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Bayesian Network Model for FPSO Offset Prediction Using LLM Under Mooring Line Failure

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Abstract. This paper presents a AI-based Bayesian Network model to predict the offset of a Floating Production Storage and Offloading (FPSO) unit subjected to mooring line failures. The model integrates environmental variables such as wind force, wave height, and ocean currents with structural parameters including mooring line integrity and yaw moment. A Large Language Model (LLM) was utilized to assist in structuring the Bayesian Network and generating the probability distributions based on historical data and domain knowledge. The probabilistic framework enables real-time risk assessment and decision-making in offshore operations. Validation is performed using experimental data from FPSO offset tests conducted at LabOceano, COPPE/UFRJ. Results indicate that the proposed model accurately estimates the probability distributions of offset distances, contributing to improved safety and operational efficiency.

1. Introduction

FPSOs (Floating Production, Storage and Offloading) are critical assets in deepwater oil production, requiring robust mooring systems to maintain position stability. The most common station keeping system for FPSOs is the so called Spread Mooring System, in which a number of mooring lines (usually from 16 to 24) are distributed around the floating unit. Such mooring systems are designed to be able to hold the unit inside a certain safe area even if one mooring line is broken. However, mooring line failures on more than one line have been reported in a worrying frequency. One possible explanation is that the lost of one mooring line is almost imperceptible on board, since the offset change is small compared to day to day changes. But if the system stays too long with a first broken line, there will be higher chances of a second one being damaged too. The breaking of more than one line can then lead to excessive offset, posing risks to production and safety.

Some tested solutions for such issue included the use of sensors at some part of the mooring lines. However, due to harsh environment those sensors don't last too long, and the operational staff can only rely on offset measurement (for instance from a DGPS system) to access the health of the mooring system.

So, a clear understanding of the factors affecting the system offset, i.e., the sources of uncertainty that contribute to the offset measurement, is fundamental on the assessment of the health of the mooring system, since any slight difference on the system behaviour may indicate a mooring line failure that may lead to more serious events [1].

Traditional deterministic models such as numerical hydrodynamic models of the forces acting on the floating hull and mooring lines and risers (the pipelines that bring the oil to the unit) provide limited insights into uncertainty quantification. This is due to the lack of information after the system commissioning and to the inherent uncertainties of the mooring system installation (segments lengths, lines pre-tensions, anchor exact positions, et cetera). Bayesian Networks offer a probabilistic approach to assess the likelihood of different offset scenarios given uncertain environmental and operational conditions. The integration of LLMs in Bayesian Network construction enhances model formulation by automating the generation of conditional probability tables and optimizing the dependency structures based on large-scale domain data.

1.1. Role of Large Language Model (LLM)

A novel aspect of the study is the use of a Large Language Model (LLM) to enhance the Bayesian Network. Previous use of LLM on dynamical systems can be found on [2]. While LLMs are traditionally associated with natural language processing, here they are repurposed to:

- Structure the Bayesian Network: Define nodes (variables) and edges (dependencies) by analyzing domain-specific textual data, such as maintenance logs, incident reports, or research literature.
- Generate Probability Distributions: Automate the creation of conditional probability tables (CPTs) by extracting patterns and correlations from historical data and expert knowledge.

This integration optimizes the BN's dependency structures and leverages large-scale data to improve model accuracy, representing a creative application of AI in offshore engineering.

2. Methodology

The development of the Bayesian Network for FPSO offset prediction was carried out through a structured process that incorporated AI-assisted techniques (Figure 2.1). A Large Language Model (LLM) was employed to facilitate the construction of the network by identifying key dependencies between environmental and structural variables. Additionally, the LLM was used to generate preliminary Conditional Probability Distributions (CPDs), which were refined using historical data and domain expertise. The steps taken in the methodology were as follows:

Data Identification & Variable Selection – A Large Language Model was employed to interpret model test reports documenting FPSO offset under various mooring line failure conditions. The LLM was tasked with:

- Identifying critical variables (e.g., mooring line status, wind speed, wave height, yaw moment).
- Proposing a BN structure by defining nodes and directed edges representing variable dependencies.

This data-driven method leverages the LLM's pattern-recognition capabilities, reducing manual effort and potentially revealing novel insights.

Bayesian Network Structure Design – The LLM suggested potential dependencies, which were validated and adjusted manually based on engineering knowledge.

CPD Generation – The LLM produced an initial set of probability distributions that were further refined using historical test data.

Implementation in Python – The LLM-proposed BN was implemented in Python using the pgmpy library, a tool for probabilistic graphical modelling [3]. Key steps included:

- Defining nodes (e.g., "Offset," "Mooring Line Status") and edges per the LLM's structure.
- Generating conditional probability tables (CPTs) with LLM assistance, based on historical data and embedded knowledge.
- Applying inference algorithms (e.g., Variable Elimination) to predict offset probabilities.
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The pgmpy implementation enables efficient querying, supporting real-time operational use.

Graph Visualization & Validation – The structure was analyzed, visualized, and validated using test results to ensure accurate offset prediction.

These AI-assisted steps allowed for an optimized Bayesian Network design, reducing manual effort in defining probability relationships and increasing model accuracy.

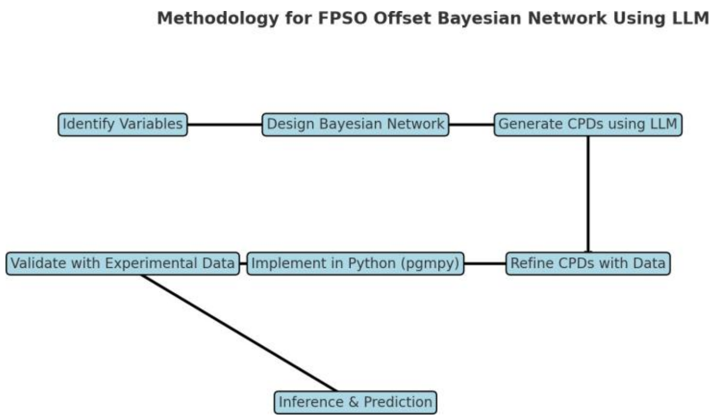

Figure 2.1 – Process for BN implementation

3. Case Study: FPSO Offset Model tests at LabOceano

To validate the proposed Bayesian Network model, we utilized experimental data from controlled FPSO offset tests conducted at LabOceano (Figure 3.1), COPPE/UFRJ [4]. The tests were designed to analyze the response of an FPSO under various mooring line failure conditions.

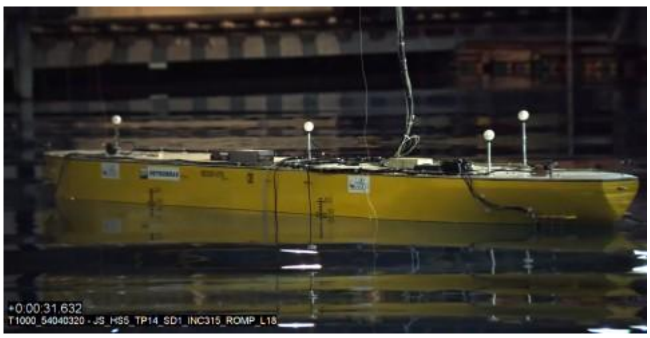

Figure 3.1 – Model tests at LabOceano

The key aspects of the case study are summarized as follows:

- Test Setup: The 1:70 scaled FPSO model was placed in a tank with a water depth of approximately 15m (or 1249 m at prototype scale). Tests were performed under both intact and failure conditions of the mooring system.

- Test Conditions: 189 tests were conducted, including 23 pullout tests, 54 decay tests, 4 transient tests, and 108 wave interaction tests.

- Offset Measurements: The FPSO's position (X, Y, Z) and heading (Yaw) were recorded during the tests to determine the impact of mooring line failure on offset distances

Findings:

- A correlation between wave height and FPSO displacement was observed, with larger wave heights leading to greater offsets.

- Yaw motion increased significantly when certain mooring lines were compromised, affecting station-keeping stability.

The collected data was used to calibrate and validate the Bayesian Network model, confirming its predictive capability in estimating offset probabilities under varying environmental and operational scenarios.

The model is validated using experimental data from controlled FPSO offset tests at LabOceano. Key findings include:

- A direct correlation between mooring line failures and offset magnitude.

- Higher wave heights and currents increase the probability of large offsets.

- The Bayesian model, enhanced with LLM-generated probability structures, outperforms deterministic models in handling uncertainty and predicting extreme events.

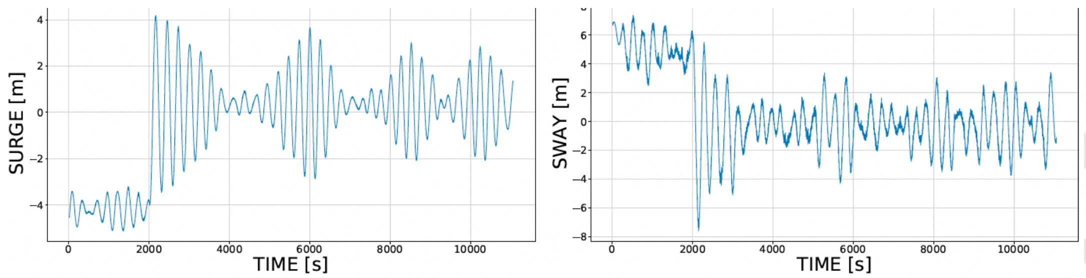

Figure 3.2 Time series examples for offset (X – Surge, Y – Sway)

4. Results and Discussion
The LLM obtained Bayesian Network after applying the flowchart presented on section 2 at the case study can be seen on Figure 4.1.

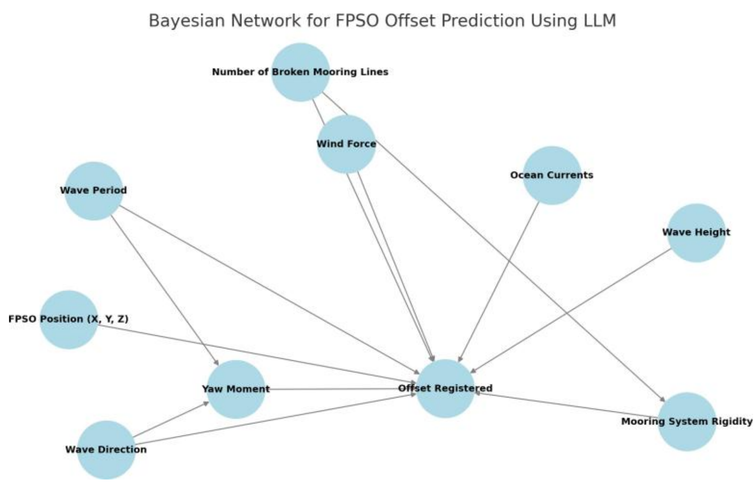

Figure 4.1 – LLM obtained Bayesian Network

The LLM-proposed BN was benchmarked against a reference BN crafted by offshore engineering specialists. The evaluation focused on:

- Structural Accuracy: Correctness of variables and dependencies.
- Predictive Performance: Accuracy of offset predictions compared to test data.
- Practical Utility: Feasibility for real-time applications, such as triggering alarms for excessive offset risks.

4.1. Trained LLM output

The LLM gave the following output:

Since the network can only access the instantaneous offset (X,Y,YawX, Y, YawX,Y,Yaw), it must infer all other relevant states, including environmental conditions, mooring line tensions, and failure indicators.

Nodes of the Bayesian Network

1. *Observed Variable (Input)*
   - *Ship Offset:*
     - *XXX (longitudinal displacement)*
     - *YYY (transverse displacement)*
     - *Yaw (heading deviation)*
2. *Latent Variables (Inferred States)*
   - *Environmental Conditions (Hidden)*
     - *Sea state (wave height, period)*
     - *Wind conditions*
     - *Current effects*
   - *Mooring Line Tension (Hidden)*
     - *Expected tension distribution across the lines*
     - *Rigidity of the mooring system*
   - *Mooring Line Status (Hidden)*
     - *Probability of one or more lines being broken*
   - *Failure Indicator*
     - *Anomalous Offset: Deviation beyond expected thresholds*
     - *Yaw Instability: Rapid or sustained yaw deviation*
     - *Offset Oscillations: Increased drift in response to external forces*

Bayesian Network Structure

- *Ship Offset (X,Y,YawX, Y, YawX,Y,Yaw) → influences Mooring Line Status*
- *Mooring Line Status → affects the Mooring Line Tension Distribution*
- *Mooring Line Tension Distribution → determines the probability of line failures*
- *Mooring Line Failures → indirectly reflect underlying Environmental Conditions (e.g., extreme sea states)*

An example of the implemented BN is shown on Figure 4.2 below.

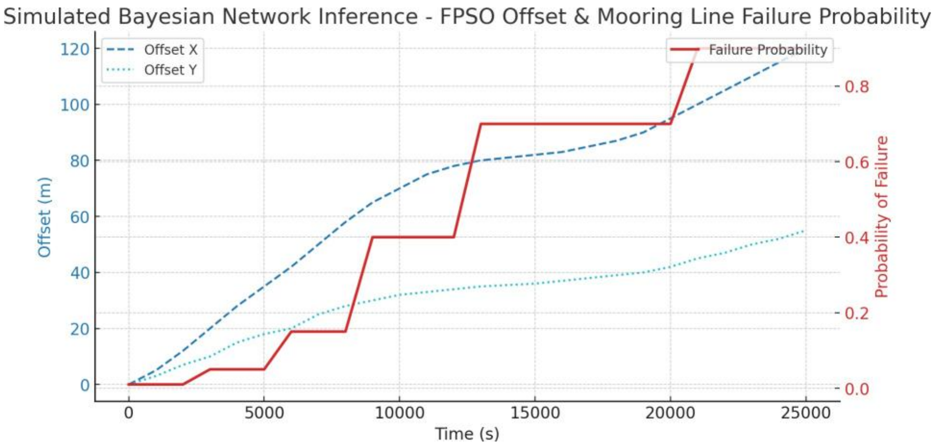

Figure 4.2 Example of AI-LLM-BN implementation for one test condition

5. Conclusion

This study demonstrated that Bayesian Networks, when combined with LLMs, provide an effective tool for FPSO offset prediction, enhancing risk assessment in offshore engineering. Future work includes real-time integration with sensor data for dynamic decision support and further refinements in LLM-assisted probability inference.

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7. References

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