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Bayesian Networks for estimating hydrodynamic forces on a submerged floating tunnel

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A submerged floating tunnel (SFT) is a novel structure that allows crossing waterways where immersed tunnels or bridges are not viable. However, no SFT has been built yet mainly, due to lack of experience. In consequence, there are several uncertainties regarding its design and construction. An effect that should be further investigated is the structural response of the SFT under the simultaneous action of waves and currents. For this purpose, extreme values of waves and currents that were generated through a vine-copula model are used as input in a statistical model based on Bayesian Networks (BNs). The BNs are used to study the conditional correlation (i.e the correlation between random variables conditionalized on a given event) between the hydrodynamic forces acting on the SFT and metocean variables such as waves and currents. This methodology was applied to a case study in China for a SFT aimed to be built at the Qiongzhou Strait. Moreover, the BN model was used to test twelve different configurations of the SFT, with varying submergence depths and diameter sizes. The proposed methodology can be used to provide a more realistic estimation of the forces on the SFT by considering the dependence between the variables of interest. Moreover, this methodology can be extended to test different configurations of the SFT and other hydraulic or maritime structures subjected to simultaneous loading.

Keywords: Submerged Floating Tunnel, Bayesian Networks, Extreme values, Vine-copula, Waves, Currents.

1. Introduction

A submerged floating tunnel (SFT) is an innovative solution for crossing deep and wide waterways (Faggiano et al., 2016). This structure can be developed in three configurations: i) as a floating tunnel with tethers anchored to the bottom that hold the tunnel stable (vertically and horizontally) using positive flotation forces, ii) supported from pontoons, and iii) as an underwater bridge on underwater piers (Grantz P.E, 2010). A SFT has not been built yet, except for a prototype in Qingdao Lake in China (Mazzolani et al., 2010). Nevertheless, several feasibility proposals have been presented worldwide (Jiang et al., 2018; Fjeld, 2012; Kanie, 2010; Long et al., 2015).

In this paper, focus is on a SFT aimed to be constructed at the Qiongzhou Strait in the south of China. The strait is approximately 30 km wide, 70 km long and with a maximum depth of 120 m (Shi et al., 2002). Building a SFT in this area would connect Hainan island with the south region of Guangdong Province. This structure would alleviate traffic flow and it would solve the bottleneck problems of travelers during holiday periods and bad weather conditions (Shengzhong et al., 2016).

There are several challenges remaining regarding the design and construction of a SFT due to lack of data and experience. One topic of interest is the structural response of the SFT under the combined action of metocean variables.

Usually, in the design of offshore structures, the simultaneous action of design values is investigated under the assumption of independence (NOR, 1999). For example, a 100-year sea state, a 100-year mean wind speed and the 10-year current velocity are used as design values without considering the dependence between them. This simplification is done as a way to represent the surrounding environmental conditions and to compute their effect on the structure. In such cases, a probabilistic model that takes into account the dependence between the variables of interest could represent the surrounding environment more realistically. In this paper, we use a data set generated by a Vine-Copula model that captures the dependence between metocean variables. This data set describes extreme events of significant wave height (defined as the average wave height of the highest one-third of the waves) for wind and swell waves (as dominant variables) and their corresponding accompanying values of wave period and velocity of currents (as concomitant variables).

Next, the hydrodynamic forces acting on the SFT (introduced the combined action of waves and currents) are computed through the Froude-Krylov (FK) equation (Chakrabarti, 2005). The simplicity of this equation provides a reasonable approximation of the hydrodynamic forces acting

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on the SFT in terms of a simple expression. Finally, both the metocean data set and the resulting forces are used as input to a probabilistic model (Bayesian Networks) that allows the evaluation of the conditional probability of the resulting forces subject to the simultaneous action of the variables mentioned previously. This procedure was performed to a total of twelve configurations of the SFT (different combinations of diameters and submerged depths). The conditional distributions of the resulting forces can later be used to assess the structural reliability of the SFT. Details about this procedure are presented in section 3.

Bayesian Networks have been widely studied in the literature to analyze the dependence between variables within a system and have been applied to several fields. For example, Sperotto et al. (2019) uses Bayesian Networks to asses the impact of climate change on water quality, while Lu et al. (2020) presents a risk analysis for reservoir regulation using BNs. Moreover, BNs have been used simulate environmental data-sets. Das and Chanda (2020) models monthly regional rainfall using local meteorological drivers in India. Another example is the work developed by Sebastian et al. (2017), where peak storm surges and precipitation are simulated to determine the hydraulic boundary conditions for a low lying coastal watershed. In Paprotny and Morales-Nápoles (2017) a BN model was used to estimate extreme river discharges in Europe.

The aim of this paper is to shed light on the probabilistic methodology used to study the conditional distribution of the hydrodynamic forces acting on a SFT under the simultaneous action of metocean variables for several SFT configurations. This methodology can be extended to other and more complex models for describing the relation between metocean variables and to test different shapes, sizes and elements of the SFT. Moreover, this methodology can also be used for other structures subject to combined loads (i.e. offshore structures, wind mills, etc)

The remainder of the paper is organized as follows. First, a description of the data is presented in section 2 followed by the probabilistic model (Section 3) . Finally, the results are discussed in section 4 followed by the main conclusions and recommendations (Section 5).

2. Data

The data consists of two main data sets, i) Ten thousand simulations of metocean variables, namely significant wave height, wave period and velocity of currents at the Qiongzhou Strait in China, and ii) the Froude-Krylov force components acting on different SFT configurations (Section 2.2).

2.1. *Metocean Variables*

The metocean data set was generated through a vine-copula model developed by Torres-Alves et al. (2021) in which the characterization of the variables takes into account the complex dependence between them. A vine or vine-copula is a graphical tool for conditional dependence of random variables (Bedford, 2002). A vine on n variables is a nested set of trees where the edges of the tree t_j are nodes of the tree t_{j+1} Kurowicka (2006). A regular vine (R-vine), is one where an edge in t_{j+1} connects two edges from t_j, only if they share one node in t_j.

The data set consists of currents (the velocity of currents at 1m from the water surface) and two types of wave data, namely i) wind waves (WW) and ii) total swell (TS) waves. In order to simulate the metocean variables through the vine copula model, the variables were classified as dominant and concomitant. The dominant variable is the one from which their respective extreme observations are extracted, while the concomitant variables refer to the other variables for which the extracted values are the ones that occur at the same time as the extreme values of the dominant variable. Thus, the observations of the concomitant variables are not necessarily extreme values. In this paper, the selected dominant variable is the significant wave height for wind waves. Table 1 depicts a summary of all the variables.

Table 1. Name and description of the variables.

Variable	Name	Type
Wave height (WW)	$H^{(1)}$	Dominant
Wave period (WW)	$T^{(1)}$	Concomitant
Wave height (TS)	$H^{(2)}$	Dominant
Wave period (TS)	$T^{(2)}$	Concomitant
Velocity (1m depth)	U	Concomitant

The metocean data set used in this paper, are not the original observations that were used as input for the vine-copula model in Torres-Alves et al. (2021). Instead, we use the simulations generated by such a model. This is done to obtain a larger data set of ten thousand simulations for each variable that conserve the probabilistic dependence between them. For more details about this vine-copula model, the reader is referred to Torres-Alves et al. (2021)

Instead of extending the previously mentioned vine-copula model by adding the resulting force components, a BN model is used. This is because, for an increasing number of nodes (variables) n, the number of nested regular vine models can increase substantially (Morales-Nápoles, 2010) resulting in a computationally expensive process.

Thus, a BN model is presented as an alternative. However, one of the limitations of a BN model is that the multivariate joint distribution can only be characterized through a Gaussian copula, while a vine-copula model can combine different types of copulas.

2.2. *Froude-Krylov force*

The Froude-Krylov (FK) force is the force on an ideal water cylinder that has the same radius and is located at the same depth as the tunnel. This force is based on the assumption that the pressure field is not affected by the presence of the tunnel and can be determined from the incident wave potential by itself (Newman, 1977). The horizontal and vertical components of the Froude-Krylov force per unit length (kN/m) are estimated as (Boccotti, 2014):

$$f_y = \rho \pi R^2 a_y \tag{1}$$

$$f_z = \rho \pi R^2 a_z \tag{2}$$

Where a_y and a_z are given by:

$$a_y(y, z, t) = g\frac{H}{2}k_c\frac{cosh(k_c z)}{cosh(k_c d)}sin(k_c y - \omega t) + o(H) \tag{3}$$

$$a_z(y, z, t) = -g\frac{H}{2}k_c\frac{sinh(k_c z)}{sinh(k_c d)}cos(k_c y - \omega t) + o(H) \tag{4}$$

Where, R is the radius of the SFT in [m], H is the Wave height in [m], g is the acceleration of gravity equal to 9.81 [m/s2], k_c is the wave number that depends also on the current velocity in [rad/m], ω is the angular frequency [rad/s], and $o(H)$ are the terms of order H.

For the purpose of this paper, it is assumed that the waves and currents travel in the same direction. The resulting variables from the FK approach are depicted in Table 2.

3. Modelling approach

3.1. *Overview of the model*

The first part of the methodology consists of computing the components of the Froude-Krylov forces acting on the SFT where the 12 SFT configurations (Table 3) and the metocean data are used as input. Next, a BN model is constructed to study the resulting conditionalized distribution of the forces based on the simultaneous action of the metocean variables on the SFT. This procedure is depicted in Fig. 1.

Table 2. Name and description of resulting variables from the FK approach.

Variable	Name
Froude-Krylov component (y direction)	f_y
Froude-Krylov component (z direction) (z direction)	f_z
New significant wave height (due to the presence of currents)	H_c
Wave number (due to the presence of currents)	k_c

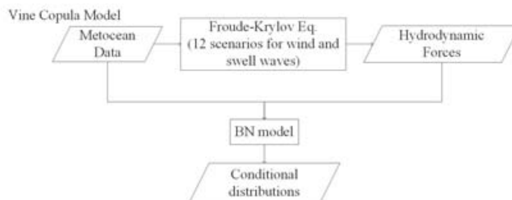

Fig. 1. Modelling approach

The analysis is divided into two main loading scenarios, i) wind waves and currents, and ii) swell waves and currents. For each main scenario, the 12 SFT configurations were evaluated. Fig. 2 depicts the general configuration scheme, where D is the SFT diameter, h is the submergence depth, and z is the distance from the center of the SFT to the seafloor. The total water depth at the strait (d) is constant and equal to 120 m. For the purpose of this paper, the SFT is simplified as a submerged horizontal cylinder with no tethers or pontoons.

Table 3. Case scenarios.

Case	D [m]	h [m]	z [m]
1	10	30	85
2	10	40	75
3	10	50	65
4	20	30	80
5	20	40	70
6	20	50	60
7	25	30	77,5
8	25	40	67,5
9	25	50	57,5
10	30	30	75
11	30	40	65
12	30	50	55

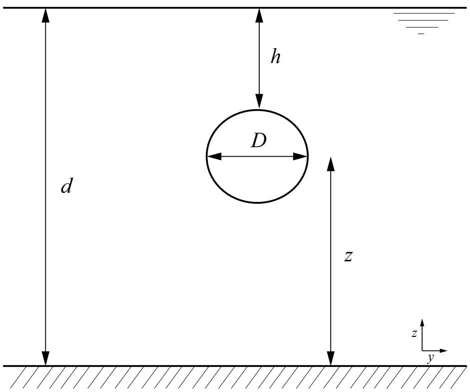

Fig. 2. Reference scheme

3.2. *Bayesian Networks (BNs)*

BNs are directed acyclic graphs (DAG) formed by nodes and arcs that represent the joint distribution of a set of variables. The nodes represent random variables that can be either continuous or discrete (Hanea et al., 2015). The arcs represent the probabilistic dependence between the variables. No arcs between nodes represent a set of (conditional) independence statements.

The direct predecessors and successors of a node are called parents and children respectively. In this way, a non-unique ordering of the variables is established. Thus, if information about one variable is to be studied, information about its predecessors should be found first (Morales-Nápoles et al., 2013). Each node with no parents is characterized by a marginal distribution while nodes with parents are represented by conditional distributions (Hanea et al., 2015). The main advantage of BNs is that they allow to update distributions given observations, this is also known as inference.

A BN is constructed using copulas. These are joint distributions with uniform margins in the interval [0,1] (Nelsen, 2006). Once all the variables and parameters are set, the joint distribution is defined. For the purpose of this paper, Gaussian copulas are used to characterize the multivariate joint distribution.

3.3. *Building the BNs*

In this paper, two BNs are presented, one for wind waves and currents (BN1) and the other for swell waves and currents (BN2). Regardless of the type of waves, the order of the nodes for both BNs is the same (Fig. 3).

To define the arrangement of the nodes, the physical relationship of the nodes needs to be considered. In general, the construction of the BN structure was done by using general knowledge on the variables and their relation with each other.

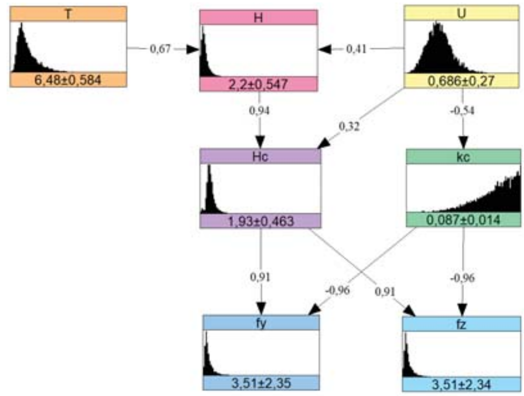

Fig. 3. Uninet visualization of the Bayesian network (BN1) for metocean variables and Froude-Krylov forces at the Qiongzhou Strait

Some relations are expected, for example, significant wave height and wave period, as well as current velocity and wave height. This is proved by their somewhat high correlation values(0.67 and 0.41 respectively). From the FK approach, a new estimation of wave height is derived, thus, it makes sense that their parent nodes are the initial significant wave height and current velocity. Finally, the force is computed from the new estimations of wave number and wave height, therefore these variables are defined as parents of the force's nodes.

In Fig. 3, the nodes are depicted as histograms with numbers that represent the mean and standard deviation of the variables. The values on the arcs are the conditional rank correlation coefficients. Each BN consists of 2 main categories, i) input values (Table 1), and the resulting variables from the FK approach (Table 2).

The BN set up presented in Fig. 3 was derived by testing several configurations. The position of the nodes shows their order relative to the force components (f_y and f_z). In order to estimate the force components given certain conditions (i.e. a specific wave height and period), the BN is updated. This means that the value of the node (or nodes) is defined based on the observations of that particular node.

The BN model was implemented using the MATLAB toolbox for Non-Parametric Bayesian Networks: BANSHEE–A (Paprotny et al., 2020) and the Uninet software was used to visualize the model (for more details see Morales-Nápoles et al. (2013)).

In this paper, it is of interest to conditionalize the BN on values that are larger than the ones available in the data set. Thus, instead of using the empirical distributions of each node, the data were fitted to univariate theoretical distributions.

Finally, a total of 10.000 samples were generated each time the BN was conditionalized. This was done to estimate the force components for a given environmental condition (different values of wave height, wave period or current velocities).

4. Results

4.1. *Univariate Fitting*

In this section, the variables of both BNs were fitted to theoretical univariate distributions. All the metocean variables are best described by a Generalized extreme value distribution. The univariate fit for the FK variables for both wind waves and swell waves cases was performed for all 12 case scenarios. Most of the scenarios are described by the same distribution. The corresponding fits are shown in Table 4.

Table 4. Univariate fitting for the FK variables

Variable	Wind Waves	Swell Waves
f_y	Loglogistic	Weibull
f_z	Loglogistic	Weibull
H_c	Loglogistic	Gamma
k_c	G.E.V	Inv. Gaussian

4.2. *Bayesian Network Model*

To validate the BNs, the dependence calibration (d-cal) score was computed. This score measures the distance between the empirical rank correlation matrix (ERC), the BN rank correlation matrix (BNRC) and the empirical normal rank correlation matrix (NCR) (Paprotny et al., 2020). If the matrices are equal, the score is equal to 1. If one matrix has a pair of perfectly correlated variables and the other one does not, the score is 0. The score tends to zero as element-wise the bivariate correlations are equal in magnitude but different in sign (Morales-Nápoles et al., 2014).

Through such diagnostic test, two properties are checked, i) that the joint Gaussian copula is adequate to represent the data, and ii) that the proposed BN is an appropriate model for the saturated graph (i.e. when all the nodes are connected to each other).

The resulting average d-cal score for all twelve scenarios of the BN1 is equal to 0.23, while the d-cal score between BNRC and NRC is equal to 0.003. Similar results were obtained for BN2. Thus, it is found that for both BNs the Gaussian copula does not represent adequately the data, nor this copula is valid for the particular configuration of the BNs presented in this paper. This is because the original data comes from a vine-copula model in which different copulas (different from a Gaussian) were used to generate the data set.

However, different d-cal score may arise if the original observations are used instead but such analysis is out of the scope of this paper. The BNs presented herein were still used to analyze the conditional distributions of forces acting of the SFT. This is done in order to show how BNs can be used to study different variables when the dependence between them is taking into account or what can be done if the empirical data were used instead.

4.2.1. *Conditional distribution of force components*

To simulate the conditional distribution of the hydrodynamic forces, the BN is updated. This means that the BNs were conditionalized on different values of significant wave height and current velocity.

This was done for all twelve case scenarios of both BNs in order to compute the forces design values from the conditional distributions (Table 5).

Table 5. Design values of f_y [kN/m] corresponding to a probability of exceedance of 0.01 for both BNs."CD" refers to the conditional distribution and "MD" to the marginal distribution of the variable.

Case	BN1		BN2	
	CD	MD	CD	MD
1	106	12	21	7
2	123	8	20	5
3	59	5	7	4
4	459	38	82	24
5	537	24	81	18
6	346	15	30	14
7	779	53	127	35
8	844	33	125	26
9	656	21	54	20
10	1111	68	182	47
11	543	42	60	36
12	1176	26	97	27

The BNs are conditionalized using different values of wave heights and velocity of currents. In this paper, we present an example using large waves and fast currents ($H^{(1)} = 15$ m, $H^{(2)} = 8$ m and $U = 1$ m/s). The design values correspond to a probability of 1/100. Table 5 shows that the design values obtained from the conditional distributions are significantly larger than the ones from the empirical distribution of f_y. In general, larger diameters and shallower submergence depths (h) lead to stronger forces. Thus, the largest force for BN2 is found in case scenario 10 with $f_y = 182$

kN/m. However, in BN1 the largest force correspond to case scenario 12 ($D = 30$ m and $h = 50$ m) with a $f_y = 1167$ kN/m. Similar results were obtained for f_z.

Overall, larges values are obtained for the CD as result of updating the BN. For example, conditionalizing the BN1 to high values of wave height and currents changed the mean of the distribution from 14.5 to 265 kN/m (case scenario 10). Fig. 4 depicts the effect of updating the BN.

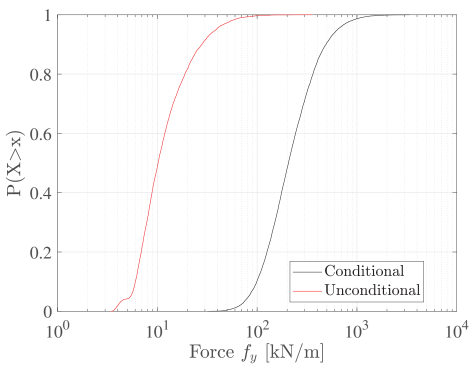

Fig. 4. Cumulative probability distribution of force: unconditional and conditionalized on 1 node (wave height) case study 10. BN1

The resulting design values provide insight into the importance of considering the dependence between the variables rather than study them independently. Moreover, the methodology also highlights the role of each variable when designing a SFT, for example, the design values from BN1 are larger than from BN2. Thus, for this particular case, wind waves generate larger forces than swell waves.

5. Conclusions and Recommendations

In this paper, we present a methodology to study the conditional distribution of the force components acting on a SFT as a result of the simultaneous action of waves and currents. The method focuses on taking into account the complex dependence structure between metocean variables and the resulting forces.

Two Bayesian Networks (BN1 and BN2 for wind and swell waves respectively) were used to characterize the joint dependence of the variables for twelve different configurations of the SFT. The BNs were conditionalized on different values of significant wave height and period for both wind waves and swell waves. Th focus is on large values of wave heights and fast current velocities to compute design values for the force components f_y and f_z. The results show that stronger forces are obtained when the conditional distributions are used instead of considering the variables as independent. This highlights the importance of dependence between variables when designing a SFT.

The methodology presented in this paper can be extended for more complex models (use of vine-copulas instead of BNs or more advanced physical models for structural response) and to analyze the SFT (or any of its elements) under different environmental variables. Therefore, this methodology can be used as a reference for other SFT configurations.

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