Extreme Value Analysis of Metocean Data for Barents Sea

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ABSTRACT: An extreme value analysis of metocean data which include wave, wind, and current data is a prerequisite for the operation and survival of offshore structures. The purpose of this study was to provide information about the return wave, wind, and current values for the Barents Sea using extreme value analysis. Hindcast datasets of the Global Reanalysis of Ocean Waves 2012 (GROW2012) for a waves, winds and currents were obtained from the Oceanweather Inc. The Gumbel distribution, 2 and 3 parameters Weibull distributions and log-normal distribution were used for the extreme value analysis. The least square method was used to estimate the parameters for the extreme value distribution. The return values, including the significant wave height, spectral peak wave period, wind speed and current speed at surface, were calculated and it will be utilized to design offshore structures to be operated in the Barents Sea.

1. Introduction

According to the National Oceanic and Atmospheric Administration (NOAA), the Earth's average temperature is increasing annually as global warming continues, and the temperature of the Arctic region is increasing twice as fast as those of other regions (NOAA, 2018). With Arctic glaciers melting owing to global warming, the importance of developing marine resources buried in the Arctic is emerging. According to the United States Geological Survey, undiscovered recoverable resources in the Arctic region include approximately 90 billion barrels (Bbbl) of oil, 1,669 trillion cubic feet (Tcf) of gas, and 44 Bbbl of natural gas liquid (Bird et al., 2008). It is estimated that 13% of the world's undiscovered oil volume and 30% of the world's undiscovered gas volume are buried in the Arctic region. In general, marine resources in the deep sea are developed by offshore structures, and it is important to collect and analyze the metocean data of sea areas where marine resources are buried for the operation and survival of offshore structures. Metocean data include wave, wind, current, water depth, tide, and soil conditions. To reflect metocean data in the design of offshore structures, extreme value analysis should be conducted (API, 2005). Metocean data can be collected from

measurement data of actual sea areas that use buoys or ships, hindcast data that estimate the desired data of the past through numerical methods based on past metocean data, and satellite data that use satellites. According to DNVGL (2015), for the design of offshore structures, the significant wave height (H_s) and spectral peak wave period (T_p) of 100-year return values should be used for waves, whereas the 100-year return value of the one-hour average wind speed at 10 m above the mean sea level (MSL) should be used for wind speed. For ocean currents, the 10-year return value of the current speed should be reflected in the design.

To derive return values through statistical methods, methods for selecting the collected data must be determined. Such methods can be primarily categorized into global and event models. Global models include the initial distribution and total sample methods that use the entire data statistically, and the event models include the peak over threshold method, which uses data above a certain threshold, and the annual maxim method, which uses only the annual maximum values (DNV, 2014).

Extreme value distributions (EVDs) used for extreme value analyses include the Gumbel, Frechet, Weibull, and log-normal distributions. Methods for estimating the parameters of EVDs include

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the method of moment, maximum likelihood estimation, and least-squares method (DNV, 2014). Jeong et al. (2004) conducted extreme value analyses using Weibull, Gumbel, Log-Pearson type-III, and log-normal distributions using the H_s data of approximately 20 years obtained from 67 ocean stations in South Korea. They provided design wave height information in the deep-sea for the return period of 50 years and suggested that Gumbel distribution was the most suitable method. In addition, they provided the extreme highest tide level information for each return period by conducting an extreme value analysis through generalized extreme value, Gumbel, and Weibull distributions using the extreme highest tide level data of 23 tide stations on the coast of South Korea, and they suggested that Gumbel distribution was the most suitable method (Jeong et al., 2008). Ko et al. (2014) developed a numerical wind speed model that numerically implemented typhoons for four locations on the west coast of the Korean Peninsula (Gunsan, Mokpo, Jeju, and Haemosu No. 1) and presented extreme wind speeds for the four locations by applying the Gumbel distribution and estimating parameters through the probability weighted moment method.

EVDs were applied to various metocean data. In the case of wave data, however, H_s and T_p were important design elements for the design of offshore structures. DNVGL (2017) and BV (2015) recommended the use of the inversed first order reliability method (I-FORM), which used the joint distribution of EVDs, to obtain the return values for H_s and T_p .

In this study, the metocean data (wave, wind, and current) of the Barents Sea in the Arctic region were collected. In addition, for the extreme value analysis of the wave data, return values were calculated using I-FORM, which used the joint distribution of the marginal probability distribution for H_s (Gumbel distribution and two- and three-parameter Weibull distributions) and the conditional probability distribution of T_p for the given H_s (log-normal distribution) (DNVGL, 2017; BV, 2015; Choi, 2016). For the wind and current speeds, which are single variables, extreme value analysis was conducted through the Gumbel distribution and two- and three-parameter Weibull distributions. The least-squares method was used for parameter estimation, and the Kolmogorov-Smirnov (K-S) test was applied as the goodness-of-fit test. Through these processes, the return values for H_s , T_p , wind speed, and current speed required for the design of offshore structures to be operated in the Barents Sea were derived.

2. Metocean Data Collection and Analysis

The project site (Fig. 1) is the Barents Sea of water depth 258 m (latitude: 73N and longitude: 44E), where gas fields were distributed around the site (Fig. 2). For the wave (H_s , T_p , and wave direction), wind (wind speed and wind direction), current (current speed and current direction), and an ice floe thickness data, the hindcast datasets of Global Reanalysis of Ocean Waves 2012 (GROW2012) from Oceanweather Inc. were purchased. In the hindcast datasets of GROW2012, wave and wind models provided by the General

Bathymetric Chart of the Oceans and Climate Forecast System Reanalysis were used to estimate the data for waves, wind, current, and ice floe (Oceanweather Inc.).

To conduct the extreme value analysis, the consistency, period, and validity of the collected data must be examined first (Van Os et al., 2011). Compared with the measurement data, the hindcast data have no possibility of missing data and generating outliers owing to typhoons or defects in the measuring equipment and can secure a data period irrespective of the installation time of the measuring equipment. The wave and wind data were recorded at one hour intervals for a decade from January 2007 to December 2016, and the current data were recorded in the water depth direction at one day intervals for two decades from January 1993 to December 2012. The ice floe thickness data during the same period as that of the current data were provided, but it was discovered that no ice existed in the project site.

Fig. 1 Project site in Barents Sea (Wikipedia, 2019)

Fig. 2 Oil and gas filed in Barents Sea (WorldMap, n.d.)

Barents Sea		Spectral peak period(s)																									sum
Significant wave height(m)	Range	0sTp<1	1sTp<2	2sTp<3	3sTp<4	4sTp<5	5sTp<6	6sTp<7	7sTp<8	8sTp<9	9sTp<10	10sTp<11	11sTp<12	12sTp<13	13sTp<14	14sTp<15	15sTp<16	16sTp<17	17sTp<18	18sTp<19	19sTp<20	20sTp<21	21sTp<22	22sTp<23	23sTp<24	24sTp<25	
	0sHs<1	0	0	0	337	2150	3111	874	334	338	561	582	365	211	156	128	43	21	14	13	0	0	0	0	0	0	9238
	1sHs<2	0	0	0	52	1465	7942	10279	5823	1642	1017	1297	1679	1431	1243	1039	479	204	161	51	30	21	13	2	2	0	35872
	2sHs<3	0	0	0	0	24	245	3871	8606	4271	1200	672	747	918	723	948	710	243	176	81	53	27	10	1	0	0	23526
	3sHs<4	0	0	0	0	0	7	80	1636	4850	2111	555	364	394	331	336	200	78	84	36	10	0	0	0	0	0	11072
	4sHs<5	0	0	0	0	0	0	3	25	920	2150	726	165	148	183	158	114	33	39	14	3	0	0	0	0	0	4681
	5sHs<6	0	0	0	0	0	0	0	0	6	488	1026	220	104	59	79	64	29	0	0	0	0	0	0	0	0	2075
	6sHs<7	0	0	0	0	0	0	0	0	0	12	264	231	67	51	71	16	0	0	0	0	0	0	0	0	0	712
	7sHs<8	0	0	0	0	0	0	0	0	0	3	40	119	30	25	26	18	0	0	0	0	0	0	0	0	0	261
	8sHs<9	0	0	0	0	0	0	0	0	0	0	0	101	39	18	0	2	1	0	0	0	0	0	0	0	0	161
	9sHs<10	0	0	0	0	0	0	0	0	0	0	0	0	14	28	8	1	0	7	0	0	0	0	0	0	0	58
	10sHs<11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	6	0	2	0	0	0	0	0	0	0	16
11sHs<12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
sum		0	0	0	389	3639	11305	15107	16424	12027	7542	5162	4005	3370	2805	2792	1646	618	474	195	96	48	23	3	2	0	87672

Fig. 3 Wave scatter diagram with H_s and T_p

Fig. 4 Wave rose and wind rose

The wave data showed the wave scatter diagram (WSD) for H_s and T_p ; the wave rose for the wave direction and T_p , and the wind data showed that the wind rose for the wind direction and wind speed (W_s) (Figs. 3 and 4). The current data represented the current increase for the current direction and current speed (C_s) at the surface and the current profile in the water depth direction (Fig. 5).

The WSD showed frequencies at 1 m intervals for H_s and at 1 s intervals for T_p , and the total number of data was approximately 87,600. The wave conditions with the highest frequencies in the

Fig. 5 Current profile and current rose at surface

project site were 1-2 m for H_s and 6-7 s for T_p . The wave, wind, and current directions could be confirmed through the rose diagrams, and the directions were categorized into east (90°), south (180°), and west (270°) in the clockwise direction from the north direction (0°). In the case of the hindcast data purchased from Oceanweather Inc., the wave and current directions were defined as the directions to which the wave and current were moving, while the wind direction was defined as the direction from which the wind was coming. The wave and wind directions with the highest frequencies were East and North-

Northwest (Fig. 4). Fig. 5 shows the current speed profile and direction in the water depth direction (z). The current speed profile was nondimensionalized with the water depth of the project site (d). The average and maximum current speeds were the fastest at the surface, and the dominant current direction at the surface was from the West to the East.

3. Extreme Value Analysis

For the extreme value analysis of metocean data, data collection, data selection, EVD selection, parameter estimation method selection, goodness-of-fit test, and return value derivation are required (Mathiesen et al., 1994). In this study, a global model that utilizes all of the collected metocean data was selected. In addition, the Gumbel distribution, two- and three-parameter Weibull distributions, and log-normal distribution were used as EVDs. The least-squares method was used to estimate the parameters of the EVDs. As the goodness-of-fit test, the K-S test that uses the maximum distance as a test statistic by comparing the cumulative distribution function (CDF) of metocean data with that of each EVD was used (Jeong et al., 2004; Jeong et al., 2008).

Eqs. (1)-(4) show the CDF of each EVD (Coles, 2001; Goda, 2000).

Gumbel distribution CDF:

$$F(Hs) = \exp\left\{-\exp\left[-\left(\frac{Hs-\gamma}{\alpha}\right)\right]\right\} \quad (1)$$

2-parameter Weibull distribution CDF:

$$F(Hs) = 1 - \exp\left[-\left(\frac{Hs}{\alpha}\right)^\beta\right] \quad (2)$$

3-parameter Weibull distribution CDF:

$$F(Hs) = 1 - \exp\left[-\left(\frac{Hs-\gamma}{\alpha}\right)^\beta\right] \quad (3)$$

Hs is the significant wave height; α , β , and γ are the scale parameter, shape parameter, and location parameter, respectively.

Log-normal distribution CDF:

$$F(Tp|Hs) = \frac{1}{2} \left[1 + \operatorname{erf}\left(\frac{\ln(Tp-\mu)}{\sqrt{2}\sigma}\right) \right] = \Phi\left(\frac{\ln(Tp-\mu)}{\sigma}\right) \quad (4)$$

Tp is the spectral peak wave period, and Φ is the CDF of the standard normal distribution (eq. (5)).

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-t^2/2} dt \quad (5)$$

μ of the log-normal distribution can be expressed with the average value of $\ln(Tp)$, as shown in Eq. (6); σ can be expressed with the standard deviation of $\ln(Tp)$, as shown in Eq. (7) (DNV, 2014).

$$\mu = E[\ln Tp] = a_0 + a_1 Hs^{a_2} \quad (6)$$

$$\sigma = \operatorname{std}[\ln Tp] = b_0 + b_1 e^{b_2 Hs} \quad (7)$$

To estimate the parameters and coefficients (a_0 , a_1 , a_2 , b_0 , b_1 and b_2) using the least-squares method, taking the log of both sides of each EVD, the log-normal distribution average equation, and the standard deviation equation followed by summarizing them into linear equations result in Eqs. (8)-(12).

Gumbel distribution:

$$-\ln[-\ln(F(Hs))] = \frac{1}{\alpha}(Hs - \gamma) \quad (8)$$

2-parameter Weibull distribution:

$$\ln[-\ln(F(Hs))] = \beta \ln(Hs) - \beta \ln \alpha \quad (9)$$

3-parameter Weibull distribution:

$$\ln[-\ln(F(Hs))] = \beta \ln(Hs - \gamma) - \beta \ln \alpha \quad (10)$$

Log-normal distribution (mean):

$$\ln(\mu - a_0) = \ln(a_1) + a_2 \ln(Hs) \quad (11)$$

Log-normal distribution(standard deviation):

$$\ln(\sigma - b_0) = \ln(b_1) + b_2 Hs \quad (12)$$

For Eqs. (8) and (9), the least-squares method can be used directly. For Eq. (10), however, the parameters for which the R^2 value was closest to 1 were estimated, while the value of γ was changed approximately 1,000 times within the range in which the value in the log was not negative. The R^2 value is the coefficient of determination that indicates the goodness-of-fit corresponding to the regression line. It approaches 1 as the samples used in statistical analysis exhibits smaller errors with the regression line.

Once the parameters are obtained through the least-squares method, the return values can be obtained using Eqs. (13)-(16).

Gumbel distribution:

$$Hs = -\alpha \ln[-\ln(F(Hs))] + \gamma \quad (13)$$

2-parameter Weibull distribution:

$$Hs = \alpha [-\ln(1 - F(Hs))]^{\frac{1}{\beta}} \quad (14)$$

3-parameter Weibull distribution:

$$Hs = \alpha [-\ln(1 - F(Hs))]^{\frac{1}{\beta}} + \gamma \quad (15)$$

Log-normal distribution CDF:

$$Tp = \exp\left[\sigma \Phi^{-1}\left(F_{Tp|Hs}(Tp)\right)\right] + \mu \quad (16)$$

After changing the variable from H_s to wind speed and current speed, their return values were derived using the same method as presented above.

3.1 Extreme value analysis on wave and results

H_s and T_p , which are wave data, can be expressed by the conditional modeling approach, and the joint probability distribution of the two variables can be expressed as the product of the marginal probability distribution of H_s and the conditional probability distribution of T_p for a given H_s (Orimolade et al., 2016; DNVGL, 2017).

In this study, the marginal probability distribution of H_s was assumed to be a Gumbel distribution and two- and three-parameter Weibull distributions using the WSD and the conditional probability distribution of T_p , as the given H_s was assumed to be a log-normal distribution to calculate return values using the I-FORM method. Extreme value analysis was conducted after transforming the EVDs from the probability distribution function form to the CDF form for the convenience of calculation. The I-FORM method was proposed by Winterstein et al. (1993), and the data of Haver and Nyhus (1986) were used for the parameter estimation equations of the EVDs used. In other words, the I-FORM method calculates the exceedance probability in advance and obtains the corresponding response rapidly.

The procedure of the I-FORM method is expressed in Eqs. (17)-(24) (Haver and Winterstein, 2009).

$$Q = 1 - F(H_s, T_p) = 1/N \quad (17)$$

Q is the exceedance probability. It is the reciprocal number of N , which is the total number of data.

$$F(H_s, T_p) = \int f(H_s, T_p) dH_s dT_p = F(H_s)F(T_p|H_s) \quad (18)$$

where $F(H_s)$ is the CDF of the marginal probability distribution, and $F(T_p|H_s)$ is the CDF of the conditional probability distribution

EVDs are moved to the space of the standard normal distributions of u_1 and u_2 .

$$\Phi(u_1) = F_{H_s}(H_s), \quad \Phi(u_2) = F_{T_p|H_s}(T_p) \quad (19)$$

A circle equation with a radius of B was introduced and represented by the relationship between the short-term period (T_{ss}) and return period (T_r).

$$\sqrt{u_1^2 + u_2^2} = B = \Phi^{-1}\left(1 - \frac{T_{ss}}{365 \times 24 \times T_r}\right) = \Phi^{-1}\left(1 - \frac{1}{N}\right) \quad (20)$$

where B is the reliability index. One hour was used for T_{ss} , T_r is the return period; 1, 10, and 100 years were used.

$$u_{1i} = Bs_i, \quad u_{2i} = \pm \sqrt{B^2 - u_{1i}^2} \quad (21)$$

s_i in Eq. (21) is a dummy index, i.e., a number in the section between -1.0 and 1.0 . Once B is determined H_s and T_p can be obtained using the inverse function of each EVD (Eqs. (22)-(24)).

$$H_{s_i} = F_{H_s}^{-1}(\Phi(u_{1i})) \quad (22)$$

$$\mu_i = a_0 + a_1 H_{s_i}^{a_2}, \quad \sigma_i = b_0 + b_1 e^{b_2 H_{s_i}} \quad (23)$$

$$T_{p_i}^{\pm} = F_{T_p|H_s}^{-1}(\Phi(\pm u_{2i})) \quad (24)$$

The parameters of each EVD were estimated using the least-squares method, and the goodness-of-fit was tested using the K-S test. The parameters for which the R^2 value was the highest were extracted using MATLAB software (Figs. 6-7). The R^2 value was 0.99, indicating that the numerical values agreed well with the actual values. The parameters were obtained using the slopes and y-intercept values (Tables 1-2).

To test the estimated parameters, the maximum distance difference between the CDF of the wave data and the CDF that included the parameters obtained by the least-squares method is shown in Fig. 8. Based on the result of the K-S test, a test statistic (D) value is presented. If this value is smaller than the threshold (D_{cri}) of 0.118 by the number of wave data at the significance level of 5%, then the null

Fig. 6 Parameter estimation of extreme value distributions using least-squares method for significant wave height

Fig. 7 Parameter estimation of log-normal distribution using least-squares method for spectral peak wave period

Table 1 Parameters of extreme value distributions for significant wave height

Parameter	Gumbel distribution	2-parameter Weibull distribution	3-parameter Weibull distribution
α (Scale)	1.009	2.014	1.616
β (Shape)	-	1.437	1.214
γ (Location)	1.198	0	0.235
R^2	0.996	0.994	0.999

Table 2 Parameters of log-normal distribution

Parameter (a)	Log-normal distribution	Parameter (b)	Log-normal distribution
a_0	1.533	b_0	0
a_1	0.415	b_1	0.380
a_2	0.412	b_2	-0.169
R^2	0.995	R^2	0.923

hypothesis that no difference exists between the two CDFs mentioned above can not be rejected (Kanji, 2006). In other words, it was discovered that the graphs of CDFs, including the parameters, agreed well with the actual data.

The contours for H_s and T_p were expressed using the I-FORM

Fig. 8 Comparison between CDF of wave data and CDF of extreme value distribution

method of Eqs. (17)-(24), as shown in Fig. 9. The contours are shown for each return period (RP), and the return values corresponding to each return period are shown in Table 3.

When the 10-year hindcast data were compared with the 10-year return values, the highest prediction values could be obtained when the Gumbel distribution was assumed as the marginal probability distribution. The next highest values were derived by the three-parameter Weibull distribution, and two-parameter Weibull distribution exhibited the most similar results to those of the collected data. This was because the Gumbel distribution had a higher degree of scatter than the Weibull distribution. In addition, when the equations for obtaining the return values of the two- and three-parameter Weibull distributions were compared, it was discovered that different results were obtained depending on the value of the location parameter.

Fig. 9 Environmental contour for significant wave height and spectral peak wave period

Table 3 Return value for wave (H_s , T_p)

Return period (yr, yrs)	Gumbel distribution		2-parameter Weibull distribution		3-parameter Weibull distribution	
	H_s (m)	T_p (s)	H_s (m)	T_p (s)	H_s (m)	T_p (s)
1	10.36	13.75	9.48	13.22	10.17	13.64
10	12.68	15.11	11.09	14.18	12.21	14.83
20	13.38	15.52	11.56	14.45	12.80	15.18
50	14.31	16.05	12.16	14.81	13.59	15.63
100	15.01	16.45	12.61	15.07	14.17	15.97

3.2 Extreme value analysis on wind and current and results

The wind speed (W_s) was distributed within the 0–27 m/s range and the total number of data was approximately 87,600. The CDF was obtained at 2 m/s intervals. The current speed (C_s) ranged from

Fig. 10 Parameter estimation of extreme value distributions using least square method for wind speed

Table 4 Parameters of extreme value distribution for wind speed

Parameter	Gumbel distribution	2-parameter Weibull distribution	3-parameter Weibull distribution
α	2.392	8.790	8.763
β	-	2.033	2.028
γ	6.543	0	0.022
R^2	0.987	0.999	0.999

0 to 70 cm/s and the total number of data was 7,200. The CDF was obtained at 5 cm/s intervals. To derive the return values for the W_s and C_s , which were single variables, the Gumbel distribution and two- and three-parameter Weibull distributions were used as EVDs, and the least-squares method was used for parameter estimation (Figs. 10 and 12). The parameters were obtained using the slopes and y-intercept values when the R^2 value was the highest (Tables 4 and 6). The K-S

Fig. 11 Comparison between CDF of wind data and CDF of extreme value distributions

Table 5 Return value for wind speed

Return period (yr, yrs)	Gumbel distribution	2-parameter Weibull distribution	3-parameter Weibull distribution
	Wind speed (W_s) (m/s)		
1	28.26	26.01	26.03
10	33.77	29.07	29.10
20	35.43	29.93	29.96
50	37.62	31.03	31.06
100	39.28	31.83	31.86

test was used to test the parameters, and test statistic (D) values are presented as results (Figs. 11 and 13). If these values are smaller than the threshold (D_{cri}) of 0.09 by the number of wind and current data at

Fig. 12 Parameter estimation of extreme value distributions using least square method for current speed at surface

Table 6 Parameters of extreme value distribution for current speed at surface

Parameter	Gumbel distribution	2-parameter Weibull distribution	3-parameter Weibull distribution
α	9.010	12.986	12.235
β	-	1.224	1.173
γ	4.800	0	0.414
R^2	0.963	0.992	0.992

the significance level of 5%, then the null hypothesis cannot be rejected. In other words, it was discovered that the graphs of the CDFs, including the parameters, agreed well with the actual data. The return values for the W_s and C_s were calculated using a method similar to the analysis of the wave data (Tables 5 and 7).

Fig. 13 Comparison between CDF of current data at surface and CDF of extreme value distributions

Table 7 Return value for current speed at surface

Return period (yr, yrs)	Gumbel distribution	2-parameter Weibull distribution	3-parameter Weibull distribution
	Current speed (C_s) (cm/s)		
1	57.95	55.38	56.01
10	78.70	72.49	74.05
20	84.95	77.46	79.32
50	93.20	83.92	86.20
100	99.45	88.73	91.35

As for the overall tendency of the return values for the W_s and C_s , the Gumbel distribution exhibited the highest prediction values, similarly to the results of the wave data, followed by the three- and

two-parameter Weibull distributions. When the maximum W_s and C_s of the 10-year hindcast data (27 m/s and 70 cm/s, respectively) were compared with the 10-year return values of the two-parameter Weibull distribution (29.07 m/s and 72.49 cm/s, respectively) large differences of 7.6% and 3.5% were discovered, respectively.

The prediction values of the Gumbel distribution were the highest because the null hypothesis was rejected as the test statistic was higher than the threshold in the K-S test results; hence, overestimated results were obtained. This was because the intervals determined to calculate the ranges and frequencies of the W_s and C_s were larger compared to the wave data; hence, errors were accumulated when the parameters were calculated using the least-squares method. The reclassification of data through the independent and identically distributed (IID) verification of changes in the intervals for extracting the frequencies of the W_s and C_s is expected to further improve the accuracy (Choi et al., 2019).

4. Conclusion

In this study, an extreme value analysis for the H_s , T_p , wind speed, and current speed was conducted using the hindcast metocean data of the Barents Sea in the Arctic region to derive return values required for the design of offshore structures. In the extreme value analysis for the H_s and T_p , the marginal probability distribution of the H_s was assumed to be a Gumbel distribution and two- and three-parameter Weibull distributions, and the conditional probability distribution of the T_p for the given H_s was assumed to be a log-normal distribution to calculate return values using the I-FORM method. For the W_s and C_s , which were single variables, return values were calculated through the Gumbel distribution and two- and three-parameter Weibull distributions. The parameters were estimated using the least-squares method and tested through the K-S test.

The return values for the H_s , T_p , and wind speed for the 100-year return period and those for current speed for the 10-year return period, which are required for the design of general offshore structures were summarized (as shown in Table 8). As the degree of scatter of metocean data increased, the differences in return values between the Gumbel and Weibull distributions increased. The Weibull distribution should be used for widely distributed metocean data, such as wind speed and current speed data.

The results of this study can be used as the metocean data design values of offshore structures to be installed in the Barents Sea;

Table 8 Extreme value for metocean data with

Metocean data		Return period	Return value
Wave	H_s (m)	100 (yrs)	12.61 ~ 15.01
	T_p (s)		15.07 ~ 16.45
Wind speed (m/s)		100 (yrs)	31.83 ~ 39.28
Current speed at surface (cm/s)		10 (yrs)	72.49 ~ 78.70

furthermore, they can be utilized as basic data for offshore structure motion and mooring analyses, structural analyses, and air gap calculations. In the future, the method of estimating parameters will be extended from the least-squares method to the moment area and maximum likelihood methods. In addition, in the case of widely distributed metocean data, such as W s and C s data, they will be reclassified through an IID verification to select appropriate intervals.

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