Proceedings of the ASME 2019 38th International
Conference on Ocean, Offshore and Arctic Engineering
OMAE2019
June 9-14, 2019, Glasgow, Scotland, UK

OMAE2019-95139

ELIMINATING THE UNCERTAINTIES IN HYDRAULIC AND ICE LOADS ON BERM BREAKWATERS

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ABSTRACT

A model for the computation of failure probabilities for partly reshaping mass-armored berm breakwaters in the Arctic is presented. The model consists of a reliable tool for the design of port structures in the rapidly changing Arctic environment and considers the simultaneous effects of wave and ice forces.

The applied probabilistic approach was based on Bayesian inference. Hydrodynamic and ice historical data from Prudhoe Bay, Alaska were collected and analyzed to supply the Bayesian network with a large pool of information for the analysis. The model performed real-time predictions based on historical data and the user's prior knowledge and assigned relevant values to load and resistance parameters. The predictive skill of the Bayesian network was validated with log-likelihood tests. Furthermore, the main outputs were applied for a Level III (fully probabilistic) reliability assessment of the structure.

The study shows that a well-formulated Bayesian network can be a powerful tool in the design process and for the purpose of reliability analysis of coastal structures in highly unpredictable environments, such as the Arctic. The model can represent the dependencies between wave and ice loads in relation to the characteristics of the breakwater, as well as, its response. The average deviation of computed probabilities of failure relative to the prior estimates was 58.7%.

Keywords: Arctic; Bayesian network; berm breakwaters; damage prediction; probabilistic design.

NOMENCLATURE

α	slope angle	[degrees °]
β_i	angle of incidence	[degrees °]
γ_β	wave angle obliqueness factor	[-]
γ_{BB}	berm factor	[-]
Δ	relative buoyancy density	[-]
μ_d	friction coefficient between rock units	[-]
μ_i	friction coefficient between ice and rock	[-]
ξ	Iribarren number	[-]
ρ_a	air density	[kg/m^3]
ρ_i	ice density	[kg/m^3]
ρ_w	mass density of the water	[kg/m^3]
A	top surface area ice floe	[m^2]
b	width of ice on structure's slope	[m]
B_r	berm width	[m]
D_{n50}	armor stone dimension	[m]
g	gravitational acceleration	[m/sec^2]
H_d	design wave height	[m]
h_{ice}	ice thickness	[m]
H_s	significant wave height	[m]
L	slope's length covered by ice pieces	[m]
L_a	ice sheet length on the slope above water	[m]
N	number of waves	[-]
N_s	number of storms	[-]
q_c	critical overtopping discharge	[m^3/m/sec]
R	return period	[years]
R_c	crest freeboard	[m]
Rec	recession	[m]
S_d	damage number	[-]
s_{op}	wave steepness	[-]
u	current speed 1 meter below ice	[m/sec]
u_{10}	wind velocity at an altitude of 10 m	[m/sec]
Z	function of reliability	[-]

INTRODUCTION

Coastal structures in the Arctic and subarctic regions, are ice prone and vulnerable to damages due to ice action. In these areas,

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attention is mainly paid to offshore structures due to the considerable oil and gas deposits. However, offshore field developments are inextricably connected to the structures on the shoreface and at the backshore. The proper design of these structures is therefore essential to withstand the external forces and protect the environment and the economy.

The most pressing threat for Arctic coastal structures in the last decades is the climate change. The rapidly shrinking sea ice cover and the more frequent extreme events, which are recorded in the Arctic zone, increase the uncertainties in the design process and hint at fundamental difficulties in the assessment of potential risks. To tackle the uncertainties and deal with the limited available data and knowledge about the Arctic, engineers need to utilize and further develop probabilistic design methods.

The necessity of the probabilistic analysis methods increases in the case of breakwaters. Breakwater design relies upon prominent experimental methods and expert's judgement as the existing codes and standards have not yet addressed guidelines for potential design cases. Additionally, the selection of their type highly depends on the environmental conditions. For the Arctic environment, previous researchers [1] have already proved that berm breakwaters demonstrate a better response.

A probabilistic model capable of capturing the simultaneous effects of ice and wave loads on a berm breakwater is missing and thus the development of a new tool is necessary. Nevertheless, its development is anticipated to be challenging as there are only few analytical relations which contribute in this effort. Bayesian networks appear to be an attractive solution, as they can be trained based on historical data and expert predictions of breakwater damages by considering dependencies among the studied parameters and conditional probabilities.

Bayesian networks have already been applied in Arctic Engineering. They have been used to model the ice-stream dynamics [2], the ship performance in ice [3], even the ice loads on offshore structures [4]. Bayesian networks have also been used in the Arctic coastal engineering field [5], as well as, in ice-free coastal environments [6].

1.1 Berm Breakwaters – Typical Characteristics

Around sixty berm breakwaters exist so far around the world as part of ports and coastal defense systems with their construction dating back to the nineteenth century [1]. Berm breakwaters are rubble mound structures with big natural rocks comprising their armor layer and smaller ones in their cores. The development of their design was based on an idea for initially unstable structures whose main armor slopes could be modified by the wave forces to a stable S-shape (Fig. 1). Nevertheless, berm breakwaters have been differentiated from the dynamically changing structures and adopted resiliency; the ability to withstand severe wave conditions in a more stable way and without longshore transportations [1].

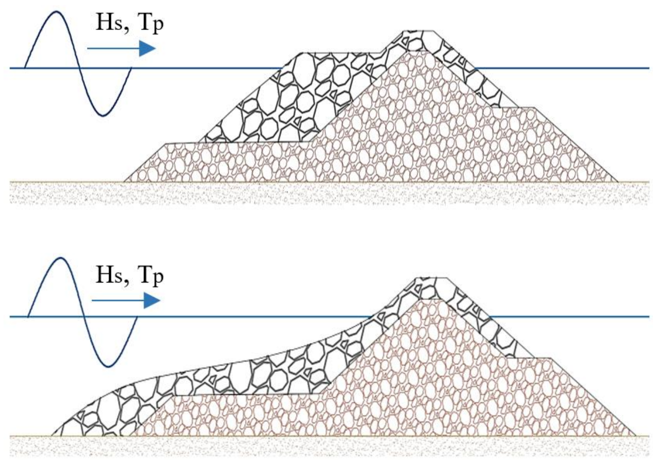

FIGURE 1: TYPICAL PROFILE OF BERM BREAKWATER (TOP), PRINCIPAL IDEA OF RECESSION (BOTTOM).

1.2 Ice Action

The Arctic is a unique environment with harsh weather conditions. The ice covers the littoral zone and complicates the construction and maintenance of coastal structures. Berm breakwaters can be subjected to ice impact during the formation of ice in the autumn, as well as, to destructed fast-ice in the spring when the structures experience both hydrodynamic and ice forces.

The ice loads on structures with rocky slopes, such as the berm breakwaters are in general quite moderate. However, their magnitude depends on variables with an inherent stochastic character. The dominant parameter in the statistical analysis of ice loads is the thickness of the features which also determines their categorization. This study focused on the examination of level ice features whose thickness does not exceed 3.2 m.

The ice-structure interaction depends on specific conditions (states): (a) the limit force state, (b) the limit stress, (c) the limit momentum (Fig. 2), with the first being the vital loading scenario in the case of a berm breakwater. According to this, the driving forces on ice features determine the magnitude of the load. This is typically the condition in structures with large diameters/width which can limit loads caused either by thin annual floes, multi-year level ice, or bigger features [7].

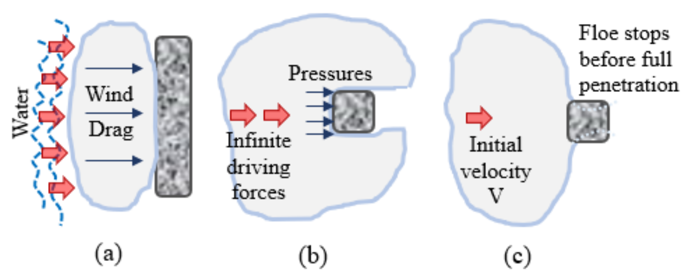

FIGURE 2: DESIGN SCENARIOS IN CASE OF ICE-STRUCTURE INTERACTION. (A) LIMIT FORCE, (B) LIMIT STRESS, (C) LIMIT MOMENTUM [7].

1.3 Study Area

The Bayesian probabilistic model was developed for an elaborated example case. An interesting area for demonstration was found in Prudhoe Bay, in Alaska (Fig. 3), which is the largest oil field in North America, covering 86,418 ha. The relatively shallow waters in the area in combination with the various ice features and high waves showed a necessity for construction of berm breakwaters as a part of the oil platforms' and coastal defense system.

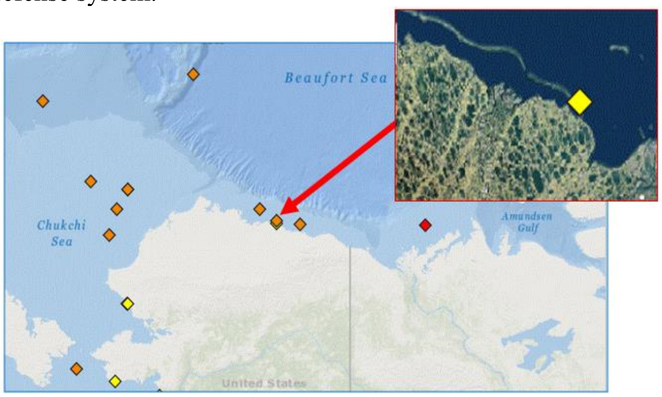

FIGURE 3: PRUDHOE BAY, ALASKA. BUOY LOCATION [8].

DATA ANALYSIS

The wind and wave conditions in the area were provided by BMT ARGOSS (WaveClimate.com database) [9]. The data source was a wave model (WaveWatchIII) and the results were based on 73056 model records where each group was recorded every 3 hours. The model wind and wave data were calibrated by means of satellite measurements covering a rectangular area with size 400x400 km. The analysis was performed for the years 1992-2016.

Daily ice reports with an overview of the ice-covered waters of Prudhoe Bay, including 3D physical ocean and sea ice variables were obtained from online catalogues in Copernicus Marine Environment Monitoring Service (CMEMS) [10]. The records had a spatial resolution of 12.5 km x 12.5 km. The offshore sea ice thickness of the Copernicus reanalysis was used in combination with the relevant historical data provided by [11] for the period 2012-2016.

Ice Conditions

Prudhoe Bay experiences high dissimilarities in ice concentration over the year. The area is ice free in late summer while the ice thickness is at its average maximum at the end of April (Fig. 4). The ice thickness is also greater in the coastal zone due to the accumulation of ice features in shallower waters.

The long-term analysis of the ice field proved that the physical phenomenon of ice generation is not stationary. Thus, the trustworthiness of any forecasts is reduced. The ice data analysis showed a linear thinning of the ice thickness over the years, described by the function -0.0076 x + 1.76, where x is the examined time interval. It was also estimated that the spring mean ice thickness offshore Prudhoe Bay has been reduced by 59.65% between the years 2012 and 2016.

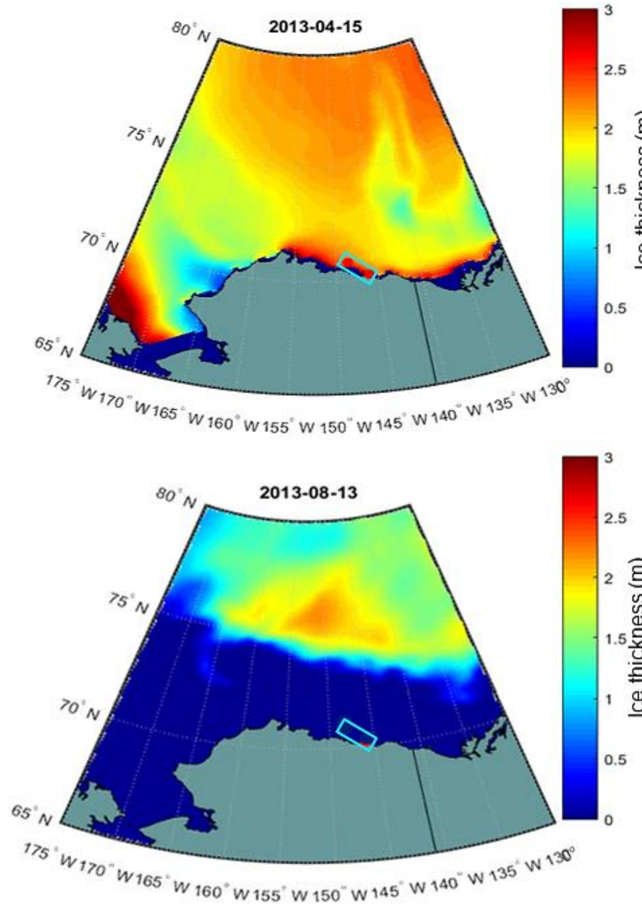

FIGURE 4: ICE THICKNESS VARIATIONS AT THE ALASKAN BEAUFORT SEA. COMPARISON OF RECORDS BETWEEN APRIL (TOP) AND AUGUST (BOTTOM) 2013. THE AREA UNDER EXAMINATION IS DENOTED BY A CYAN RECTANGLE.

Wave Climate

Prudhoe Bay has a northeasterly orientation where the wave field energy is determined by the wind generated waves (Fig. 5). Thus, the extreme storm waves were of interest while swells were disregarded. The dataset of storms was derived after processing the timeseries by means of the peak-over-threshold (PoT) method. With a threshold level of 2m, 11 storms per year were found (Fig. 6). The threshold level was quite low, but a good rule of thumb is to aim for approximately Ns = 10 storms per year [12].

The future wave heights and the corresponding probabilities of exceedance (Q) were estimated after statistical data analysis for a return period (R) of 500 years. The Exponential distribution was used for the extreme value analysis. The computed mean value of the design wave height was $H_{d,500} = 6.26$ m with Q = 5E-04.

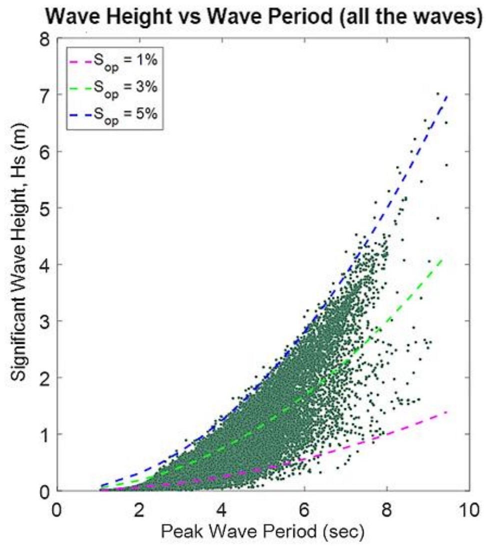

FIGURE 5: HOMOGENEITY EXAMINATION OF THE WAVE CLIMATE AT PRUDHOE BAY, ALASKA.

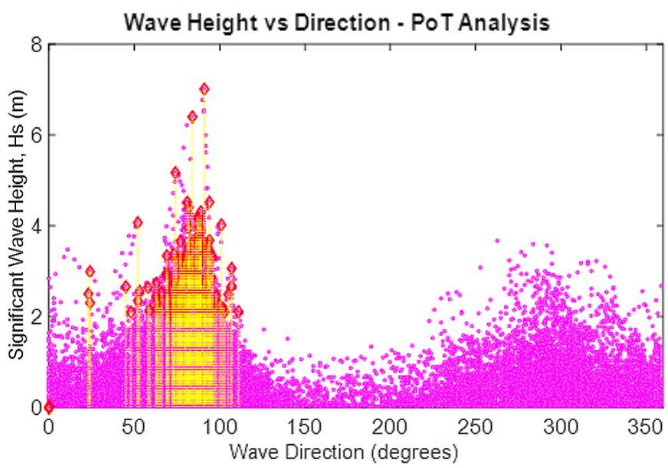

FIGURE 6: STORMS IN THE WAVE CLIMATE OF PRUDHOE BAY OBTAINED AFTER APPLYING THE PEAK OVER THRESHOLD (POT) METHOD ON THE TARGET DIRECTIONAL RANGE.

Ice-Wave Correlation

Correlation analysis among the wave and ice records was performed for the construction of the conditional probability tables (CPTs) which provide the input to the Bayesian network. The investigation of the dependencies of wave heights on wind speeds and ice fraction showed that in case of wind waves the wind velocity is crucial only in the case of an open water environment. The wave impact was drastically decreased where the ice fraction rates were higher. Despite the existence of intense winds, the wave properties were negligible during intervals with more ice features at Prudhoe Bay (Fig. 7).

Figure 8 demonstrates the relation between wave heights and ice fraction in comparison with ice thickness. It appeared that the higher the ice fraction, the thicker the ice features were. Nevertheless, wind waves seemed to be significantly affected by the ice thickness as noticeable wave height records existed in case of increased fraction rates but not necessarily when bigger ice features were present in Prudhoe Bay.

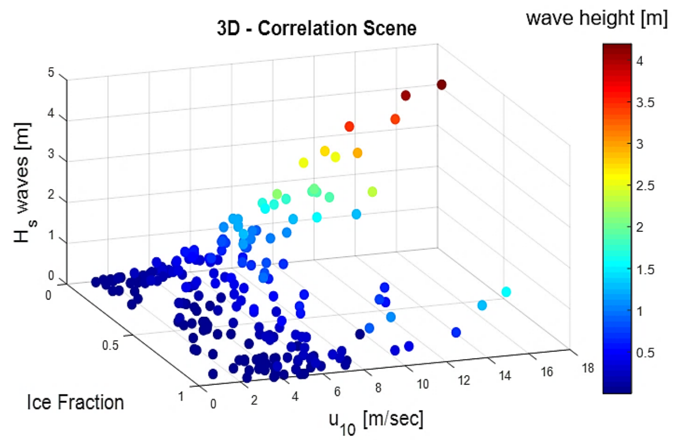

FIGURE 7: WIND WAVE HEIGHTS AT PRUDHOE BAY, IN NORTHERN ALASKA, PLOTTED VERSUS THE ICE FRACTION AND THE WIND SPEED VELOCITY.

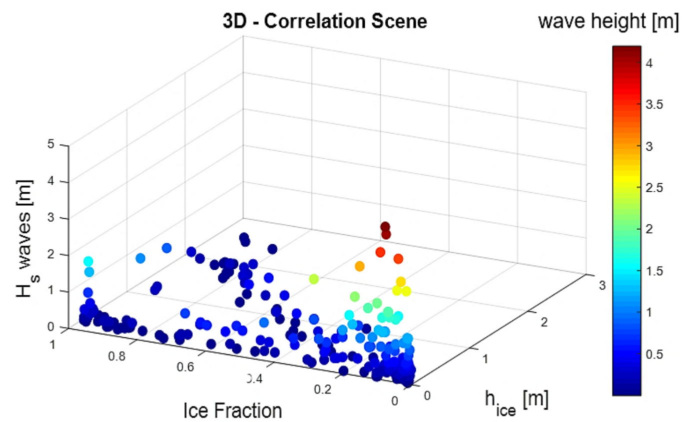

FIGURE 8: WIND WAVE HEIGHTS AT PRUDHOE BAY, IN NORTHERN ALASKA, PLOTTED VERSUS THE ICE FRACTION AND THE ICE THICKNESS.

FAILURE MECHANISMS

Reliability analysis of the structure requires a good insight into the loads acting on it and the corresponding response of the structure. A berm breakwater is considered as a reliable system only if it can be verified that the resistance (R) of the structure is bigger than the forces (S) acting on it, such that the limit state function is positive (Z=R-S>0). Failure could occur whenever a specific limit state condition is exceeded. Some of the most important initiating failure mechanisms that threaten the integrity of a berm breakwater in the Arctic could be wave overtopping, recession and the instability of individual rocks due to ice action.

In an open sea environment and during the period of the degradation of the ice cover, the waves are a threat for a berm breakwater. The static stability of the armor layer was evaluated with the original Van der Meer formulae [13] in an open sea environment. Prudhoe Bay is dominated by plunging waves and thus the design formula (Eq. 1) was rewritten and formed the reliability function (Eq. 2).

$$\frac{H_{s,t}}{\Delta * D_{n,50}} = 6.2 * P^{0.18} * \xi^{-0.5} * \left(\frac{S_d}{\sqrt{N}}\right)^{0.2} \tag{1}$$

$$Z = \frac{H_d}{\Delta * D_{n.50}} - 6.2 * P^{0.18} * \xi^{-0.5} * \left(\frac{S_d}{\sqrt{N}}\right)^{0.2} \tag{2}$$

The calculation of the wave overtopping over a berm breakwater was based on the formula that is used in the case of a conventional rubble mound breakwater [1,12]. Hence, the reliability function is (Eq. 3):

$$Z = q_c - 0.1035 * \exp\left[\left(-1.35 \frac{R_c}{\gamma_\beta \, \gamma_{BB} \, H_s}\right)^{1.3}\right] \tag{3}$$

where the reduction factors γ are defined as:

$\gamma_\beta = 1 - 0.0063 * |\beta i|$, if $0^o \leq \beta i \leq 80^o$
$\gamma_\beta = 0.5$ if $80^o \leq \beta i$
the berm factor: $\gamma_{BB} = 0.68 - 4.5 * s_{op} - 0.05 * B_r/H_s$
and H_s is H_{mo} in shallow waters.

The failure mechanism of recession may take place when the wave run-up exceeds the height of the breakwaters and water reaches the rear side of the structure. The average recession distance Rec, is the recession of the average profile, averaged between the water level and the top of the structure's berm. The limit state function is formed as follows:

$$Z = X_{cr} - 1.6 * \left(\frac{H_s}{\Delta * D_{n50}} - 1.0\right)^{2.5} \tag{4}$$

The armor stones should also withstand the ice-generated forces. The horizontal driving forces of the ice floes impact the stability of the stones and this can lead to edge failure of the structure [14]. The berm breakwater can also be affected by the ice ride-up (Fig. 9).

The horizontal driving force on the floe is expressed as [15]:

$$F_{ex} = F_{wind} + F_{water} \tag{5}$$

$$F_{wind} = 0.003 \ \rho_\alpha \ u_{10}^2 \ A \tag{6}$$

$$F_{water} = 0.003 \ \rho_w \ u \ A \tag{7}$$

The weight of a rock and the buoyancy were estimated as:

$$W = \rho_d \ g \ D_{n50}^3 \tag{8}$$

$$B = \rho_w \ g \ D_{n50}^3 \tag{9}$$

The friction force acting on a rock is:

$$F_{fric} = \mu_d \ (W - B) \cos\alpha \tag{10}$$

Individual rock instability occurs when $Z < 0$ (Eq. 11).

$$Z = (W - B) \left[\tan\alpha + \mu_d \right] - F_{ex} \tag{11}$$

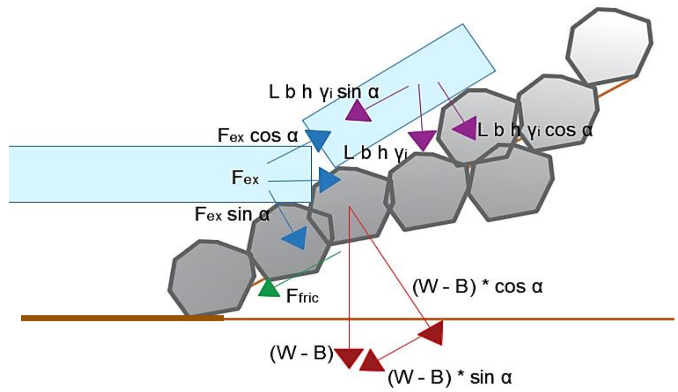

FIGURE 9: ICE SHEET IN CONTACT WITH THE ARMOUR ROCKS AND ICE RIDE-UP.

Ice starts to ride-up the slope once [15]:

$$F_{ex} \cos a > R \tag{12}$$

$$F_{ex} > L_a \ \gamma_i \ b \ h \ (\tan\alpha + \mu_i) \tag{13}$$

The resistance R was found as:

$$R = L \ w_i \ b \ h \ (\sin\alpha + \mu_i \cos\alpha) \tag{14}$$

Rock stability is lost when equation 15 obtains negative values.

$$Z = R + (W - B) \left[\tan\alpha + \mu_d \right] - F_{ex} \tag{15}$$

PROBABILISTIC MODEL

Uncertainty is the very reason that the application of probabilistic design becomes a necessity. In the case of marine terminal and shore protection structures there are many elements which cannot be controlled due to their stochasticity and the not-well-defined correlations between them. Uncertainties in the safety of the system also exist because of the empirical character of the design formulas which are obtained based on laboratory tests and modelling, as well as, there might be differences between the properties of construction materials even if they are of the same type.

A berm breakwater can be considered strong enough to withstand the acting forces if it is at a specific stability state. To ensure a desired reliability target in this study, the probabilistic method of Bayesian networks is applied.

3.1 Bayesian Network

Bayesian networks are probabilistic graphical models that can predict the likelihood of damages given a certain forcing. They are based on Bayes rule [16], which assigns probabilistic relations between two stochastic variables, in case their conditional dependencies are provided (Eq. 16)

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)} \qquad (16)$$

where, P(X|Y) is the conditional (posterior) probability of A given that Y occurs, P(X) is the independent (prior) probability of X occurring and P(Y|X) is the conditional probability of observing Y given that A occurs and P(Y) is the probability of Y occurring.

Probabilistic Model Development

The developed Bayesian network was decided to be a pure belief net which would consist only of nature nodes, probabilistically connected to their direct predecessors. The links started from the node which could cause an event or contribute to that (parent node) and ended in one or more nodes which could accept this influence (child node) (Fig. 10). For the development of the Bayesian network the NETICA Application [17] was implemented.

Findings (evidences) were inserted in the Bayesian network for the two main categories of variables; the structural and the load parameters. For the first group, the size of the crest freeboard was considered as critical, especially in the overtopping prediction, as the lower the crest, the higher the discharge is expected to be. Moreover, the slope of the structure has a noticeable effect on the stone stability and the recession of the breakwater. In berm breakwaters a steeper slope could cause instabilities, while a smaller slope angle is acceptable and expected after a storm event and the recession of the breakwater. The examination of the berm width was also necessary as it is one of the structural parameters which is expected to change after recession. The longer the width of the berm is the more wave energy is attenuated and thus less overtopping is assumed. Finally, the stone size has a strong influence on the breakwater stability. The resistance and stability of the stones and thus of the structure's section, increase rapidly as the stone diameters increase. All the structural parameters were defined as discrete variables.

The second group of findings was inserted in the nodes related to hydrodynamic and ice parameters, all of which are stochastic variables. Waves was the first variable inspected in the breakwater's design and probably the most important. It is not only the wave overtopping that is larger in a storm scenario, but also the probability of loss of structural stability is growing. Additionally, wave overtopping is a function of wave steepness, which is combined with the seaward slope of the breakwater by the means of the Iribarren number (surf similarity parameter) and characterize the breaking type of the waves. For these load parent nodes, the historical records per variable were sorted in intervals and inserted as continuous variables in NETICA.

The probability distributions of the stochastic variables were discretized before being inserted in the model. Each node then followed the same discretization without deviating from the real distribution of the recorded data. Plant and Holland [18] mention that wider value ranges in a node could reduce the computational time significantly. Nevertheless, node bins had to be narrow enough to embody several data points, prevent the production of extra uncertainties and generate meaningful predictions.

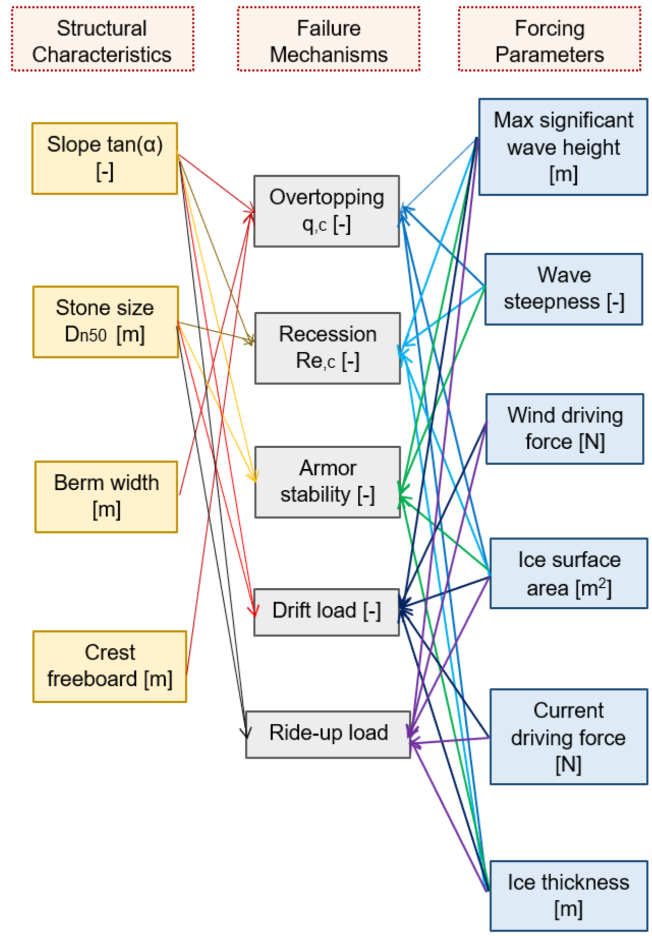

FIGURE 10: BAYESIAN NETWORK CONFIGURATION. CONCEPTUAL DESIGN IN A LABELLED-BOX FORMAT, WITHOUT PRIOR BELIEFS.

The studied damages were the overtopping discharge, recession, armor stone instability, as well as, stone damage due to ice collision and ice ride-up. These parameters were inserted in the model in the form of nodes, as previously described for the load and structural variables. The damage nodes were considered as direct successors (children) of parent nodes. After that, link matrices were formed and made available to each child node. Each of these nodes was supplied with a conditional probability table (CPT) which included the probabilities of the variable, conditioned on the values of its parent nodes.

Model's Logical Validation

The Bayesian model was logically validated before the actual predictions to eliminate meaningless results and test the capability to give meaningful predictions. For this scope, a primary configuration that consisted of wider parameter ranges was implemented. Pitchforth and Mengersen, [19] describe this as a network's face validity.

For the test, concentration was applied in the higher range of wave height values, while the distributions in the rest of the nodes remained the same. In all the belief nodes of the failure mechanisms (Fig. 11) changes occurred. The overtopping graph was shifted to the right and presented a higher mean value but with more uncertainty. Larger mean values were found in the recession and armor stability graphs too. In contrast, the ice related nodes were not influenced significantly due to the weaker correlations among them.

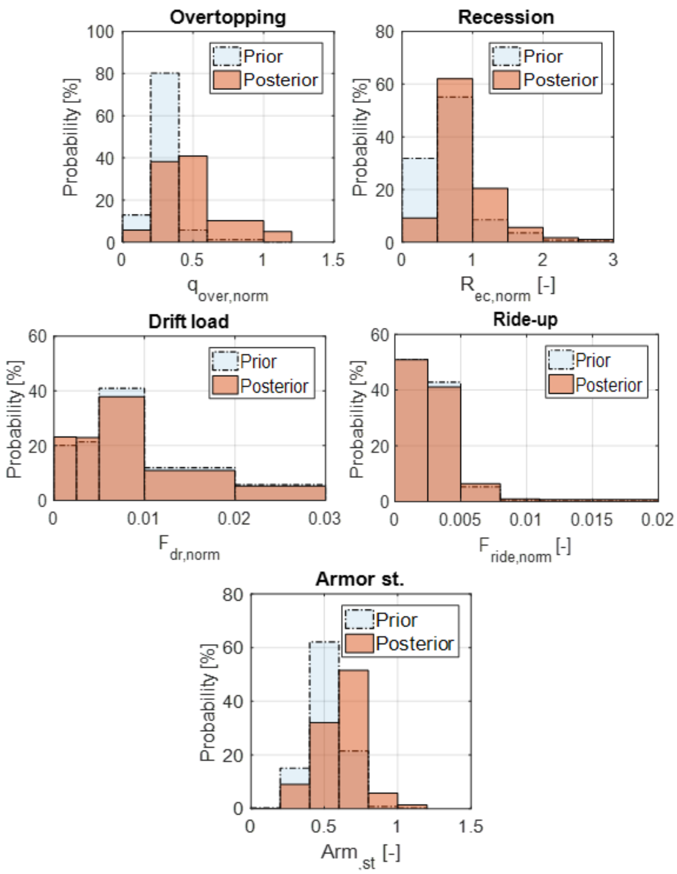

FIGURE 11: UPDATED FAILURE MECHANISMS NODES FOR THE FIRST VALIDITY TEST.

BAYESIAN NETWORK RESULTS

After performing the logical validity test a network was formed with non-normalized values. The new network followed the same configuration as the one in Figure 10. The ultimate results were extracted after updating the new network. The update was based on case files which were generated by scripts provided by OpenEarth [20]. Each case file consisted of nodes adjusted to different mean values of the loads.

The prior distributions of the failure mechanisms were generated with a Monte Carlo (MC) sampler model. The idea was to produce a Markov chain that would have a stationary distribution after generating a noteworthy number of samples.

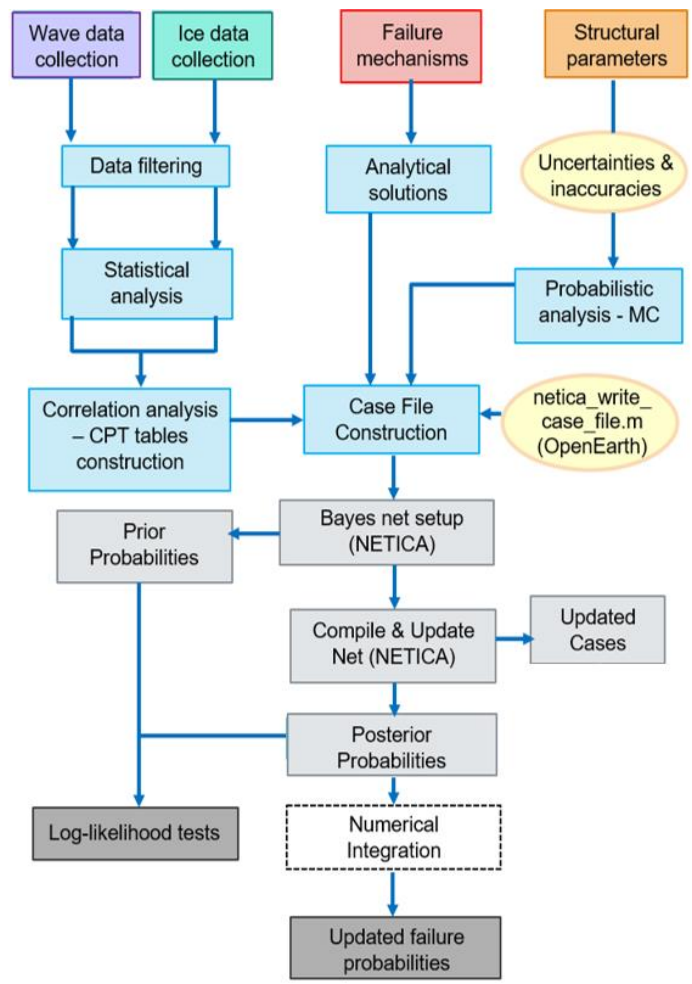

FIGURE 12: FLOW CHART FOR THE DAMAGE PREDICTION ANALYSIS OF BERM BREAKWATERS.

NETICA performed belief updating, which was a means of probabilistic inference in the compiled net, to find the missing probabilities in the nodes. In other words, the program assigned beliefs (marginal posterior probabilities) to nodes using the existing findings and posterior probabilities were generated by considering the prior ones. Subsequently, the damages were predicted, and the various failure probabilities were calculated after performing numerical integration. The belief updating did not change the model structure nor the dependencies between the nodes. However, the conditional probability tables were adjusted to the new beliefs.

A flow chart illustrates the main steps that were followed for the prediction analysis (Fig. 12). In Figure 13, there is a graphical presentation of the obtained results. Prior and posterior distributions are compared for the different failure mechanisms.

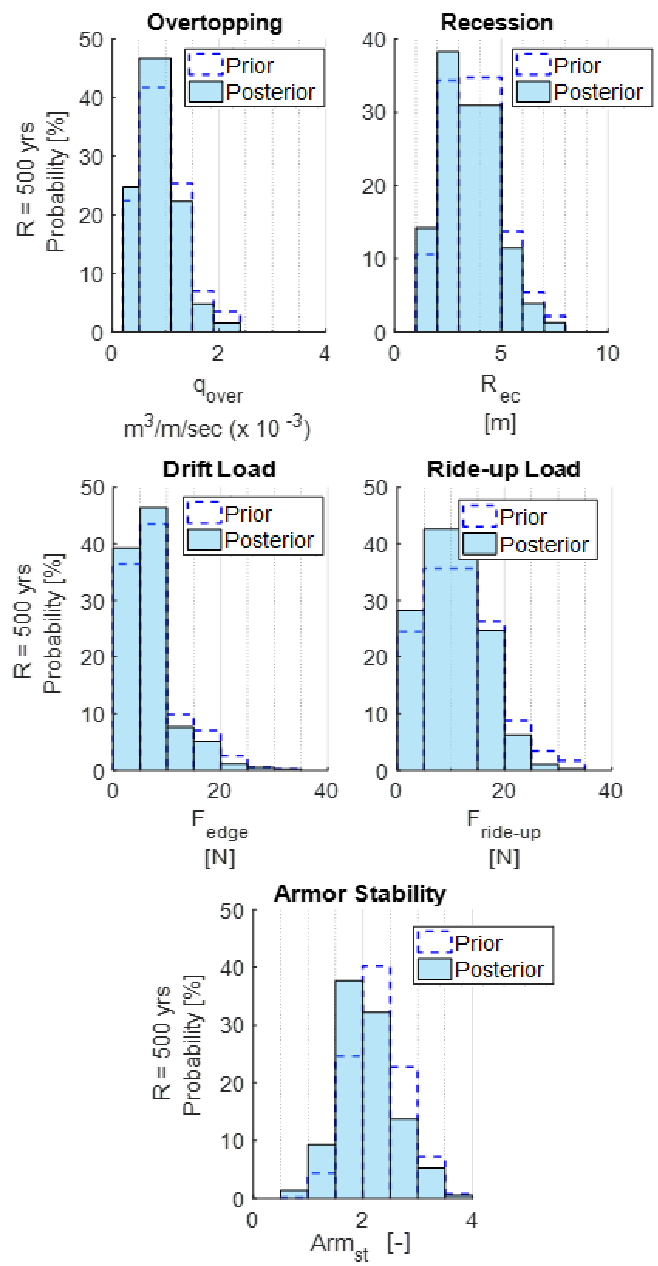

FIGURE 13: PRIOR AND POSTERIOR PROBABILITIES FOR A RETURN PERIOD OF 500 YEARS.

FAILURE PREDICTION

The posterior probabilities were implemented in a Level III probabilistic analysis and the failure probabilities and reliability indexes were estimated after performing numerical integration (MATLAB generated code) (Table 1). It was estimated that the lower probabilities in the higher ranges of the posterior results led to decreased failure probabilities. Another interesting finding is that the posterior failure probabilities satisfied the imposed requirements in all different scenarios, even though the relevant prior ones were higher in most cases. The scenarios corresponding to a significantly diminished ice cover in the Arctic in the forthcoming decades showed less damages on the coastal structures as caused by ice features.

TABLE 1: COMPARISON TABLE OF RELIABILITY INDEXES (β) AND FAILURE PROBABILITIES (Pf) FOR THE EXAMINED FORCING MECHANISMS, BEFORE AND AFTER THE BAYESIAN NETWORK UPDATING FOR R = 500 YEARS.

	Prior		Posterior	
	Pf	β	Pf	β
Overtopping	0.0046	2.6403	0.0019	2.9970
Recession	8.500e-04	3.1382	4.100e-04	3.3528
Ice drift	7.430e-05	3.2047	3.150e-04	3.5701
Ice ride-up	3.340e-05	3.4123	5.870e-05	3.2996
Armor stability	6.470e-04	3.2160	3.502e-04	3.3896

PREDICTION TESTING

Each set of findings that was entered in the nodes of the constructed Bayesian network was saved before a new update of the model as a different case. At the end of the predictions, the case files were used directly by the NETICA application to test the predictive skill of the network with log-likelihood tests. Specifically, the beliefs included in the case files were transformed to predictions. After that, the reliability of the outcomes and how far they were consistent with the historical wave and ice records at Prudhoe Bay were evaluated. The examination of the prediction accuracy allowed the detection of weak points in the structure.

6.1 Log-likelihood test

The log-likelihood test is a method of statistical inference that examines the predictive skill of a probabilistic model and is based on the likelihood ratio (LLR). In the developed Bayesian network, the likelihood ratios described whether a test was valid by comparing the prior odds to the posterior ones and were estimated with equation 17 [21]. The aggregate of individual ratios provided the network's overall predictive skill. Nevertheless, the network's credibility would be greater in case of an assessment based on posterior probabilities of the failure mechanisms and real damage observations.

$$\mathrm{LLR_j} = \log_{10}\{\, \mathrm{P}(\mathrm{F_i} \mid \mathcal{O}_\mathrm{j})_{\mathrm{F_i}=\mathcal{O}_\mathrm{j}} \} - \log_{10}\{\, \mathrm{P}(\mathrm{F_i})_{\,\mathrm{F_i}=\mathcal{O}_\mathrm{j}}\} \qquad (17)$$

where P (Fi | $\mathcal{O}_j$) is the posterior probability of prediction Fi given an observation $\mathcal{O}_j$ and P(Fi) is the prior probability of prediction Fi and j indicates the test case examined each time.

The prediction skill was characterized in terms of excellent, good and bad. The predictions with the larger positive LLR were characterized as excellent, and good corresponds to predictions with ratios closer to zero, while negative log-likelihood ratios imply bad forecasts. The positive rates proved that estimations with posterior probabilities provided better results than those where only prior probabilities were implemented. The numerical results from the analysis are presented in Table 2.

TABLE 2: LOG-LIKELIHOOD SKILL TEST RESULTS PRESENTED PER FAILURE MECHANISM AND RETURN PERIOD.

LLR for R = 500 yrs	
Overtopping	-0.1327
Recession	-0.0971
Ice drift	0.5705
Ice ride-up	0.5239
Armor stability	1.1014

DISCUSSION

Historical data can be used as informative priors in a probabilistic inference and their utilization is considered important in domains where numerical models have not yet been sufficiently developed. On the one hand, bulk recorded data can be filtered, analyzed and correlated against other data, based on empirical and analytical correlations. In this way, a probabilistic model is supplied with conditional dependencies from a large pool of information. On the other hand, Bayesian models represent a proficient tool for statistical inferences based on historical data as they extract parameters from different datasets and reasonably combine them by following assigned conditional dependencies. A Bayesian model could also adjust itself and perform meta-analysis as it is expected from its prior sets. This study verified that the strong dependencies between the wave and ice features directly affect failure mechanisms on a berm breakwater, although, these impacts have not been included in analytical solutions yet.

A Bayesian network could sufficiently perform failure predictions in complex natural systems, such as the Arctic. It was found that a well-constructed network can illustrate the cause and effect relations with a directed acyclic graph and automatically generate posterior findings with the use of the constructed CPTs. Moreover, an application like NETICA produces performance results which evaluate the accuracy of the posterior probability distributions. In this study, log-likelihood tests were used with similar overall results. In general, they demonstrated an improvement in the predictions when the number of files was larger. However, this was not noticed in the case of the ice ride-up force, maybe due to inadequate analytical approximations or weak estimated correlations. Therefore, the validation of the results with experimental data and actual damage observations from the site is necessary.

The wave height and ice surface area were found to be the most important parameters in overtopping, with direct and indirect effects respectively, with the wave steepness coming third. The ice ride-up and ice drift loads are mainly affected by wind and current loads, with the size of the ice feature also having an important influence on the latter. Furthermore, the examination of armor stability and recession was based on analytical approximations which have been formed with only wave forcing variables. The ice impact was considered in the construction of the conditional probability tables though, as the data analysis showed considerable effects on the waves.

The scenarios could be built with changing nodes (wave height, wave steepness, ice thickness and ice surface) after applying extreme value and trend value analysis over the next years. Updating the Bayesian network was an attempt to interpret the relations among the parent and child nodes, as well as, to obtain posterior distributions which could be used in the calculation of failure probabilities for different mean load values.

This study was based on several assumptions and it was limited by practical issues. The validation of the model is recommended, and it can be achieved with laboratory experiments, as field experiments are restricted in the hostile Arctic Ocean. Close observations of berm breakwater damages would allow a better understanding of the complex failure mechanisms and the quantifications of wave and ice loads on the structure.

CONCLUSIONS

A Bayesian probabilistic analysis was performed with the scope to perform reliability analysis of berm breakwaters in the Arctic and compute the relevant probabilities of failure. The probabilistic analysis was based on the development of a Bayesian network in NETICA software. The NETICA program was suitable for the purposes of this study. It was found to be a complete and powerful application that could process large data amounts efficiently.

The model was applied to data from Prudhoe Bay (Sagavanirktok), in Alaska. This area was selected as there are enough ice and wave records, as well as, actual coastal structures which facilitate the offshore activities in the largest oil field in the United States. In addition, Prudhoe Bay is noticeably susceptible to the consequences of climate change. Prudhoe Bay is mainly affected by waves, ice features and their interactions. The key role of short wind waves and the negligible height of swells in this area led to the exclusion of the latter from the probabilistic analysis.

The extensive study of the seasonal variations in the ice cover showed a diminishing trend in ice extent and ice thickness. The ice thickness in the coastal zone demonstrated higher values than the ice thickness further offshore as the ice features could accumulate due to shallower waters. Yet, the bigger ice features were supposed to stop in front of the breakwater and act as a shield for the structure. Hence, loads due to ice features thicker than a threshold water depth (3.2 m) were not included in the network's nodes. It was also observed that there were strong correlations between the ice and wave forces; wave characteristics varied due to the existence or not of ice and the ice features could alter after being influenced by the wave action.

These observations marked the need for a probabilistic model able to represent the conditional dependencies among the variables. A belief network was constructed, and the program carried out probabilistic inference. The Bayesian network appeared to be an attractive solution for high-level probabilistic design concepts. It was trained based on historical data and expert predictions on berm breakwater's damages by incorporating the non-well investigated wave-ice interactions.

ACKNOWLEDGEMENTS

The authors express their thanks to BMT ARGOSS and Peter Groenewoud for providing the oceanographic data of Prudhoe Bay. Thanks also to Ilija Samardžija from the Norwegian University of Science and Technology for the fruitful meetings, his help in processing the ice data and his supportive comments.

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