F_C(u_C) = F_E(u_E) \times F_T(u_T). \tag{12}$$

Figure 6 shows the combined probability distribution calculated by equation (12). The combined probability distribution shows good agreement with measurement for the recurrence period shorter than 5 years, but large uncertainties may be included for longer recurrence period. The uncertainty of the estimated combined probability distribution is calculated on the basis of equation (36).

3. ESTIMATION OF EXTREME WIND SPEED BY MONTE CARLO SIMULATION

Estimation of extreme wind speed by MCS is expected to have smaller uncertainty than those based on measurement because simulation for longer periods (e.g., 10,000 years) is possible. In this section, an MCS of tropical cyclones proposed by Ishihara *et al.*[10] is described, and application of this method to the offshore site is shown.

The flowchart of the MCS of tropical cyclones is shown in Figure 7. First, five tropical cyclone parameters (central pressure depth, radius of maximum wind speed, translation speed and direction, and minimum distance) are evaluated from a historical track record of past tropical cyclones. Then, synthetic tropical cyclones are generated for longer periods to satisfy the probability distributions and their correlations using a modified orthogonal decomposition (MOD) method. Gradient wind speeds are estimated from the pressure distribution of the synthetic tropical cyclones, and surface wind speeds are predicted considering the topography and roughness. Finally, the extreme wind distributions of tropical cyclones are estimated.

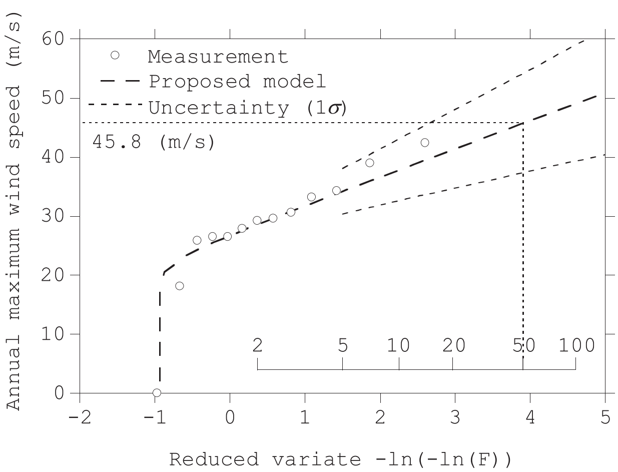

Figure 5. Comparison of predicted and observed extreme wind speeds caused by tropical cyclones.

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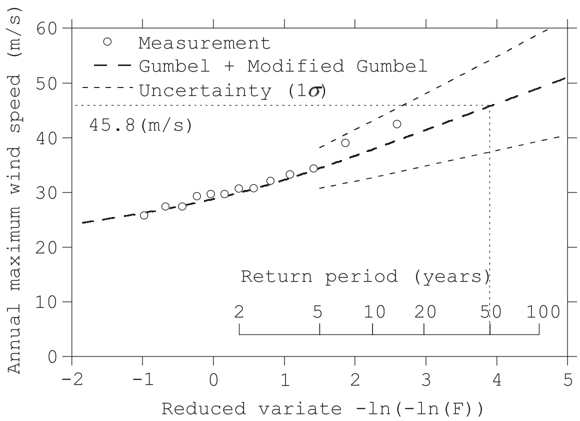

Figure 6. Comparison of predicted and observed extreme wind speeds in mixed climate by the MCP method.

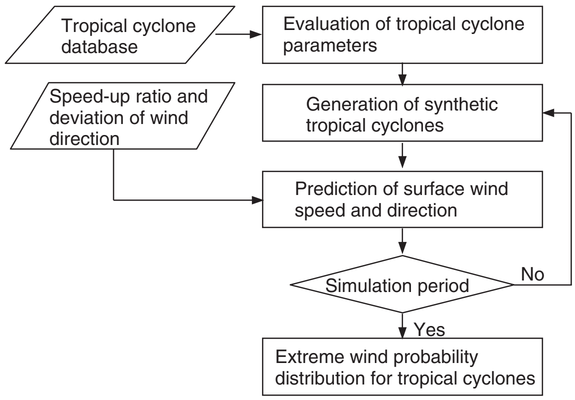

Figure 7. Flowchart of the Monte Carlo simulation of tropical cyclones.

3.1. Estimation of the tropical cyclone parameters

Tropical cyclone parameters are estimated on the basis of the historical track record of tropical cyclones provided by Japan Meteorological Agency from 1961 to 2007, which includes the surface pressure measurement data and digitized weather chart for same period.

The number of tropical cyclones per year λ is defined as the number of tropical cyclones passed within the simulation circle with the radius of 500 km from the site of interest and estimated from the historical track record. The central pressure p_C, translation speed and direction C and θ, and the minimum distance $d_{\min}$ are also estimated from the historical track record. The radius of maximum wind speed R_m is estimated by the pressure model proposed by Schloemer:[11]

$$\frac{p(r) - p_c}{p_\infty - p_c} = \exp\left(\frac{R_m}{r}\right) \tag{13}$$

where $p(r)$ is the surface pressure at the distance r from the center of the tropical cyclone. In this study, R_m is estimated by least square method so that the error between the pressure model and the measured surface pressure is minimized. The ambient pressure p_∞ can also be estimated by the least square method, in which case, the central pressure depth is calculated by $\Delta p = p_\infty - p_C$.

In this study, the five tropical cyclone parameters and the number of tropical cyclones per year are modeled by using the probability distribution functions shown in Table I. The definition typhoon direction θ is 0° for southbound tropical cyclone and measured counterclockwise. Δp, R_m and C are modeled by mixed probability of log normal and Weibull distributions (Ishihara *et al.*[10]), θ by normal distribution (Vickery and Twisdale[12]), $d_{\min}$ by quadratic function and λ by Poisson

Table I. Probability distribution and distribution functions of tropical cyclone parameters.

Parameter	Type	Probability density function	Value at Choshi
Central pressure depth Δp (hPa)	Mixed	$f_{\mathrm{M}}(x) = a \times \frac{1}{\sqrt{2\pi}\sigma_{\ln x}} \exp\left[-\frac{1}{2}\left(\frac{\ln x - \mu_{\ln x}}{\sigma_{\ln x}}\right)^2\right] + (1-a) \times \frac{k}{c}\left(\frac{x}{c}\right)^{k-1} \exp\left[-\left(\frac{x}{c}\right)^k\right]$	$\mu = 1.584$ $\sigma = 0.115$ $k = 4.158$ $c = 43.733$ $a = 1.000$
Radius of maximum wind speed R_m (km)			$\mu = 2.102$ $\sigma = 0.246$ $k = 1.917$ $c = 164.679$ $a = 0.521$
Translation speed C (m s^{-1})			$\mu = 1.657$ $\sigma = 0.227$ $k = 2.484$ $c = 57.481$ $a = 0.000$
Translation direction θ (degree)	Normal	$f_{\mathrm{N}}(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right]$	$\mu = 143.349$ $\sigma = 25.738$
Minimum distance $d_{\min}$ (km)	Polynomial	$x = zF_{\mathrm{p}}(x)^2 - (z - 2r)F_{\mathrm{p}}(x) - r$	$z = -409.980$ $r = 500.000$
Number of tropical cyclones per year λ	Poisson	$f_p(x) = \frac{\lambda_m^x \exp(-\lambda_m)}{x!}$	$\lambda_m = 2.787$

distribution. The model parameters estimated at Choshi meteorological station are also shown in Table I. The correlation coefficients between parameters are also calculated and shown in Table II.

3.2. Generation of synthetic tropical cyclones

Synthetic tropical cyclones are generated for *N* years to satisfy the modeled probability distributions and the correlations of tropical cyclone parameters. The change in pressure field of tropical cyclones during one event can be neglected since wind speeds and directions are estimated only when tropical cyclones are located inside the simulation circle with a diameter of 500 km. A MOD method proposed by Ishihara *et al.*[10] is used to satisfy the statistical distribution of each parameters and the correlations between them. The detailed procedure of the MOD method is described in the succeeding text. Five parameters describing a tropical cyclone are normalized and written in vector form as follows:

$$\mathbf{x}^T = \{\ln(\Delta \mathrm{p}), \ln(R_m), \ln(C), \theta, d_{\min}\}. \tag{14}$$

The covariance matrix of $\mathbf{x}$ is defined as $\mathbf{S}$. The eigenvalues $\lambda^{(k)}$ and the eigenvectors $\mathbf{\Phi}^{(k)}$ are calculated by solving the following equation:

$$\left[\mathbf{S} - \lambda^{(k)}\mathbf{E}\right]\mathbf{\Phi}^{(k)} = 0. \tag{15}$$

The independent parameters z_i with five components are then generated following the approximated distributions to the intended ones for specified years and the number of the generated vectors following the estimated annual occurrence rate. The correlated parameters $\mathbf{x}_i$ can be obtained by the following equation:

Table II. Correlation coefficients between measured tropical cyclone parameters.

	$\ln(\Delta p)$	$\ln(R_m)$	$\ln(C)$	θ	$d_{\min}$
$\ln(\Delta p)$	1.00	−0.37	−0.02	−0.03	0.27
$\ln(R_m)$	−0.37	1.00	0.42	−0.06	−0.28
$\ln(C)$	−0.02	0.42	1.00	−0.31	−0.27
θ	−0.03	−0.06	−0.31	1.00	−0.35
$d_{\min}$	0.27	−0.28	−0.27	−0.35	1.00

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$$\mathbf{x}_i = \left[\boldsymbol{\Phi}^{(1)} \;\; \boldsymbol{\Phi}^{(2)} \;\; \cdots \;\; \boldsymbol{\Phi}^{(5)}\right]^{-1} z_i = 0. \tag{16}$$

These vectors $\mathbf{x}_i$ should be considered as a set of parameters for tropical cyclones. Although the correlation between each component of $\mathbf{x}_i$ satisfies the target correlations, their probability distributions do not follow the target ones. The $\mathbf{x}_i$ should be rearranged in ascending order and modified so that its probability distribution follows the target probability distributions. This operation hardly affects the correlations because it does not change the set of parameters.

Table III shows the correlations between generated tropical cyclone parameters by using the proposed modified orthogonal decomposition. These correlations show good agreement with the intended correlations shown in Table II. The probability distribution functions of generated parameters also show good agreement with the intended ones (Figure 8).

To verify the probability distribution models, the probability distribution of annual maximum gradient wind speed based on synthetic tropical cyclones is compared with that based on identified tropical cyclones. The gradient wind can be calculated assuming that pressure gradient force balances with centrifugal force and Coriolli's force:

$$\theta_G\left(\overrightarrow{\mathbf{x}}, t\right) = \pi - \phi \tag{17}$$

$$u_G\left(\overrightarrow{\mathbf{x}}, t\right) = \frac{C\sin(\theta - \phi) - fr}{2} + \sqrt{\left(\frac{C\sin(\theta - \phi) - fr}{2}\right)^2 + \frac{r}{\rho}\frac{\partial p}{\partial r}} \tag{18}$$

Table III. Correlation coefficients between estimated tropical cyclone parameters.

	$\ln(\Delta p)$	$\ln(R_m)$	$\ln(C)$	θ	$d_{\min}$
$\ln(\Delta p)$	1.00	−0.36	0.01	−0.03	0.25
$\ln(R_m)$	−0.36	1.00	0.38	−0.05	−0.27
$\ln(C)$	0.01	0.38	1.00	−0.28	−0.25
θ	−0.03	−0.05	−0.28	1.00	−0.35
$d_{\min}$	0.25	−0.27	−0.25	−0.35	1.00

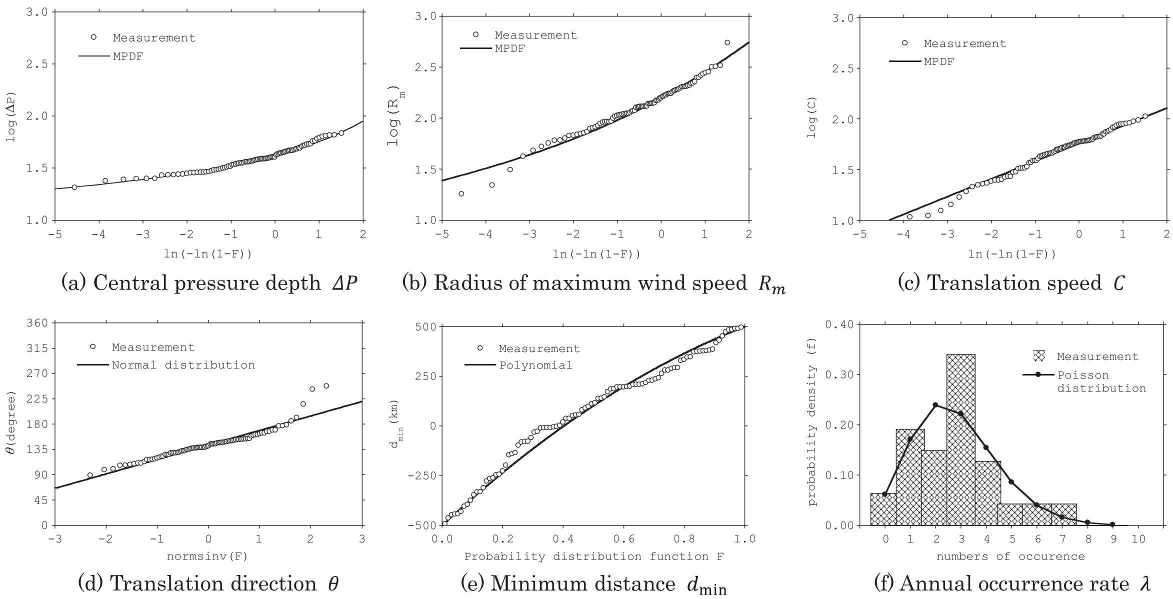

Figure 8. Comparison of probability density functions of tropical cyclone parameters and observed data.

where $\theta_G(\vec{\mathbf{x}}, t)$ and $u_G(\vec{\mathbf{x}}, t)$ are the gradient wind direction and speed, f is the Coriolis parameter, ρ is the air density and θ is the translation direction of the tropical cyclone.[4] $\vec{\mathbf{x}} = (r, \phi)$ is the location shown in polar coordinate the origin of which is at the center of the tropical cyclone.

Figure 9 shows the probability distribution of annual maximum gradient wind speed based on synthetic tropical cyclones and the identified tropical cyclones at Choshi meteorological station. The distribution based on synthetic tropical cyclones shows good agreement with that based on the identified ones.

3.3. Estimation of surface wind speed

The horizontal scale of a tropical cyclone is a few hundred kilometers. Meanwhile, the horizontal scale of topography is a few kilometers. In other words, the scale of the topography is so small compared with the scale of the typhoon that we can separate the effect of the topography from the effect of the tropical cyclone's pressure field. This concept is represented in the following equation for wind speed, $u_t(\vec{\mathbf{x}}, z, t)$, and the wind direction, $\theta_t(\vec{\mathbf{x}}, z, t)$.

$$u_t(\vec{\mathbf{x}}, z, t) = u_F(\vec{\mathbf{x}}, z, t) \times S_t(\vec{\mathbf{x}}, z) \tag{19}$$

$$\theta_t(\vec{\mathbf{x}}, z, t) = \theta_F(\vec{\mathbf{x}}, z, t) + D_t(\vec{\mathbf{x}}, z) \tag{20}$$

where $u_F(\vec{\mathbf{x}}, z, t)$ and $\theta_F(\vec{\mathbf{x}}, z, t)$ are the surface wind speed and direction caused by the tropical cyclone's pressure field on a flat terrain and will be explained later, and $S_t(\vec{\mathbf{x}})$ and $D_t(\vec{\mathbf{x}})$ are the speedup and the change in wind direction as functions of wind direction sector i which can be evaluated by flow simulation as follows.

$$S_t(\vec{\mathbf{x}}, z) = \frac{U_{Ti}(\vec{\mathbf{x}}, z)}{U_{Fi}(\vec{\mathbf{x}}, z)} \tag{21}$$

$$D_t(\vec{\mathbf{x}}, z) = \Theta_{Ti}(\vec{\mathbf{x}}, z) - \Theta_{Fi}(\vec{\mathbf{x}}, z) \tag{22}$$

where $U_{Ti}(\vec{\mathbf{x}}, z)$ and $\Theta_{Ti}(\vec{\mathbf{x}}, z)$ are the wind speed and direction over real terrain and $U_{Fi}(\vec{\mathbf{x}})$ and $\Theta_{Fi}(\vec{\mathbf{x}})$ are those over flat terrain estimated by flow simulations. The idea of the proposed method is shown graphically in Figure 10.

The vertical profile of wind speed and the change in wind direction over flat terrain with constant surface roughness is given in an exponential form as follows.

$$u_F(\vec{\mathbf{x}}, z, t) = u_G(\vec{\mathbf{x}}, t)\left(\frac{z}{z_g}\right)^{\alpha_u} \tag{23}$$

$$\theta_F(\vec{\mathbf{x}}, z, t) = \theta_G(\vec{\mathbf{x}}, t) + \gamma_s\left(1.0 - 0.4\frac{z}{z_g}\right)^{1.1} \tag{24}$$

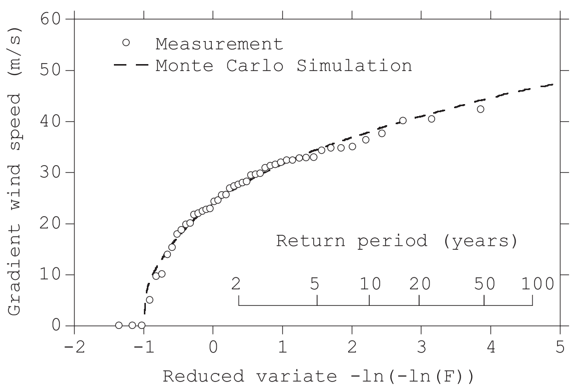

Figure 9. Probability distribution of annual maximum gradient wind speed based on synthetic tropical cyclones and identified tropical cyclones at Choshi meteorological station.

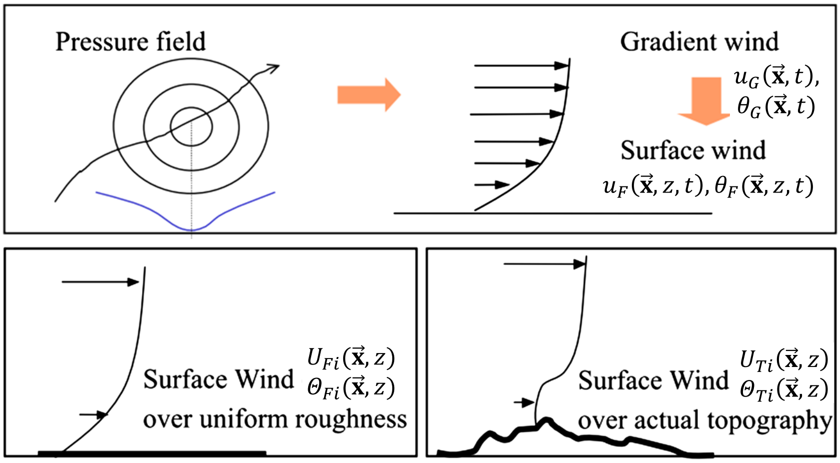

Figure 10. Estimation of surface wind speed.

Here,

$$\alpha_u = 0.27 + 0.09\log(z_0) + 0.018\log^2(z_0) + 0.0016\log^3(z_0) \tag{25}$$

$$z_g = 0.052\frac{u_G(\vec{x},t)}{f_\lambda}(\log Ro_\lambda)^{-1.45} \tag{26}$$

$$\gamma_s = (69 + 100\,\xi)(\log Ro_\lambda)^{-1.13} \tag{27}$$

$$f_\lambda = \left(\frac{\partial u_G(\vec{x},t)}{\partial r} + \frac{u_G(\vec{x},t)}{r} + f\right)^{1/2}\left(2\frac{u_G(\vec{x},t)}{r} + f\right)^{1/2} \tag{28}$$

$$\xi = \left(2\frac{u_G(\vec{x},t)}{r} + f\right)^{1/2} \Bigg/ \left(\frac{\partial u_G(\vec{x},t)}{\partial r} + \frac{u_G(\vec{x},t)}{r} + f\right)^{1/2} \tag{29}$$

where $Ro_\lambda\left(= u_G(\vec{x},t)/f_\lambda z_0\right)$ is a non-dimensional parameter called modified surface Rossby number, f is the Coriolis parameter and z_0 is the surface roughness length. This model is a semi-theoretical formulae showing the relationship among the exponent of vertical profile, gradient wind height, change in wind direction, surface roughness length and the characteristic of tropical cyclone while having the advantage of exponential form widely used in wind engineering field.

In this study, the wind speed and direction over flat terrain was estimated assuming the exponent $\alpha_u = 0.1$ according to ISO4354.[13] The wind speed and the direction at the offshore site affected by surrounding terrain were estimated by using equations (19) and (20) obtained from the flow simulation. Figure 11 shows the speedup at the offshore site relative to the flat terrain for each wind direction. When the wind direction is between 67.5° and 180°, the speedup is almost equal to 1.0 as the wind blows from sea. For the other wind directions, the speedup is significantly smaller then 1.0 and strongly affected by land. This means that near the coastline, the surface roughness is uneven and the effect of topography and surface r-oughness have to be taken into consideration.

The wind speed estimated by MCS has the averaging time of 3 h.[14] To estimate the 10 min average extreme wind speed, this difference in averaging time has to be considered. Yasui *et al.*[14] showed that the difference of 3 h average wind speed and 10 min average wind speed can be modeled as normal distribution and the standard deviation σ_a of which can be written as follows:

$$\sigma_a = 0.1 \times u_T. \tag{30}$$

The coefficient 0.1 is the value proposed by Yasui *et al.*[14] Yamaguchi *et al.*[15] showed this value changes depending on the averaging time.

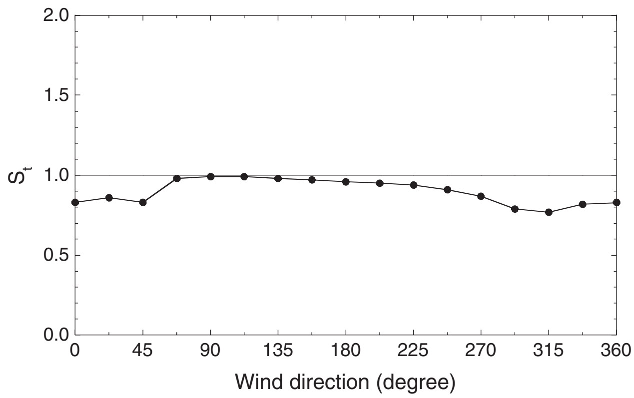

Figure 11. Variation of speed-up ratio of mean wind speed with wind direction.

Figure 12 shows the probability distribution of annual maximum wind speed based on Monte Carlo simulation. The estimated distribution shows good agreement with the measurement. The uncertainty of the estimated probability distribution is calculated as the sum of the uncertainty related to the length of simulation and related to the length of the pressure measurement, as shown in equation (34). Clearly, the uncertainty decreases compared with Figure 5.

Not only 50 year recurrence wind speed, but also the exponent of vertical wind speed profile and turbulence intensity are needed for the estimation of wind load on wind turbines. In this study, the average wind direction for the wind direction between 50 year recurrence wind speed -0.5 and $+0.5\,\mathrm{m\,s^{-1}}$ was calculated and used for the estimation of vertical wind speed profile and the exponent of turbulence intensity. In this site, this wind direction is southerly, and the exponent and the turbulence intensity are 0.1 and 0.11, respectively.

3.4. Extreme wind speed in mixed climate

The extreme wind speed in mixed climate are estimated considering the extreme wind speed induced by tropical and extratropical cyclones using the method described in Section 2.4. The mixed probability distribution of annual maximum wind speed based on the distribution estimated by using MCS for tropical cyclone and the distribution estimated by using MCP method for extratropical cyclones is shown in dotted line in Figure 13. The calculation of the uncertainty of the probability distribution is based on equation (36). The mixed probability distribution shows good agreement with measurement for wide range of recurrence period. After obtaining the mixed distribution, the 50 year recurrence wind speed is $48.1\,\mathrm{m\,s^{-1}}$, which is the same as the value for only tropical cyclone case (Figure 12). This indicates that for this site, the tropical cyclone dominates the extreme wind speed with recurrence period of 50 years. As shown in Figure 6, the 50 year recurrence wind speed estimated by MCP method ($45.8\,\mathrm{m\,s^{-1}}$) is smaller than the value by proposed method, and it is necessary to use the MCS to estimate the extreme wind speed induced by tropical cyclones.

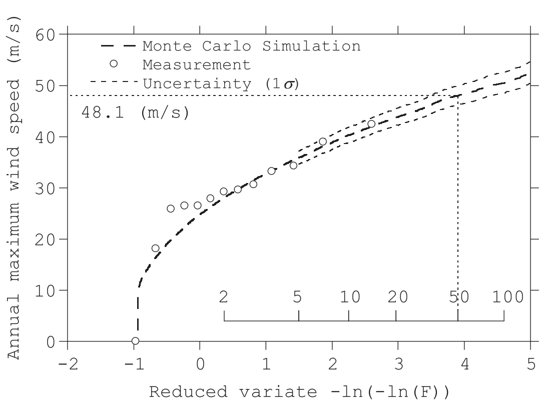

Figure 12. Probability distribution of annual maximum wind speed estimated by using MCS and measurement data.

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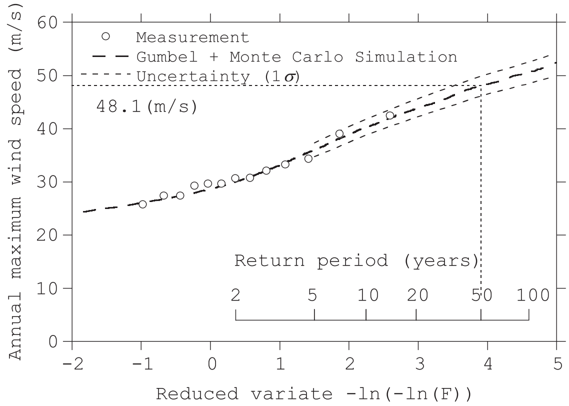

Figure 13. Comparison of predicted and observed extreme winds in mixed climate by the MCS method.

4. THE UNCERTAINTIES OF EXTREME WIND SPEED

The sources of the uncertainty of the extreme wind speed estimated by MCS are the limited number of annual maximum wind speed and the limited length of the pressure measurement data used for the estimation of the tropical cyclone parameters. In this section, the standard deviations of 50 year recurrence wind speeds are investigated to examine theses uncertainties of extreme wind speed. Formulae to evaluate the extreme wind speed considering the uncertainties are also proposed for both tropical and extratropical cyclones.

4.1. The uncertainties of extreme wind speed related to the number of annual maximum wind speed

According to Gumbel,[9] the variance of extrapolated extreme wind speed can be estimated by

$$\sigma_u^2 = \frac{\sigma_N^2}{N}\left[1 + 0.885(y-\gamma) + 0.6687(y-\gamma)^2\right] \tag{31}$$

where N is the number of the annual maximum wind speed, σ_N is the standard deviation of annual maximum wind speed and y is the reduced variate for the recurrence period of interest. This equation shows that the uncertainty of the predicted extreme wind speed increases when the number of annual maximum wind speed decreases or the standard deviation of the annual maximum wind speed increases.

The applicability of this equation is investigated by using 10,000 annual maximum wind speeds obtained from the Monte Carlo simulation. The 10,000 annual maximum wind speeds are divided into 10,000/ N subsets, each having N annual maximum wind speeds. On the basis of each subsets, 50 year recurrence wind speeds are calculated. Then, the standard deviation of these 50 year recurrence wind speeds are calculated and plotted against N in Figure 14. In this study, N was taken as 100, 200, 500, 1000 and 2000. Theoretical values of the standard deviations of predicted 50 year recurrence wind speed estimated by using equation (29) is also plotted in Figure 14 with a dotted line. Both the estimated standard deviation and the theoretical values decreases with the number of the measurement data (N) and show good agreement with each other. Using this model, the uncertainty of extreme wind speed predicted from 10,000 annual maximum wind speed is estimated as 0.3 m s^{-1} (0.6% of the estimation).

The uncertainty of the estimated extreme wind speed does not only depend on the number of annual maximum wind speed but also the standard deviation (σ_N) of the original extreme wind speed. This causes the difference of uncertainty of extreme wind speed induced by extratropical cyclones and the tropical cyclones even for the same recurrence period. For example, the standard deviation of 50 year recurrence wind speed at Choshi meteorological stations is 1.9 m s^{-1} (5.7% of estimation) for extratropical cyclone, whereas it shows the larger value of 5.7 m s^{-1} (12.4% of estimation) for tropical cyclones (Figure 16).

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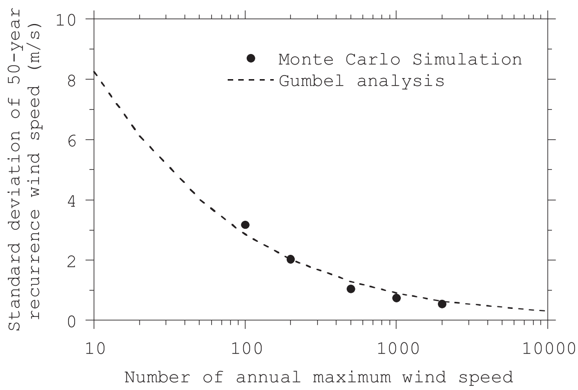

Figure 14. Comparison of standard deviation of 50 year recurrence wind speed obtained by the MCS method and Gumbel theory.

4.2. The effect of the pressure measurement period on the uncertainty of the extreme wind speed

In the Monte Carlo simulation, the tropical cyclone parameters are estimated on the basis of the pressure measurement data, which also affects the uncertainty of the extreme wind speed. To evaluate this effect, a relationship between the length of the pressure measurement and the 50 year recurrence wind speed is investigated.

The pressure measurement data for 47 years (from 1961 to 2007) are divided into five subsets, each having 10 years of measurement data. On the basis of each subset, tropical cyclone parameters are estimated, and MCS was carried out to estimate the extreme wind speed. The same were carried out by using the subsets each having 20, 30, 40 years.

The standard deviation σ_p and the coefficient of variation $\gamma_p(=\sigma_p/u_T)$ of the extreme wind speed with recurrence period of 50, 100 and 500 years were calculated for different length of the pressure measurement and shown in Figure 15. The coefficients of variations do not depend on the recurrence period and decrease as the length of the pressure measurement increases. In this study, this coefficient of variation was modeled by using following equation.

$$\gamma_p = 0.004\exp(-0.2(Y-21)) + 0.031, Y \geq 10 \tag{32}$$

Here, Y denotes the length of pressure measurement. When the pressure measurement period is 10 years, the coefficient of variation is 4.1%. The coefficient of variation decreases as the pressure measurement period becomes longer, and when 30 years or more pressure measurement were used, the coefficient of variation approaches to 3.0%. In this case, the value of σ_p (1.5 m s^{-1}) is larger than the standard deviation σ_u (0.3 m s^{-1}) resulting from the number of annual maximum wind speed (10,000 years), indicating that the former uncertainty is dominant.

It should be noted that the standard deviation of the 50 year recurrence wind speed induced by tropical cyclones estimated directly from the measured annual maximum wind speeds for 13 years is 5.7 m s^{-1}, which is larger than the value

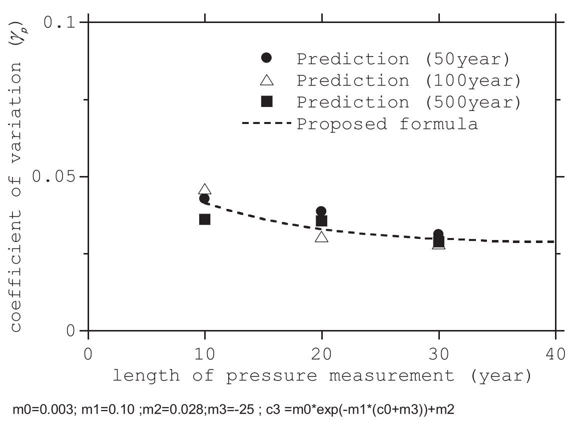

Figure 15. Relationship between a coefficient of variation of 50 year recurrence wind speed and the length of pressure measurement.

estimated by using MCS based on the pressure measurement data for 10 years. Clearly, the use of MCS reduces the uncertainty of the extreme wind speed.

Generally, the total uncertainty (σ_T) of the extreme wind speed estimated by using MCS can be written as,

$$\sigma_T = \sqrt{\sigma_u^2 + 2\beta\sigma_u\sigma_p + \sigma_p^2} \tag{33}$$

where β is the correlation coefficient between two uncertainties and takes the value between 0 and 1. As the most conservative case, β is assumed to be 1, and the total standard deviation can be written as

$$\sigma_T = \sigma_u + \sigma_p = \sigma_u + \gamma_p u_T. \tag{34}$$

Thus, when 47 years of the pressure measurement data was used to estimate the tropical cyclone parameters σ_p (1.5 m s^{-1}) and 10,000 years of MCS was carried out σ_u (0.3 m s^{-1}), the total uncertainty σ_T can be estimated to be 1.8 m s^{-1}. This value is comparable with the standard deviation of annual maximum wind speed estimated by MCP approach with 50 year recurrence period for the extratropical cyclones as shown in Figure 16.

4.3. Estimation of extreme wind speed considering the uncertainties

Generally, the design extreme wind speed ($\hat{u}_C$) considering the uncertainty can be written as

$$\hat{u}_C = u_C + k\sigma_C \tag{35}$$

where u_C is the extreme wind speed without considering the uncertainty, σ_C is the standard deviation of the predicted extreme wind speed and k is a constant value.

In the estimation of σ_C, both tropical and extra tropical cyclone has to be considered. In this study, the following equation is proposed to estimate σ_C.

$$\sigma_C = \alpha\sigma_E + (1-\alpha)\sigma_T \tag{36}$$

where σ_E and σ_T are the standard deviations of the extreme wind speed induced by extratropical and tropical cyclones, respectively. The weight factor α shows dominant phenomena for the extreme wind speed and can be calculated by following equation.

$$\alpha = (u_C - u_T)/[(u_C - u_T) + (u_C - u_E)] \tag{37}$$

When tropical cyclones are dominant, ($u_C = u_T$), the weight factor α becomes 0. On the other hand, when extratropical cyclones are dominant ($u_C = u_E$), the weight factor α becomes 1. The weight factor α for different recurrence period R is shown in Figure 17. For long recurrence periods, tropical cyclones are dominant, and the weight factor α is close to 0. On the other hand, the extratropical cyclones are dominant for shorter recurrence period, and the weight factor α is close to unity.

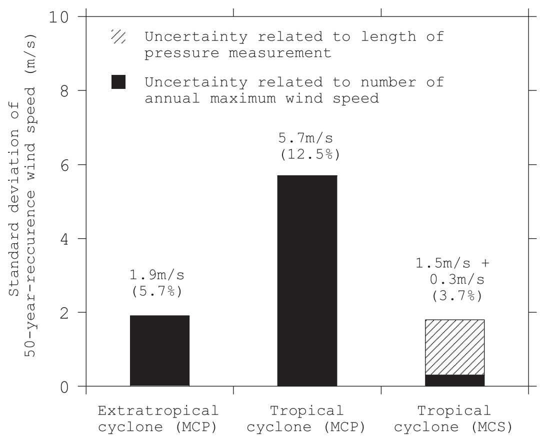

Figure 16. Comparison of standard deviation of 50 year recurrence wind speed.

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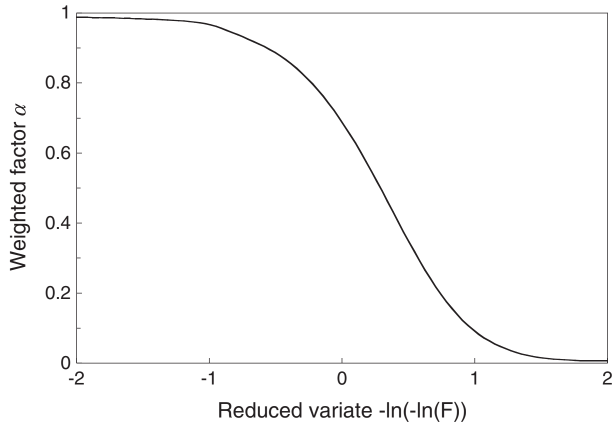

Figure 17. The weighting factor as a function of recurrence period.

Table IV. Fifty-year-recurrence wind speed with and without considering the uncertainties estimated by MCP and MCS methods.

Extreme wind speed	MCP	MCS
u_C (without uncertainties)	45.8 m s^{-1}	48.1 m s^{-1}
$\hat{u}_C$ (with uncertainties)	51.5 m s^{-1}	49.9 m s^{-1}

Table IV shows the comparison of the extreme wind speeds with 50 year recurrence period estimated with and without considering the uncertainties. Here, the parameter k is assumed to be 1.0. Without considering the uncertainties, the MCS estimates the extreme wind speed as 48.1 m s^{-1}, whereas the estimated extreme wind speed from 13 years of measurement data by using MCP method is 45.8 m s^{-1}. This means that the use of the limited number of the measurement data without considering the uncertainties may underestimate the extreme wind speeds. If the uncertainties are taken into consideration, the estimated extreme wind speed based on 13 years of measurement data shows 51.5 m s^{-1}, which is higher than that estimated by Monte Carlo simulations (49.9 m s^{-1}).

The uncertainty of the extreme wind speed is strongly related with the partial safety factor used in design. The partial safety factor in IEC61400-1 is based on the assumption that the uncertainty of the extreme wind speed is 10%.[16] When MCS is used, the uncertainty of the extreme wind speed is less than 10%, and additional uncertainty does not have to be considered. However, if tropical cyclone-induced extreme wind speed is predicted directly by using the 10 years of wind speed measurement data, without considering additional uncertainty, extreme wind speed may be underestimated.

5. CONCLUSIONS

The estimation of the extreme wind speed by MCS of tropical cyclones and 'measure-correlate-predict' methods were investigated and verified by comparing with the measurement. The uncertainties related to the number of annual maximum wind speeds and the length of the pressure measurement data are quantitatively evaluated, and a method to estimate the extreme wind speed including those uncertainties are proposed. The following results were obtained:

1. Conventional MCP method with Gumbel fitting shows good performance for the estimation of extreme wind speed induced by extratropical cyclones but shows large uncertainty for the extreme wind speed induced by tropical cyclone, which implies the possibility of underestimation. In the mixed climate region, extreme wind speed based on about 10 years of measurement annual maximum wind speed may be underestimated.
2. The proposed MCS of tropical cyclones can accurately estimate the probability distribution of annual maximum wind speed induced by tropical cyclones. This means that MCS method is needed for the estimation of the extreme wind speed in the mixed climate region.
3. When conventional MCP and Gumbel fitting is used, a larger uncertainty is introduced in the estimation of extreme wind speed induced by them that induced by tropical cyclones.

4. The uncertainty of the MCS is dominated by the limited period of the pressure measurement for the estimation of tropical cyclone parameters. The total uncertainty in the estimation of extreme wind speed by MCS is comparable with the MCP and Gumbel fitting for extratropical cyclones.

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