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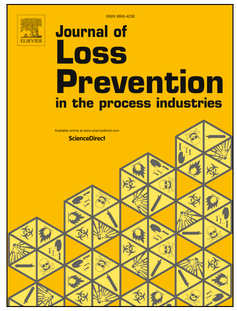

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Reliability Analysis of Subsea Blowout Preventers with Condition-based Maintenance using Stochastic Petri Nets

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ABSTRACT

Blowout Preventer (BOP) has maintained its function as a safety barrier and the last line of defence against oil and gas spills since its development in the early 1900s. However, as drilling and exploration activities move further offshore, challenges pertaining to reliable operation of the subsea BOP systems continue to be a source of concern for stakeholders in the industry. In spite of recent advancements in reliability analysis of safety instrumented systems (SISs), the research on reliability assessment of BOP is still lacking in some regards. There are gaps in the literature with respect to the incorporation of preventive maintenance (PM) strategies as well as dynamic operating conditions into BOP reliability analysis. To address these gaps, this paper develops an advanced analysis method using stochastic Petri nets (SPN) to estimate the reliability of subsea BOP systems subject to condition-based maintenance (CBM) with different failure modes. The BOP system is divided into five subsystems which are connected in series with each other and categorised into degrading and binary units. The performance of the BOP system in terms of availability, reliability and mean-time-between failures (MTBF) is obtained and analysed. A sensitivity analysis is also performed to evaluate the effect of fault coverage factor and redundancy design on system performance. The results show that both the fault coverage factor and redundancy have significant impact on the BOP's reliability, availability and MTBF.

Keywords: Blowout preventer (BOP); Condition-based maintenance (CBM); Reliability; Availability; Mean-time between failures (MTBF); Stochastic Petri nets (SPN).

1 Introduction

A large number of safety instrumented systems (SISs) are in use within the oil and gas industry for drilling, production, processing and storage purposes (Liu, 2014; Liu and Rausand, 2016). The complexities associated with these systems are amplified when taking into account the myriad of challenges within the offshore environment. The blowout preventer (BOP) is one of the most important SISs in the subsea oil and gas sector which is employed in the event of the failure of the primary well control process.

The main function of a BOP is to seal the well in the event of a blowout (i.e. an uncontrolled flow of liquid and gases during the drilling process) (Holand and Rausand, 1987). BOPs are one of the most critical SISs among all drilling equipment and, as a result, the downtime associated with removal of the BOP stack is known as one of the costliest activities in offshore drilling operations (Zou *et al.*, 2016). The main components of a subsea BOP system are: one or two annular preventers (which work to seal around tubulars in the well and around an open hole); three to six ram preventers (which can seal several pipes within the well and seal an empty hole depending on dressing); the wellhead connector and the lower marine riser package connector (which link the entire BOP to the wellhead and to the riser directly hooked to the drilling platform); and a number of choke and kill valves and lines (which work to manipulate pressurized fluid pumped in and taken out of the well) (Shafiee *et al*., 2019b). Figure 1 shows typical configurations for a conventional and a modern BOP.

**** Figure 1 ****

Figure 1. Conventional (left) and modern (right) BOP configurations (Liu *et al*., 2015b).

Based on operators' choice, BOP subsystems can differ in number, size and capacity, especially when exploration into deeper waters is seemingly the most likely way forward (Hu *et al.*, 2013). Aside from its main function of monitoring and maintaining well integrity, the BOP system has some other functions such as (*i*) sealing off well fluids (*ii*) providing an avenue for the controlled addition and extraction of fluid into and out of the well; and (*iii*) sealing the wellhead.

Since its development in the early 1900s, the BOP's main purpose has been to function as a safety barrier during drilling operations. Its nature and complex assembly have ensured that only minor modifications have been made since its adoption as last line of defense for any drilling or workover operation. However, the shift of exploration to reserves in deeper waters and harsher environments has ensured that the setbacks to reliable operation of the subsea BOP and its subsystems remains a focal point for stakeholders within the oil and gas industry. The BOP failures usually result in injury, loss of life, economic losses or environmental damage, a prime example of which is the Macondo incident on the Deepwater Horizon oil rig in the Gulf of Mexico (Animah and Shafiee, 2020).

In spite of recent advancements in reliability analysis of SISs, the research on reliability assessment of BOP is still lacking in some regards. There are gaps in the literature with respect to the incorporation of preventive maintenance (PM) strategies as well as dynamic operating conditions into BOP reliability analysis. To address these gaps, this paper develops a stochastic Petri nets (SPN) model to estimate the reliability of subsea BOP systems subject to condition-based maintenance (CBM) with different failure modes. The BOP system is divided into five subsystems which are connected in series with each other and categorised into degrading and binary units. The annular preventers, ram preventers, hydraulic connectors, and choke and kill system are considered as degrading units; whereas the MUX control system is considered as a binary unit. Four different condition states – namely: normal, degraded, critical and failed – are considered for each failure mode. The advanced reliability analysis metrics such as failure criticality index and reliability importance are obtained, in addition to standard metrics such as the reliability, availability and mean-time between failures (MTBF). This study, to the best of the author's knowledge, is the first attempt to improve the robustness of the state-of-the-art reliability analysis methods by modelling the operation of the subsea BOP system with multiple degradation states.

The rest of this paper is organised as follows. Section 2 reviews the literature on BOP reliability and provides an overview on Petri-nets modelling. In section 3, stochastic Petri-net models are developed for different BOP subsystems. Section 4 presents the results of the analysis, and section 5 concludes the study and proposes directions for future research.

2 Literature review

2.1 Reliability analysis of subsea BOP

The reliability analysis of BOP systems has come into prominence in response to recent incidents that have happened in the oil and gas industry (Liu *et al.*, 2015a). The reliability assessment techniques for subsea BOP systems have evolved considerably since the first study by Holand and Rausand (1987). They employed fault tree analysis (FTA) to estimate the probability of a blowout event using the real data from drilling documents, BOP tests and well equipment failure reports. Some years later, Fowler and Roche (1993) also used FTA in addition to failure mode and effects analysis (FMEA) to analyse the reliability of a subsea BOP and a hydraulic control system. Zou *et al.* (2016) applied the reliability block diagram (RBD) technique to analyse the reliability of subsea BOPs. The results were then compared against design requirements. Recently, Shafiee *et al*. (2019c) proposed an integrated FTA and FMEA model to analyse the reliability of subsea BOPs. They weighted the minimal cut sets derived from the fault trees based on Birnbaum's measure of importance and then used the weights to update Risk Priority Numbers (RPNs) obtained from the use of traditional FMEA.

There are significant drawbacks to using conventional reliability assessment techniques (Animah and Shafiee, 2018). According to Bai and Bai (2010), complex and dynamic systems are difficult to model using conventional techniques; thus, the numerical analysis of the system's reliability can be extremely arduous. Both the FTA and FMEA techniques only work well for non-repairable systems, and do not possess a time element which is vital a characteristic when analysing complex subsea systems like the BOP. Furthermore, differentiating between severe failures caused by compound faults and common-cause failures is impossible using the FMEA (Liu *et al*., 2015a).

Attempts have been made to overcome some of the drawbacks of the conventional reliability assessment techniques (Shafiee *et al*., 2019a). Advanced reliability techniques such as Bayesian Network (BN), Markov analysis, Monte-Carlo simulation

(MCS), Petri Net (PN), and their different variations have been developed and applied to assess the reliability of subsea BOPs (Liu *et al.*, 2017).

BN has recently gained prominence as a robust tool for the reliability analysis of BOP systems (see Liu *et al.*, 2015b). This is mainly as a result of its ability to perform fault diagnosis as well as predictive analytics (Cai *et al.*, 2012). Markovian models, such as homogeneous Markov chains or hidden Markov models, have also been used to evaluate the reliability of complex systems such as subsea BOPs. Markov models are very flexible in representing the dynamic behaviour of engineering systems (Boyd, 1998). MCS is also a widely used technique to verify the BOP reliability analysis results obtained with different analytical methods recommended in IEC 61508 (2010). MCS provides to incorporate all practical aspects of system operation (such as failure and repair information) into reliability assessment (Wu *et al.*, 2018). The PN technique, which is used in this study, is a numerical and graphical tool used to model asynchronous, simultaneous, distributed and parallel systems (Sadou and Demmou, 2009). One of its variations, Stochastic Petri Net (SPN) explicitly introduces a time parameter (Cai *et al.*, 2013), making it very suitable for reliability analysis of SISs such as subsea BOPs. In the next subsection, the PN methods are briefly reviewed.

2.2 Petri Nets

A Petri Net (PN) is a graphical modelling tool developed by Carl Petri as part of his PhD dissertation (Petri, 1962) to determine the most appropriate method for a defined theory of communication. It is used to model and analyse complex systems which are defined as distributed, stochastic, simultaneous and non-deterministic (Murata, 1989).

A typical PN model comprises of four essential graphical features, namely: places, transitions, arcs and tokens. Places, which represent the state of a system, subsystem or component, are denoted by a hollow circle (Leigh and Dunnett, 2016). Transitions allow the system to change states, making it possible to model the dynamic behaviour of a system and is denoted by a rectangle. Tokens are little solid circles always located within places and represent the current state of the system. Arcs connect places to transitions and vice-versa and are represented by solid arrows (Le and Andrews, 2016). The state of the system being modelled changes when one or more tokens are fired. A token being fired signifies that it has been transferred from one place to another. This event occurs as a result of a transition becoming enabled (Liu *et al.*, 2015a). A transition becomes enabled only when pre-defined requirements are met.

In reliability and safety engineering, the PN technique has been applied towards different subject areas, including: remaining useful life (RUL) prediction (Elmeliani *et al.*, 2013), reliability evaluation (Liu *et al.*, 2017), safety analysis (Leveson and Stolzy, 1987), and maintenance modelling (Rochdi *et al.*, 1999).

The conventional PN, which does not take changes in time into consideration, is defined as a 5-tuple or a finite sequence of five elements (Liu *et al.*, 2013). Those elements are represented as follows:

$$PN = (P, T, F, W, M_0), \tag{1}$$

where:

$P = (P_1, P_2, P_3, \dots, P_m)$ represents a finite set of places;

$T = (T_1, T_2, T_3, \dots, T_q)$ represents a finite set of transitions;

$F \subseteq (P \times T) \cup (T \times P)$ represents a set of arcs;

$W : F \to N - \{\emptyset\}$ represents a weight function; and

$M_0 : P \to N$ represents the initial marking, with $P \cap T = \emptyset, P \cup T \neq \emptyset$.

Stochastic Petri net (SPN) is a variation of the conventional PN model which was developed to take the concept of time into account when performing reliability analysis (Kleyner and Volovoi, 2010). The SPN which forms the basis of our model in this study takes the concept of time into account and helps to analyse the dynamic behaviour of systems. The transitions for SPNs have delay time and this delay can either be deterministic or follow a probability distribution. An SPN is a 6-tuple given by (Liu *et al.*, 2017):

$$SPN = (P, T, F, W, M_0, \lambda), \tag{2}$$

where P, T, F, W and M_0 are defined as above, and $\lambda = \{\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_l\}$ represents the set of transition firing rates.

3 The proposed SPN model

A SPN model is developed in this section to analyse the degradation performance and reliability of subsea BOPs. Due to the complexity of the system, it is broken into five subsystems. These subsystems include: the ram preventers, annular preventers, choke and kill system, hydraulic connectors and the Multiplex Electro-Hydraulic (MUX) control system. The first four of the aforementioned five subsystems can be described as degrading units, meaning that a measurable amount of time passes from when a fault is detected to when functional failure actually occurs. This time interval is represented by a curve called P-F. The P-F curve is a graph that shows the health of a system over time to identify the interval between potential failure and functional failure (Elusakin *et al.*, 2019). The fifth subsystem, i.e., the MUX control system, is described as a binary unit since a fault in the system immediately causes functional failure. The BOP subsystems are connected in series with each other, meaning that if one of these subsystems fails the entire system will stop functioning. Redundancies can occur on some of the subsystems such as the annular and ram preventers as well as the MUX control system. The effect of redundancy design on the BOP system performance will be discussed in section 4.2.

The SPN technique is employed in this study to model the degradation of different BOP subsystems after which the RBD technique is used to combine results obtained from each individual subsystem and assess the reliability of the whole system. The software tool used to develop the SPN model is TimeNET Version 4 (for more see: https://timenet.tu-ilmenau.de/). TimeNET was developed at the Technische Universität of Berlin to model SPNs. The ReliaSoft BlockSim 10 software tool was also used to build an RBD model for the entire BOP system and perform the overall reliability analysis (for more see: https://www.reliasoft.com/products/reliability-analysis/blocksim). Each component is modelled separately given that they are subject to different failure modes with different causes having different effects on the overall system.

3.1 SPN model for degrading subsystems

The models developed for the four degrading subsystems (i.e., the ram preventers, annular preventers, choke and kill system, and hydraulic connectors) are different but they have a common basis. Each component possesses different failure modes associated with its operation. These failure modes show different ways that the subsystem may fail. Therefore, they occur with different frequencies and their repair times are also different. Four different states are considered to present the health condition of subsystems. These include: normal, degraded, critical and failed. A transition between two states represents the events that take place for degradation to progress from one state to another. In this study, the transitions signify the continued operation of the system as well as the repair process. This means that the condition of each subsystem degrades from the normal state to the degraded state, then to the critical state, and eventually to the functional failure state. The times/delays associated with each transition represent how long it takes for the subsystem to further degrade. In the case of repair, it represents the duration of repair. The movement of the token signifies the change in the asset condition; therefore, the token being situated within the *degraded* place signifies that the asset is in the degraded state.

The SPN models developed for the four degrading subsystems of the annular preventer, choke and kill system, hydraulic connectors and the ram preventers are presented in Figure 2Figure 3, Figure 4 and Figure 5, respectively. As can be seen, the models for degrading subsystems begin with a token residing in the normal state, signifying that the subsystem is operating as it normally should. The transition right after the normal state in the prevalent failure mode is enabled and the token is fired.

**** Figure 2 ****

Figure 2. Petri net model for the annular preventer system.

**** Figure 3 ****

Figure 3. Petri net model for the choke and kill system.

**** Figure 4 ****

Figure 4. Petri net model for the hydraulic connectors.

**** Figure 5 ****

Figure 5. Petri net model for the ram preventers.

The failure transition parameters follow Weibull distribution as it most aptly represents condition deterioration in failure-prone systems. The two-parameter Weibull probability distribution function is given by (Nielsen, 2011):

$$f(t|\gamma,\beta) = {}^{\gamma}/_{\beta}\, t^{(\gamma-1)} \exp\left\{-\left(\frac{t}{\beta}\right)^{\gamma}\right\}, \text{ for } \gamma > 0, \text{ and } \beta > 0\ , \tag{3}$$

where γ is the shape parameter and β is the scale parameter. Failure data was sourced from the literature, and the maximum likelihood estimator (MLE) technique was applied to estimate the corresponding shape and scale parameters for each subsystem. On the other hand, the repair transitions are assumed to follow exponential distribution. The model input parameters for the four degrading subsystems are given in Table 1.

**** Table 1 ****

Table 1. Life data for degrading BOP subsystems.

The repair action begins before a failure occurs and after it is determined that the component is in the degraded state; therefore, repair paths are created for each failure mode. This is represented by the token travelling from the degraded state back through the repair transition to the normal state. It is only in the event that the repair action does not take place, that the token continues its movement from the degraded state to the critical state and then to the failed state, signifying functional failure.

3.2 SPN model for binary systems

The SPN model for binary systems (i.e., the MUX control subsystem) begins with the token residing in the normal state, indicating that it is operating normally. Since this is a binary system, only two states are involved: normal and failed. The SPN model developed for the MUX control subsystem is presented in Figure 6.

**** Figure 6 ****

Figure 6. Petri net model for the MUX control subsystem.

There are also six exponential transitions between both states, with each transition representing a different mode by which the control system may fail. Upon failure, which is signified by the token being in the failed state, the repair transition is activated and the token is fired, taking the control system back into the normal state. The transitions for the MUX control subsystem are exponential transitions as there is no requirement to model degradation. The model input parameters for the MUX control subsystem are obtained from Holand and Awan (2012), and are given in Table 2.

**** Table 2 ****

Table 2. Model input parameters for the MUX control subsystem.

The reliability data obtained from the SPN simulation of each BOP subsystem is then used as an input data for reliability modelling of the entire BOP system using the RBD technique.

4 Results and analysis

4.1 Reliability

The reliability of a system is defined as the probability that it will perform its intended function(s) for a specified period of time under the specified conditions (Zengkai *et al.*, 2013). The subsystems of the BOP system are all connected in series. Therefore, the failure of one subsystem will invariably lead to the failure of the entire BOP system. Therefore, the BOP system's reliability is calculated by:

$$R(t) = \prod_{i=1}^{n} R_i(t) \, , \tag{4}$$

where n represents the number of subsystems and $R_i(t)$ represents the reliability of the subsystem i in the system.

The transient reliability plots for the five BOP subsystems are depicted in Figure 7. As can be seen, the reliability of the MUX control subsystem decreases more sharply than the reliability of other subsystems, meaning that it is the least reliable subsystem of the BOP. The reliability plots of the annular and ram preventer systems follow very similar trajectories, gradually decreasing until they reach zero after about 50 years. The hydraulic connector subsystem is seen to have slightly higher reliability over time; however, its reliability reaches zero at the same time as the annular and ram preventers. Lastly, the choke and kill system is shown to have the highest reliability over time by a significantly margin.

**** Figure 7 ****

Figure 7. Reliability of five main BOP subsystems.

The reliability of the entire BOP system is plotted in Figure 8. The graph shows that the BOP reliability decreases rapidly during the early years of operation and then reduces gradually until it reaches zero. This means that the probability that the system will successfully perform its required functions eventually drops to zero.

**** Figure 8 ****

Figure 8. Reliability of the entire BOP system.

The availability of the BOP system over the first five years is also shown in Figure 9. It is seen that the availability of the system drops significantly during the first year of operation. Availability values are reliant on failure rates as well as repair times of the BOP subsystems.

**** Figure 9 ****

Figure 9. Transient availability of the entire BOP system.

In order to determine the effects of the reliability of each examined subsystem on the overall BOP system reliability, the reliability importance (RI) of each subsystem is plotted over time. RI is used as a means of determining the relative reliability significance of each subsystem with respect to the overall system reliability. The formula to obtain reliability importance is given by:

$$\mathrm{I}_R(t) = \frac{\partial R_s(t)}{\partial R_i(t)}\ , \tag{5}$$

where $R_s(t)$ and $R_i(t)$ denote the overall system reliability and the subsystem reliability at a given time *t*, respectively.

**** Figure 10 ****

Figure 2. Reliability importance of five main BOP subsystems.

Since the BOP is considered as a series system, the least reliable component will have the highest impact on the reliability of the system and hence the highest reliability importance. From Figure 2, the MUX control system can be seen to have the highest reliability importance. This is in agreement with the study performed by Holand and Awan (2012), showing the control subsystem to be the most critical subsystem within the BOP system. This also indicates that the control system requires the most attention with regards to inspection and maintenance.

The failure criticality index (FCI), which identifies the contribution of each subsystem to the overall BOP system failure, is also determined. FCI can be calculated by the following equation:

$$\mathrm{FCI}_i = \frac{\text{Number of failures caused by subsystem } i \text{ in } (0,t)}{\text{Number of BOP systsem failures in } (0,t)} \,, \tag{6}$$

The FCI plot in Figure 11 shows that the MUX control system has the highest FCI by a considerable margin with a value of 49.7%, followed by the annular preventer at 15.5%, ram preventer at 14.3%, hydraulic connectors at 12.1% and the choke and kill system at 8.4%. This therefore means the MUX control system is responsible for nearly half of the BOP failures.

**** Figure 11 ****

Figure 3. Failure criticality index for five main BOP subsystems.

The mean time between failure (MTBF) for the entire system is also obtained. The MTBF is an important reliability metric which is calculated by dividing the total amount of time the system should be in operation by the number of times maintenance actions occurred. Therefore,

$$MTBF = \frac{T}{M}, \tag{7}$$

The MTBF of the BOP system is calculated as 1.14 years.

4.2 Sensitivity analysis

A sensitivity analysis is performed to evaluate the effect of key decisions (such as changing the fault coverage factor and adding redundancy) on the BOP system performance. The fault coverage factor is a key metric in assessing the effectiveness of condition monitoring (CM) solutions. This factor refers to the percentage of faults that can be detected during the monitoring of any engineered system. The fault coverage can range from 0% to 95–100%, depending on the chosen CM technique for every given fault.

The effects of the fault coverage factor on the system availability, failure criticality index and MTBF are analysed. Figure 4 shows the effect of different fault coverage factors on BOP availability.

**** Figure 12 ****

Figure 4. Effect of fault coverage factor on BOP system availability.

As can be seen, the availability of the BOP system decreases as the fault coverage factor drops. The lower the coverage factor, the less likely it is for failure to be detected and the lower the system availability.

Figure 13 shows the effects of different fault coverage factors at 80%, 60%, 40% and 20% on the system failure criticality index (FCI).

**** Figure 13 ****

Figure 13. The effects of (*a*) 80% (*b*) 60% (*c*) 40% (*d*) 20% fault coverage factor on BOP system failure criticality index (FCI).

As can be seen, a decrease in fault coverage factor results in corresponding decrease in FCI for the MUX control system. The fault coverage factor, however, does not seem to affect the order of subsystems in the FCI plots as there is no discernible pattern in subsystem order as the fault coverage factor decreases.

The effect of variation in fault coverage factor on the MTBF is also investigated. The results of this analysis are given in Table 3.

**** Table 3 ****

Table 3. The effect of fault coverage factor on MTBF.

The MTBF of the BOP system is seen to decrease when the coverage factor reduces. This therefore means that the amount of time that the system remains in operation reduces as fault detection becomes less effective.

A new redundant BOP configuration by adding a second MUX control system to the conventional BOP is introduced. The MUX control system is chosen because it is the most critical subsystem. The effect of redundancy on BOP system availability is investigated and the results show that the BOP system availability increased by 0.03%

from 0.9922 to 0.9925. The effect of redundancy on the MTBF of the BOP system is also investigated with the results showing an increase of 4.4% in MTBF from 1.14 years to 1.19 years. The increases in both MTBF and availability reflect the benefit of redundancy to subsea BOP systems.

5 Conclusion and future works

This paper presented an advanced reliability analysis technique using stochastic petri nets (SPN) and reliability-block diagram (RBD) for subsea blowout preventer (BOP) systems while incorporating the degradation and condition monitoring (CM) information. The subsea BOP was divided into five subsystems (including annular preventers, ram preventers, hydraulic connectors, choke and kill system, and MUX control system) which are connected in series with each other. The reliability, availability and mean time between failures (MTBF) of the BOP system were estimated. The control system was concluded as being the least reliable subsystem and this was confirmed by the control system having the highest reliability importance by a significant margin as well as being responsible for nearly half of the total system failures. The MTBF of the entire BOP system was determined to be 1.14 years. A sensitivity analysis was also performed to evaluate the effect of improving fault coverage as well as adding redundancy (in the form of an additional MUX control system) on the BOP system performance. The results showed that both the fault coverage and redundancy had significant impact on the system availability and MTBF but little discernible effect on the failure criticality index (FCI). As coverage factor decreased, so did the system availability and MTBF emphasising the importance of accurate detection of faults in subsea BOP operation. Adding a second MUX control system also led to increase in system availability and MTBF.

There is a lot of potential for future research in the area of reliability analysis of subsea safety instrumented systems. For this research, we only studied the reliability of the subsea BOP system when taking into account CM and system degradation. A promising avenue for future research can be the adaptation of the methodology applied in this research study for other subsea assets. Another promising avenue for further research can be on the performance of reliability analysis of subsea safety instrumented systems based on different forms of degradation. Research on the use of coloured Petri nets (CPNs) for reliability analysis of complex subsea systems is another opportunity which can be explored in the future (see Noori and Waag (2019)).

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Table 1. Life data for degrading BOP subsystems.

Subsystem	Failure Mode	Degraded Condition (year)	Critical Condition (year)	Functional Failure (year)	Failure Mode Repair time (years)	Subsystem Repair time (years)
Annular preventer	Failure to close	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	0.0306	0.0112
	Failure to fully open	$\gamma = 0.53$ $\beta = 1.35$	$\gamma = 0.53$ $\beta = 1.35$	$\gamma = 0.53$ $\beta = 1.35$	0.0012	
	Internal control fluid leakage	$\gamma = 1.48$ $\beta = 2.36$	$\gamma = 1.48$ $\beta = 2.36$	$\gamma = 1.48$ $\beta = 2.36$	0.0038	
	Internal leakage through a closed annular	$\gamma = 0.48$ $\beta = 0.60$	$\gamma = 0.48$ $\beta = 0.60$	$\gamma = 0.48$ $\beta = 0.60$	0.0020	
	Other	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	0.0027	
Ram preventer	External leakage	$\gamma = 1.47$ $\beta = 12.55$	$\gamma = 1.47$ $\beta = 12.55$	$\gamma = 1.47$ $\beta = 12.55$	0.0411	0.0088
	Failure to close	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	0.0007	
	Failure to fully open	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	0.0027	
	Internal leakage	$\gamma = 0.43$ $\beta = 0.46$	$\gamma = 0.43$ $\beta = 0.46$	$\gamma = 0.43$ $\beta = 0.46$	0.0072	
	Unknown failure	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	0.0009	
Choke and kill system	External leakage of BOP attached line	$\gamma = 0.74$ $\beta = 1.83$	$\gamma = 0.74$ $\beta = 1.83$	$\gamma = 0.74$ $\beta = 1.83$	0.0209	0.0134
	Unknown failure	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	0.0027	
	External leakage on jumper hose line	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	0.0027	
	External leakage on riser attached line	$\gamma = 0.47$ $\beta = 0.35$	$\gamma = 0.47$ $\beta = 0.35$	$\gamma = 0.47$ $\beta = 0.35$	0.0126	
Hydraulic connectors	External leakage	$\gamma = 0.94$ $\beta = 4.19$	$\gamma = 0.94$ $\beta = 4.19$	$\gamma = 0.94$ $\beta = 4.19$	0.0096	0.0091
	Failure to lock	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	0.0192	
	Failure to unlock	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	0.0109	
	Spurious unlock	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	0.0027	
	Unknown failure	$\gamma = 1.46$ $\beta = 2.57$	$\gamma = 1.46$ $\beta = 2.57$	$\gamma = 1.46$ $\beta = 2.57$	0.0056	

Table 2. Model input parameters for the MUX control subsystem.

Subsystem	**Failure Mode**	**MTTF (years)**	**Failure Mode Repair time (years)**	**Subsystem Repair Time (years)**
MUX Control System	Loss of all functions: both pods	9.85×10^{-3}	2.05×10^{-6}	0.0074
	Loss of all functions: one pod	8.21×10^{-4}	1.6×10^{-5}	
	Loss of one function: both pods	2.48×10^{-3}	1.71×10^{-6}	
	Loss of several functions: one pod	9.85×10^{-3}	0.61×10^{-6}	
	Other	5.22×10^{-4}	1.15×10^{-5}	
	Unknown failure	1.23×10^{-3}	3.42×10^{-6}	

Table 3. The effect of fault coverage factor on MTBF.

Coverage Factor (%)	Mean Time Between Failures (Years)
100	1.14
80	1.06
60	1.00
40	0.99
20	0.98

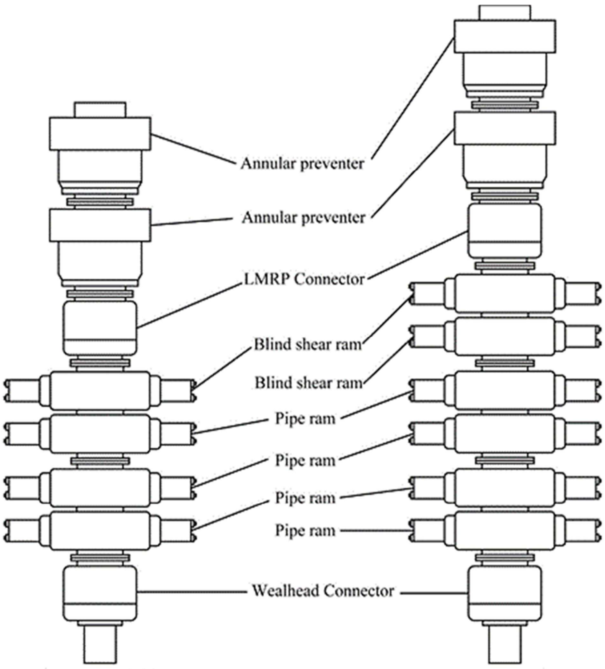

Figure 1. Conventional (left) and modern (right) BOP configurations (Liu *et al*., 2015b).

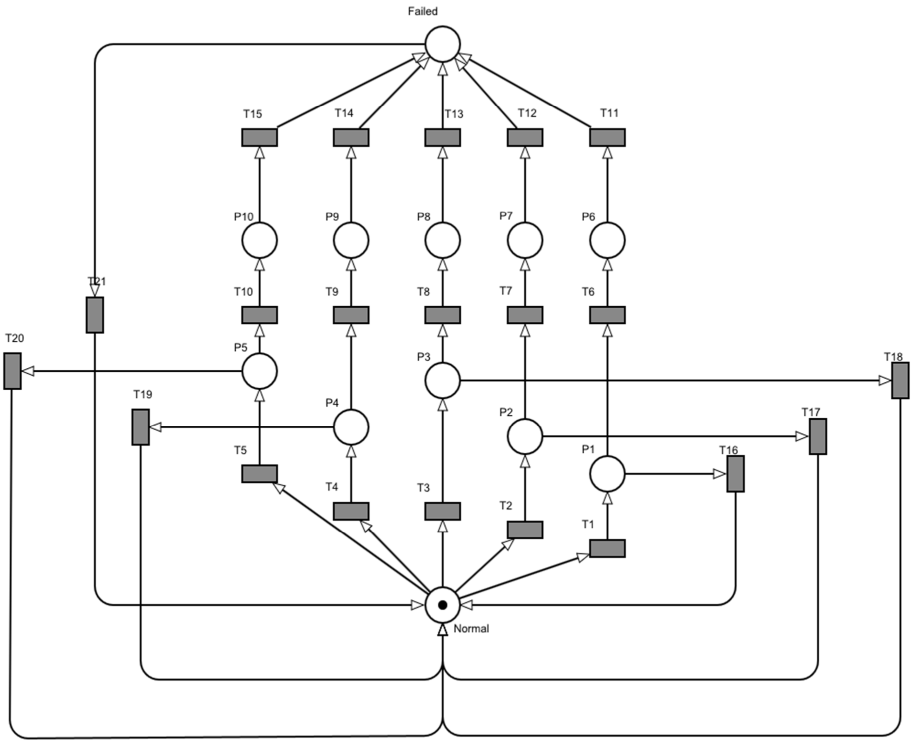

Figure 2. Petri net model for the annular preventer system.

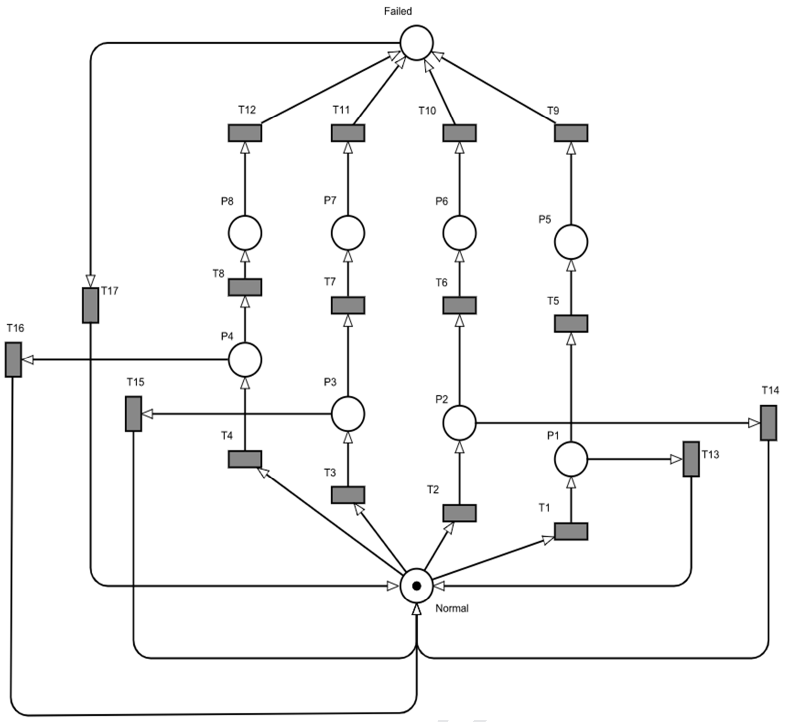

Figure 3. Petri net model for the choke and kill system.

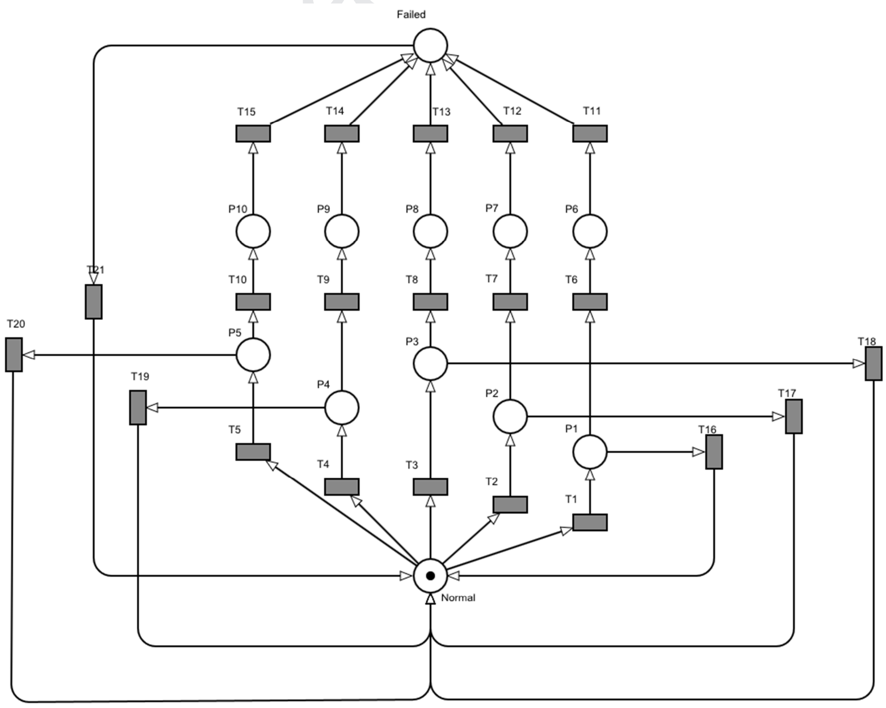

Figure 4. Petri net model for the hydraulic connectors.

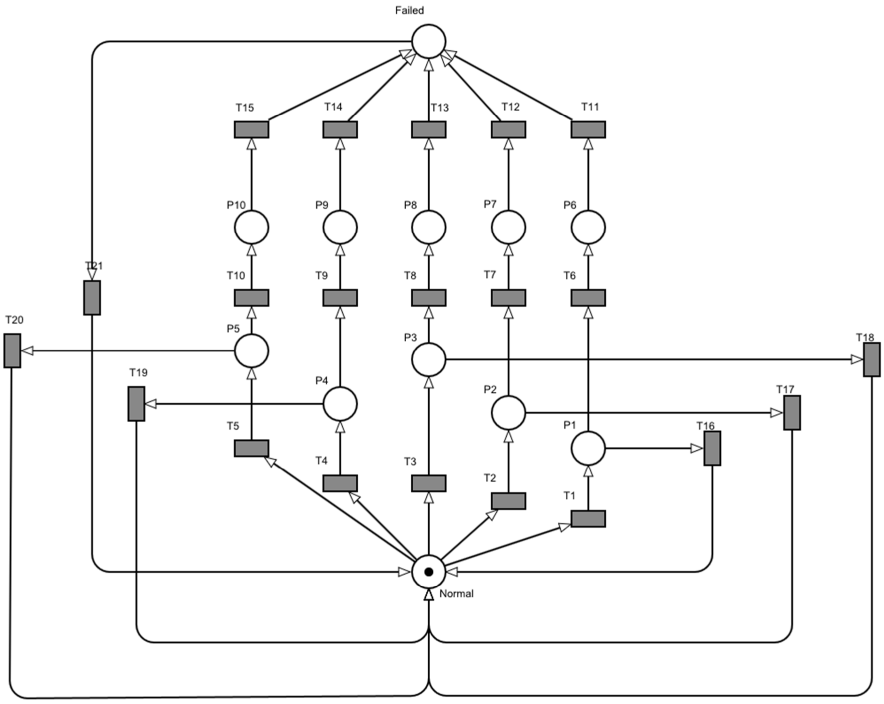

Figure 5. Petri net model for the ram preventers.

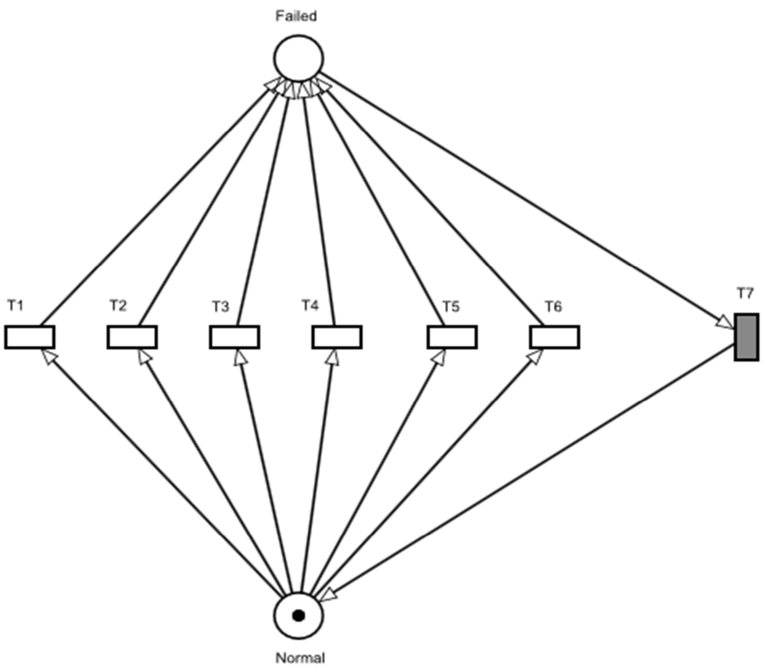

Figure 6. Petri net model for the MUX control subsystem.

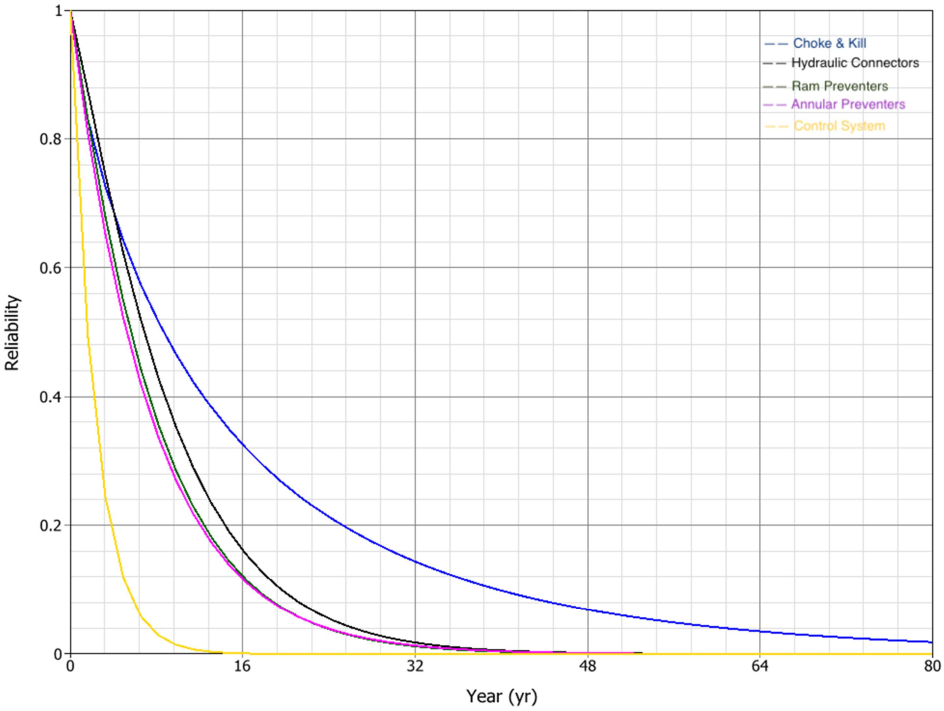

Figure 7. Reliability of five main BOP subsystems.

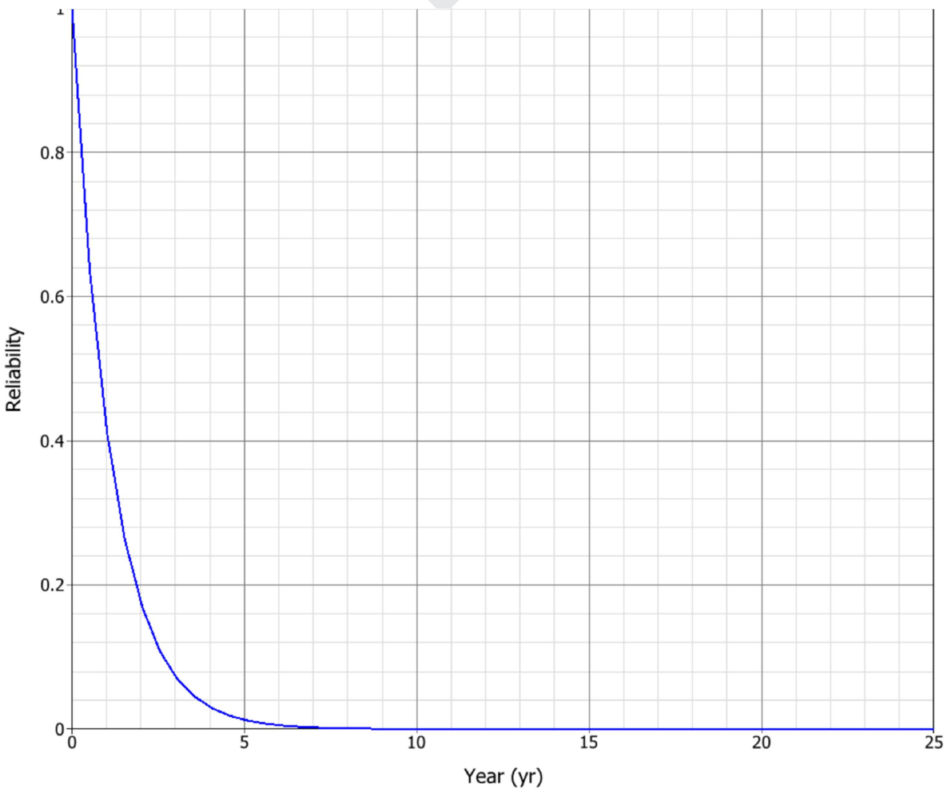

Figure 8. Reliability of the entire BOP system.

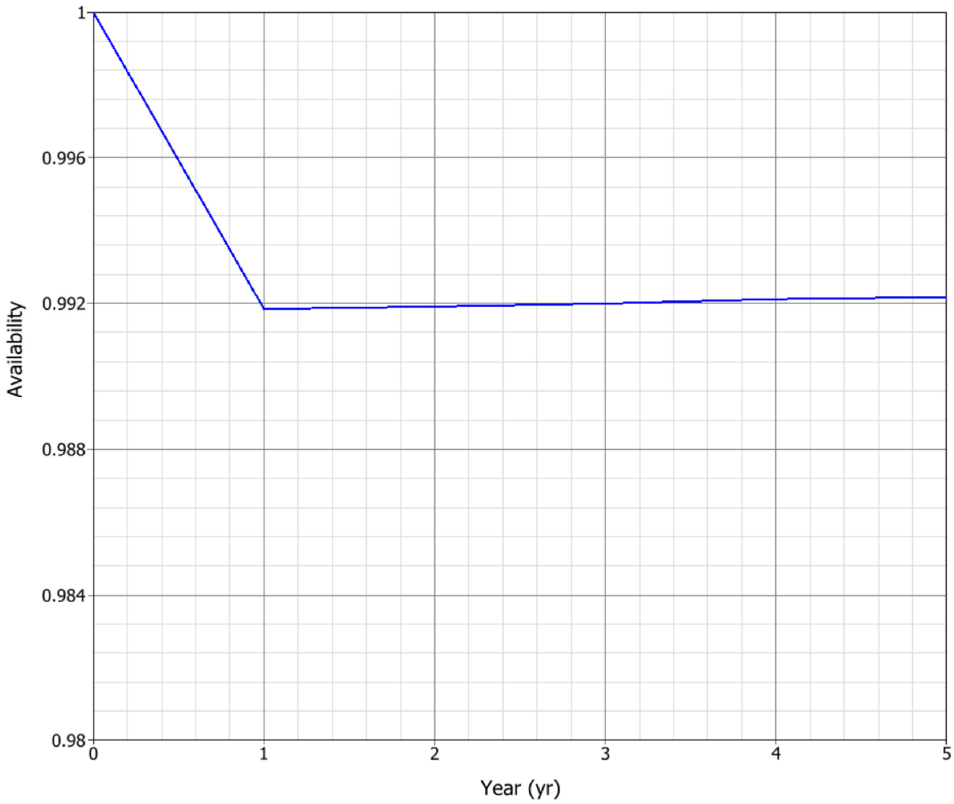

Figure 9. Transient availability of the entire BOP system.

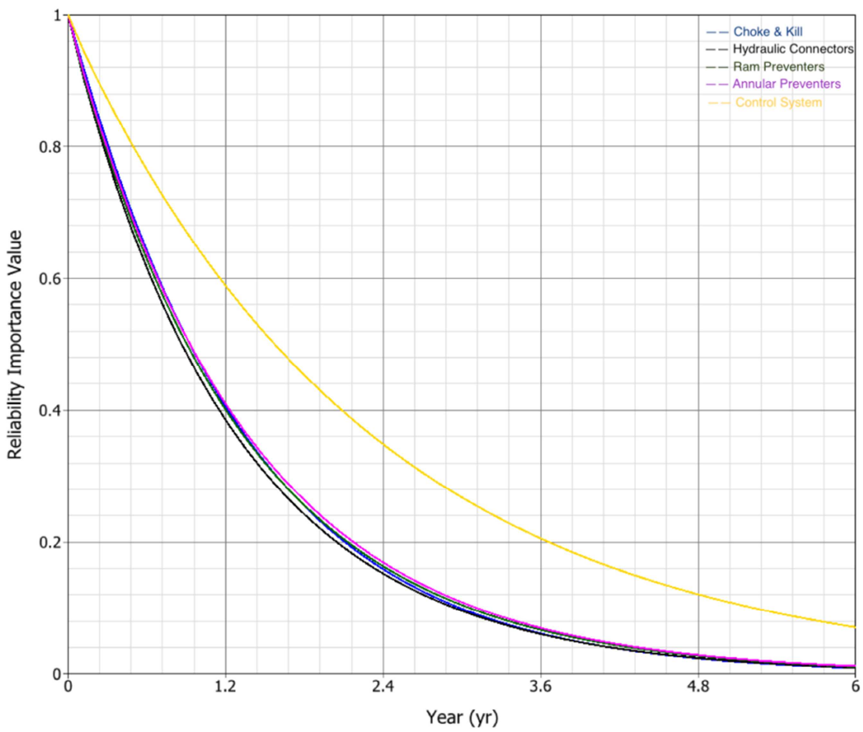

Figure 2. Reliability importance of five main BOP subsystems.

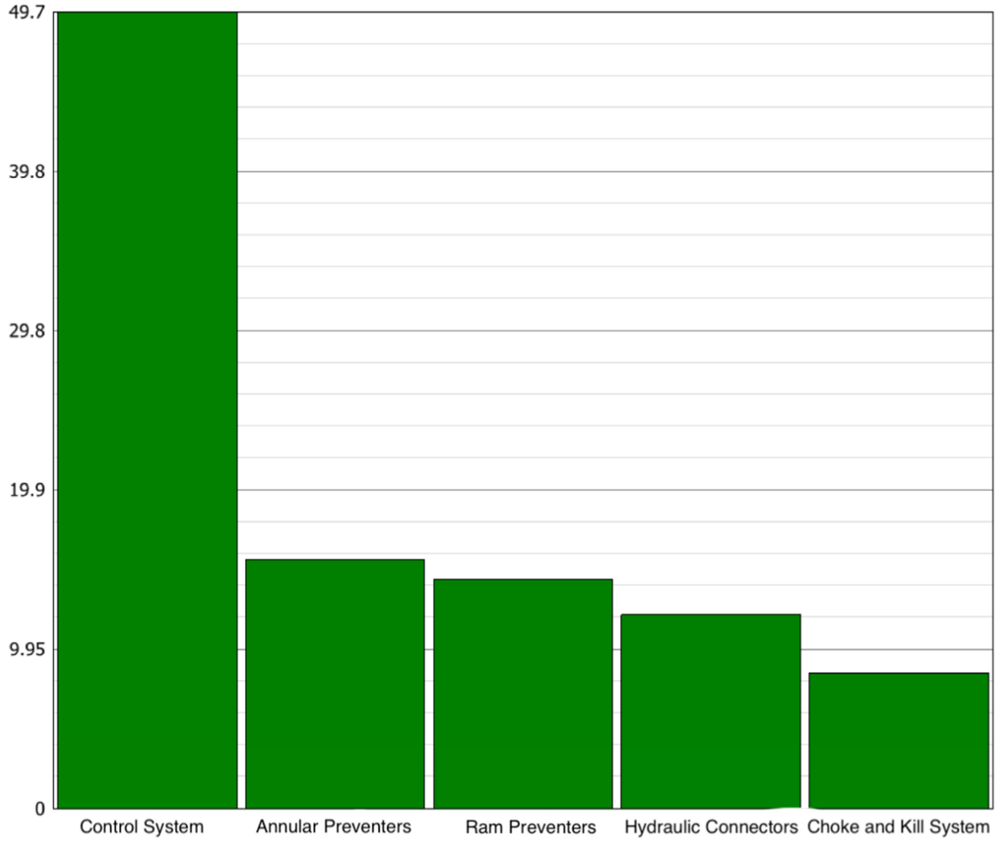

Figure 3. Failure criticality index for five main BOP subsystems.

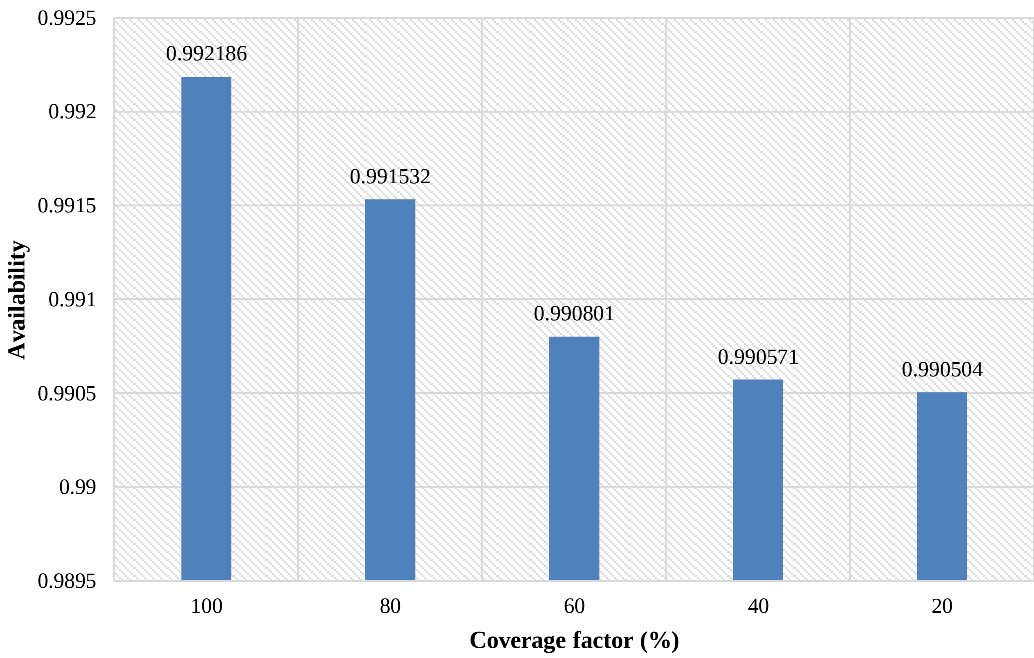

Figure 4. Effect of fault coverage factor on BOP system availability.

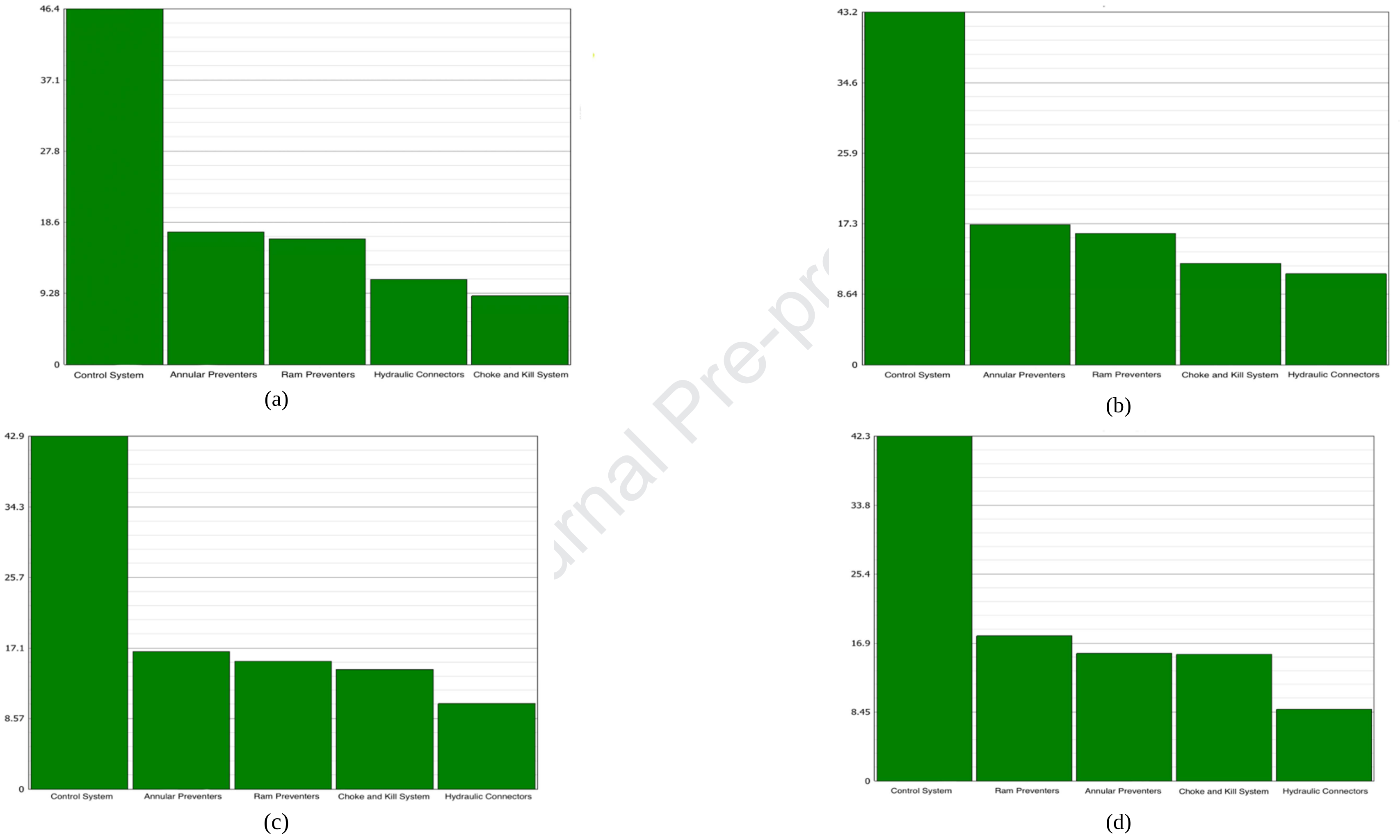

Figure 5. The effects of (a) 80% coverage factor (b) 60% coverage factor (c) 40% coverage factor (d) 20% coverage factor on the system failure criticality index (FCI).

RESEARCH HIGHLIGHTS

- An advanced reliability analysis method using stochastic Petri-net (SPN) and reliability block diagram (RBD) for subsea BOP systems;
- To incorporate system degradation and condition monitoring (CM) information in the BOP reliability analysis;
- To assess the performance of five BOP subsystems in terms of availability, reliability and mean-time-between failures (MTBF);
- To quantify the effect of fault coverage factor and redundancy design on the BOP system performance.

AUTHOR DECLARATION

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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Signed by all authors as follows: Tobi Elusakin , Mahmood Shafiee , 24th November 2019

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Tobi Elusakin: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data curation, Writing - Original Draft, Visualization, Project administration.

Mahmood Shafiee: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Writing - Review & Editing, Visualization, Supervision.