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Reliability-based Assessment of Operational Modes for Dynamic Positioning Systems of Drilling Vessels

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This study presents a mode-dependent reliability modelling framework for Dynamic Positioning systems in offshore drilling vessels, aimed at supporting risk-informed operational decisions between Critical Activity Mode and Task Appropriate Mode. Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) are employed to model failure combinations and consequence propagation, enabling the estimation of the probability of loss of position (P_{LOP}) under different operational demands and redundancy configurations. Reliability is formulated as a function of operational mode, explicitly capturing how redundancy requirements, degradation patterns, and component availability influence station-keeping capability. Bayesian updating is incorporated to revise component reliability parameters as new in-service data become available, allowing the probability of basic events in the FTA to evolve over time without altering the logical structure of the model. This probabilistic refinement enables the system-level reliability to reflect accumulated operational evidence and changing mission conditions. The drillship case study demonstrates that the probability of loss of position increases nonlinearly with operational demand, rising by nearly 4,700% from low to moderate demand and by approximately 1,100% from moderate to high demand, reflecting the strong sensitivity of system-level risk to redundancy thresholds and demand intensity.

Keywords: Dynamic positioning systems; Operational modes; Reliability modelling; Fault tree analysis; Event tree analysis; Bayesian updating.

1. Introduction

Dynamic Positioning (DP) systems constitute a Safety Barrier (SB) in offshore drilling and marine operations, where Loss of Position (LOP) may compromise well integrity, induce collision hazards, or cause environmental damage (Tannuri et al., 2010; Hogenboom et al., 2021; Skogdalen & Vinnem, 2012). Within barrier-based safety frameworks for offshore drilling, DP operates as an operational safeguard responsible for maintaining station-keeping capability under continuously varying environmental loads. Quantitative risk assessments of drilling activities emphasize the importance of modelling barrier degradation and system interdependencies to prevent major accidents (Skogdalen & Vinnem, 2012).

A defining characteristic of DP operations is the adoption of Operational Modes, particularly Critical Activity Mode (CAM) and Task Appropriate Mode (TAM), which impose distinct requirements in terms of redundancy, fault tolerance, and allowable failure combinations. In CAM, LOP is unacceptable, and the system must withstand worst-case failures with sufficient reserve capacity, whereas TAM permits reduced redundancy or alternative equipment configurations provided that station-keeping capability remains acceptable for the ongoing activity. Consequently, the reliability envelope of a DP system is inherently mode-dependent.

Changes in operational mode directly alter system configuration, fault-tolerance logic, and failure propagation pathways. In current industrial practice, CAM and TAM compliance is typically verified through deterministic worst-case failure analyses derived from DP system FMEA (Failure Modes and Effects Analysis) documentation and class requirements, where predefined redundancy criteria must be satisfied for each operational mode. These assessments are primarily configuration-based and focus on verifying whether the system can withstand prescribed failure scenarios under nominal assumptions.

Traditional reliability analyses in marine and offshore systems have relied on qualitative and semi-quantitative techniques such as FMEA, FMECA (Failure Modes, Effects and Criticality Analysis) and HAZOP (Hazard and Operability Study), which provide identification of failure modes and critical components but do not explicitly quantify dynamic system reliability (Melani et al., 2018; Arellano-Ortega et al., 2025). FTA has been widely employed to model causal failure combinations in marine systems (Jovanovic et al., 2025), yet it is typically implemented using fixed logical structures and static reliability parameters, assuming invariant system configurations. Even when applied to DP systems (Tannuri et al., 2010), such models generally represent predefined architectures rather than demand-driven reconfigurable states.

Recent advances have attempted to overcome these limitations through dynamic reliability modelling and decision-support tools. Dynamic Fault Trees (DFT) introduce sequence-dependent gates and spare activation logic to capture event ordering effects (Xing et al., 2019), while temporal decision-making frameworks for DP operations emphasize operational context and evolving risk exposure (Hogenboom et al., 2021). Probabilistic formulations have demonstrated that redundancy effectiveness and minimal cut sets may vary as system availability evolves over time (Dagal, 2026). Additionally, Bayesian updating approaches have been proposed to incorporate life-cycle operational evidence into reliability assessment (Peng et al., 2023).

Despite these advances, existing frameworks address isolated aspects of the problem. Qualitative barrier analyses lack probabilistic depth; static FTA does not capture mode-dependent architectural reconfiguration; DFT captures event ordering but does not explicitly represent operational mode transitions such as CAM and TAM; and Bayesian updating is seldom integrated with demand-driven redundancy modelling in DP systems. Consequently, operational mode transitions are often treated as discrete configuration switches rather than as probabilistic shifts in system vulnerability, and the impact of accumulated degradation or updated failure data on system-level loss-of-position probability remains insufficiently quantified.

In environments characterized by continuously varying environmental loads and evolving component conditions, this limitation becomes particularly relevant. To address this limitation, this paper proposes a demand-based probabilistic reliability modelling framework that explicitly accounts for CAM/TAM-dependent redundancy thresholds and logical reconfiguration of fault trees. The methodology integrates mode-specific FTA structures with event tree consequence modelling and Bayesian updating of component reliability parameters, enabling the probability of LOP to evolve as operational evidence accumulates. CAM and TAM are therefore treated not as hierarchical stages, but as distinct operational philosophies activated according to the task being performed, each characterized by predefined redundancy requirements and risk acceptance criteria.

The approach is demonstrated through a case study of a DP system of a drillship, where different operational scenarios are analysed to illustrate how mode transitions impact redundancy requirements and system vulnerability. The remainder of the paper is

organized as follows: Section 2 presents the proposed methodology; Section 3 details the drillship case study and modelling assumptions; Section 4 discusses the results; and Section 5 concludes the paper with final remarks and perspectives for future work.

2. Methodology

The proposed methodology to quantify the reliability DP systems under different operational modes integrates scenario-dependent environmental demand modelling, mode-driven redundancy reconfiguration, FTA, ETA, and Bayesian updating of component reliability parameters. The framework explicitly captures how CAM and TAM configurations modify redundancy thresholds and failure logic, allowing the probability of LOP to be evaluated as a function of operational demand and accumulated reliability data. Fig. 1 illustrates the methodological pipeline adopted in this study.

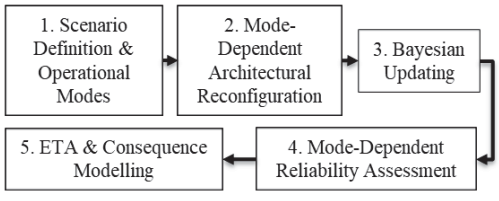

Fig. 1. Proposed methodology framework.

2.1. *Scenario Definition & Operational Modes*

Block 1 establishes the operational context for the reliability assessment by defining how environmental loading and operational mode constraints govern redundancy requirements. Representative drilling campaign conditions, including wind, wave, and current loads, are first characterized. These environmental parameters are converted into thrust and electrical power demand through established DP load models, enabling the determination of the minimum number of thrusters and diesel generators required online to preserve station-keeping capability.

2.2. *Mode-Dependent Architectural Reconfiguration*

In Block 2, the system architecture adopted for the reliability assessment is reconfigured in accordance with the redundancy requirements defined in the scenario phase. A baseline FTA model is initially developed to represent the principal causal pathways leading to loss of position, encompassing propulsion, power generation, and relevant supporting subsystems. This baseline structure captures the physical and functional dependencies within the DP system while remaining configuration-neutral with respect to operational mode.

2.3. *Reliability Estimation and Bayesian Updating*

Block 4 deals with the reliability estimation of the Basic Events (BE) listed in FTA, which can be based on failure database. In the present application, the reliability is modeled by a Weibull two-parameter distribution, $W(\beta, \eta)$, due to its versatility and adaptability to various failure modes (Elsayed, 2012). The lifetime of a component for the Weibull distribution with shape parameter β and scale parameter η. The probability density function and reliability function are given as Eq. 2, for $t > 0$.

$$f(t|\beta,\eta) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{(\beta-1)} exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \quad (2)$$

Assume that, over the course of the campaign, the vessel accumulates n_f failure times $\{t_1, \dots, t_{n_f}\}$ and n_c censored observations $\{u_1, \dots, u_{n_c}\}$, corresponding to components that have survived up to times u_j. The estimative of β and η is based on Maximum Likelihood Estimation Method (MLE). When new failure information is added to the database, the MLE method is run and the new β and η parameters are calculated. If the reliability of a basic event is defined based on a public database, when new failure information is recorded, the Bayesian updating can be used to update the reliability function through Eq. (3) (Peng, 2023).

$$p(\beta,\eta|t,u) = \frac{\prod_{i=1}^{n_f} f(t_i|\beta,\eta)\ \prod_{j=1}^{n_c} R(u_j|\beta,\eta) p(\beta,\eta)}{\iint_0^{\infty} L(\beta,\eta|t,u)\, p(\beta,\eta) d\beta d\eta} \quad (3)$$

Once the posterior parameters are obtained, the BE probability for a component failure within a reference mission time t_m is updated for a BE, resulting in Eq. 4. These posterior BE probabilities replace the prior values in the mode-dependent FTA structures (FTA_{CAM} and FTA_{TAM}).

$$p_{BE}^{post}(t_m) = 1 - R(t_m|\,\beta^{post}, \eta^{post}) = 1 - \exp\left[-\left(\frac{t_m}{\eta^{post}}\right)^{\beta^{post}}\right] \quad (4)$$

Because CAM and TAM differ in redundancy requirements and voting logic, the impact of updated component parameters on the system-level probability of LOP is inherently mode-specific. Repeating this updating process as new operational evidence becomes available allows the reliability model to track the actual degradation patterns of THRs and DGs, rather than relying on static, pre-campaign assumptions.

2.4. *Mode-Dependent Reliability Assessment Updating*

To formalize the mode-dependent reliability computation, the reconfigurable FTA structure is represented by a voting-based k/N gate governing the top event, defined as LOP. Fig. 2 illustrates a simplified conceptual architecture in which system availability depends on the number of operational redundant components, such as thrusters or diesel generators.

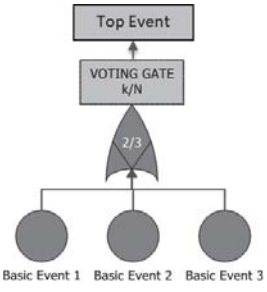

Fig. 2. FTA architecture with mode-dependent voting gate representing redundant components.

In this formulation, N denotes the total number of identical components and k represents the minimum number of component failures required to trigger system unavailability under a given operational mode. Let $q(t_m)$ denote the probability of component failure within the reference mission time t_m, obtained from the posterior reliability models updated through Bayesian inference. Assuming statistically identical components, the probability of failure of the k/N structure is expressed by Eq. 5.

$$P_{fail}^{\frac{k}{N}}(t_m) = \sum_{i=k}^{N} \binom{N}{i} q(t_m)^i \,[1 - q(t_m)]^{N-i} \quad (5)$$

The system-level probability of LOP under operational mode m is subsequently obtained by combining the FTA initiating event probability with the ETA consequence modelling, as presented in Eq. 6.

$$P_{LOP}^{m}(t_m) = \sum_{i=1}^{N_c} P(C_i|IE, m) \cdot P_{IE}^{(m)}(t_m) \quad (6)$$

where C_i denotes the i-th consequence path in the ETA and $P(C_i \mid \mathrm{IE}, m)$ represents the corresponding mode-conditioned consequence probability.

2.5. *Event Tree Analysis (ETA) & Consequence Modelling*

ETA complements the FTA by modelling how initiating failures propagate into system-level consequences (Xing, 2019). In an ETA, the analysis begins with an Initiating Event (IE), which represents a loss of function that challenges the system's ability to maintain position. For each IE, the ETA evaluates the performance of a sequence of intermediate functions, here analogous to the SB (Xing, 2019), that must succeed or fail for the vessel to avoid the LOP.

Each barrier is represented by a binary branching: the upper branch denotes successful function, while the lower branch denotes failure. The accumulation of these binary outcomes defines a unique event sequence leading to a final operational state, such as Maintain Position or LOP. Fig. 3, adapted from Xing (2019), presents a conceptual ETA structure illustrating an IE, branching of operational barriers into success/failure outcomes, and corresponding final consequences (Ci).

For each IE, the ETA maps the sequence of subsequent system responses, such as failure detection and standby equipment activation for load redistribution using remaining thrust or power margins. These sequences differ between CAM and TAM: in CAM, failure-handling logic assumes strict reserve capacity and rapid escalation to critical outcomes when redundancy is compromised; in TAM, relaxed redundancy thresholds may prevent escalation or classify the event as operationally tolerable.

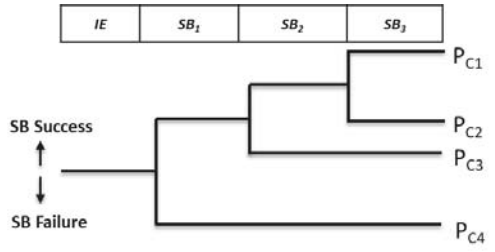

Fig. 3. Conceptual Event Tree Structure.

The probability of each consequence is obtained by multiplying the conditional probabilities along its corresponding path, as shown for P_{C3} by Eq. 1.

$$P_{C3} = (1 - P_{SB1}) \cdot P_{SB2} \quad (1)$$

By integrating the ETA with the reconfigured FTA models, the methodology captures the joint effect of initiating failure likelihood and scenario-dependent propagation dynamics. This allows distinguishing, for instance, whether a given failure path is critical only in CAM, or whether it remains tolerable in TAM.

3. Case Study

The case study focuses on quantifying the probability of LOP (P_{LOP}) under different operational demands and availability assumptions of a DP power generation and propulsion subsystem for a drillship, with emphasis on Diesel Generators (DGs) and Thrusters (THRs) as the primary contributors to LOP events under varying operational demands.

The case study scope is defined in accordance with the Worst-Case Failure (WCF) and in the certified DP system FMEA used as the technical reference for this study. The concept of WCF establishes the maximum admissible degradation of the DP system resulting from any single failure. Fig. 4 details the electrical architecture linking DGs and THRs through segregated high-voltage switchboards.

These representations clarify why WCF scenarios are expressed in terms of coupled THR–DG pairs rather than isolated component failures. WCF is defined as the loss of one thruster redundancy group, corresponding to a coupled loss of thrust and electrical supply, together with the loss of up to two diesel generators, without resulting in a LOP or violation of the DP class requirements.

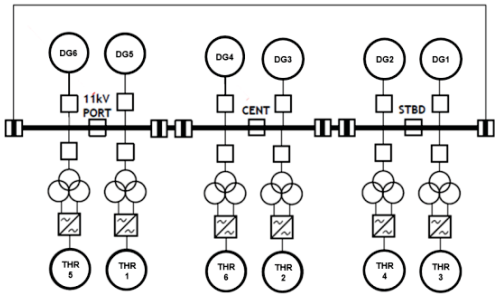

Fig. 4. Electrical architecture coupling DGs and THRs through segregated high-voltage switchboards.

3.2 *Scenario Definition and Operational Modes*

The relationship between operational demand and the minimum number of required THR-DG pairs is formalized through a capacity balance. Let D denote the operational demand, expressed as a fraction of the total installed capacity, and let C_{pair} represent the fraction of capacity provided by a single THR–DG pair. The minimum number of pairs required to satisfy the demand is given by Eq. 7.

$$n_{req} = \left\lceil \frac{D}{C_{pair}} \right\rceil \quad (7)$$

where n_{req} is the minimum number of operational THR-DG pairs required to maintain position.

The total installed thrust and power capacity is distributed across six identical THR-DG pairs. As a result, each functional pair contributes approximately 16.75% of the total installed capacity. This value is used to discretize the operational demand levels and determine the n_{req} of switchboards, as summarized in Table 1.

Column 1 defines the demand levels, expressed as a percentage of the total installed thrust and power capacity, representing increasing environmental and operational severity.

Column 2 presents the corresponding minimum number of operational switchboards required ($N_{req,SB}$) to satisfy the demand, acknowledging that THR–DG pairs are electrically grouped. through independent and segregated busbars. The $N_{req,SB}$, is obtained from

the capacity balance described in Eq. 8, and multiplied by 1/2, once each switchboard covers 2 THR-DG equipment.

Column 3 expresses the system-level voting logic associated with each demand level in terms of a failure-based k/N gate at the switchboard level, as implemented in the FTA. The number of voting elements is $N = 3$ corresponding to the three independent and segregated busbars.

Table. 1. Operational demand levels discretized in terms of switchboards required

Demand *(D)* **(%)**		**N_{req} (Switchboard)** $N_{req\_SB} = \left\lceil \frac{D}{C_{pair} \cdot 2} \right\rceil$	**Switchboard (*k* | *N*) votes for N=3** $k = (N - N_{req\_SB}) + 1$
Low	10	0.3 ≅ 1	3|3
	20	0.6 ≅ 1	3|3
	30	0.9 ≅ 1	3|3
Moderate	40	1.2 ≅ 2	2|3
	50	1.5 ≅ 2	2|3
	60	1.8 ≅ 2	2|3
	67	2	2|3
High	70	2.1 ≅ 3	1|3
	83	2.4 ≅ 3	1|3
	90	2.7 ≅ 3	1|3
	100	3	1|3

3.3 *Mode-Dependent Architectural Reconfiguration*

Initially, a baseline FTA structure is defined to represent the DP power generation and propulsion subsystem, explicitly capturing the segregation of the system into three independent switchboards (Port, Center and Starboard) and their associated THR-DG groups. This baseline structure, illustrated in Fig. 5, represents the reference configuration from which all scenario-specific FTAs are derived. Under CAM, all generation and propulsion equipment are assumed to be available, reflecting operations where maximum redundancy must be preserved.

The top event is formulated using a failure-based voting gate, consistent with the demand-dependent logic defined in Table 1, such that LOP occurs when the number of failed switchboards exceeds the minimum operational configuration required to satisfy the demand.

Low, moderate and high demand regimes were defined in Table 1. For each demand level, the FTA voting logic is reconfigured to reflect the corresponding k/N threshold, while preserving the same physical and functional structure of the FTA. The FTA configurations results for demand levels are derived from the baseline structure and are illustrated in Fig. 5, highlighting how increasing demand progressively reduces the system's tolerance to switchboard failures. For TAM philosophy the loss of generation or propulsion equipment would be more permissible, allowing WCF overcoming.

3.4. *Bayesian Updating*

This section presents the refinement of the probabilistic inputs of the model. To support this refinement, the failure behavior of the DG and THR is initially characterized using two-parameter Weibull models obtained through a Life Data Analysis (LDA) approach. The Weibull parameters were estimated via MLE using ReliaSoft the Weibull++ software, based on historical failure event data collected from the fleet drillship under study over the period from January 2018 to July 2025. Table 2 presents the obtained prior and posterior values for the Weibull parameters for each equipment for Bayesian and MLE methods.

Table. 2. prior and posterior values for the Weibull parameters using Bayesian and MLE methods

Equipment	W2P β_0, η_0(h)	Updated η_1(h) Bayesian	Updated η_1(h) MLE
DG1	1.4, 50800	51489	51030
DG2	1.2, 52740	54145	53092
DG3	1.9, 48723	48851	48766
DG4	2.5, 55922	55937	55925
DG5	1.7, 46432	46691	46475
DG6	2.1, 54801	54859	54816
THR1	1.5, 8139	9312	8380
THR2	1.7, 9974	10716	10100
THR3	2.7, 11952	12057	11965
THR4	2.5, 12412	12553	12432
THR5	2.8, 14403	14466	14414
THR6	2.1, 8681	9113	8769

Fig. 6 presents the event tree corresponding to the CAM scenario, in which the P_{LOP} obtained from the FTA is used as the initiating event. The operating time is treated as right-censored data and incorporated into the Weibull model while keeping the shape parameter β_0 unchanged, assuming that additional failure-free operation affects the characteristic life but not the underlying failure mechanism.

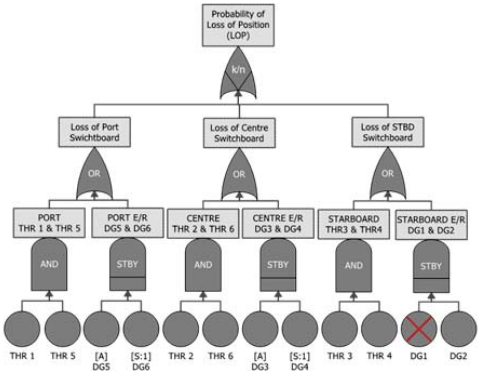

Fig. 5. FTA baseline arrangement

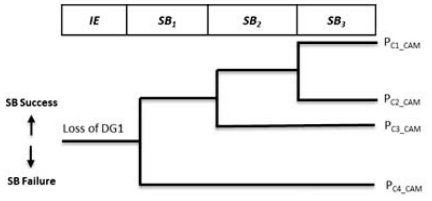

Fig. 6. ETA for CAM Scenario

Bayesian and MLE updates were therefore applied to the scale parameter η_0, yielding an updated estimate η_1 that reflects the accumulated operational evidence. Both approaches produced similar results, with minor differences due to the influence of the Bayesian prior under predominantly right-censored data. The updated Bayesian parameter η_1 was then used as input to the mode-dependent FTA configurations, enabling the impact of additional operational time on the probability of loss of position to be quantified without altering the FTA logic.

3.5 Mode-Dependent Reliability Assessment

The P_{LOP} results were evaluated for all demand levels, considering CAM scenario (apenas um barramento pode ser perdido), and outcomes obtained using prior and posterior Weibull reliability parameters.

All P_{LOP} were evaluated as conditional probabilities for a drillship mission duration exceeding 3000h, assuming approximately 3000h of prior operation have already been accumulated without observed failures. Table 3 presents the SB results for the CAM scenario, expressed in terms of the conditional probability of SB failure (P_{SB}).

The SB_1 corresponds to the STBY DG functionality (standby), reflecting the ability of the power management system to synchronize and connect the standby unit following a running DG failure.

The low P_{SB} value indicates a high likelihood of successful load transfer and preservation of generation capacity. The SB_2 and SB_3 represent the availability of the CENTRE and PORT switchboards. Table 4 presents the resulting P_{LOP} for the CAM scenario as a function of operational demand.

Table. 3. P_{SB} Results in CAM mode

SB		P_{SB}	Rational
SB_1	DG2 STBY generator	0.031	FTA (Fig.5)
SB_2	CENTRE Switchboard	0.010	
SB_3	PORT Switchboard	0.002	

Table. 4. P_{LOP} Results in CAM mode

IE	Demand	$k \mid N$	P_{LOP}	Rational
Loss of DG_1	Low	3 | 3	3.07×10^{-4}	FTA (Fig.5) & Eq. 6
	Moderate	2 | 3	1.47×10^{-2}	
	High	1 | 3	0.176	

Under the High Demand (1|3) configuration, the effect of Bayesian updating is evidenced by the reduction of the system-level P_{LOP} from 0.1999 (prior) to 0.1762 after incorporation of 3000 hours of failure-free operational data (6000 hours in total).

The variation results from the revision of the Weibull scale parameter η and its propagation through the mode-dependent FTA and ETA structures as presented in Fig 7, demonstrating that the proposed framework dynamically updates system reliability rather than providing a static pre-campaign estimate.

3.6 ETA & Consequence Assessment

As demand increases from moderate to high levels, the k threshold becomes progressively more restrictive, leading to an increase in P_{LOP}. Table 5 presents the consequence probabilities for CAM by subsequent ETA branches.

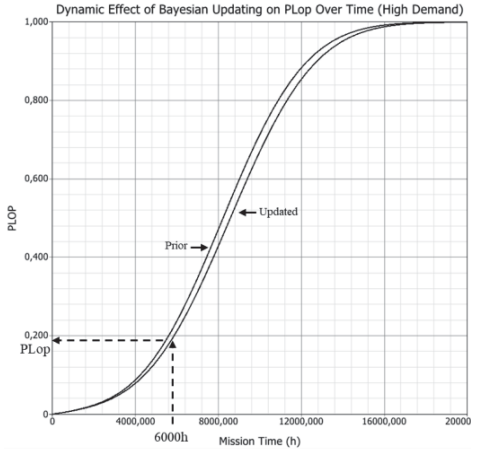

Fig. 7. Bayesian updating effect on P_{LOP}

Table 5. Consequence assessment results for CAM

Consequence	Pc	Rational
C1	0.96	Eq. 1 & Fig.6
C2	0.0019	
C3	0.0097	
C4	0.031	

The dominant outcome C_1 corresponds to successful recovery or limited degradation, while the probability of more severe consequences C_2, C_3, C_4 remains comparatively low.

5. Conclusions

The proposed reliability-based framework incorporates operational mode transitions and demand-dependent redundancy in DP systems. Through scenario-driven FTA reconfiguration, ET modelling and Bayesian updating, it captures the evolution of P_{LOP} with operational demand and accumulated in-service evidence. The drillship case study shows that CAM configurations exhibit distinct reliability behaviour as demand increases, indicating that DP reliability assessment should be treated as a mode-dependent and updateable problem. The approach supports risk-informed operational decisions and justification of redundancy requirements.

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