Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
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doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P9362-cd

Validation of Human Centred Bayesian Networks - Case Study on a Cable Cut of an Export Cable of an Offshore Wind farm

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Bayesian networks are a commonly used method in the risk and reliability domain to assess the likelihood of certain scenarios or the resilience of an infrastructure. This study is conducted based on a literature review of Bayesian networks in the maritime domain. Even though there are about 78 journal papers published on Bayesian networks in the maritime domain between 2018-2022, it is challenging to gather suitable data in the development process. Further, either a-priori or conditional probabilities are necessary depending on the node. Especially acquiring conditional probabilities is challenging due to that fact that for every state of the parent node(s) a conditional probability needs to be defined. In this work, we investigate validation methods for Bayesian networks. The selected methods have been chosen based on a careful review of the state of the art and encompass benchmark exercises, formal walkthroughs, qualitative feature tests and sensitivity analysis. The validation methods formal walk through and qualitative feature are then discussed at hand of a case study. For this purpose, a Bayesian network has been developed for a maritime security scenario. The results indicate that the validation process improves the design as well as the parametrization of Bayesian networks.

Keywords: Bayesian networks, Offshore Wind farm, Validation.

1. Introduction

Bayesian networks (BNs) require a high understanding of the studied infrastructure or process (Smith 2017). Not only all involved factors but also the dependencies and independencies have to be known. Furthermore, probabilities for every hypotheses of all nodes are required. These are, in case of root nodes, a-priori probabilities, while inner nodes require conditional probabilities for each hypothesis (Cai 2020; Zinke and Melnychuk et al. 2020). Subjects of the Bayesian network can vary. Usually they can be divided into two groups: Either a specific infrastructure (e.g. Zinke and Melnychuk et al. 2020) or a specific process/task (e.g. Akhtar and Utne 2014). We name BNs focusing on a process or a task that emanate from a person “human-center BNs”. For example, this could be an attack of an infrastructure or a critical process step of a factory. It is important to note that a human-centered BN not necessarily includes nodes like “Attacker turns right”. Instead a node could be called “Attacker reaches target one”. This is necessary as determining probabilities for human interactions are very specific for the situation (e.g. lighting situations, corridor with etc.) and often hard to determine. With the different framing other aspects like the presents of physical barriers can be considered in the human-centered BN. These are probabilities which at least can be easier quantified.

Validation and verification are fundamental aspects in modelling and design (German Research Foundation 2019). Both describe the process of evaluating the software or model. According to Carson, verification is the process in which the model developer examines the model for modelling errors. The aim is to investigate if the predefined specifications and assumptions are met. On the other hand, validation describes the process in which the model developer includes experts review and evaluates the model. The goal is to determine if the model represents the real world or the system to a sufficient level. (Carson 2002)

This work discusses critically validation methods for human centered BN. The rest of this work is structured as follows. Section 2 describes the maritime infrastructure Offshore Wind farms (OWFs). Section 3 introduces the current state of the art in terms of BN and its validation. Section 4 describes a specific validation method applied in this work, which is then applied in a case study detailed in Section 5. Section 6 discusses the results, while Section 7 concludes this work.

2. Offshore Wind farms

Due to political decisions and the changes in the external affairs of Germany, it can be expected that the Offshore Wind industry will gain more importance in the near future (see WindSeeG). Based on the design of the OWFs, there are several challenges the safety and security. For example, OWFs are a distributed infrastructure. The energy is produced in the Offshore Wind turbines and transported via the electricity grid to an Offshore Substation (OSS). The OSS collects the energy produced by the entire OWF, which is then transported to the shore where it is fed into the onshore energy grid or, in case of long distances, to high voltage direct current converter platform (HVDC). This platform changes the voltage level and transforms the alternating current to direct current before it is sent to the shore (Hau 2014). Some of these connections, typically the link between the OSS and HVDC as well as to the landside grid, are single connections. That means, there are no redundancies. The connection to the landside energy grid often relies on cables stretching hundreds of kilometers, passing through traffic separation schemes, other wind farms, and environmentally protected areas (Stiftung Offshore Wind 2014). Procedures exist to protect underwater cables, such as burying them in deeper sediment layers or installing physical barriers made of materials like steel (BVG Associate, unknown). However, not all sections of the cable can be safeguarded using these methods.

3. State of the art

This section describes the theoretic background of BN. It also provides insights into the foundations of validations of BN.

3.1. *Bayesian networks*

BNs belong to the probabilistic models and are applied in many different research disciplines (Ramirez-Agudelo, Köpke and Sill Torres 2020). In a quantitative risk analysis, BNs combine the individual risks of system parts to an overall risk of the entire system. Furthermore, dependencies of systems can be graphically represented (Tecklenburg 2022). An abstract example can be seen in Fig. 1. From a mathematical point of view, BNs are direct acyclic graphs and consist of nodes and edges. In BNs, a node represents the smallest partial risk in a system (see Fig. 1). The edges indicate dependencies or independencies and are represented by arrows. The hypotheses $P(H_i)$ describe the state, in which the node can be, as the related probability (Cai 2020; Zinke and Melnychuk et al. 2020).

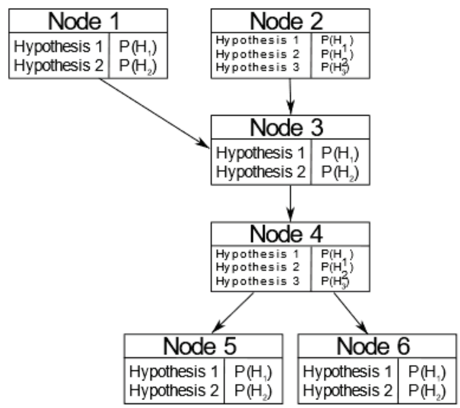

Fig. 1: Basic structure of a Bayesian Network (BN)

Let $K_1 \dots K_n$ be some of the random variables of the graph. Then, the probability distribution of child nodes, i.e. nodes with one or predecessor *parents()*, can be estimated via Eq. (1). The Bayes theorem (Eq. (2)) elaborates the causal correlation between two predecessor nodes. Here, E describes an event with a hypothesis K_j of the same node. The probability of the event E is described as $P(E)$ (Cai 2020; Zinke and Melnychuk et al. 2020).

$$P(K_1, \dots, K_n) = \prod_{i=1}^{n} P(K_i | parents(K_i)) \tag{1}$$

$$P(K_j|E) = \frac{P(E|K_j) * P(K_j)}{\sum_{j=1}^{m} P(E|K_j) * P(K_j)} \tag{2}$$

3.2. *Validation of Bayesian networks*

Animah performed a literature review to investigate journal articles that use BNs in the maritime domain (Animah 2024). Between the years 2000 and 2022 in total 115 relevant contributions have been determined. Only 76 of the 115 journal papers perform some sort of validation. Most of the times only one validation method is applied. In most cases (55 times) a sensitivity analysis is executed. Other reported techniques are cross-validation, comparison with previous models and expert judgement, but with a significant lower application rate.

Pitchforth and Mengersen published a methodical approach for the validation of BN. For example, they state that different aspects of a BN need to be validated. This includes development process, networks structure, discretization, parametrization and the result of a BN. To achieve this, the authors present seven different validation types (Pitchforth and Mengersen 2013):

- **Nomological validity** determines if the BN fits to published BN in the literature
- **Face validity** focuses on network structure, discretization, parametrisation of compares BN with expert assessments and literature
- **Content validity** investigates if all known factors and relationships from the literature are included in the BN
- **Concurrent validity** compares the behaviour of sections or an entire BN with the existing BN, a data comparison is preferred
- **Convergent validity** evaluates if the BN is similar to other BN in terms of structure, discretisation, and parameterisation.
- **Discriminant validity** is similar to convergent validity but focuses on differences
- **Predictive validity** determines to which degree a model's behaviour and output accurately reflect the system it should represent

For each validity different methods exist. Some of them are described in the next section.

4. Validation methods

Not all validation methods are suitable for all topics of nodes in a BN. This section introduces the validation methods later applied in the paper including formal walkthroughs or qualitative feature tests.

4.1 Formal walkthrough

The formal walkthrough is a method used to establish predictive validity. As a validation source, it relies on expert judgment. The procedure follows these steps: Researchers meet with the expert, either online or in person, and provide a detailed explanation of the BN. The discussion focuses on key questions, such as whether all relevant factors are included and whether any nodes should be omitted. Afterward, the discussion is summarized in a formal protocol (Pitchforth & Mengersen, 2013).

4.2 Behaviour sensitivity test

The behaviour sensitivity test is another method used to establish predictive validity. This validation approach can involve experts, but the developer’s knowledge is also valuable. The procedure depends on the capabilities of the Bayesian Network (BN) software being used. If the software supports a behaviour sensitivity test, the function simply needs to be activated. However, if the software lacks this feature, the developer must conduct the test manually. This involves systematically adjusting the probabilities of parent nodes in increments of ±0.05, ±0.1, and ±0.15. The results help determine which nodes have the most significant impact on the characteristics of the child nodes. (Pitchforth & Mengersen, 2013).

4.3 Qualitative Feature Test

The Qualitative Feature Test is another method used to assess predictive validity. In this approach, the favouring and inhibiting factors for each node are identified. In the next step, either the favouring or inhibiting hypothesis is assigned to each node as hard or virtual evidence. The resulting probability distribution of the target node is then analysed and compared with the outcomes of the other selected hypotheses. This comparison serves as the basis for discussion and validation (Pitchforth & Mengersen, 2013).

4.4 Case study

The last test performed here is a “Case study”. A case study also belongs to the predictive validation approaches. The core element of this method is that the BN is compared to a past event such as accidents. Based on the accidents description the triggering circumstances are extracted. These are then transformed into hypotheses of a BN and used as hard or soft evidences. The final step is to compare the results with selected hypotheses with the baseline of the BN (Pitchforth and Mengersen 2013).

5. Use case "anchor dragging"

The topic of the use case is the cutting of an export cable of an OWF. The scenario is that a vessel is drifting in the traffic separation scheme. The crew decides to bring out the anchor to prevent further drifting. To build the Bayesian Network (BN), the procedure outlined in Tecklenburg (2022) was followed. First, the scenario was converted into a Functional Resonance Analysis Method (FRAM) model, which was then translated into a BN. Fig. 2 depicts the initial version of the BN.

5.1. *Validation*

The BN combines different aspects, for example a small weather model, the main attack path, and information regarding the attack vessel. Not all parts of the BN can be validated with the same method. The main focus for validation in this work are the not- data driven nodes. In the following the different validation methods will be described.

5.1.1. *Formal walkthrough*

A total of two discussions with experts were conducted. The experts had diverse backgrounds, ranging from maritime expertise to probabilistic modelling. Table 1 provides an overview of both experts. One discussion was held in person, while the other took place via video conference due to geographical constraints. On average, each discussion lasted approximately one hour.

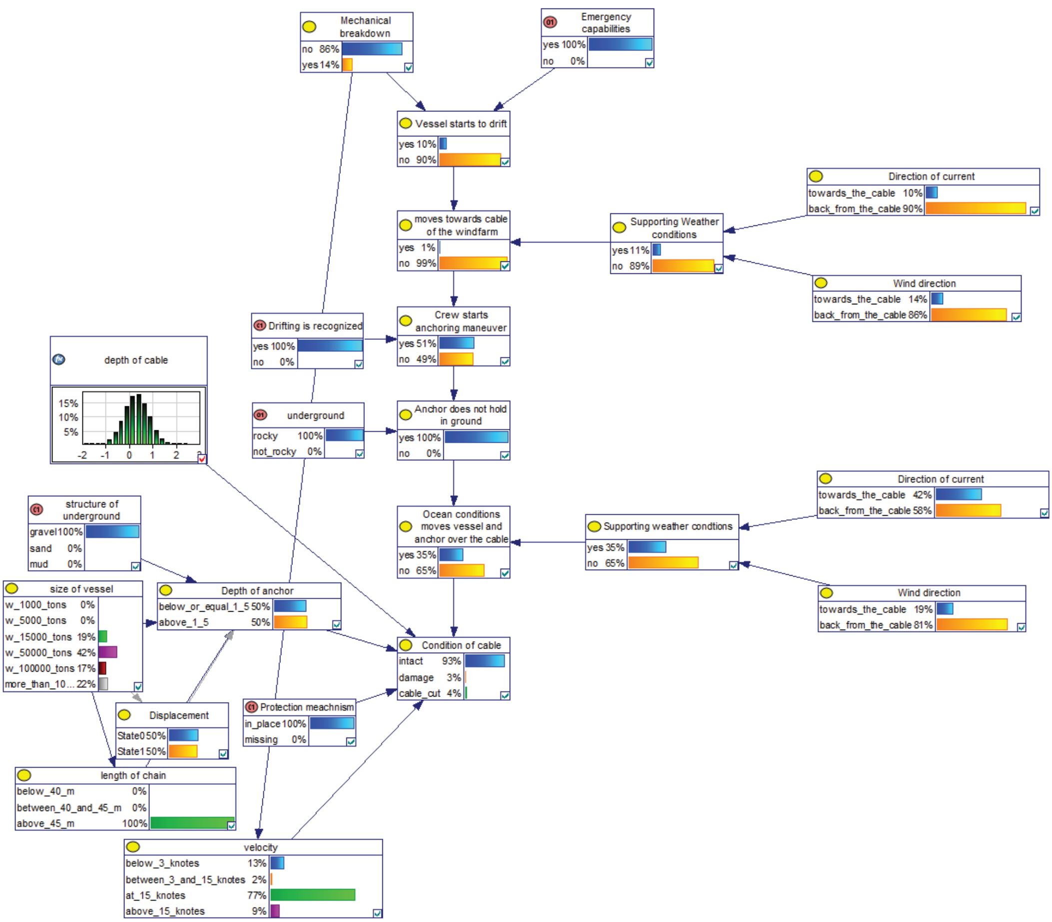

Fig. 2: Initial version of a cable cut of an OWF

The procedure followed a structured approach. After an introduction, the author provided a detailed explanation of the BN, describing each node. At this stage, discussions often emerged naturally. However, the authors also prepared guiding questions, such as: "*Would you like to add any aspects?*" or "*Do the probabilities seem accurate?*"

Each expert focused on different issues. For instance, in the discussion with Expert 1, the design of the attack scenario was reviewed. Initially, the scenario involved a vessel drifting in a traffic separation scheme due to a mechanical failure, leading to anchor deployment, which coincidentally damaged an underwater cable. However, Expert 1 pointed out that this scenario was unrealistic from a nautical perspective (Expert 1, August 2024).

Following this feedback, the scenario was revised: a vessel navigating within the traffic separation scheme experiences an incident due to human error, resulting in an unsecured anchor that deploys uncontrollably. Before consulting the next expert, the BN was adjusted accordingly.

In the discussion with Expert 2, the focus shifted to weather conditions and modelling capabilities within GeNIe. The expert suggested incorporating weather conditions as nodes, as poor weather reduces visibility and, consequently, the likelihood of detection by other vessels. Additionally, the expert and the author explored the possibility of using a section-defined function to represent probabilities (Expert 2, August 28, 2024).

Table 1. Overview about the experts for the formal walkthrough.

Expert	Domain	Job description	Experience
1	Maritime	Former captain	6 years
2	Probabilistic	Researcher	6 years

5.2.2. *Behaviour sensitivity test*

GeNIe offers a function for the behavior sensitivity test (BayesFusion 2024). The strength of influence is presented by the thickness of the connection arrows. Figure 2 shows one example of a behavior sensitivity test. The target node is the node "depth of anchor". It can be seen that the node "released chain" has the highest impact of the three nodes. From a content point of view, it makes sense because the length of the chain determines if the anchor is even cable of reaching the ground. If not, there is no damage to the cable. If yes, the probability of a damage increases.

5.2.3. *Qualitative Feature Test*

Due to design of the network, some root nodes are deterministic nodes. They where chosen as baseline parameters and has not been changed during the Qualitative Feature Test. See Table 2 for summary of the baseline parameter. Table 3 shows three selected nodes either in their best or worst state as well as the resulting probabilities for the target node.

Table 2. Summary of the baseline parameter for the BN "Cut of export cable"

Node	Hypothesis
Daytime	Night
Season	Spring
Structure of underground	Mud
Protection mechanism	missing

5.2.4. *Case study*

The selected accident for the case study is the cable cut in the Baltic Sea by the vessel "NewNew Polar Bear" in October 2023.

Table 3. Extraction of the probabilities for the Qualitative Feature Test

Node	p_{intact}	p_{damage}	$p_{cable\ cut}$
Baseline scenario	0,99	0	0
Anchor hits cable	Worst state		
Yes	1	0	0
	Best state		
No	0,14	0,33	0,53
Vessel passes cable location	Worst state		
Yes	0,15	0,33	0,52
	Best state		
No	1	0	0
Oversee light	Worst state		
yes	0,99	0	0
	Best state		
no	1	0	0

The container vessel was Chinese owned and sailed under the flag of Hongkong. During the night it accidently, so the official version, dropped its anchor and dragged it on the ocean floor for 100 nautical miles, passing the Sweden. All three infrastructures were damaged (Bermingham 2. August 2024; Expert 1 August 2024; Tegler 29. November 2023). Based on publicly available information the hypotheses in Table 4 have been determined. Baltic connector pipeline and two telecommunication cables between Estonia and Sweden have been damaged.

Table 4: Defined hypotheses for the case study "NewNew Polar Bear"

Node	Hypothesis
Season	Spring
Daytime	Night
Structure of underground	Mud
Released chain	More than one shackle
Protection mechanism	Missing
Anchor hits cable	Yes
Condition of cable	9 % intact, 35% damage, 56% cut

The BN calculates a probability of 55% for a cable cut and 35% of a damage. This is a significant change in the probabilities because the baseline for the scenario is 99% intact cable probability.

5.2.5. *Validated BN*

The validation methods were applied sequentially, following the order in which they were described. After each validation step, any identified weaknesses were addressed and adjustments were made to the BN before proceeding to the next validation method. Examples of these weaknesses have been discussed in the respective sections. Once all validation methods were completed, the final BN was developed, as shown in Fig. 4.

6. Discussion

This study presents an approach to validating an entire BN or specific components of it. In summary, all applied validation methods contributed positively to the validation process. Their benefits ranged from refining the attack scenario design (formal walkthrough) to improving the BN's structure (e.g., formal walkthrough) and assessing its behaviour (qualitative feature test or case study).

The approach presented here is specifically tailored to BNs that focus on security-oriented incidents. One of the key challenges in designing such a BN is the difficulty of obtaining reliable probability data, particularly from databases. While maritime security incidents have reportedly increased in recent years, their overall numbers remain relatively low. As a result, the development process often relies on literature sources, expert input, and well-reasoned assumptions.

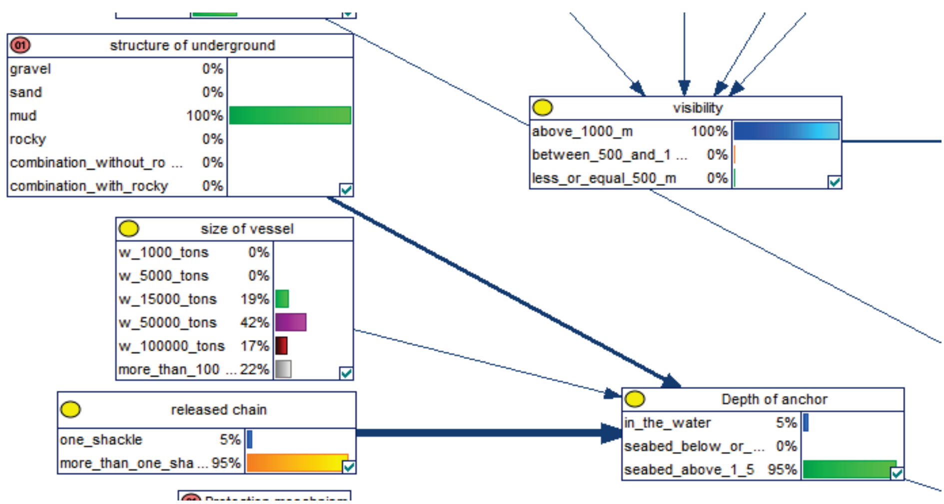

Fig. 3: Behaviour sensitivity test for the node "depth of anchor"

For validation, additional data is often required. In this study, the authors leveraged expert knowledge and mathematical tests as viable validation methods, particularly for BN components related to human-cantered actions. However, for other aspects—such as nodes representing weather phenomena—statistical tests and comparisons with historical time series data remain irreplaceable.

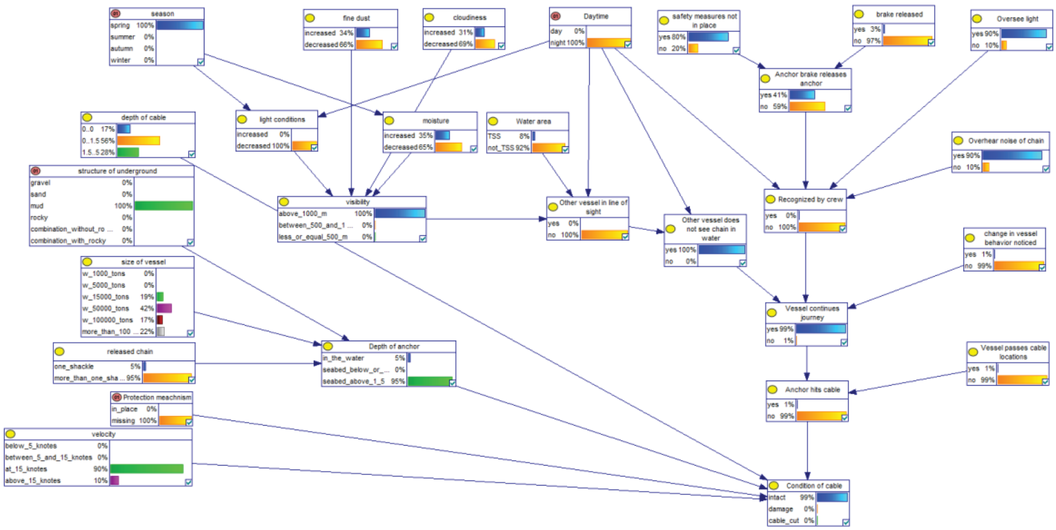

Fig. 4: Validated BN of the scenario cut of an underwater cable

7. Conclusion and Outlook

In this study, the authors discuss methods for validating Bayesian Networks (BN), with a particular focus on components based on expert knowledge and literature sources. To this end, validation methods such as the formal walkthrough, behaviour sensitivity test, qualitative feature test, and case study were introduced and applied to a use case centred on the "anchor dragging cable" scenario. The results demonstrate that all these methods are suitable for BN validation.

For future research, the authors aim to focus on data-driven nodes—typically those related to weather conditions in this case. The goal is to explore statistical tests for validating these nodes, thereby enabling comprehensive validation across all node types. Ultimately, this would expand the toolbox for BN validation and enhance the overall reliability of such models.

8. Acknowledgement

This conference contribution is part of the research project "Applied OWF Security and Resilience Assessment" (OSRA) which is financed by the German Aerospace Center (DLR). The authors would like to thank the interview participants for time and shared knowledge in the interviews.

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