Proceedings of the Ninth (2010) ISOPE Pacific/Asia Offshore Mechanics Symposium
Busan, Korea, November 14-17, 2010

ISBN 978-1-880653-79-1: ISSN 1946-004X. www.isope.org

Prediction of Extreme Wind Speed under the Background of Climate Change

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ABSTRACT

In this paper, 64-year tropical cyclone (TC) data in the Northwest Pacific (NWP) were analyzed to predict extreme wind speed under the background of climate change. The extreme value theory is presented in order to obtain extreme wind speed with different return periods in both stationary and non-stationary processes in the NWP. Results show that the non-stationary extreme wind speed of 50-year return periods is 3.2% higher than the stationary one in the NWP. As a result, it is proposed that the non-stationary effects of long-term variation in atmospheric general circulation should be considered in the offshore engineering standard or criterion revision.

KEY WORDS: Marine environment; Tropical cyclone; Climate change; Non-stationary; Extreme wind speed; Return period.

INTRODUCTION

The NWP is the place where the most frequent and intense TCs occur among the global sea areas, and the reliability of offshore structures in this area are heavily affected by TCs, which may bring strong winds and corresponding huge destructive waves inducing great damage of social property and economic. On the other hand, with the development of the human economy, the climate change induced by greenhouse gases (e.g. CO_2 and CH_4 et.al.) emission has become an unchangeable fact. The annual report released by IPCC (Intergovernmental Panel on Climate Change) in 2007 persuasively confirmed that the global temperature has risen by 0.74℃ in the past one hundred years (1906-2005). Under the background of climate change, the extreme marine events evidently occur more often than ever. For example, when the hurricanes of Katrina which is the most destructive natural disaster in American history (Demirbilek, 2010; D.H. Levinso et al., 2010)and Rita were haunting about the Mexico gulf in 2005, the 167 offshore platforms and 183 oil pipelines were destroyed, resulting in 40 percent oil production of Gulf of Mexico interruption. In the South China Sea (SCS), a great many of offshore structures were also threatened by super strong typhoons such as Zhenzhu in 2006. Very probably the above accidents can be attributed to the underestimation of marine environment parameters under the background of climate change, for instance, the designed wind speed with different return period in the ocean engineering. So how to reasonably estimate the extreme wind speed with different return period under the background of climate change become a challenging issue we have to confront, which will exert significant effect on the criterion revision of marine engineering constructions.

Many studies have been undertaken to estimate the TC extreme wind speed in the sea areas where offshore structures located. Poisson-Gumbel compound extreme value distribution had developed by Liu and Ma (1980) to compute the design wave height and wind speed and this method proved quite reasonable. Shi and Zhou (1999) used moment estimate to estimate parameters of wind speed distribution functions, which proved good for practical purposes. In 2005, Liu et al. used the further developed extreme value theory to analyze the long-term data of hurricane speeds and simultaneous water levels of Mississippi river. It is found that the return period of hurricane Katrina is 50 years rather than 200 years based on the former prevention design criteria. By using the 3-parameter Weibull distribution model, Qi et al. (2010) calculated the extreme wind, wave and current with different return periods in the SCS deepwater areas, intending to provide primary reference for design and management of ocean engineering.

Though such works already have been done in the past, there still exist some important and critical problems: how to take the non-stationary process influence into consideration in the estimation of extreme wind speed, which is become more and more important for ocean engineering under the background of climate change. In this paper, according to the analysis of 64-year TC database in the NWP, the TC activity is considered as a non-stationary process. By establishing the non-stationary extreme value model, this paper aims at obtaining the variation of extreme wind speed with different return period both in the NWP and providing instruction for offshore engineering construction.

The 64-year (1845-2008) TC data used in this paper is collected from China Meteorological Administration and the method for revising recorded TC wind speed data is introduced by Emanuel Kerry

(2005a).The paper is organized as following. First, extreme value theory and the method of parameter estimation are introduced. Then, non-stationary extreme value model was established and the extreme wind speed with different return periods in NWP was calculated.

EXTREM VALUE THEORY AND METHOD OF PARAMETER ESTIMATION

Extreme value theory

Extreme value theory is unique as a statistical discipline in that it develops techniques and models for describing the unusual rather than usual. So in this paper extreme value theory is used to estimate TC extreme wind speed in the NWP.

A brief introduction to extreme value theory is given below. Let ξ represents a random variable and its distribution function is *G(x)*. Designate ξ_i as the i[th] independent observation value of ξ ($i=1...n$), and let n be a random variable independent of ξ, with its range of value in positive integers. Let P{i=k}=P_k(k=1,2,…), and define the random variable ζ as:

$$\zeta = \operatorname*{Max}_{1\le i\le n}\{\xi_i\} \qquad i=1,...,n \tag{1}$$

Then, the distribution function of ζ is

$$F(\zeta)=\sum_{k=1}^{\infty}P_k[G(\zeta)]^k=1-R \tag{2}$$

For a given design frequency R, T=1/R is called the return period, e.g. if R=0.01, $\zeta_R = \zeta_{0.01}$ is the extreme value occurring once in 100 years.

Candidate distribution functions and parameter estimation methods

There are totally about 1440 TCs events in the NWP identified from 64-year time series of TC database and almost half of the TCs with maximum wind speed recorded in their lifetime are less than 30m/s. In this paper we force on the behavior of strong wind speed, so only TCs with lifetime maximum wind speed larger than 30m/s are counted in the following statistics. In the following text, when we refer to TCs, it means TCs with lifetime maximum wind speed larger than 30m/s. Because the number of TCs occurring in the NWP is positive integers varying each year, the TC annual frequency forms a discrete distribution. The TC wind speed may be considered as a kind of continuous distribution as there are a large number of TCs occurring in 64 years. Applying the above conclusion in this paper, the TC frequency is noted as random variable n and the wind speed is noted as ξ, their corresponding distribution functions are P_k and *G(x)* respectively.

Based on the statistical analysis of the number of TCs occurring each year in the NWP, we found that the TC frequency fits to Poisson distribution (Fig. 1):

$$P_k=\frac{e^{-\lambda}\lambda^k}{k!} \tag{3}$$

where λ is the average number of TC frequency. From Fig. 1 we can see that the minimum number of TC occurring in one year is 7 and the maximum number is 23.When the TC annual frequency fits to Poisson distribution, the distribution of $\hat{V}$, which is defined as the annual maximum wind speed will have a simple form as Eq. 4.

$$F(\hat{V})=\sum_{k=0}^{\infty}p_k[G(\hat{V})]^k=\sum_{k=0}^{\infty}e^{-\lambda}\frac{\lambda^k}{k!}[G(\hat{V})]^k=e^{-\lambda[1-G(\hat{V})]}=1-R \tag{4}$$

where G(x) is the wind speed distribution function.

There are three candidate distribution functions list below that are commonly used describing the wind speed distribution:

Gumbel distribution: $$G(v\le V)=\exp[-\exp(-\frac{V-\beta}{\gamma})] \tag{5}$$

Exponential distribution: $$G(v\le V)=1-\exp(-\frac{V-\beta}{\gamma}) \tag{6}$$

Weibull distribution: $$G(v\le V)=1-\exp[-(\frac{V-\beta}{\gamma})^{\alpha}] \quad \alpha>0 \tag{7}$$

where α, β and γ are shape parameter, location parameter and scale parameter of the wind speed distribution functions.

Many methods can be applied to estimate the parameters of the wind speed distribution functions, such as the least-square method and moment estimation. In this paper, the least-square method is used to determine the parameters α,β and γ in Eqs. 5 ~ 7 to select the most suitable candidate wind speed distribution function. In order to apply the least-square method for the parameter estimation of Candidate distribution functions, Eqs. 5 ~ 7 need to be transformed into the linear form of

$$y=A*x+B \tag{8}$$

where A and B are coefficients related to parameters α, β and γ. Table 1 lists the three distribution functions linearly transformed from Eqs. 5 ~ 7.

Table 1: Eqs. 5 ~ 7 are transformed into the linear form of y=A*x+B.

	Gumbel	Exponential	Weibull
y	$\hat{V}$	$\hat{V}$	$\hat{V}$
x	-ln(-lnG)	-ln(1-G)	[-ln(1-G)]^(1/α)
A	β	β	β
B	γ	γ	γ

Based on the statistics of the 64 years TC database in the NWP, We compared the three candidate distribution functions using the least-square method in Fig. 2~4. We can see that the Gumbel and Exponential distribution functions can’t describe the wind speed distribution well and Weibull distribution function is a suitable choice.

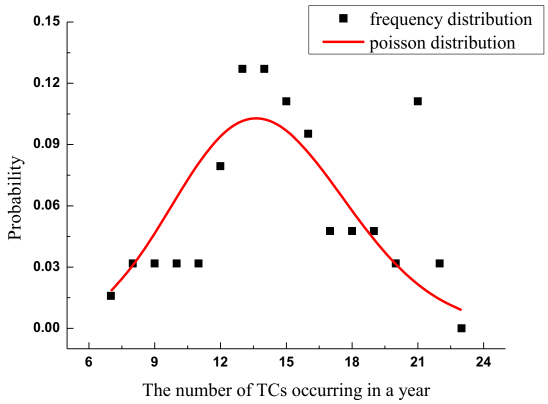


Fig. 1 Curve fitting of the TC frequency distribution

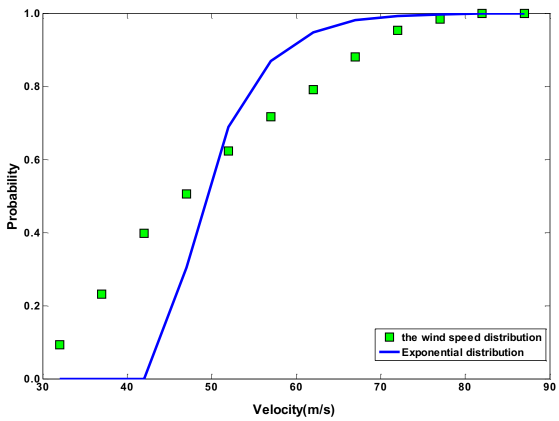


Fig. 2 Curve fitting of the TC wind speed distribution with Exponential distribution

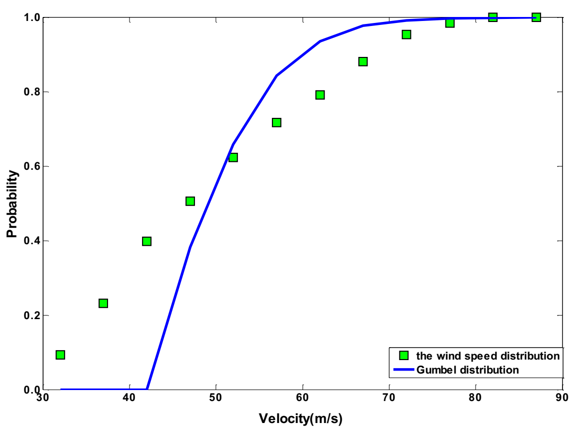


Fig. 3 Curve fitting of the TC wind speed distribution with Gumbel distribution

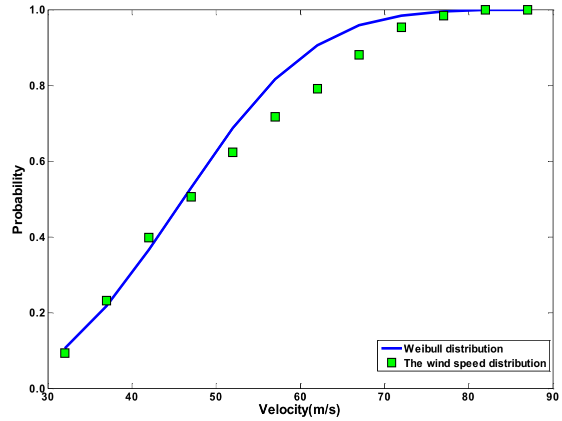


Fig. 4 Curve fitting of the TC wind speed distribution with Weibull distribution

For Weibull distribution function, moment estimation method can also be used to calculate parameters as blow, and this method will reveals the physical meaning of three parameters.

$$C_a = \frac{\mu_3}{\sigma^3} = g(\Gamma(\alpha)) \tag{9}$$

$$\gamma = \frac{\sigma}{\sqrt{d(\Gamma(\alpha))}} \tag{10}$$

$$\beta = \overline{V} - \gamma \times e(\Gamma(\alpha)) \tag{11}$$

where Ca is the coefficient of skewness; μ_3 is the third central moments; $\Gamma(\alpha)$ is the gamma function of shape parameter α; $\overline{V}$ and σ are the mean and standard deviation of wind speed respectively. From Eqs. 10~11 we can see that the location parameter β and scale parameter γ of Weibull distribution function are physically connected to the mean and standard deviation of TC wind speed. Non-stationary TC activity will arouse the mean and standard deviation of TC wind speed variation with time, which will exert effort on the parameters estimation of Weibull distribution. So it makes good sense to use the moment estimation method of definite physical significance for non-stationary process. When substituting Weibull distribution in to Eq. 4, by inverse solution we can get the extreme wind speed with different return period.

$$\hat{V} = [-\ln(-\frac{1}{\lambda}\ln(1-R))]^{\frac{1}{\alpha}} \times \gamma + \beta \tag{12}$$

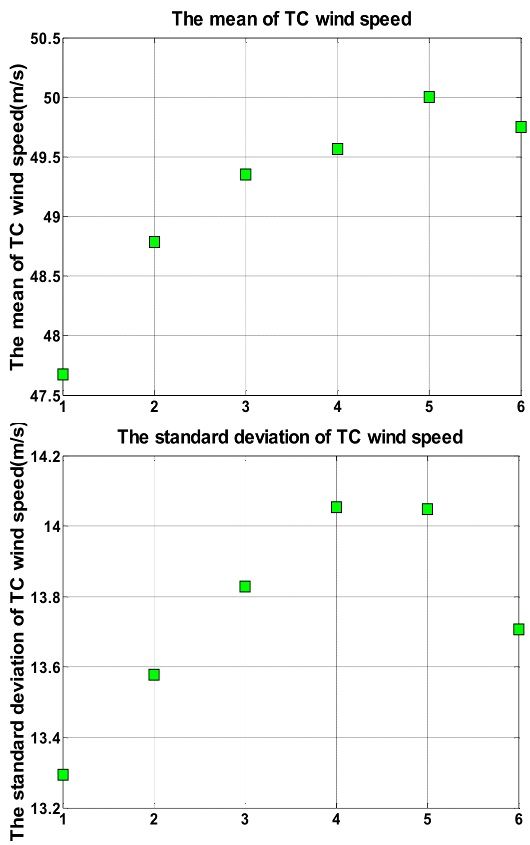
where R is the probability that the wind speed exceed the certain extreme wind speed, if R=0.01, then $\hat{V}$ is the extreme wind speed with 100-year return period.

NON-STATIONARY EXTREME VALUE MODEL

The non-stationary variation of TC activity

Non-stationary processes have characteristics that change systematically through time (Coles, 2001). In the context of TC activity, non-stationary feature is apparent because of the rising sea surface temperature (SST). From above analysis we know that TC annual frequency fits to Poisson distribution and Weibull distribution is a suitable description for wind speed distribution. So the apparent trend in the 64-year TC data raises doubts about the suitability of the extreme model which assumes a constant distribution through time. So in the parameter estimation process, assuming all the three parameters of Weibull distribution are constant during time changing may be unsuitable.

By dividing the 64-year TC data into 6 sections: 1945-1983, 1950-1988, …, 1970-2008 with each section 38 years, we calculate the mean and standard deviation of TC wind speed and the average numbers of typhoon occurring in one year in each section. As showing in Fig. 5, the mean and standard deviation of TC wind speed and the number of TC occurring in one year are all showing increase trend in the NWP.



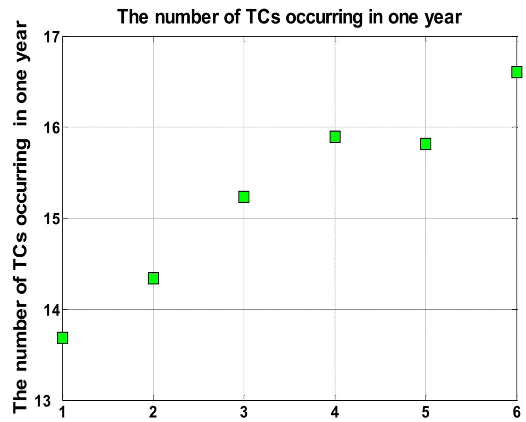


Fig. 5 The variation of mean and standard deviation of wind speed and the frequency of TCs in the NWP

The nonstationary extreme value model

According to experience, we assume shape parameter α of Weibull distribution as a constant, and then the location parameter β and scale parameter γ changing with time can be obtained based on the modified Eqs. 13~14. The variation of location parameter β and scale parameter γ is shown in Fig. 6.

$$\gamma(t) = \gamma_0 \frac{\sigma(t)}{\sqrt{d(\Gamma(\alpha))}} \tag{13}$$

$$\beta(t) = \bar{V}(t) - \beta_0 \times \gamma(t) \times e(\Gamma(\alpha)) \tag{14}$$

where $\sigma(t)$, $\bar{V}(t)$ and $\lambda(t)$ are the linear fitting results based on the Fig. 5. After the parameter λ, β, γ are all reasonable estimated, the extreme wind speed with different return period in the non-stationary process can be expressed as following:

$$\hat{V}(t) = [-\ln(-\frac{1}{\lambda(t)}\ln(1-R))]^{\frac{1}{\alpha}} \times \gamma(t) + \beta(t) \tag{15}$$

If R=0.01, then $\hat{V}(t)$ is the non-stationary extreme wind speed with 100-year return period.

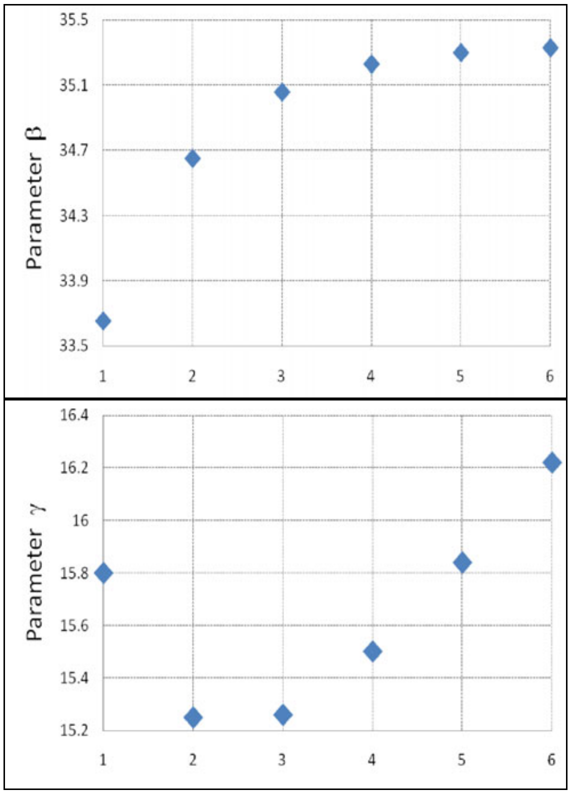


Fig. 6 The variation of parameter β and γ of Weibull distribution in the NWP.

ESTIMATION OF TC EXTREME WIND SPEED OF NON-STATIONARY PROCESS

Diagnosis and comparison between stationary model and non-stationary model

After having estimated the parameters of Weibull distribution of non-stationary process in the NWP, we also need to ensure whether the model fits for the TC wind speed distribution well. So probability plot and quantile plot (Coles, 2001) are presented here. As shown in Fig. 7, the points of probability plot and quantile plot in non-stationary model lie close to the diagonal line, which means that non-stationary model is acceptable. But there exists a substantial argument we have to prove. With an obvious strength of TC activity exhibited by statistics of 64-year data in the NWP, is the non-stationary model indeed a more suitable candidate than stationary model? So in this paper we define a parameter ρ to describe the relative error between the probability of stationary and non-stationary Weibull distribution model and the empirical wind speed distribution.

$$\rho = \sum (P_{model} - P_{empirical})^2 / P_{empirical} \quad (16)$$

where P_{model} and $P_{empirical}$ is the probability of Weibull distribution model and the empirical wind speed disribution respectively. The variations of parameter ρ of stationary and non-stationary model are both shown in Fig. 8. Evidently ρ of non-stationary model is smaller than that of stationary at all 6 sections. Then we can make the conclusion that the non-stationary Weibull distribution model is better than the stationary model for describing TC wind speed distribution in the NWP.

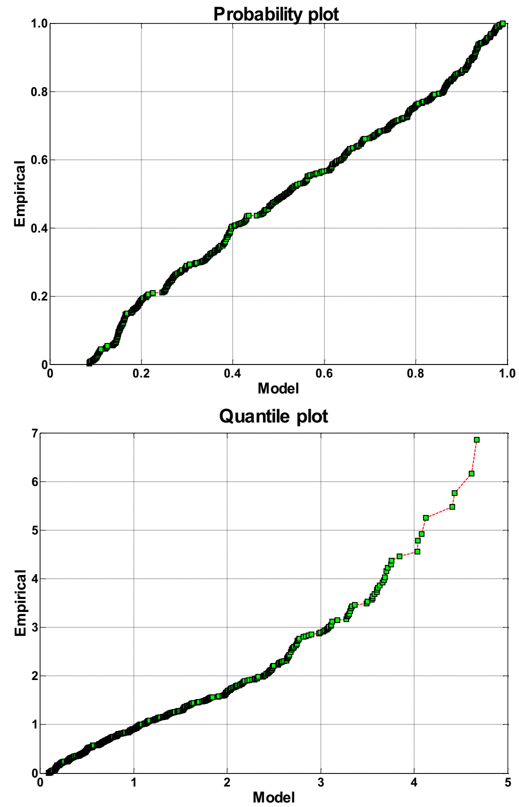


Fig. 7 Non-stationary Weibull distribution model diagnostic in the NWP

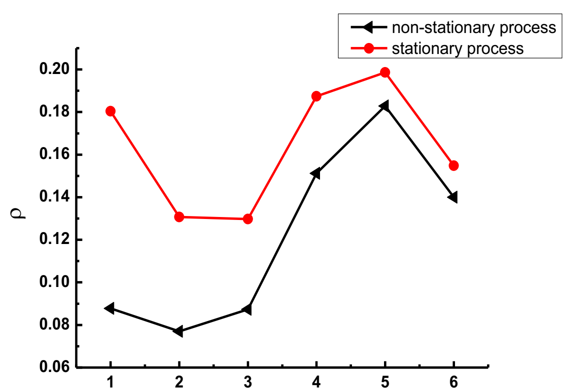


Fig. 8 Comparison between stationary and non-stationary model in the NWP

Results comparison between stationary model and non-

stationary model in the NWP

From the above analysis, the TC wind speed distribution satisfies Weibull distribution (Fig. 4) and the TC frequency agrees well with Poisson distribution (Fig. 1) in the NWP. And the parameter λ and Weibull distribution parameters with temporal dependence is showed in Fig. 5 and Fig. 6. When substituting their non-stationary parameters into Eq. 15 based on non-stationary extreme value model established above, we can obtain the non-stationary extreme wind speed different return period. As shown in Fig. 9, the extreme wind speed of non-stationary process with 50-year return period is 81.7m/s and 84.34m/s respectively. Comparing with each other, the extreme wind speed with return period of 50 years in non-stationary process has increased 3.2%.

This TC extreme wind speed increase rate we made above is consistent with the theoretical and modeling studies in recent year. Studies by many scholars (Kerry, 2005a; Kerry, 2005b; Henderson-Sellers A, 2007; Kossin J. P, 2007; Landsea C. W, 2007; Kerry, 2008) indicate that there were strong correlations between TC activity and the rising SST. Using a single-column radiative-convective model, Kerry (1987, 2003) argued that the potential intensity of tropical cyclones increase by approximately 3.5 ms^{-1} for each 1ºC increase in tropical SST. Integrating Coupled Model Inter-comparison Project (CMIP21) climate models with a nested regional model, Knutson（1999，2001，2004，2007) found the average results of 6% increase in TCs maximum surface wind speed under the assumption of 80-yr linear trends from +1% yr^{-1} CO_2 increase. In the 64 years from 1945 to 2008, the SST rises about 0.5℃provided by Climatic Research Unit in the United Kingdom. So in our statistics, approximately 2.6m/s increase in 64 years is a credible and reasonable result comparing with the theoretical and modeling studies.

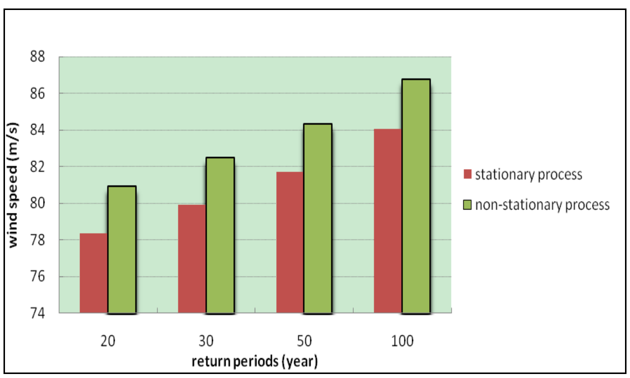


Fig. 9 The extreme wind speed with return period of 20, 30, 50 and 100 years in both stationary and non-stationary process in the NWP.

The extreme wind speed distribution in the sea areas near China

In the vast region of the NWP, the analysis of TCs spatial distribution is also carried out so that we are able to identify the place of frequent TC occurrence. From Fig. 10 we can see that the most frequent occurrence of TCs happen in the region which lies to the east of Philippine islands. In particular, the subarea of 15º~20º N，125º~130º E is the place where TC happened most frequently, i.e. totally we have 374 TCs in 64 years resulting in 6 TCs per year on average.

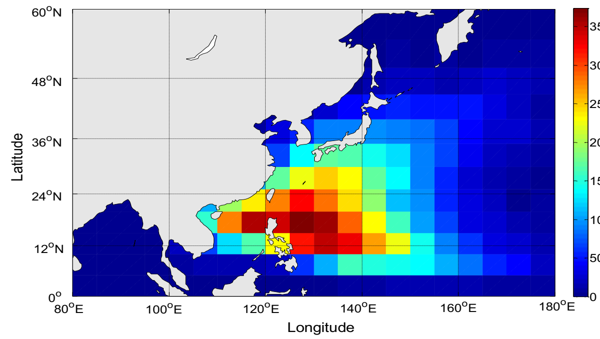


Fig. 10 64-year numbers of TCs in occurrence in the 5º×5º subareas of the NWP are presented. The color bar of the right displays the color image of the numbers of TCs occurrence in 64 years.

It can be concluded from above results that the number of TCs occurrence in 64 years in each subarea in the NWP are inhomogeneous. So in the offshore platforms design and construction, the extreme wind speeds with different return period probably differ greatly in each subarea. In order to obtain the wind speed distribution in the sea areas near China where oil and gas resource are abundant, extreme value model established above is used to calculate extreme wind speed in subareas. From Fig. 11 we can know that the extreme wind speeds in the different subareas are unevenly distributed. The 50-year return periods wind speed in the area of Yellow Sea(30ºN-35ºN，120ºE-125ºE) and the East China sea(25ºN-30ºN，120ºE-125ºE) are 47.1m/s and 65m/s respectively. With regard to SCS, the area(15ºN-20ºN，115ºE-120ºE) of ZhongSha and DongSha islands, west to the Philippines, the region of the strong typhoon occurrence frequently with the extreme wind speed of 50 years reach to 68.2m/s.

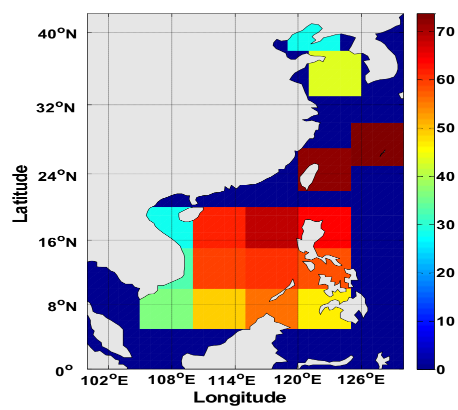


Fig. 11 The extreme wind speed distribution with return period of 50 years in the 5°× 5° subareas. The color bar of the right displays the scale of extreme wind speed.

CONCLUSION

In this paper, extreme value theory is used to estimate the extreme wind speed with different return periods. Because there is an observational increase of the TC activity with the enhancement of TC intensity and the growth of the TC frequency, it is appropriate to treat the recorded 64-year TC database as a non-stationary process. Extreme wind speed with different return period in both stationary and non-stationary process are calculated and compared with each other in the NWP. Because the location parameter β, scale parameter γ of Weibull distribution and the parameter λ of Poisson distribution is increasing with time, the non-stationary process give more intense extreme wind speed than that of stationary one. Taking 50-year return period for example, the extreme wind speed of non-stationary process reaches to 84.34m/s, resulting in 3.2% higher than that of stationary process. And the conclusion we made above is consistent with the theoretical and modeling studies in recent year. So the effects of non-stationary variation in atmospheric general circulation can no longer be neglected and should be considered in the standard or criterion revision. Extreme wind speed distribution in different small subareas in the sea areas near China which is abundant in oil and gas resource is inhomogeneous. The area (15^{o}N-20^{o}N，115^{o}E-120^{o}E) of ZhongSha and DongSha island, west to the Philippine islands is the place of strong typhoon occurrence with the 50-year return periods wind speed of 68.2m/s, and the area(30^{o}N-35^{o}N，120^{o}E-125^{o}E) of Yellow Sea with the 50-year return periods wind speed of 47.1m/s.

In a word, the variation of TC activity turns out a non-stationary process and it is reasonable to use non-stationary extreme value model to estimate extreme wind speed under the background of climate change. Obviously, their effects on the design of ocean engineering now have become an issue of great concern, which is of great significance for the revision of offshore engineering standard and criterion.

ACKNOWLEDGEMENTS

The study was supported by Ministry of Science Technology (863 program) (Grant No. 2006AA09A103-4) and CAS knowledge innovation program (Grant No. KJCX-YW-L02). We are also grateful to China Meteorological Administration for their permission of using TC database.

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