

## Subsea tree valve inspection and maintenance optimization using varying inspection intervals

David Semwogerere

*Department of Geoscience, Norwegian University of Science and Technology, Norway. E-mail: david.semwogerere@ntnu.no*

Jørn Vatn

*Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Norway. E-mail: jorn.vatn@ntnu.no*

Sigbjørn Sangesland

*Department of Geoscience, Norwegian University of Science and Technology, Norway. E-mail: sigbjorn.sangesland@ntnu.no*

Condition-based maintenance (CBM) allows us to identify and rectify potential well integrity issues on a well for safe operations and prolonged well barrier health. The Christmas tree (XT) valves provide the final well barrier on a well and are key in preventing hydrocarbon release to the environment. Choosing the right maintenance and inspection policy is essential in reducing both the failure risk and maintenance costs, albeit with increased availability of the XT system. This paper proposes a varying inspection XT valve maintenance policy that achieves these objectives. Results show that after a failure, the 90-day inspection interval achieves approximately a similar probability of failure on demand and lower cost than the 30 and 90-day inspection intervals recommended by NORSOK-D010. The varying inspections model can find application in late-life well integrity management by matching the inspection intervals with the failure rate of the well barriers.

*Keywords:* well integrity, xmas tree valves, maintenance

### 1. Introduction

The subsea christmas tree (XT) is the final well-integrity barrier connecting the well to the downstream production systems. It sits on the wellhead and has bores connecting the tubing and A-annulus to external flow lines. To control flow and access to the well annuli, an array of gate valves are installed on the XT as shown in Fig. 1. The swab valve (SV) provides well access for wireline, slickline or coiled tubing intervention operations in the tubing or annulus. The Production Wing Valve (PWV) controls flow to the production flow line while the Annulus Wing Valve (AWV) controls the flow to the A-annulus for circulation or killing operations. The Lower Master Valve (LMV) is a primary barrier for shutting in the well in case of emergency while the Upper Master Valve (UMV) is the secondary barrier. It also acts as a tool deployment seat when setting up intervention bottom-hole assemblies. Subsea XTs come in vertical and horizontal tree designs with the difference being that horizontal trees allow direct Blowout Preventer (BOP) installation and workover access while vertical trees need to be removed, and a BOP installed on the well for workover operations to commence.

Inspection and preventive maintenance can reduce failure risk and prolong valve service time. To ascertain the integrity of the XT valves, frequent inspection and testing is required. Typical testing exercises include visual inspection with an ROV, cycling the valve and determining closing speed, torque and number of closing turns to ensure there's no obstruction when closing the valve. Routine inspection exercises also involve greasing the valves to replace degraded grease, which also acts as a barrier in the valve. An integrity pressure test is then performed to ensure the valve can still contain the rated well pressure with a negligible leak rate

According to NORSOK D-010 rev5, the valves ought to be function and pressure tested 3 times consecutively without failure monthly, every 3 months and thereafter every 6 months to be well integrity qualified. In these test intervals the well

integrity inflow testing in the direction of flow at low- and high-pressure tests.

One of the most predominant valve failure modes is the Leakage in Closed Position (LCP). The LCP is a failure mode where the valve is closed but continues to leak at rates higher than those specified in Raj et al (2014), API RP 14B and ISO 16530 i.e 0.4l/min or 0.42Sm<sup>3</sup>/min. If these volumes cannot be directly measured, the differential pressure downstream of the valve can be monitored during the test.

In XT gate valves, the LCP is usually caused by gate erosion from production solids, corrosion deposits (Feng et al) and damage to the seal or stem packing. The main maintenance action therefore is to ensure the valve is fully open, cycling to remove any deposits and pumping grease to improve the sealing mechanism and lubricate moving parts in the valve. The valve is then pressure tested to ensure a negligible leak rate i.e below 0.4l/min. However, while more frequent inspection and leak testing reduces failure risk, it can also increase maintenance-induced failures due to wear and tear of internal components (de Azevedo et al 2018). In addition, high inspection frequency results in lost production whenever the well is shut-in for the inspection exercise, resulting in financial loss.

Subsea component and system degradation modeling and maintenance policies in the literature takes on different approaches. Zhang et al (2025) proposed a maintenance strategy that combines predictive and emergency maintenance and optimized based on integrated resilience throughout the lifecycle of the subsea XT. From a system perspective, Fan et al (2021) catered for stochastic dependency among XT components by using an optimized maintenance policy based on grouping. Wang et al (2020) used fault trees and Dynamic Bayesian networks based on Markov state modeling to determine XT availability under perfect and imperfect repair. Zhang et al (2025) used multi-agent deep learning in predictive maintenance of subsea XT systems

Tekin et al (2025) used continuous Markov Chain models to model degradation and maintenance policies of protection systems and under perfect and imperfect inspection. Dinh et al (2025) used a dynamic inspection model where the maintenance is based on varying levels of inspection quality

In other related work, Lui et al (2020) used Markov models to determine the influence of the availability on the control systems of all-electric subsea XT depending on the maintenance strategy. Liu, et al (2021) also used Markov degradation models for determining subsea electric XT control system availability and MTTR. Zhang et al (2022) exemplified use of Markovian models in modeling the reliability of gate valves in deep water environments while Cai et al (2022) exemplified condition-based maintenance (CBM). Xia et al (2024) used Markov state models to express degradation in steel pipelines

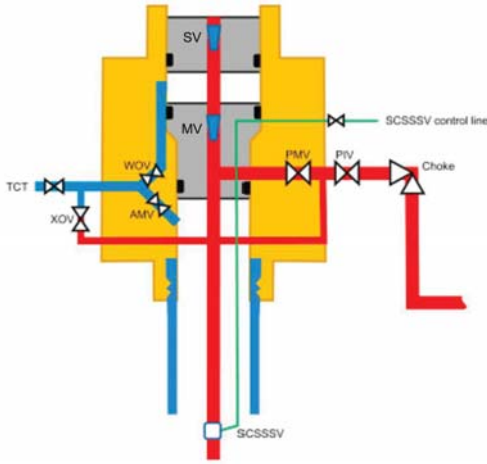


Fig. 1: Horizontal XT schematic (Adapted from Bai et al (2019))

The majority of the models presented in the literature aim at finding a fixed inspection interval that optimizes for the lowest inspection cost. The varying inspection interval model presented here differs from those proposed in Cai et al (2022) and Dinh et al (2024) in that we also aims to optimize for a reduced probability of failure in addition. The objective is to develop a maintenance strategy that strikes a balance between reducing failure risk without affecting well uptime. We shall also compare it with the existing NORSOK D-010 rev5 inspection model as a performance baseline.

## 2. Degradation and maintenance modelling methodology

### 2.1. Markov model

A simple 2-state model has only the healthy and failed states. However, between the healthy and fail states,

realistically, there exists a series of intermediate states that represent the degradation level of the valve. We can use Markov modelling (Rausand et al) to represent XT valve degradation by splitting the degradation into several states representing the degradation levels. Where the beginning state 0 represents full functionality, intermediate states are different levels of the valve degradation and  $k$  is the failed state. In Fig. 2 we propose a Markov state degradation state transition diagram. The states 0 to  $k$  represent increasing levels of degradation where 0 - Healthy, 1 - Slightly degraded, 2 - Very degraded etc until the final stage  $k$  - Failed.

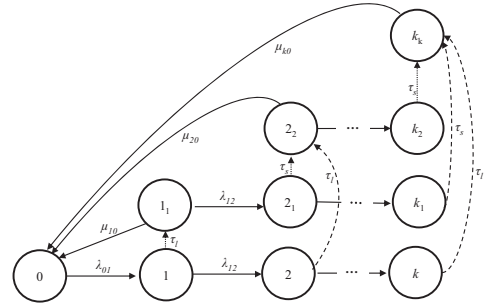


Fig. 2: Markov state transition diagram

The main index is the actual state of the valve, hidden and only revealed at inspection. The sub-index is the state we believe the valve to be in, based on the previous inspection. Where the sub-index is not given, we believe we are in state 0, the healthy state. The state transition rates such as  $\lambda_{12}$  represent how fast to transition from state 1 to state 2 while  $\mu_{20}$  represents the repair rate from state 2 to healthy state 0. We assume perfect repair which means the valve is restored to state 0 with negligible leakage rate. The dashed lines are the transitions that only take place at an inspection when there is a transition from the hidden/belief state to the evident state.

We carry out inspection at varying intervals denoted by  $\tau$ . We have short and long intervals. Short intervals  $\tau_s$  apply when we believe we are in state of degradation such as 1 or 2 while long intervals  $\tau_l$  apply when we believe we are in the healthy state 0.

Our current belief about the state of the valve is backed by the revealed or repair state at the previous inspection. This means that when we believe we are in a healthy state, we apply a long inspection interval until the next inspection. If we however believe that we are in a degraded state, we apply a short inspection interval. The objective therefore is to apply a maintenance policy where we change the future inspection interval depending on the revealed state of the valve at the current inspection.

In this Markov model, three assumptions are taken. The first assumption is that the sojourn time spent in each state,  $T_i$  is



$$PFD_{avg} = \frac{1}{\tau} \int_0^{\tau} P_k(t) dt \quad (6)$$

Where  $P_k(t)$  is the instantaneous PFD related to the failure rate by Eq. (7):

$$P_k(t) = 1 - \exp \left[ - \int_0^t z(t) dt \right] \quad (7)$$

For this model, the PFD is for the total probability of the time spent in the failed state  $k$ , here, the probability of critical leakage upon a demand for closing the valve corresponds to PFD. The frequency of entering failed state  $k_i$  is not of any interest but rather the total time spent there. In this case

$$PFD_{avg} = \frac{1}{\tau} \sum_{n=0}^{i=k} P_{ki}(t) \quad (8)$$

Where  $i$  is sub-index of the failed state  $k$ . We assume perfect repair at every inspection.

### 2.3. Inspection interval optimization.

In most inspection optimization, cost is the major concern and driver for maintenance decisions and hence is used in deciding the inspection and maintenance interval. The goal is to optimize for inspection frequency by choosing an inspection interval that minimizes the inspection cost while maximizing the well availability for production, and minimizing the PFD. In this work we consider the maintenance and inspection cost Eq. (9) to find the minimum costs due to failures in state  $k$  and repairs across the degraded intermediate states 1 and 2.

$$c(\tau) = c_i/t + (c_f + c_m)\lambda_e(\tau) + c_r\mu_e(\tau) \quad (9)$$

Where  $c_i$  is the inspection cost,  $c_f$  the failure cost in terms of lost production,  $c_m$  corrective maintenance cost,  $c_r$  the renewal cost,  $\lambda_e$  is the effective failure rate and  $\mu_e$  the effective repair rate. Here,  $c_r$  refers to the cost of restoring the valve health to as good as new i.e in healthy state 0. The effective failure rate depends on the maintenance limit and can be derived from the transition matrices for each limit. The effective repair rate is then the average probability of being in the failed state. Similarly, the renewal rate is the average probability of being in the state of the maintenance limit  $l$ .

### 3. Case study

The leakage in closed position failure mode is the most prevalent failure mode in subsea XT valves. According to the OREDA database, XT gate valve has a MTTF of 475 years (166666 days) if the valve is operated without maintenance. Using these values, we compare the NORSOK D010 maintenance policy with the proposed Markov model with varying inspection regimes. The metrics of interest are the  $PFD_{avg}$  and the inspection cost  $c(\tau)$ .

#### 3.1. NORSOK-D010 model

The NORSOK model is a classic two-state Markov model with no intermediate states considered. It therefore assumes the valve is either in the healthy or failed state. The NORSOKD-010 rev5 also recommends a varying inspection model after a well barrier has been restored to as good as new. The barrier must be tested 3 times every 30 days and then 3 times every 90 days. The PFD for every interval is calculated and the corresponding  $PFD_{avg}$  for 360 days is obtained using Eq. (10).

$$PFD = \frac{\lambda\tau}{2} \quad (10)$$

According to OREDA, the failure rate of a subsea XT valve for the leakage in closed position failure mode is  $5.76 \times 10^{-6}/\text{day}$  ( $0.24 \times 10^{-7}/\text{hr}$ ). For a 365-day period, the calculated  $PFD_{avg} = 4.83 \times 10^{-4}$  with a total of 6 inspections plotted in Fig. 3.

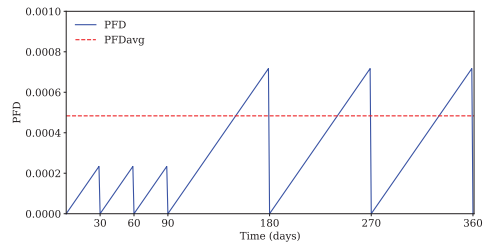


Fig. 3: NORSOK D010 maintenance policy

#### 3.2. Applying varying inspection interval Markov model

Suppose the XT valve undergoes a  $k = 3$  Markov state leakage degradation process represented by the Markov model according to Fig. 2, where the XT valve degradation level is divided into states that correspond to a fluid leak rate, a typical degradation indicator for the leakage in closed position (LCP) failure mode is the leakage rate such that:

- 0 – Healthy: 0 - 0.09l/min
- 1 – Slightly degraded: 0.1 - 0.19l/min
- 2 – Very degraded: 0.2- 0.39l/min
- 3 – Failed: leakage rate: 0.4l/min and above

Assume the XT valve degradation transition rates  $\lambda$  described in Table 1 such that:

$$\sum_{i=1}^n \frac{1}{\lambda_i} = MTTF \quad (11)$$

The equivalent renewal rates  $\mu$  to restore the valve state to as good as new are also shown.

Table 1: Model parameters

Parameter	Value
$\lambda_{01}$	1/35000
$\lambda_{12}$	1/20000
$\lambda_{23}$	1/7050
$\mu_{10}$	1/2
$\mu_{20}$	1/5
$\mu_{30}$	1/10

Maintenance matrices are obtained with  $M_L$  performing inspection transitions for states 1,2 and 3 for the long inspection interval  $\tau_l$  and another  $M_s$  for inspection transitions at  $\tau_s$  for states 2<sub>1</sub>, 3<sub>1</sub>, and 3<sub>2</sub>.

4. Results and discussion

The Markov model was simulated for a total running time of 360 days to determine the PFD, number and cost of inspections in a year. To calculate PFD at any instant, we sum up the probabilities in the failed state 3 according to Eq. (11).

$$PFD = P[3] + P[3_1] + P[3_2] + P[3_3] \quad (11)$$

The  $PFD_{avg}$  is then calculated from Eq. 8. The results were plotted as shown in Fig. 4. Different combinations of  $\tau$  were

considered for a period of 360 days. 6 scenarios are assumed as described below

- Scenario 1: Stick to longest interval of 180 days in all states. This is also synonymous to NORSOK-D010 rev 5 inspection intervals under no failure.
- Scenario 2, 3, 5: Stick to long interval when in belief states 0 and short interval when in belief states 1 and 2.
- Scenario 4, 6: Stick to reduced intervals of 90 and 30 days respectively for all states.

Slight model variations were also made based on repair options described below:

- Mode 1: No repair from state 2<sub>1</sub> to 0
- Model 2: Repair from state 2<sub>1</sub> to 0 instead of 1<sub>1</sub> to 0
- Model 3: Repair from both states 2<sub>1</sub> and 1<sub>1</sub> to 0.

The results obtained from the 3 models under the 6 scenarios are shown in Table 2. The percentage inspection cost compared to the NORSOK D010 model, which has 6 inspections in a year is also indicated.

Table 2: Scenarios under different values of  $\tau$  with perfect repair

Scenarios	$\tau_l$	$\tau_s$	$PFD_{avg}$			MTTI (days)	Inspection per year	% Cost vs NORSOK
			Model 1	Model 2	Model 3			
1	180	180	7.66E-9	8.05E-9	7.470E-9	180	2	-66.67
2	180	90	7.09E-9	7.35E-9	7.03E-9	135	3	-50.00
3	180	30	6.70E-9	6.85E-9	6.70E-9	105	3	-50.00
4	90	90	1.42E-9	1.83E-9	1.34E-9	90	4	-33.33
5	90	30	1.11E-9	1.34E-9	1.10E-9	60	7	16.67
6	30	30	1.30E-10	4.06E-10	1.13E-10	30	12	100.00

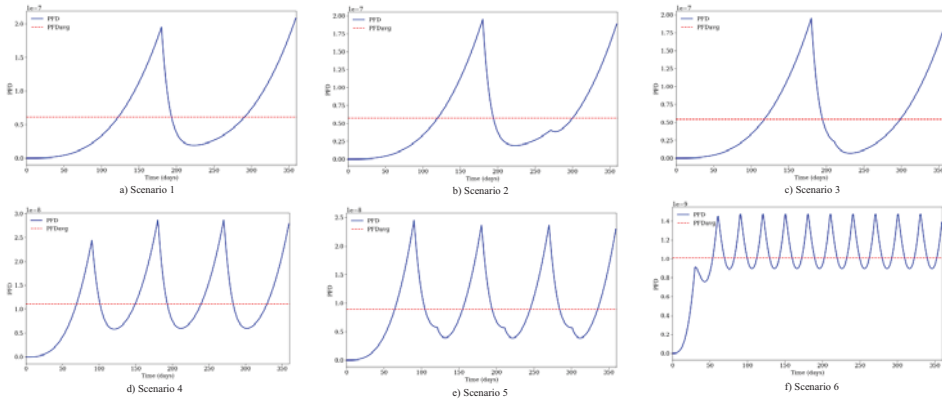


Fig. 4: PFD plot of Model 1 under 6 scenarios

**4.1. Cost optimization with  $\tau_l$  and  $\tau_s$**

There are costs associated with the repair transitions associated with the repair activities such as equipment mobilization, rig up and testing. In addition, we might have production losses from the failed state. Using Eq (9), different combinations of  $\tau_s$  and  $\tau_l$  were evaluated with an objective of achieving the combination with the minimum inspection cost, irrespective of maintenance limit  $l$ . The simulation was run to achieve the effective failure rate  $\lambda_e$  and effective renewal rate  $\mu_e$ . Here we use  $c_f + c_m = 1 \times 10^6$  USD and  $c_r = 1 \times 10^5$  USD for illustration

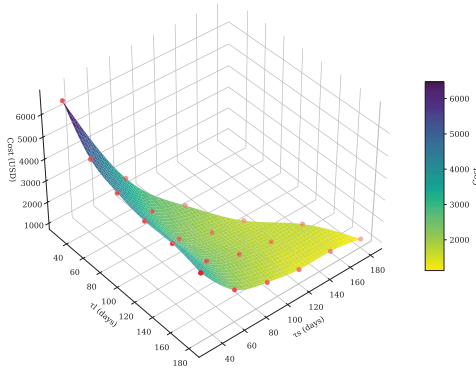


Fig.5: Cost of different combinations of  $\tau_s$  and  $\tau_l$

In general, maintenance policies that involve the  $\tau_s = 30$  interval are more costly compared to other  $\tau$  combinations. Scenario 1 of  $\tau_s = \tau_l = 180$  days had the least inspection costs. An inspection interval of 180 days achieves the lowest cost savings and lower  $PF_{D_{avg}}$  compared to the NORSOK D010 inspection model.

**4.1. Model PFD comparison**

Using the NORSOK D010 model, the calculated  $PF_{D_{avg}} = 4.83 \times 10^{-4}$  which is higher than the  $PF_{D_{avg}}$  calculated from the varying inspection Markov model in Table 2 and plotted in Fig 6. The results also show that although scenario 5 is also has a combination of 90 days and 30 days inspection intervals, the  $PF_{D_{avg}}$  is much lower than the NORSOK D010 model. This can be attributed to the fact that the varying inspection intervals model has more states than the simple 2-state NOROK D010 model, allowing failures to be detected and repaired. The NORSOK model contains both detected and undetected

failures. In addition, because the varying intervals model does not immediately repair the failed state to state 0, the PFD does not return to 0 at inspection as in the NORSOK D010 model. However, this maintenance policy is more costly by a cost increase of 16.67% due to an extra inspection compared to the NOROSK D10 model. Scenario 4 of inspection intervals of  $\tau = \tau_l, \tau_s = 90$  days gives reduced  $PF_{D_{avg}}$  and is thus the preferred inspection policy with 4 inspections, less than NORSOK and scenarios 5 and 65.

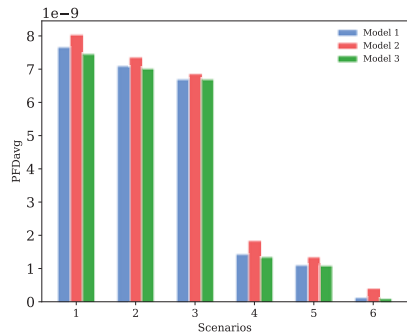


Fig. 6:  $PF_{D_{avg}}$  values for different models under different scenarios

Scenario 6 gives the lowest  $PF_{D_{avg}}$  across the three models. This is expected due to the reduction in  $\tau_l$  from 180 to 90 days. In addition, Model 3 gives the least  $PF_{D_{avg}}$  for all scenarios.

**4.2. Limitations**

- For ease of maintenance administration, we have used 30-day intervals in the maintenance administration
- We assume that the true state of the XT valve is revealed with 100% accuracy at every inspection, which might not always be the case, especially in the subsea environment where visibility and access are limited.
- Applying this model in a group maintenance policy for all valves on the XT would be a more practical solution that reduces the number of inspections than focusing on individual valves.

**5. Conclusion**

We have proposed a varying interval maintenance strategy where we reduce the inspection interval when a degraded state is observed. The Markov model discussed in this text takes into account the evidence-based aspect of the human decision maker and is thus a realistic model.

We compared the results with the recommended NORSOK-D010 inspection policy. The evidence-based varying

inspection intervals Markov model had a lower PFD<sub>avg</sub> for all scenarios of long and short maintenance intervals. The results also show that the varying inspection scenarios involving 30-day intervals greatly reduce PFD<sub>avg</sub>, however they also lead to increased inspection costs. The scenario 4 of equal 90-day inspection intervals strikes a balance between cost and PFD<sub>avg</sub> reduction. Therefore, instead of the 3 consecutive 30-day and 90-day inspections after a valve failure, 4 consecutive 90-day inspections can be used to achieve lower PFD at a lower inspection cost.

This model can be applied to inspection of other well barriers, especially in late well life where degradation accelerates and we match the inspection frequency to the barrier degradation rate. This can be used for decision support on life extension projects both for costs and risk in repairable well barrier systems. The benefit is increased well uptime with reduced failures but also reducing the costs of unplanned failure both in lost production and equipment damage.

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#### References

- API RP 14B
- API 6A
- API 17D
- Bai, Yong, and Qiang Bai. *Subsea engineering handbook*. Gulf Professional Publishing, 2018.
- ISO/TS 16530-1.
- ISO/TS 16530-2. "Well integrity-Part 2: Well integrity for the operational phase." (2014).
- Standard, N. O. R. S. O. K. "Well integrity in drilling and well operations." *D-010, rev 3* (2004).
- OREDA, Handbook. "Offshore and onshore reliability data." (2015).
- Zhang, Yanping, et al. "A synergistic maintenance optimization method driven by integrated-resilience: Subsea Christmas tree as a case." *Ocean Engineering* 341 (2025): 122550.
- Wang, Chuan, et al. "Reliability and availability modeling of Subsea Xmas tree system using Dynamic Bayesian network with different maintenance methods." *Journal of Loss Prevention in the Process Industries* 64 (2020): 104066.
- Fan, Dongming, et al. "Group maintenance optimization of subsea Xmas trees with stochastic dependency." *Reliability Engineering & System Safety* 209 (2021): 107450.
- Dinh, Duc-Hanh, et al. "A dynamic inspection model for predictive maintenance considering different degrees of inspection quality." *Reliability Engineering & System Safety* 261 (2025): 111165.
- Tekin, Salih, Niyazi Onur Bakır, and Büşra Keleş. "Maintenance policies for protection systems with imperfect inspection and imperfect repair." *Reliability Engineering & System Safety* 257 (2025): 110798.
- Liu, Peng, et al. "Reliability analysis method of a control system for subsea all-electric Christmas tree." *Journal of Marine Science and Application* 20.2 (2021): 354-370.
- Zhang, Yanping, et al. "A system-centered predictive maintenance re-optimization method based on multi-agent deep reinforcement learning." *Expert Systems with Applications* 274 (2025): 127034.
- Cai, Baoping, et al. "Condition-based maintenance method for multi-component system based on RUL prediction: Subsea tree system as a case study." *Computers & Industrial Engineering* 173 (2022): 108650.
- Zhang, Ning, et al. "Research On Reliability Evaluation Of Deep-Water Manual Gate Valve Based On Markov Method." *Journal of Applied Science and Engineering* 26.8 (2022): 1141-1149.
- Xia, Li, et al. "Prediction of Steel Pipeline Internal Corrosion Status with Markov Chain Theory." *2024 International Conference on Intelligent Computing and Robotics (ICICR)*. IEEE, 2024.
- Wang, Chuan, et al. "Reliability and availability modeling of Subsea Xmas tree system using Dynamic Bayesian network with different maintenance methods." *Journal of Loss Prevention in the Process Industries* 64 (2020): 104066.
- Feng, Da Cheng, et al. "Comprehensive Failure Analysis of Christmas Tree Gate Valves in Erosion-Corrosion Coupling Condition." *Journal of Failure Analysis and Prevention* (2025): 1-13.
- Raj, M. "Well integrity—Christmas tree acceptable leakage rate and sustained casing pressure." *Society of Chemical Industry, Hazards* 24 (2014).
- de Azevedo Vale, Guilherme. *Testing of Safety Systems: Bad Effects and Their Modelling with Comparative Studies*. MS thesis. NTNU, 2018.
- Rausand, Marvin, and Arnljot Hoyland. *System reliability theory: models, statistical methods, and applications*. Vol. 396. John Wiley & Sons, 2003.
- Maintenance Optimization course J. Vatn
- Pang, Nan, et al. "Dynamic Bayesian network-based reliability and safety assessment of the subsea Christmas tree." *Process safety and environmental protection* 145 (2021): 435-446.
- Requirements Elicitation for Barrier Monitoring System Anar Ahadov
- Lee, Shenae, et al. "A risk aspect of periodic testing on pressure relief valves." (2022).