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Bayesian Network-Based Reliability Assessment of an Integrated Subsea Production Architecture

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Growing operational challenges in deepwater production have intensified the demand for subsea systems that combine robustness, reliability, and efficiency in maintenance and risk control. This work advances the reliability assessment of subsea systems by extending the analysis beyond the Subsea Christmas Tree (XT) to encompass the entire subsea architecture. A subsea architecture is composed of multiple interconnected equipment, such as flowlines, manifolds, and the XT itself, whose interactions define the overall system performance. However, most studies in the literature focus on isolated components, which limits the understanding of global reliability behavior and its implications for design and maintenance strategies. Furthermore, traditional reliability tools face challenges in representing dynamic interdependencies and dealing with inherent uncertainties of complex subsea environments. To overcome these limitations, this study proposes an integrated framework that combines Event Sequence Diagrams (ESDs) and Fault Trees (FTs) within a unified Bayesian Network (BN) structure. This approach enables both predictive and diagnostic reasoning through bidirectional inference, allowing the identification of the most probable causes of system failure and the estimation of failure probabilities for individual components. Such capability provides theoretical support for decision-making during the design phase and the planning of maintenance routines under uncertain conditions. The proposed method is applied to a satellite-type subsea layout, where each well is directly connected to the Floating Production Storage and Offloading (FPSO) unit. This study explicitly includes the XT in the reliability modeling, recognizing its crucial role even in architectures where it is often assumed as a standard element and, therefore, neglected in comparative analyses. Preliminary results demonstrate that the proposed Bayesian framework can effectively predict the most failure-prone modules and critical elements within the architecture.

Keywords: Bayesian Networks, Reliability Analysis, Subsea Systems, Event Sequence Diagrams, Fault Trees.

1. Introduction

Offshore oil exploration and production, particularly in deep and ultra-deep waters, represent highly complex activities that require the implementation of sophisticated and reliable subsea architectures. These architectures consist of a wide range of interconnected components, including manifolds, risers, flowlines, and connection modules, whose operation is crucial for maintaining continuity, ensuring the safety of installations, and protecting the environment. Given the challenging nature of these scenarios and the high costs associated with potential failures in these infrastructures, reliability analysis of subsea systems has become a strategic priority in the oil and gas industry (Silva et al., 2023). Such analyses aim to anticipate possible failures, minimize risks, and optimize maintenance interventions.

Despite the relevance of the topic, a large portion of the studies available in the literature focuses on the reliability assessment of individual components, with particular emphasis on the Subsea Christmas Tree (XT), as it is considered a standard element of subsea architectures. Such an approach limits the consideration of the other elements that compose the architecture, as well as the interactions among them. As a consequence, it becomes difficult to understand the reliability behavior of the system as a whole, particularly with respect to interdependencies among equipment, cascading failure effects, and the temporal evolution of operational states under conditions of uncertainty.

In this context, Bayesian networks emerge as a powerful tool to model causal relationships in complex systems such as subsea architectures (Tingting Li et al., 2022). Bayesian networks are directed probabilistic graphs that represent conditional dependencies between variables and allow for predictive (forward) inferences. In predictive analyses, Bayesian networks compute the probability of future events based on prior data, whereas diagnostic analyses determine the most probable causes of an observed event (Carriger et al., 2021; Langseth et al., 2014). This flexibility makes Bayesian networks well-suited to capturing the dynamics of complex systems with multiple interdependencies, enabling more accurate and comprehensive assessments of the reliability of equipment and systems.

Given this scenario, the present work aims to deepen the reliability analysis of subsea architectures using Bayesian networks. Through forward inferences, it seeks to evaluate the reliability of critical equipment and their interdependencies, based on technical and structural information extracted from system documentation. This study also explores the potential of Bayesian networks for integrating complex information, contributing to more informed and safer decision-making in the management of subsea operations

2. Literature Review

Bayesian Networks (BNs) are directed acyclic graphs widely used to model probabilistic relationships among variables in complex systems (Khan et al., 2021; Parviainen et al., 2021). Each node in a BN represents a variable, while the edges indicate causal influences between parent and child variables. To model dependencies between variables, Conditional Probability Tables (CPTs) are employed to quantify how the states of one variable influence connected variables. This structure enables both predictive inferences to be performed in an integrated manner.

Predictive inference calculates the probability of future events based on known causes (Afrin et al., 2021). For instance, it can anticipate potential operational disruptions by estimating the probability of system failure given the failure rates of its components. Conversely, diagnostic inference seeks to determine the most likely causes of an observed event, such as identifying which component failed following a system issue. These two approaches make Bayesian Networks exceptionally flexible tools for reliability analysis in dynamic and interdependent systems (Koseoglu Balta et al., 2021).

The functioning of Bayesian Networks is grounded in Bayes' Theorem, which provides a mathematical framework to update the probabilities of a hypothesis (A) based on new evidence (B). The theorem is expressed as Eq. (1):

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

where P(A|B) is the posterior probability of A given evidence B, P(B|A) is the likelihood, P(A) is the prior probability, and P(B) is the evidence (Carriger & Parker, 2021).

In practice, reliability analysis often employs Event Sequence Diagrams (ESDs) and Fault Trees (FTs) to model the progression of events and their consequences (Liu et al., 2022). ESDs are visual tools used to represent the sequence of events that can lead to failures in complex systems. In an ESD, events are depicted as nodes connected by arrows indicating temporal or logical relationships. The diagram begins with an initiating event and maps potential developments leading to a final event, known as the Top Event (TE). This type of diagram is widely used in reliability analysis to identify critical event chains and understand how different scenarios can result in systemic failures.

Fault Trees (FTs), on the other hand, are hierarchical models that describe how basic events contribute to a Top Event. FTs are constructed by identifying the Top Event and connecting it through logical gates (such as AND and OR) to intermediate and basic events. These models are extensively employed for qualitative and quantitative reliability assessments. In qualitative analysis, minimal cut sets — the smallest combinations of failures that can cause the Top Event — are identified. In quantitative analysis, the probability of the Top Event is calculated based on the probabilities of the basic events (Liu et al., 2022).

Bayesian Networks stand out as particularly useful tools in reliability analysis for engineering systems, enabling the integration of traditional methods, which often face limitations in addressing uncertainties and dependencies between components. In contrast, BNs provide more flexible probabilistic reasoning, including the handling of common-cause failures and statistical dependencies, making them ideal for modeling highly complex systems (Xinhong Li et al., 2021; Yin et al., 2021).

Although the literature includes studies that use Bayesian Networks for reliability analysis, most of these works focus on specific equipment, neglecting the reliability assessment of complete subsea architectures. A recent review from 2024 highlighted that, despite Bayesian Networks being widely applied in reliability modeling, their use is often limited to the analysis of individual components, such as valves or pipelines, without exploring the integration of these elements within a complete subsea architecture (Nunes et al., 2024).

To address these limitations, this study proposes an innovative approach that transforms traditional analysis mechanisms, such as Event Sequence Diagrams (ESDs) and Fault Trees (FTs), into Bayesian Networks (BNs). This methodology enables detailed inferences about the reliability of an entire subsea architecture, addressing critical aspects such as interdependencies between components, common-cause failures, and preventive maintenance scenarios. By integrating these tools, the study aims to expand the scope of reliability analysis, providing a comprehensive and probabilistically robust view of operations in subsea environments.

The conversion of an ESD into an FT involves translating the sequential progression of events into a logical hierarchical structure. The Top Event identified in the ESD becomes the main event in the FT, while intermediate and basic events are organized into successive levels. The next step is converting the FT into a Bayesian Network. In this process, each basic event in the FT is transformed into a root node in the BN, and intermediate events and the Top Event become internal nodes. The logical gates in the FT, such as AND and OR, are replaced with CPTs, enabling the modeling of uncertainties and statistical dependencies between events. Moreover, BN enables the updating of probabilities in the presence of new evidence, a capability that static FT models do not provide (Bhardwaj et al., 2022; Pang et al., 2021; Wang et al., 2020).

3. Methodology

The subsea architecture chosen for the case study is known as the "satellite" architecture. In this configuration, there are no hubs that concentrate the production from the oil wells, meaning that the production flows directly from the wells to the Floating Production Storage and Offloading (FPSO) via pipelines. For simplification, the analysis will focus solely on factors and equipment that affect oil production, considering only the production pipelines and the gas lift service/injection pipelines. Control lines will not be considered in this study.

The selected architecture is represented by the Event Sequence Diagram (ESD) shown in Figure 1, which should be interpreted from left to right. The path to the right of a block indicates the occurrence of the analysed event, whereas the downward path represents the opposite scenario. The initial event of the ESD corresponds to the condition of a “producer well without failure,” which represents the Subsea Christmas Tree (XT) operating without failure. The first possible event considered is a “production flow failure,” and if this event occurs, the system evolves to a “total production loss from a well,” which constitutes the final event to the right of this block. If the production flow failure does not occur, the diagram proceeds to the subsequent block, which evaluates a “gas lift flow failure.” If this event materializes, the consequence is a “reduction of X% in the production of a well.” If none of the failures occur, the system evolves to the final block, corresponding to the condition of “no losses.”

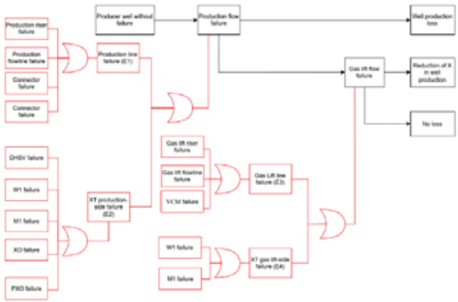

Fig. 1 – ESD of the Satellite Subsea Architecture

Each failure event in the ESD can be detailed in small Fault Trees (FTs), which are connected by OR logic gates. For example, the "production line failure" could be caused by failures in one or more of the following components: production riser, gas lift riser, connector, or rigid spool. Similarly, the "gas lift line failure" event can be explained by three possible branches in its fault tree: failure in the gas lift riser, failure in the gas lift flowline, or failure in the vertical connection module (VCM).

Based on this ESD, which simplifies the representation of the architecture considering only one well (this can be replicated for other wells in the architecture), we can construct a larger fault tree, as illustrated in Figure 2. Each event is identified by a letter for notation purposes, as detailed in Table 1. This larger fault tree describes the production issue of the subsea architecture. The top event, defined as "Production Issue," refers to any condition that negatively affects the oil production of the well, including partial reduction or total production loss. In this model, a production issue occurs if one of two main events happens: production flow failure or gas lift flow failure. The small fault trees contained in the ESD and described earlier will be attached as branches to this larger fault tree.

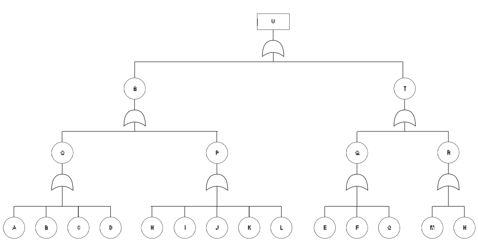

Fig. 2 - Fault Tree for the Satellite Subsea Architecture

Table 1 - Fault tree node identification

Letter	Component
A	Production riser
B	Production Flowline
C	Connector
D	Rigid Spool
E	Gas Lift Riser
F	Gas Lift Flowline
G	VCM
H	DHSV valve
I	Wing valve (W1)
J	Master valve (M1)
K	Cross-over valve (XO)
L	Piggy cross-over valve (PXO)
M	Wing valve (W2)
N	Master valve (M2)
O	Production Line
P	Production XT
Q	Gas Lift Line
R	Gas Lift XT
S	Production Flow
T	Gas Lift Flow
U	Production Issue

The next step involves converting this fault tree into a Bayesian Network, as presented in Figure 3. Each event, whether basic or intermediate, will be transformed into a node in the Bayesian network. The root nodes of the network will receive the same probabilities associated with the corresponding basic events, and the child nodes will be connected to their antecedent events, as described in the Fault Trees.

The Bayesian Network (BN) model is represented as a directed acyclic graph (DAG), where nodes correspond to system components and edges represent probabilistic dependencies. Each node is modeled as a binary variable indicating failure or non-failure. Root nodes are parameterized by marginal failure probabilities derived from reliability databases, while the remaining nodes are defined through conditional probability tables (CPTs) based on the logical structure of the fault tree. Since the relationships between events are represented by OR gates, a child event occurs whenever at least one parent event fails. Table 2 presents the CPT of the Gas Lift Line node, which depends on failures in the gas lift riser and the gas lift flowline.

Table 2 - CPT for the Gas Lift Line node

Gas Lift Riser	Gas Lift Flowline	P(Gas Lift Line = Failure)
0	0	0
1	0	1
0	1	1
1	1	1

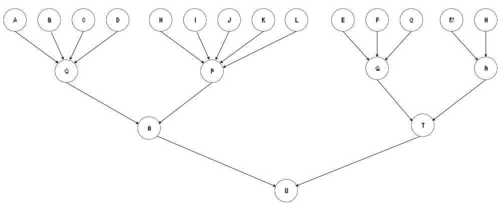

Fig. 3 - Bayesian Network for Reliability Analysis

The failure probabilities associated with the root nodes will be calculated from failure rates extracted from the OREDA and PARLOC databases, whose values are presented in Table 3,4, and 5 below.

Table 3 - Failure Rates of Lines

Line	Riser (per year)	Flowline (per km-year)
Production	$4.4\ x\ 10^{-3}$	$5.7\ x\ 10^{-4}$
Gas Lift	$2.0\ x\ 10^{-3}$	$5.4\ x\ 10^{-3}$

Table 4- Failure Rates of Components

Component	Failure rate (per 10^6 hours)
Connector	0.06
Rigid Spool	0.03
VCM	0.14

Table 5 - Failure Rates of Valves

Valve	Failure rate (per year)
DHSV	0,002756301
Wing	0,000585142
Mater	0,000585142
XO	7,39489E-05
PXO	7,39489E-05

Since failures follow an exponential distribution, the failure probabilities can be calculated using the Eq. 2:

$$P\ (failure) = 1 - \ e^{-\lambda t} \tag{2}$$

Where $\boldsymbol{\lambda}$ is the failure rate and t represents time. For this study, the failure calculations will be done considering a total length of 2 km for the lines and risers, and the time t will be 20 years.

The Bayesian Network was implemented in Python using the pgmpy library (Ankan et al., 2024). The failure probabilities of each event will be presented in Table 6. From these probabilities, it will be possible to make inferences about the reliability of the subsea architecture and analyse the impacts of failures on the system's critical components.

Table 6 - Failure Probabilities of Each Node

Letter	Component	Probability
A	Production riser	0,039210561
B	Production Flowline	0,022542044
C	Connector	0,005245793
D	Rigid Spool	0,010464067
E	Gas Lift Riser	0,084239123
F	Gas Lift Flowline	0,194264698
G	VCM	0,024246026
H	DHSV valve	0,053634124
I	Wing valve (W1)	0,011634628
J	Master valve (M1)	0,011634628
K	Cross-over valve (XO)	0,001477884
L	Piggy cross-over valve (PXO)	0,001477884

M	Wing valve (W2)	0,011634628
N	Master valve (M2)	0,011634628

4. Results

The probabilities in Table 5 enable detailed inferences about the reliability of the subsea architecture and facilitate the analysis of how failures impact the system's critical components. Based on these values, the conditional probabilities of the intermediate events were determined from the possible combinations of the input event states. In general, for an intermediate event that depends on n binary events, the number of possible combinations is given by 2^n, corresponding to all configurations of occurrence and non-occurrence of these events. This approach enables the systematic construction of conditional probability tables, ensuring an appropriate representation of the interdependencies among the considered events.

The total probability is determined by summing the contributions of each scenario, where each scenario's contribution is calculated as the product of its conditional probability and the probability of the scenario occurring. This process is exemplified for the XT gas lift-side failure case below, as shown in Equation 3. Uppercase letters (A, B, C, …) indicate failure events, while lowercase letters (a, b, c, …) denote non-failure events. While Eq. 3 specifically addresses XT gas lift-side failure, all other components and intermediate events can be calculated in a similar manner by applying the same methodology to account for the additional combinations.

$$\begin{aligned} P(R) = P(R|MN) \,.\, P(MN) \\ + P(R|Mn) \,.\, P(Mn) \\ + P(R|mN) \,.\, P(Mn) \\ + P(R|mn) \,.\, P(mn) \end{aligned} \qquad (3)$$

By systematically applying this approach to the entire fault tree, the marginal probabilities of the top-level events are obtained. In particular, the overall probability of a production issue reported in Table 7 results from aggregating the contributions of all relevant scenarios defined in the underlying Event Sequence Diagram and Fault Tree structure.

Table 7 - Probability of Production Issue

Event	State	Probability
Production Issue	No	0.5988
Production Issue	Yes	0.4012

The Bayesian Network inference was first performed without evidence to estimate the overall probability of a production issue in the subsea architecture. The results indicate a probability of 0.4012 for the occurrence of a production issue, while normal operation presents a probability of 0.5988. This result reflects the combined effect of component failure rates and the logical structure of the architecture, highlighting a non-negligible vulnerability of the system at the production level, as summarized in Table 6.

To identify the main contributors to production issues, inference was performed by conditioning the model on the occurrence of a production issue. According to the posterior probabilities reported in Table 8, gas lift flow failure presents a posterior probability of 0.7400, whereas production flow failure presents a probability of 0.3697. This indicates that, given a production issue, failures in the gas lift system are significantly more likely to be involved than failures in the production flow, emphasizing the critical role of the artificial lift subsystem in the overall production reliability.

Table 8 - Posterior Probabilities of Intermediate Events Conditioned on Production Issue

Event	Failure	No failure
Production Flow Failure	0.3697	0.6303
Gas Lift Flow Failure	0.7400	0.2600

When analysing the production flow subsystem, Table 9, similar posterior probabilities were obtained for failures in the production line (0.1889) and the production tree (0.1956). This suggests that production flow issues are not dominated by a single component but rather result from a balanced contribution of both flowline and subsea tree failures.

Table 9 - Posterior Probabilities of Production Flow Components

Component	Failure	No failure
Production Line	0.1889	0.8111
Production XT	0.1956	0.8044

A more pronounced imbalance is observed in the gas lift subsystem, as shown in Table 10. While the probability of failure of the gas lift tree is relatively low (0.0580), the gas lift line failure reaches 0.6983. This result indicates that gas lift-related production issues are predominantly driven by failures in the transport system, particularly the riser and flowline, rather than by the subsea tree itself.

Table 10 - Posterior Probabilities of Gas Lift Components

Component	Failure	No failure
Gas Lift Line	0.6983	0.3017
Gas Lift XT	0.0580	0.9420

The posterior probabilities obtained for basic components are consistent with their expected operational behaviour and exposure, as summarized in Table 11. Passive components such as connectors and isolation valves present low failure probabilities, while extended elements such as flowlines and risers show significantly higher values. This coherence between physical intuition and probabilistic results supports the validity of the proposed Bayesian Network model.

Table 11 - Component-level Failure Events Conditioned to a Production Issue

Component	Failure	No failure
Production Riser	0.0980	0.9020
Production Flowline	0.0563	0.9437
Connector	0.0132	0.9868
Rigid Spool	0.0262	0.9738
DHSV	0.1339	0.8661
W1	0.0292	0.9708
M1	0.0292	0.9708
XO	0.0037	0.9963
PXO	0.0037	0.9963
Gas Lift Riser	0.2101	0.7899
Gas Lift Flowline	0.4843	0.5157
VCM	0.0606	0.9394
W2	0.0292	0.9708
M2	0.0292	0.9708

Overall, the inference results demonstrate the capability of the proposed Bayesian Network to quantify production risks, identify critical subsystems, and support diagnostic reasoning. The gas lift transport system emerges as the main vulnerability of the analysed architecture, suggesting that reliability improvements in this subsystem may lead to significant reductions in production issues.

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