

Statistical models for improving significant wave height predictions in offshore operations

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1 **Statistical Models For Improving Significant Wave Height Predictions In** 2 **Offshore Operations**

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4 By

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31 **Abstract**

32 Installation and maintenance strategies regarding offshore wind farm operations involve
33 extensive logistics. The main focus is the right temporal and spatial placement of personnel
34 and equipment, while taking into account forecasted meteorological and hydrodynamic
35 conditions. For these operations to be successful, weather windows characterized by certain
36 permissive wave, wind and current conditions are of enormous importance, whereas unforeseen
37 events result in high cost and risk in terms of safety. Numerical modelling of waves, water
38 levels and current related variables has been used extensively in engineering practice to forecast
39 ocean conditions. To account for the inherited model uncertainty, several error modelling
40 techniques, such as Artificial Neural Networks (ANN), Copulas, Stochastic Interpolation, and
41 Linear Regression, can be implemented for the numerical model forecasts to be corrected. In
42 this study, various Bayesian Network (BN) models are incorporated, in order to enhance the
43 accuracy of the significant wave height (H_s) predictions and to be compared with the
44 aforementioned techniques in conditions resembling the real-time nature of the application.
45 The implemented BN models differ in terms of training and structure and provide overall the
46 most satisfying performance in comparison to the rest of the techniques, when tested with data
47 retrieved from stations deployed in the Irish Sea. It is shown that the BN models illustrate
48 significant advantages as both quantitative and conceptual tools, since they produce estimates
49 for the underlying uncertainty of the phenomena, in the form of 95% confidence intervals
50 extracted by the significant wave height (H_s) conditional distribution, while providing
51 information about the incorporated variables' dependence relationships through their structure.

52 **Keywords:** Bayesian Networks; offshore operations; real-time predictions; statistical
53 techniques; model coupling

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57 **1. Introduction**

58 Marine structures like offshore wind turbines can ensure safety and serve their main function
59 adequately, in both reliability and economy terms, when most – if not all – of the variables
60 involved in their design are modelled as accurately as possible. The specification of the
61 uncertainties related to the environmental variables describing the ocean conditions is
62 continuously gaining importance and interest by the offshore, coastal, and the emerging
63 renewable energy industries. Several studies have been conducted in order to describe, classify,
64 or quantify the uncertainties and errors related to meteorological and ocean climate variables
65 (see e.g. Bitner – Gregersen et al., 2014; Haver and Moan, 1983; Bitner – Gregersen and Hagen,
66 1990). Simplistically, the uncertainty can be classified as: (a) Phenomenon related uncertainty,
67 which is a product of the natural randomness and stochastic nature of the variables incorporated
68 and cannot be reduced, (b) data related uncertainty, which surfaces either from the measuring
69 devices' accuracy, or the insufficient number or quality of the observations, and (c) model
70 related uncertainty, which constitutes a product of inaccurate idealisations, crude assumptions,
71 or even insufficient use of either the meteorological or the hydrodynamic model. It is obvious
72 that the true nature of any phenomenon cannot be modelled exactly and that even if the
73 probability distributions of some variables are known a priori, the extreme complexity of the
74 met-ocean environment makes the distributions of the rest completely unknown. The
75 estimation of the bias, or systematic error, and the random error evaluation are the first steps
76 to quantify the uncertainty of any variable.

77 In the case of offshore wind farms, the installation and maintenance strategies involve
78 extensive logistics. The main focus is the right placement, in time and space, of both the
79 personnel and the equipment, while taking into account forecasted meteorological and
80 hydrodynamic conditions. In order for the aforementioned procedures to be carried out
81 successfully, weather windows, interwoven with certain permissive wave, wind and current

82 conditions, are of major importance, while unforeseen weather or sea climate events result in
83 high cost and risk, primarily in terms of safety. Subsequently, successful operations require
84 accurate and representative data for the wind farm sites, which unfortunately are inadequately
85 - if at all - provided by surrounding stations.

86 In order to produce forecasts of the hydrodynamic conditions in a specific area, numerical
87 models can be used. Wind speeds, as well as the air and water temperatures, resulting from a
88 meteorological model serve as an input for numerical modelling of waves, water levels and
89 current related variables. In that regard, SWAN (see Booij et al., 1999a; 1999b) is a third-
90 generation wave model, developed at Delft University of Technology, which computes
91 random, short-crested wind-generated waves in coastal regions and inland waters and provides
92 output quantities in numerical files containing tables, maps and timeseries. Comparison of the
93 wave model forecasts with observations is essential for characterizing the model deficiencies,
94 identifying systematic and random model errors, thus providing areas for improvement.

95 Several techniques exist and can be implemented in order for the numerical model forecasts to
96 be corrected. The Artificial Neural Networks (ANNs), which are information processing
97 paradigms composed of a large number of highly interconnected processing elements (neurons)
98 working together, have been used extensively in offshore and coastal applications (see e.g. Deo
99 et al., 2001; Tsai et al., 2002; Makarynskyy, 2004; Malekmohamadi et al., 2008; Kumar et al.,
100 2017; Deo and Sridhar Naidu, 1999; Makarynskyy et al., 2005; Londhe et al., 2016; Agrawal
101 and Deo, 2002; Mandal et al., 2005; Londhe and Panchang, 2005; Zhang et al., 2006;
102 Deshmukh et al., 2016; Makarynskyy, 2007; Londhe and Panchang, 2006; Makarynskyy,
103 2005). Supplementary, Copulas (see e.g. Genest and Favre, 2007; Embrechts et al., 2001;
104 Nelsen, 2006; Schmidt, 2006) have been utilized in various occasions to model the dependency
105 of ocean related variables and predict their behavior, as it has been done in the works of
106 Leontaris et al. (2016) and Jane et al. (2016). Simpler but equally effective methods are the

107 linear regression and the stochastic interpolation. Both of these techniques have been used
108 extensively in a variety of engineering applications, including offshore and coastal (see e.g.
109 Asma et al., 2012; Scotto and Guedes Soares, 2007). They do not require substantial training
110 and pose serious advantages in terms of computational time and load.

111 All of the aforementioned techniques constitute soft computing methods and ensure a
112 reasonable computational load. A number of them require training using historical or present
113 time data, while others can be incorporated forthwith. Some studies have tried to produce valid
114 met-ocean climate forecasts using coupled (hybrid) method (e.g. Deshmukh et al., 2016), as
115 the ones discussed in this paper, or incorporate solely one of the techniques discussed
116 previously to predict the environmental conditions therewithal. By “coupled” or “hybrid”
117 methods the use of more than one error modelling techniques, or a combination of a soft
118 computing method and a numerical model, is implied. Certainly, the use of a single soft
119 computing method for prediction reduces the computational time significantly, but often at the
120 expense of accuracy.

121 In this study, special attention is given to the implementation of the Bayesian Networks (BNs),
122 graphical models which allow the representation of a probability distribution over more than
123 one variables and whose use has not been that widespread in offshore applications (an example
124 can be found in Malekmohamadi et al., 2011), but has been tested effectively in other
125 engineering problems, such as coastal morphology (see e.g. Poelhekke et al., 2016; Kroon et
126 al., 2017; Wilson et al., 2015; Plant and Holland, 2011), environmental modelling (see Chen
127 and Pollino, 2012; Aguilera et al., 2011), construction reliability (Morales-Napoles and
128 Steenbergen, 2014), traffic prediction (Worm et al., 2011), or flood risk analysis (Sebastian et
129 al., 2017). Supplementary, many applications of the BNs on dependability, risk analysis and
130 maintenance can be found in Weber et al. (2012) and Medina Oliva et al. (2009). An overview
131 of many BN applications is given in the work of Hanea et al. (2015). Many of the applications,

132 however, use networks consisting of nodes that represent discrete random variables. Those
133 networks are characterized as discrete BNs and suffer from serious limitations, since the
134 provided discrete representation of variables for many important problems is inadequate.

135 The perspective of this research deviates from providing a forecast, accompanied with a desired
136 level of accuracy. The aim is to use automated tools to quantify the possible errors present in
137 numerical model forecasts of the significant wave height (H_s), learn from these errors while
138 understanding and quantifying the underlying relations induced by certain phenomena to
139 eventually improve the predictions of the numerical model, which is solely based on
140 empirically and theoretically derived formulas. The consideration of Bayesian Networks aims
141 to the description and representation of the underlying uncertainty in nature's behavior, as
142 accurately as possible. While most models, such as Copulas or ANNs, would just need past
143 measurements, numerical model data and/or numerical model forecasts of the significant wave
144 height, to produce a possible correction, the nature of Bayesian Networks imposes the use of
145 more variables (e.g. wind velocity, wave period, etc.), whose dependency with the variable of
146 interest can produce a forecast of enhanced accuracy.

147 In Section 2 of this paper some information on the data used for the analysis, as well as a
148 description of the theoretical background and functionality of the BN models, are outlined. To
149 grant the desired corrections, several models that differ in terms of their training, their structure,
150 and the incorporated variables were created and tested. A comparison of the performance of all
151 the implemented statistical and stochastic techniques took place, to ascertain which one
152 performs better, employing widely used evaluation metrics and more specific indicators created
153 for the purposes of the application under consideration. Additionally, the ability of the error
154 correction techniques to perform in operational (real-time) conditions was investigated, to
155 evaluate their performance even in possible absence of measurements. The results and
156 comparison of the different techniques can be found in Section 3, along with a discussion on

157 the influence of different BN structures on the quality of the outcome. Finally, Section 4
158 contains the conclusions of this study, supplemented by future research paths.

159 **2. Materials and Methods**

160 The error correction models described here, are essentially forecasting tools, which attempt to
161 predict the hydrodynamic conditions in open seas more accurately than a numerical model (in
162 this case SWAN), while using the results provided by the latter as an input. Hence, they are
163 referred to as “error correction” models, since their nature and behavior deviates slightly from
164 a pure predictive tool (see e.g. Emmanouil, 2018).

165 In general, the models are able to perform both in non-operational (offline) and operational
166 (online) situations. By operational situations, the continuous flow of the required data in real-
167 time is implied, while in non-operational mode, the model interacts with data stored in the
168 computer’s memory. Nevertheless, in both cases the nature of the data, and the number of
169 variables included in each simulation, are the same. The error correction models require three
170 types of data: (1) on-site measurements (observations), which are processed before used, (2)
171 numerical model hindcast¹ data for a time interval prior to the one under consideration. Instead
172 of using hindcast data for the analysis, one could alternatively use past forecast data of the
173 numerical model, which of course will be less accurate, due to the input of wind data produced
174 also by a numerical model (e.g. HIRLAM; see Cats and Wolters, 1996) incorporating and
175 transferring uncertainties of its own, and (3) numerical model forecast data for the time interval
176 under consideration (48 hours ahead of current time). In a real-time scenario, the numerical
177 model forecasts is produced every 6 hours, so there would be 4 forecasts per day, each one for

¹ The numerical model hindcast data are produced by incorporation of observational wind data as input to the model and a reverse procedure to obtain the results (i.e. the opposite of a forecast procedure).

178 48 hours ahead. Depending on the error correction method some of the above data may or may
179 not be used.

180 **2.1. Bayesian Networks (BN) Model**

181 **2.1.1. Brief Theoretical Background**

182 Bayesian Networks (BNs) are graphical models, which allow the representation of a probability
183 distribution over a set of random variables (see Jensen and Nielsen, 2007; Morales-Napoles et
184 al., 2013; Hanea et al., 2015; Weber et al., 2012). They consist of a directed acyclic graph
185 (DAG) built on discrete (discrete networks), continuous (continuous networks), or both kinds
186 (hybrid networks) of random variables (X_1, X_2, \dots, X_n), and a set of (conditional) distributions.
187 A DAG is constituted by a set of nodes, that represent random variables, and a set of arcs, in a
188 way that a directed cycle cannot be created. Within the graph, an ordering of the variables can
189 be established, given the directionality, which provides information on the sampling order, i.e.
190 the order which has to be followed so that a sample can be taken from this joint distribution.
191 As a result, some of the nodes are characterized as “parents” and others as “children”,
192 depending on whether they precede or success the node of interest. A marginal distribution is
193 assigned to each node with no parent, and a conditional distribution is associated with each
194 child node, providing quantitative information about the dependences between the variables,
195 which can be either retrieved from data or from expert judgment (see e.g. Cooke, 1991).

196 Denoting the parent nodes of i as $Pa(i)$, the joint density of X_1, X_2, \dots, X_n is given by:

$$197 f_{X_1, \dots, X_n}(x_1, \dots, x_n) = \prod_{i=1}^n f_{X_i | X_{Pa(i)}}(x_i | x_{Pa(i)}) \quad (2.1)$$

198 where $f_{X_i | X_j}$ denotes the conditional densities. The factorization of the joint distribution relies
199 on the local Markov property of conditional independence.

200 BNs are quantitative tools, able to evaluate conditional probabilities between variables, and at
201 the same time constitute valuable conceptual models, since they visually represent independent
202 and dependent variables in causation relationships (see Chen and Pollino, 2012; Palmsten et
203 al., 2014; Stewart-Koster et al., 2010). The principles of BNs as a modelling tool are described
204 thoroughly in Pearl (1988) and Jensen (1996). The main property of the BNs is inference, which
205 constitutes their ability to provide updated distributions, given observations, but also
206 characterization of the relationship between the variables. Generally, the simple visualization
207 of the complicated relationships between the random variables, as well as their polyvalence,
208 i.e. the ability to deal with issues such as prediction, diagnosis, optimization, data analysis of
209 feedback experience, and model updating, makes the use of BNs appealing.

210 **2.1.2. Training Methodology**

211 The Bayesian Networks, as most of the data driven techniques, need a sufficient amount of
212 data in order to be trained sufficiently and be able to represent the desired relations. When the
213 BN structure is acquired through the data, then a significant amount of data is needed. In every
214 application the characterization of a training procedure as “sufficient” depends largely on the
215 type and behavior of the data. A sensitivity analysis would be in place to determine what
216 “sufficient amount” actually means for the application. The significant wave height, for
217 instance, is a variable whose behavior is highly dynamic, i.e. it can change radically in short
218 time intervals (e.g. hours). As a result, the more training the model has the better, since it can
219 assimilate to, and later reflect a larger range of behaviors.

220 Here, the training techniques are divided into two major categories; (1) the long training, which
221 involves past observational and numerical data, even from 3 years prior to the current date, and
222 (2) the short training, which only involves measurements and numerical model data from 48
223 hours prior to the start of the forecast.

224 In order to obtain the structure of the Bayesian Network, the `bnlearn` package of R is used.

225 In general, there are two broad categories of algorithms to learn the structure of a BN, the score-
226 based and the constraint-based. The constraint-based case employs conditional independence
227 tests to identify a set of edge constraints for the graph and then finds the best DAG that satisfies
228 these constraints; see e.g. Scutari (2005). The score-based approach (see Russell and Norvig,
229 2009; Korb and Nicholson, 2010) first defines a criterion to evaluate how well the BN fits the
230 data, and then searches over the space of DAGs for a structure with maximal score.

231 For this study, a hill climbing (HC) score-based structure learning algorithm was used to train
232 the network, which made use of an AIC criterion. The package also assumes a multivariate
233 normal distribution for continuous variables (such as the hydrodynamic variables in hand). This
234 assumption can be considered restricting in many occasions, but as it will become obvious, the
235 results of such an analysis are quite reasonable. In case the assumption of multivariate
236 normality is violated, the non-parametric Bayesian Networks could produce a more accurate
237 conditional distribution and possibly more accurate forecasting results; see e.g Hanea et al.
238 (2015). Nevertheless, the assumption of multivariate normality was considered sufficient to
239 test the BN behavior and performance, and the open-source `bnlearn` package as the most
240 suitable one for this particular application.

241 For the case of long training, the training dataset is continuously enriched with new
242 measurements, as well as with past numerical model data for the variable of interest only.
243 Certainly, this requires a relatively large part of the computer's memory. This effect can be
244 impugned by incorporation of new variables and deletion of older, or with smaller training sets,
245 i.e. in the order of months instead of years.

246 In general, the user can impute his/her own structure, by whitelisting or blacklisting certain
247 relations, i.e. providing a custom fit. This, certainly, creates large differences in the results,

248 since in many occasions the whitelisted arc is not supported by the BN structure in representing
249 the joint density. Thus, it is suggested by the writers that the procedure should be carried out
250 using data-driven structure learning and fitting techniques, even if a given relation might not
251 be supported intuitively.

252 **2.1.3. Predictions and Uncertainty Bounds**

253 The predictions provided by the BN models are retrieved from the conditional distribution of
254 the variable of interest, given the information about certain other variables.

255 Since it is impossible to have future measurements for the incorporated variables, forecasted
256 numerical model data for these variables are used to construct the conditional distribution for
257 every point prediction. In other words, the network is trained and fitted with past observational
258 data, as well as numerical model data for the variable of interest, subsequently providing a
259 forecast based on forecasted numerical model data (essentially we are conditionalizing on
260 forecast numerical model data). The point prediction is the expected value of the conditional
261 distribution, which is assumed to be normal. Since the significant wave height (H_s) is not
262 normally distributed (see e.g. Tayfun, 1980), the assumption is in certain occasions not
263 appropriate. Consequently, this assumption prevents us from retrieving realistic uncertainty
264 bounds for the significant wave height. Nevertheless, the symmetrical uncertainty intervals can
265 provide a fairly good coverage of the observations (more information and examples can be
266 found in the following sections).

267 The standard 95% are obtained from the 2.5th and 97.5th quantiles of the conditional
268 distribution, Since the wave heights seemed to follow a log-normal distribution, a log-
269 transformation of the significant wave height (H_s) has been applied. The network was thus
270 trained with the transformed data. The obtained predictions were transformed back to their

271 original form, which yield the log-normal intervals. Again the 2.5th and the 97.5th quantiles
272 were used.

273

274 **2.2. The Data**

275 The data were retrieved from stations deployed in the Irish Sea. The measurement stations,
276 which are actually wave rider buoys and meteorological masts, are adjacent to the wind farms
277 of Gwynt-y-Mor² and Rhyl Flats³, located within the Liverpool Bay. The received datasets
278 consist of measurements of hydrodynamic and meteorological data, obtained between 01-09-
279 2012 to 31-01-2018. It has to be stressed that the error correction techniques are suitable for
280 any offshore environment, given the required training, and are not limited in the area of the
281 Irish Sea. The case presented here serves as an example of the applicability of the models in
282 real-life applications. The same procedures and techniques would have to be followed in any
283 similar case, aiming to accurately predict the variables' behavior in mild offshore
284 environments.

285 A fit test was carried out for the significant wave height (H_s) data by means of the FDB tool in
286 Matlab[®], which incorporates certain criteria (AIC, BIC, etc.) to define the best parametric
287 distribution for the data in hand. As can be seen in Figure 1, the log-normal distribution
288 provides a good fit for the significant wave height data (H_s), which will be proved really useful
289 in the simulations to follow.

² Gwynt-y-Mor Offshore Wind Farm (53°27'N 03°35'W) is located off the coast of North Wales and is the 4th largest operating wind farm in the world (160 wind turbines).

³ Rhyl Flats Offshore Wind Farm (53°22'N 03°39'W) is a 25 turbine wind farm, located approximately 8 km north-east of Llandudno in North Wales.

290 **2.2.1. Training and Fitting Datasets**

291 Different error correction techniques require different sets for training, while some of them do
292 not need substantial training at all. To be more exact, the simple linear regression and the
293 Bernstein stochastic interpolation (see e.g. Kolibal and Howard, 2006; 2008; Seyfarth et al.,
294 2006) utilized here, take as an input only numerical data and measurements corresponding to a
295 time interval just 48 hours prior to the forecast. The three-layered, feed forward ANN (see e.g.
296 Deo and Sridhar Naidu, 1999), which uses a back-propagation algorithm (see e.g. Tsai and Lee,
297 1999), as well as the bivariate Copula (chosen to be Gumbel based on a simple Cramér-Von
298 Mises criterion test incorporating numerically modelled and observed data; see Anderson, 1962), were
299 trained with 6 months of data corresponding to the period March – August 2015, and then used
300 implementing the same input delineated for the aforementioned techniques. It has to be stressed
301 that only H_s data were used by all these techniques.

302 The BN models incorporate three different types of training; (1) long-training with data from
303 01-01-2014 to 31-12-2016, i.e. 3 years of training, (2) short-training with hourly data
304 corresponding to 48 hours prior to the forecast, i.e. 2 days of training, and (3) a fixed structure,
305 produced by 3 years of training (2014 - 2016), and fitted with data tallying to 48 hours prior to
306 the respective 48-hr forecast, i.e. 3 years for training and 48 hours for fitting and retrieving the
307 required variable relations, necessary to produce a prediction. The term “fixed” was used to
308 stress out that, while the power of the underlying relations between the variables constantly
309 altered due to the dynamic behaviour of hydrodynamic and meteorological variables, the
310 structure was not changing because of the significant amount of training.

311 **2.2.2. BN Input Data**

312 When producing a prediction with the BN model, there should be an input of the variables
313 based on which the conditional distribution is being produced (this is often referred to as
314 *conditionalization*). The variables were selected to represent nodes in the network based on

315 their relation to the significant wave height, their availability, and finally their quality. In order
316 to simulate a realistic scenario, where measurements and numerical model data exist, the
317 following variables were selected: (1) the zero-crossing wave period (T_z), (2) the wave
318 direction (D_{irp}), (3) the wind velocity 10 m above the sea level (U_{10}), (4) the wind direction
319 (U_{dir}), and (5) the numerical significant wave height ($H_{s,num}$). As stated before, the numerical
320 model forecast data (48 hours ahead) for the rest of the selected variables are used as
321 conditionalizing values to generate accurate predictions for the variable of interest, namely the
322 significant wave height (H_s).

323 **2.2.3. Model Testing and Validation Datasets**

324 For testing and comparison between the different incorporated techniques, data retrieved for
325 the year of 2017 were used (01-01-2017 to 31-12-2017). In order to simulate effectively the
326 real-time nature of the application, a forecast was corrected every 6 hours of each day. Because
327 SWAN produced 4 forecasts per day, one every 6 hours, each one of the error correction
328 techniques, generated a potential corrected (potentially more accurate) prediction an equal
329 number of times. It can be realized that the extremely large amount of information makes it
330 impossible for all the results to be presented. Thus, a collective set, encapsulating different
331 types of behaviours, is going to be displayed.

332 **3. Results - Discussion**

333 In this section, the summative results for simulations corresponding to the whole year of 2017
334 (from 01-01-2017 to 31-12-2017) are presented. As previously stated, the measurement
335 stations were situated near the Gwynt-y-Mor (GyM) and Rhyl Flats (RF) offshore wind farms.

336 **3.1. Method Comparison**

337 In order to establish a basis for comparison between the methods, certain well-known
338 evaluation metrics, namely the Root-Mean-Square-Error (RMSE), the Bias, and the Unbiased-
339 RMSE (URMSE) were employed. For reasons of brevity, only the Gwynt-y-Mor results are
340 presented here (Table 1).

341 Both the long-trained and custom-fixed BNs displayed satisfying performance in terms of their
342 error distribution, which is reflected on their bias values, while introducing an enhancement in
343 accuracy, larger than any other method, with the exception of linear regression. Yet, even if
344 the metrics of Table 1 are indicative of the general behavior of the models, it has to be stressed
345 out that evaluating the techniques' performance solely based on them is impossible. This issue,
346 regarding the robust and consistent validation of the predictions, can be resolved with the use
347 of case specific metrics, i.e. indicators displaying the models' accuracy within and around the
348 significant wave height boundaries of this specific application, i.e. $0.5 \leq H_s \leq 1.5$ m.
349 Particular interest is given around the upper boundary of 1.5 m, which is certainly the most
350 crucial for offshore maintenance operations, since it ensures nautical safety (see Table 2).

351 Consequently, three extra indicators were taken into account: (1) the percentage of the critically
352 accurate predictions, i.e. the forecasts for which the measurements were higher than 1.5 m and
353 the respective model managed to predict, (2) the false positive forecast percentage, which
354 provides information on the amount of predictions above 1.5 m when the measurement was
355 below, and (3) the percentage of the critically inaccurate forecasts, i.e. the amount of
356 predictions below the 1.5 m upper boundary, when the measurement was above that limit.
357 Notice that the percentages were calculated over the whole time interval, i.e. in terms of the
358 whole dataset, hence their values are small. In any case, they provide the needed means for
359 comparison in this stage.

360 An example of a correction to the numerical model's 48-hr forecast, given at critical values for
361 an operation, is shown in Figure 2. The BN model incorporating the so-called fixed structure
362 managed to predict relatively accurate the offshore conditions while simultaneously prevented
363 (hypothetically) any operation that might endanger the crews and the equipment.

364 **3.2. Uncertainty Estimates**

365 One major advantage of the BN methods, in comparison to the rest of the techniques is their
366 ability to provide estimates of the uncertainty governing the variable of interest; in this case
367 the significant wave height (H_s). The only one of the other techniques able to produce
368 confidence intervals is the Gumbel Copula. Nevertheless, the assumption of a Gumbel Copula
369 influences the confidence intervals' performance significantly.

370 Regarding the BN methods, the normality assumption for the conditional distribution of H_s
371 governs the predictions. As a result of the aforementioned supposition, the uncertainty
372 boundaries given by the BN models are symmetrical. Despite the restrictive nature of this
373 assumption, the predictions acquired by the BN models in our study are quite satisfying,
374 providing a correction of the SWAN forecast in most of the cases. That of course might not
375 influence their performance or their usefulness.

376 Since the H_s data follow a log-normal distribution (see also Section 2.1.3), a log-transformation
377 of the data has been considered for the BN methods. Note that the uncertainty bounds are no
378 longer symmetric.. Table 3 provides the the results of uncertainty quantification from standard
379 BN methods and BN methods applied to the log-transformation of the data, as well as from the
380 Copula. The log-normal uncertainty bounds provide smaller coverage percentages (percentage
381 of measurements in the test data within the confidence interval) with similar or larger average
382 lengths of the confidence intervals or larger percentages accompanied with unrealistically large
383 average lengths (approximately 1.18 m). As a result, the normal confidence intervals are more

384 efficient and accurate. The most useful uncertainty boundaries seem to be the ones provided
385 by the BN model incorporating the fixed structure, which have a reasonably high coverage
386 percentage (86.1%) accompanied by a satisfying average length, in comparison to the bounds
387 given by the long-trained BN model, which are 10 cm larger but only 3% more accurate.

388 Considering the overall performance in terms of the given uncertainty, in combination with the
389 point predictions provided previously, it seems that the BN method incorporating a fixed
390 structure, alongside with the respective normal confidence intervals, is the most suitable one
391 for the Gwynt-y-Mor case study. The long-trained BN normal boundaries have also a steady
392 and robust performance, which makes the corresponding model an attractive and satisfying
393 alternative.

394 Finally, it has to be noted that the extremely large coverage percentage given by the log-normal
395 uncertainty boundaries, for the case of the long-trained BN model, is justified by the similarly
396 large average length of the intervals, which makes the solution less suitable. The log-normal
397 boundaries have a more realistic form (i.e. only positive values and a match with the parametric
398 distribution fitting the H_s), but in case the performance is taken into account the normal
399 confidence intervals pose many advantages.

400 **3.3. BN Structures and Configurations**

401 Up until now, the incorporated BN structures involved 6 nodes. Figure 3 displays the long-
402 trained structure, which has also been used for the fixed BN model. The simulations were
403 carried out using data driven structures, i.e. structures acquired by the nature of the data and
404 not imposed a priori. In general, it was noted that trying to create a structure using general
405 knowledge on the incorporated variables (i.e. knowledge on the underlying relations procured
406 by the literature or by experts) only hindered the prediction/correction procedure instead of
407 enhancing its accuracy (see also Emmanouil, 2018).

408 Some of the relations governing the structures are anticipated, when others oppose what would
409 be expected by the common knowledge on the variables at hand. The most distinctive examples
410 here are the relations between the observed significant wave height (H_s) and the wind velocity
411 (U_{10}), as well as the wind (U_{dir}) and wave (D_{irp}) directions. In a situation represented by the
412 dependencies described in the literature (see e.g. Hasselmann and Olbers, 1973), one would
413 expect the wind direction to influence the wave direction, i.e. the arc connecting those two
414 nodes to have a direction from U_{dir} to D_{irp} . Nevertheless, the data-driven analysis conducted in
415 this study implies that the wind direction depends on the wave direction, something which is
416 certainly not the case. But a reasonable explanation exists, justifying this kind of behaviour.
417 The wind and wave directions are measured at the same locations, a fact that insinuates that
418 the variables influence one another in one specific area. Still, waves are created by storms
419 occurred many kilometres (or miles in the nautical language) away from the location of the
420 measurement. As a result, the measured wind directions might indeed not have any influence
421 on the wave directions. Further, the wave direction is influenced by many effects, such as
422 diffraction due to islands or other obstacles, so it can be totally irrelevant to the values given
423 by the wind direction. That of course raises the question on whether the wind direction could
424 be omitted by the analysis, which will be addressed hereupon.

425 On the other hand, the significant wave height and wave direction relation is a different story.
426 For the case of the long training (3 years of data), presented in Figure 3, the relation is the one
427 expected by the descriptions available in the literature, corresponding to the experts' opinions;
428 see e.g. Pierson and Moskowitz (1964), Hasselmann and Olbers (1973), as well as Phillips
429 (2006). To be more exact, the wind velocity influences the significant wave height, a
430 dependence which is highlighted by the high correlation between the variables (correlation
431 coefficient equal to 0.795), shown in Table 4. In the same table other relations are also visible,
432 as for instance between the wind and wave direction, which justifies the structure's form. Also

433 visible is the extremely high dependency between the observed and numerically derived wave
434 heights, which gives the character of correction instead of pure prediction, since the quality of
435 the numerical model (SWAN) results influence highly the long-trained models' accuracy.

436 Contrarily, the short-trained BN model provides a variety of relations between the wind
437 velocity and the observed significant wave height, due to the dynamic nature of the offshore
438 events, which force the data to rapidly change behaviour. There is no clear relation between
439 the two aforementioned variables, since the direction of the connection changes repeatedly,
440 and in some occasions becomes even inexistent. That of course is again explained by the wave
441 creation by distant storms, or secondary effects like diffraction or reflection, since also those
442 two variables are measured in the same location.

443 It is interesting to examine how different configurations of the BN structures (see Figure 4),
444 i.e. a different number of nodes with a selection of variables influence the predictions and the
445 provided uncertainty. This comparison will shed some light on whether one or more of the
446 incorporated variables influence the models' accuracy positively and will reveal if the erratic
447 behaviour of the models incorporating short-term past data can be casted off.

448 The exclusion of the meteorological variables, i.e. the wind velocity and direction, only
449 triggered a reduction of the fixed structure's accuracy, to a point where it became equal to the
450 short-trained BN models' one; hence the presentation of these results was considered needless.

451 Regarding the percentage of coverage and the average length of the uncertainty bounds, again
452 a reduction in performance was noticed in the case of the fixed structure, while a small and
453 insignificant enhancement of accuracy is observed in the short – and long-trained BN models.

454 As a result, it can be concluded that for the Gwynt-y-Mor case the exclusion of the
455 meteorological variables had an undesirable effect, and the 6-variable structure would be
456 generally suggested. Further testing was conducted with a 5-variable BN structure,

457 incorporating supplementary the wind velocity (U_{10}). Examples of the arc directions for the
458 case of Gwynt-y-Mor are shown in Figure 4, where the relations discussed previously between
459 the meteorological and the hydrodynamic variables are again varying depending on the training
460 of the BN model (long or short training). The explanation here is quite the same, since for the
461 largest part of the year the wind velocity can in general influence the significant wave height,
462 while in certain occasions this might not happen due to the origin of the waves. The
463 performance of the models is only enhanced slightly (approximately 0.5%), while being more
464 consistent for the BNs incorporating short-term past data. Even so, the RMSE values were in
465 general smaller for all BN models, with the one provided by the fixed structure being the
466 smallest in comparison to the rest of the error correction techniques (0.208). The accuracy in
467 predictions close to the critical boundary also increased, particularly in terms of the false
468 positive percentages (nearly 8%; a value of 1.95% for the case of the fixed structure).

469 Regarding the uncertainty estimates, the coverage percentages and the average lengths were
470 similar to the 6-variable BN models' figures, without any improvement to the length of the
471 long-trained log-normal confidence intervals. It is truly difficult to determine which boundary
472 is the most suitable and it always depends on the applications needs. Nevertheless, for this case
473 both kinds of confidence intervals display superiority when compared to the uncertainty
474 estimates given by the Gumbel Copula. Of particular interest are the results produced for the
475 case of Rhyl Flats. As shown in Table 5, there is a significant improvement in terms of all
476 metrics. Table 6 illustrates that also in terms of critical performance, around the 1.5 m upper
477 boundary, the fixed structure BN model's performance is enhanced. Moreover, the behaviour
478 of the 5-variable structures regarding models which include short-term past data (i.e. 48 hours
479 prior to the forecast), is quite consistent and robust in comparison to the structures
480 incorporating 6 variables. Here, the point that the wind direction causes unsteadiness to the
481 predictions is proved.

482 Because the uncertainty estimates display large improvement as well, it seemed fit to present
483 them here in comparison to the results given by the 6-variable BN structure (see Table 7). The
484 normal confidence intervals of the fixed-structured BN reach a coverage percentage of nearly
485 91% of the total observations, with an average length of just 49 cm. Certainly, the form of the
486 boundaries is not ideal, since they are symmetrical, but still their performance provides a
487 significant enhancement in accuracy, making the BN models a valuable correction tool for this
488 application. The long-trained BN model is equally good in terms of accuracy, regardless the
489 number of incorporated variables, making it also a robust and reliable tool, which with the
490 inclusion of its uncertainty bounds introduces a significant improvement of the significant
491 wave height (H_s) predictions. As such, it can be concluded that the 5-variable BN models would
492 need to be used for the case of Rhyl Flats, due to its robust behaviour, in comparison to similar
493 techniques incorporating 6 variables.

494 **4. Conclusions**

495 The results provided by the methods under consideration are largely dependent on the data
496 quality and availability. Due to the topology (Irish Sea) which induces secondary events in
497 terms of hydrodynamics (reflection, diffraction, etc.), some direct variable relations that would
498 seem obvious are not so trivial after all. For instance, some dependencies between
499 meteorological and hydrodynamic variables, as the wind (U_{dir}) and wave directions (D_{irp}), are
500 not that obvious when the analysis is data-driven. Thus, data-driven approaches were used and
501 are recommended when the morphology of the area, or the way the measurements were
502 collected (e.g. with wave-rider buoys and met-masts), induce many uncertainties.

503 The BN method incorporating the so-called fixed structure (a long-trained structure in
504 combination with short-term past data) seems to be the best overall, out-performing any other
505 error correction technique. In Gwynt-y-Mor the BN models incorporating 6 variables, namely

506 the observed significant wave height (H_s), the numerically produced significant wave height
507 ($H_{s,num}$), the wave direction (D_{irp}), the zero-crossing wave period (T_z), the wind velocity (U_{10}),
508 and the wind direction (U_{dir}), serves the application equally good to the 5-variable structures,
509 where the wind direction is excluded. A general comment is that the 6-variable BN structures
510 behave erratically in certain occasions, when short-term past data (i.e. data retrieved 48 hours
511 prior to the forecast) are incorporated. On the other hand, for the Rhyl Flats dataset, the
512 exclusion of the wind direction is imperative in order for all the BN models to be able to
513 produce results of enhanced accuracy, due to the condition of the aforementioned variable's
514 dataset. Certainly, the long-trained BN model, regardless of the number of variables
515 incorporated, provides robust and consistent results for both stations, and with the inclusion of
516 the uncertainty estimates provided it becomes also an attractive and equally suitable technique.

517 In offline mode it is easy to establish and recognise which variable/s reduces the respective
518 models' accuracy, but when the models run operationally it is impossible to interfere. The final
519 goal is to manage to emulate the real-time nature of the application and draw conclusions for
520 the applicability of the methods under consideration in operational environments. In that
521 regard, the 5-variable fixed-structured BN model outperforms any other technique. Certainly,
522 this kind of model has one major disadvantage; the fact that it needs short-term past data (48-
523 hrs prior to the forecast) makes it unable to produce corrected forecasts in the absence of recent
524 observations. This effect is not an issue with the long-trained BN model, which displays equally
525 good metrics, but is underperforming in terms of the critical situations (close to the upper 1.5
526 m boundary), presenting a more conservative behaviour and failing to predict significant wave
527 height peaks in certain occasions. Consequently, it is really a matter of subject and data
528 availability to distinguish which model is better in terms of its operational performance. Surely,
529 the ability of the long-trained BN model to produce forecasts of enhanced accuracy constantly,
530 even in the absence of recent observations makes it attractive for real-time use. Yet, the

531 satisfying performance of the fixed-structured BN cannot be overlooked, especially when
532 producing critical predictions (close the application's upper boundary), which constitutes
533 probably its most important virtue while incorporated.

534 All in all, it can be concluded that the BN methods provide the most suitable solution in terms
535 of error correction when compared to the rest of the techniques presented in the preceding
536 sections. A major benefit is the information acquired by the structures and uncertainty
537 estimates, which can be either provided in normal or log-normal form and cover nearly 90%
538 of the total number of measurements in the validation set. The normal confidence intervals
539 seem to be the most suitable for this application, since they demonstrate good performance,
540 especially in terms of the higher and most crucial boundary. Moreover, they introduce an
541 acceptable average length of 50-60 cm, in comparison to their log-normal counterparts. The
542 log-normal uncertainty boundaries grant behaviours closer to reality, but their average length,
543 especially the one given by the long-trained technique (≈ 1.18 m), exhibit high levels of
544 uncertainty. Nevertheless, it can be generally concluded that the BN methods enhance the
545 uncertainty estimates' performance in comparison to the Gumbel Copula model, enhancing the
546 SWAN forecasts significantly and ensuring nautical and operational safety in most of the
547 occasions.

548 The techniques described in this study provide a useful tool for the decision making process of
549 installation and maintenance operations in offshore wind farms. Further, the applicability of
550 the models in real-time scenarios could assure the right temporal and spatial placement of the
551 personnel and the equipment in dynamic circumstances, hence leading to an optimal utilization
552 of the available resources. Since the success of offshore operations is based on the accurate
553 prediction of specific weather windows, the improved H_s forecasts provided by the BN models
554 will lessen the risk of high cost, while ensuring the safety of the crews.

555 For the future, extensive real-time testing would provide a more concise and consistent
556 validation of the models' performance. Supplementary, some variables (e.g., wind direction)
557 could be discretized rather than used as an additional continuous variable, leading to a hybrid
558 network. As such the models' accuracy could be evaluated based on the type of events (e.g. for
559 wind coming from NW in comparison to SE). Finally, it could be stated that the differences
560 between the models are in certain occasions small. An application-based impact assessment
561 would highlight the importance and contribution of each model, expressed in monetary and
562 risk terms, showing that these small differences could lead actually to large benefits.

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760 **Tables**

761 Table 1. Evaluation metrics for the year of 2017 (Gwynt-y-Mor).

Method	SWAN	BN Long Training	BN Short Training	BN Fixed Structure	REG	ANN	Copula	SI
RMSE (m)	0.231	0.218	0.253	0.209	0.206	0.225	0.246	0.325
BIAS (m)	-0.046	-0.011	-0.051	0.005	0.004	0.0365	-0.076	-0.016
URMSE (m)	0.226	0.218	0.248	0.209	0.206	0.222	0.234	0.324

762

763 Table 2. Application specific metrics for the year of 2017 (Gwynt-y-Mor).

Method	SWAN	BN Long Training	BN Short Training	BN Fixed Structure	REG	ANN	Copula	SI
Critically Accurate (%)	19.72	21.16	20.27	22.31	22.00	23.05	16.89	20.83
Critically Inaccurate (%)	2.55	2.82	3.79	2.10	2.34	1.90	4.72	1.96
False Positive (%)	2.26	1.93	1.50	2.10	1.97	3.01	0.82	3.01

764

765 Table 3. Uncertainty comparison for the Gwynt-y-Mor case study.

Method	BN Long Training	BN Fixed Structure	BN Short Training	Copula	BN Long Training (Log-N)	BN Short Training (Log-N)	BN Fixed Structure (Log-N)
Coverage (%)	89.2	86.1	75.3	68.5	95.4	73.1	76.5

Average Length (m)	0.630	0.531	0.356	0.375	1.185	0.550	0.594
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766

767 Table 4. Correlation matrix for the long-trained BN models for the Gwynt-y-Mor case.

Variable	D_{irp}	T_z	U₁₀	U_{dir}	H_{s,num}	H_s
D_{irp}	1.000	0.381	0.001	0.515	0.245	0.249
T_z	0.381	1.000	0.596	0.359	0.842	0.874
U₁₀	0.001	0.596	1.000	0.110	0.820	0.795
U_{dir}	0.515	0.359	0.110	1.000	0.319	0.329
H_{s,num}	0.245	0.842	0.820	0.319	1.000	0.964
H_s	0.249	0.874	0.795	0.329	0.964	1.000

768

769 Table 5. Evaluation metrics for the case of the 5-variable BN models (Rhyl Flats).

Method	SWAN	BN Long Training	BN Short Training	BN Fixed Structure	BN Long Training	BN Short Training	BN Fixed Structure
		6 Nodes			5 Nodes		
RMSE (m)	0.203	0.178	0.200	0.201	0.178	0.195	0.163
BIAS (m)	-0.004	-0.010	-0.037	0.003	-0.013	-0.038	0.003
URMSE (m)	0.203	0.178	0.196	0.201	0.177	0.191	0.163

770

771 Table 6. Application-specific evaluation metrics for the case of the 5-variable BN models
772 (Rhyl Flats).

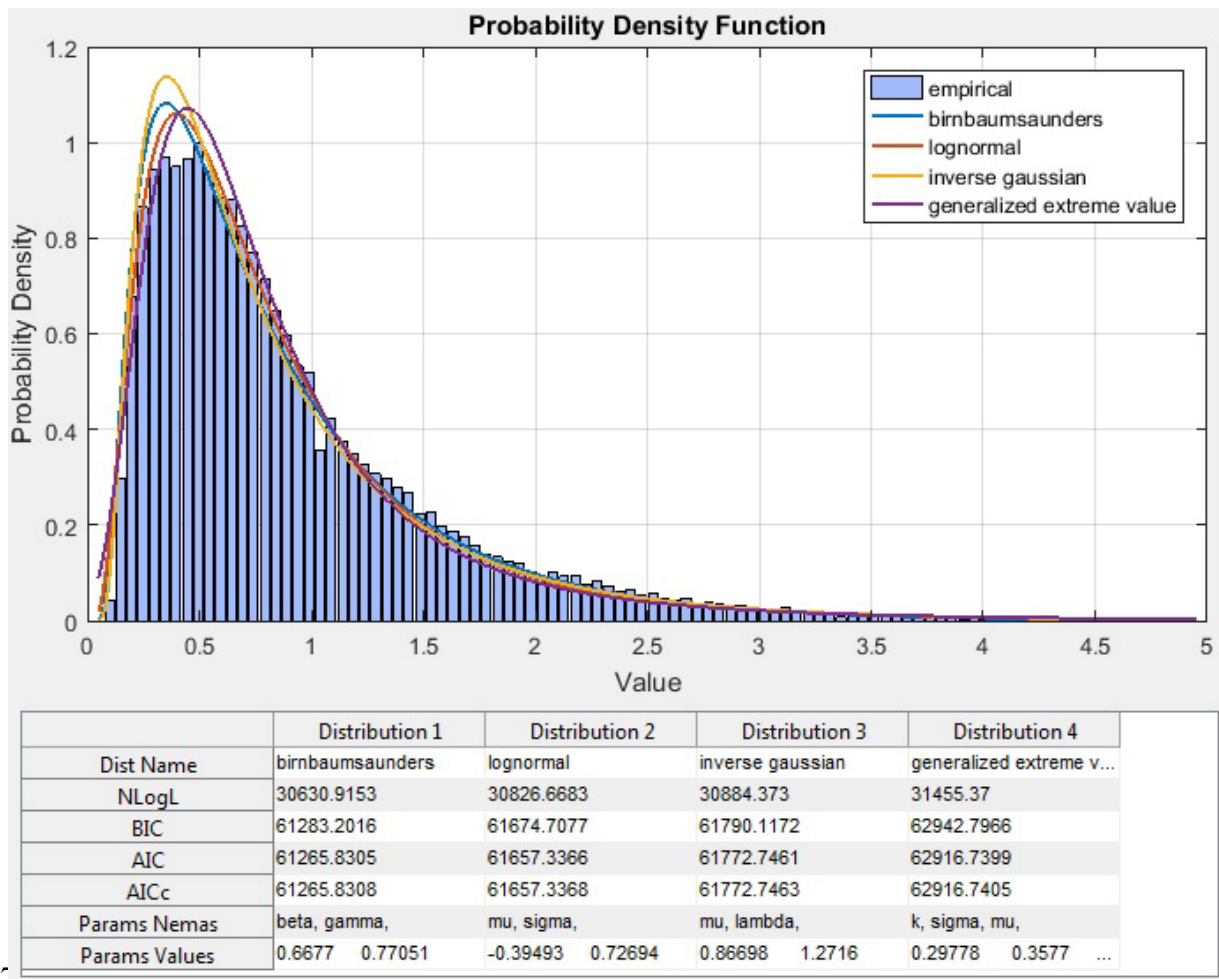
Method	SWAN	BN Long Training	BN Short Training	BN Fixed Structure	BN Long Training	BN Short Training	BN Fixed Structure
		6 Nodes			5 Nodes		
Critically Accurate (%)	18.02	17.01	16.04	18.82	16.87	16.08	18.03
Critically Inaccurate (%)	1.05	2.28	2.50	1.34	2.30	2.45	1.47
False Positive (%)	2.55	1.16	1.03	1.58	1.14	0.84	1.14

773

774 Table 7. Uncertainty estimates' performance for the case of a 5-variable BN structure (Rhyll
775 Flats).

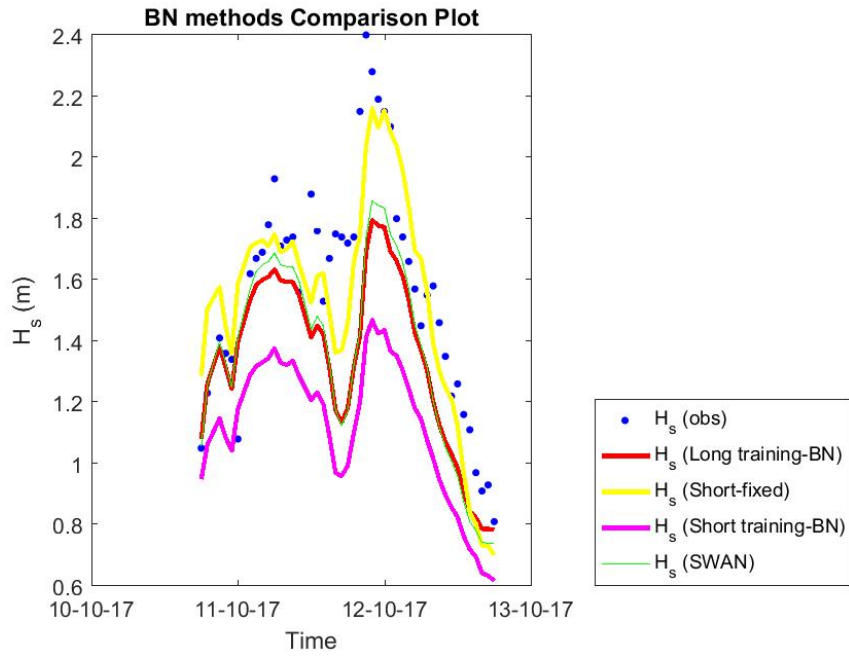
Method	BN Long Training	BN Fixed Structure	BN Short Training	Copula	BN Long Training (Log-N)	BN Short Training (Log-N)	BN Fixed Structure (Log-N)
5 Variables							
Coverage (%)	89.6	90.8	77.2	70.9	95.0	77.1	73.2
Average Length (m)	0.527	0.489	0.430	0.327	1.024	0.505	0.460
6 Variables							
Coverage (%)	89.7	64.7	69.8	70.9	94.7	68.9	61.0
Average Length (m)	0.527	0.491	0.427	0.327	0.948	0.466	0.425

776 **Figures**



777

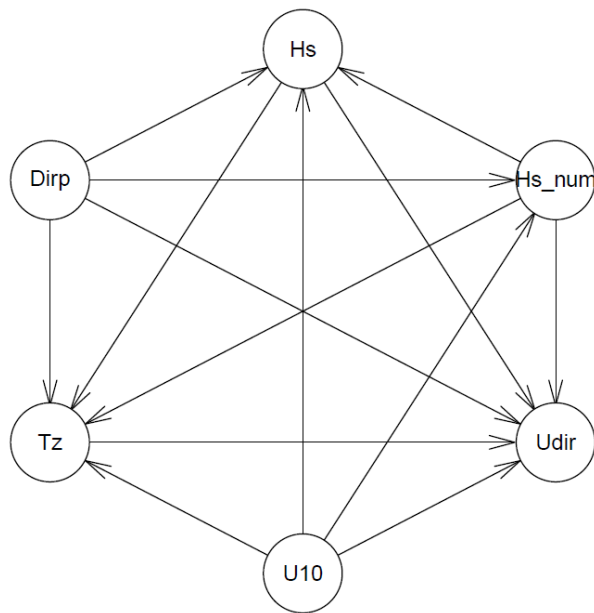
778 Figure 1. Results of the parametric distribution fitting procedure to the significant wave
 779 height (H_s) data of Gwynt-y-Mor. (*colored)



780

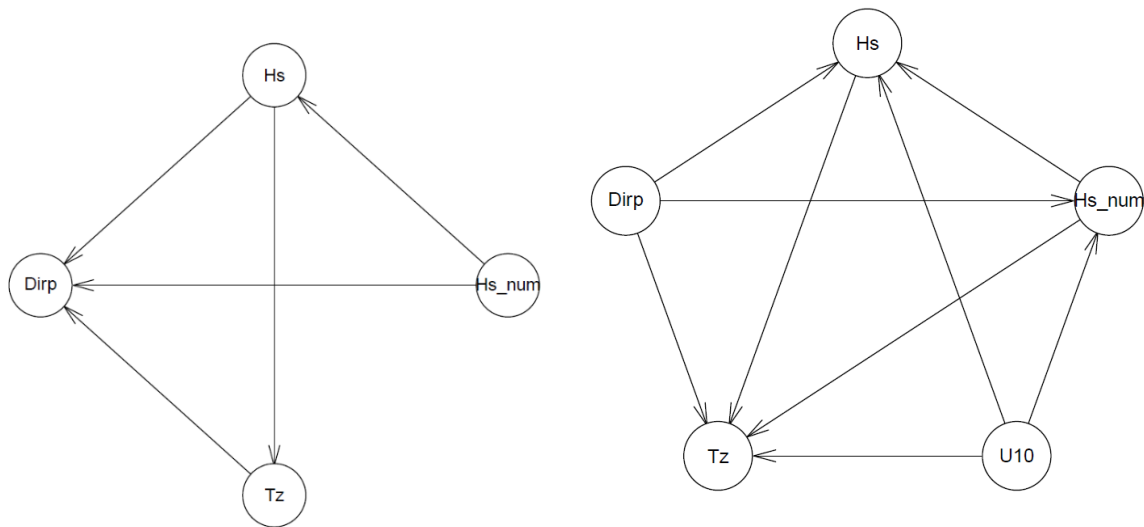
781 Figure 2. Example of a correction to the SWAN forecast under critical conditions given by
 782 the BN models (Gwynt-y-Mor).

783



784

785 Figure 3. Structure for the long-trained and fixed BN models, incorporating 6 variables
 786 (Gwynt-y-Mor).



787 Figure 4. BN structures incorporating 4 and 5 variables for the long-trained models (Gwynt-
788 t-Mor)

789 **Table Captions**

790 Table 1. Evaluation metrics for the year of 2017 (Gwynt-y-Mor).

791 Table 2. Application specific metrics for the year of 2017 (Gwynt-y-Mor).

792 Table 3. Uncertainty comparison for the Gwynt-y-Mor case study.

793 Table 4. Correlation matrix for the long-trained BN models for the Gwynt-y-Mor case.

794 Table 5. Evaluation metrics for the case of the 5-variable BN models (Rhyl Flats).

795 Table 6. Application specific evaluation metrics for the case of the 5-variable BN models
796 (Rhyl Flats).

797 Table 7. Uncertainty estimates' performance for the case of a 5-variable BN structure (Rhyl
798 Flats).

799 **Figure Captions**

800 Figure 1. Results of the parametric distribution fitting procedure to the significant wave
801 height (H_s) data of Gwynt-y-Mor.

802 Figure 2. Example of a correction to the SWAN forecast under critical conditions given by
803 the BN models (Gwynt-y-Mor).

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805 (Gwynt-y-Mor).

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807 t-Mor).