Optimization of Blowout Preventer Design for Optimal Cost and Reliability

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Abstract: The Deepwater Horizon blowout and other such incidents necessitate the need for reliable, yet still practicably cost-efficient blowout preventers on offshore drilling platforms. Insufficient preventative maintenance can lead to substantial economic loss due to the expenses of performing corrective maintenance. However, frequent yet ineffective maintenance can result in increased maintenance cost with little change in BOP reliability. Previously, a model based on fault tree analysis related the failure probability of each component to the failure probability of BOP system and provides a globally optimized preventive maintenance schedule with minimum maintenance cost subject to a minimum reliability threshold. A number of BOP designs are presented, and a pareto-optimal frontier for determining the best cost-reliability balance is presented for each design.

Keywords: BOP, Preventative Maintenance, Reliability, Global Optimization, Multi-Objective Optimization

Introduction

Need for BOP reliability from the perspective of safety and economics

Blowouts are one of the most devastating incidents that can occur in offshore systems. Table 1 shows some of the major blowout incidents and near misses(Cai, Liu, Liu, Tian, Li, *et al.*, 2012; Drægebø, 2014). Apart from the potential for fatality and damages that could result in millions of dollars of losses, the likelihood of a blowout occurring in wells operating under high temperature, high pressure (HTHP) conditions is as high as 1.9 x 10^{-3} per year(SINTEF, 2013). Therefore, the risk of a blowout in HTHP conditions is astronomical without proper safeguards in place to prevent it.

Table 1: Blowout incidents and near misses

Location	Incidents
Macondo Prospect, USA	Deepwater Horizon, 2010
Santa Barbara Channel, USA	Union Oil, 1969
North Sea, UK	Ocean Odyssey, 1988
North Sea, Norway	Ekofisk B, 1977 West Vanguard, 1985 Snorre A, 2004 Gullfaks C, 2010
Campos Basin, Brazil	Enchova, 1984 Frade, 2011
Bay of Campeche, Mexico	Ixtoc, 1979

A subsea blowout preventer (BOP) is used to seal, control and monitor oil and gas wells, thus preventing blowout incidents. Subsea BOP's act as one of the most important safety systems in offshore operations, as they are frequently the last line of defence against blowouts. A properly installed and maintained BOP can prevent incidents such as the Deepwater Horizon blowout and explosion of 2010, which resulted in 11 fatalities and dozens of injuries(Barstow, Rohde and Saul, 2010). Therefore, proper design and maintenance of BOP is essential from the perspective of safety.

Apart from the perspective of keeping the risk associated with an offshore platform below the required standards, the design and maintenance of BOP systems also plays a significant role in the profitability associated with offshore drilling platforms. The installation of a new BOP costs millions of dollars, and corrective BOP maintenance may cost even more. Corrective BOP maintenance may require pulling the entire BOP stack on the surface of the offshore platform and the maintenance downtime associated with this activity usually is within a range of 1-2 weeks(Drægebø, 2014). It is observed that around 2% of offshore rig operational time is lost due to BOP failures(Holand and Rausand, 1987). Corrective BOP maintenance is one of the most expensive downtime events for an offshore platform(Shanks *et al.*, 2003).

Unless a risk-based approach is taken to assess the most cost-optimal approach to the design and preventative maintenance of BOP systems, the potential installation and preventative maintenance costs may result in massive financial losses without significant increase in safety. To assist with this, there are a number of different methods that can be used to assess a given BOP system's reliability under a given preventative maintenance schedule. Each method has its own advantages and disadvantages. Simpler methods like Fault Tree Analysis (FTA) have been successfully implemented to analyze BOP reliability(Holand, 2001). Similarly, the Markov method has been proven to be instrumental in analyzing the performance of subsea BOP systems and the effect of BOP stack configuration and mount types from the perspective of BOP reliability(Cai, Liu, Liu, Tian, Zhang, *et al.*, 2012). The relatively complex stochastic Petri-net method has also been applied for evaluation of the reliability of subsea BOP systems along with the associated system availability(Cai, Liu, Liu, Tian, Li, *et al.*, 2012). Apart from focusing on the entire BOP system, studies focusing on the control system of the BOP alone have been carried out since it has been observed that the control system is subject to frequent failures as compared to other components(In, 2013). The Petri-net method has also observed to be effective in analyzing the control system of the BOP as well(Zengkai *et al.*, 2017). Similarly, a simpler Markov method for reliability analysis of BOP control system has been successfully implemented(Cai, Liu, Liu, Tian, Li, *et al.*, 2012). The analysis of the two control system configurations for BOP, triple modular redundancy (TMR) control system and double dual modular redundancy (DDMR) control system by Markov model revealed that the TMR configuration has slightly higher reliability than the DDMR configuration. The Dynamic Bayesian Network (DBN) method has been implemented to evaluate the real-time reliability of BOP and its associated components(Cai, Liu, Liu, Tian, Zhang, *et al.*, 2012). DBN has displayed the ability to consider the effects of common-cause failure, imperfect coverage and imperfect repair of BOP components during their required preventative maintenance(Cai *et al.*, 2013). FTA is implemented in this study for BOP reliability evaluation due to its relative simplicity, which serves to reduce the model of the system and allow for faster, more efficient computation.

BOP reliability has been an area of focus in offshore industry research for some time. However, there is a large disjoint between the focus of the BOP design and end users. The BOP manufacturers determine a reasonable maintenance schedule for each component, and the end users use this schedule to determine the configuration of the BOP stack. The focus behind current research has been on assessing the reliability of a given BOP system based on a given maintenance schedule, and adapting the BOP system until it fits acceptable reliability criterion. Many methods have assessed the reliability of BOP systems under multiple configurations. However, to find a cost-optimal combination of BOP design and maintenance scheduling, both of which have a large effect on the reliability of the BOP system, it is necessary to perform a global assessment of the reliability of the overall BOP system under an optimal maintenance schedule for multiple configurations. This work outlines a framework for the simultaneous optimization the BOP configuration and the optimal maintenance schedule in order to attain the most cost-optimal design and operation of the BOP system under reliability constraints.

BOP configuration

BOP configurations vary based on the requirements of the offshore rig. The BOP configuration used in this study is denoted in Table 2, along with the failure and repair rates of each component collected from the BSEE BOP-RAM report(In, 2013). It is assumed that the maintenance involves replacing specific components in the BOP system and restoring their reliability to their original state. The cost of replacing these components is represented in Table 2 as well. The BOP contains eight choke/kill valves, but they are treated as one component for maintenance purposes. The configuration of the BOP stack was varied along a range so that the optimal number of annular and ram preventers could be determined. Configurations that are considered are listed in Table 2.

In order to assess the reliability of the entire BOP system, it is essential to understand the relationship between the BOP system components with respect to their reliability. The reliability relationship of these components is represented in Figure 1. Since the functionality of each listed component is critical to the functionality of the BOP, each subsystem is assumed to be in series, as well as each set of components.

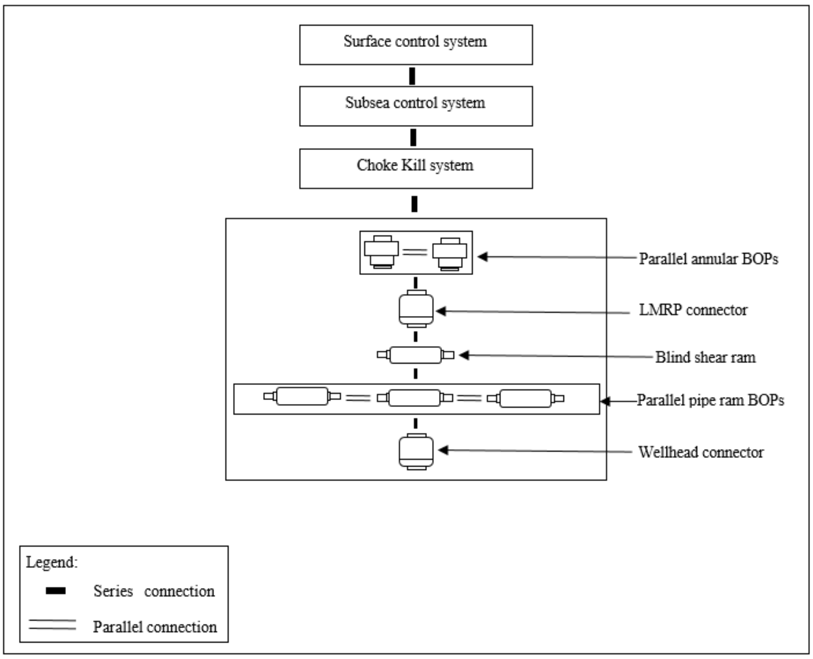

Figure 1: BOP system reliability block diagram

Note: All components in surface control system, subsea control system and choke/kill system are in series with respect to their reliabilities.

Table 2: BOP configuration and component mean failure and repair rates

Sr No.	Category of Component	Components	Number of Components	Mean Time to Failure (MTTF) (hours)	Mean Time to Repair (MTTR) (hours)	Cost of Replacement of Single Component ($)
1	BOP Stack	Annular Preventer	1,2,3,4	20041	6.88	25000
2		LMRP Connector (LMRPC)	1	76698	3.95	1500
3		Shear Ram	0,1,2,3	61358	5.64	1500
4		Pipe Ram	0,1,2,3	40035	5.64	2400
5		Test Ram	1	40035	5.64	2400
6		Wellhead Connector	1	76698	3.95	2000
7	Surface Control System	Hydraulic Power Unit (HPU)	1	69553	59.9	25000
8		Uninterruptible Power Supply (UPS)	2	9499764	3.69	25000
9		MUX Cable Reel	2	63938	40.00	20
10		Rigid Conduit & Hotline System	2	1219512	2.00	20000
11		100 HP Pumps	3	16458	34.00	5000
12		Control Panels	2	96847	5.90	200
13		Central Control Console (CCC)	2	10345	0.77	2000
14	Subsea Control System	Subsea Electronic Module (SEM)	2	43827	0.77	2000
15		Subsea Electrical Power	2	74357512	4.27	200
16		LMRP Stack Accumulators	1	1942272	2.92	1500
17		Power Distribution Panel	2	102156	5.74	200
18	Choke/Kill System	Choke/Kill (CK) Lines	1	21264	117.00	500
19		Choke/Kill (CK) Valves (8)	1	8295	33.6	400

Pareto-optimal multi-objective optimization

The epsilon constraint method, shown as Formulation F1, is used to solve for the optimal cost-reliability balance(Antipova *et al.*, 2015).

$$\underset{x}{\text{minimize}} \quad z(x) \tag{F1}$$

$$subject\ to\ f(x) \ \leq\ \epsilon$$

$$g(x) \ \leq\ 0$$

$$h(x) \ =\ 0$$

One of the objective variables, $z(x)$, is selected as the primary objective variable and is solved for. Another objective variable is constrained by a parameter, ϵ, that is chosen by the user. The system variables, x, are constrained by system constraints $g(x)$ and $h(x)$. Multiple values of ϵ are chosen and solved for, and a pareto-optimal set of non-inferior solutions is obtained.

A non-inferior solution is one in which improving one objective requires the deterioration of another. A pareto-optimal frontier is the set of non-inferior solutions for each value of ϵ selected. Since the value of ϵ determines the value of the other objective variable, any relaxation in the ϵ constraint produces a larger feasible region, which produces an improvement in the primary objective at the cost of a deterioration in the secondary variable. A tightening of the constraint produces a deterioration in the primary variable and an improvement in the secondary variable.

The pareto-optimal frontier provides the most desirable value of the primary objective for each given ϵ constraint, and can thus be used in decision-making to determine the most optimal solution set.

Optimization algorithm

This study proposes a simple algorithm, Formulation F2, to determine a cost-optimal predictive maintenance schedule through the multi-objective MINLP optimization of the maintenance schedule of a BOP system. The models are reduced to decrease computational time for the optimization platform used to solve the optimization problem (General Algebraic Modelling System/GAMS®).

The objective of the algorithm is to minimize the cost and maximize the reliability. Cost is chosen as the objective variable to be minimized, and an epsilon constraint, $\boldsymbol{R_{low}}$, is defined to set a minimum reliability threshold for the reliability. This epsilon constraint prevents the reliability of the overall BOP system from dropping below the threshold at any time step.

Furthermore, since there is uncertainty associated with the failure rate, it is important to perform a sensitivity analysis of the data with increased and decreased rates of failure. An assessment was performed with a 30% increase and decrease of the MTTF, based on 90% confidence intervals for year-to-year failure rate estimates of subsea BOP stacks used during explorational drilling by semi-submersible rigs(Holand and Rausand, 1987).

The inputs to the algorithm are the failure rates, the cost of maintenance and the configuration of the BOP components. Eq F2.1 states that the objective is to minimize the total maintenance cost. A big-M formulation is used in Eq F2.2, F2.3, F2.4, and F2.5 to distinguish the reliability of components undergoing maintenance from the ones that are not(Watkins, 1990). Eq F2.2 and F2.3 set the reliability to degrade at a constant failure rate if maintenance is nsot performed. Eq F2.4 and F2.5 set the reliability to equal one if maintenance is performed. Eq F2.6 solves for the reliability of parallel components, and Eq F2.7 solves for the reliability of components in series. Eq F2.8 and F2.9 set constraints on the reliability. Eq F2.8 sets the epsilon constraint on the system reliability. Since reliability is a probability value, Eq F2.8 sets the value of the Big M to equal the maximum value of the reliability, one. Eq F2.9 sets the all reliability values to be between the minimum and maximum values, zero and one. Eq F2.10 declares $\boldsymbol{x_{i,t}}$ to be a binary variable. This algorithm was run for each BOP stack configuration listed in Table 2.

Objective function: (F2)

$$\underset{R}{\text{minimize}} \quad cost = \sum_{t=1}^{T} \sum_{i=1}^{n} c_{i,t} * x_{i,t} * m_i \tag{F2.1}$$

subject to the following constraints:

$$R_{i,t} \leq e^{-\lambda_i{}^{\beta}} R_{i,t-1} + x_{i,t} M \ \ \forall\ i,t \tag{F2.2}$$

$$R_{i,t} \geq e^{-\lambda_i{}^{\beta}} R_{i,t-1} - x_{i,t} M \ \ \forall\ i,t \tag{F2.3}$$

$$R_{i,t} \leq 1 + \left(1 - x_{i,t}\right) M \ \ \forall\ i,t \tag{F2.4}$$

$$R_{i,t} \geq 1 - \left(1 - x_{i,t}\right) M \ \ \forall\ i,t \tag{F2.5}$$

$$R_{p,i,t} = \ 1 - \left(1 - R_{i,t}\right)^{m_i} \ \forall\ i,t \tag{F2.6}$$

$$R_{s,t} = \prod_{i=1}^{n} R_{p,i,t} \ \ \forall\, t \quad \text{(F2.7)}$$

$$R_{low} \leq R_{s,t} \leq 1 \ \ \forall\, t \quad \text{(F2.8)}$$

$$0 \leq R_{i,t} \leq 1 \ \ \forall\, i, t \quad \text{(F2.9)}$$

$$x_{i,t} \in \{0,1\} \ \ \forall\, i, t \quad \text{(F2.10)}$$

The model sets are defined as follows:

i: Index of component

t: Time step (days)

The model parameters are defined as follows:

m_i: Number of parallel components of component i

M: Big M formulation constant; M = 1

$c_{i,t}$: Cost of maintenance for component i at time t ($)

λ_i: Failure rate of component i

The model variables are defined as follows:

$R_{i,t}$: Reliability of component, i, at time t

$R_{p,i,t}$: Reliability of parallel subsystem of component i at time t

$R_{s,t}$: Reliability of BOP system at time t

R_{low}: Minimum reliability threshold of BOP system

$x_{i,t}$: Binary variable used to determine which, if any, component i is maintained at time t

Several assumptions in F2 are given, as well as their physical justification.

1. Preventative maintenance downtime is negligible compared to the time between drilling jobs and components will be maintained on time by the beginning of the next drilling job

Preventative maintenance downtime is determined by the amount of time scheduled between jobs. If the amount of time scheduled between jobs is sufficient, then the mean time to repair does not need to be considered. The validity of this assumption depends on the need for the blowout preventer and varies from organization to organization, and from situation to situation.

2. Preventative maintenance is performed before each drilling job is started, and not during jobs

Preventative maintenance is typically performed before each drilling job for BOP systems because when each component is removed, drilling operations may be interrupted(Holand, 2001; Cai, Liu, Liu, Tian, Zhang, *et al.*, 2012). Therefore, it is most cost effective to perform maintenance operations before the drilling job has started.

3. It is possible to maintain components at any time in between drilling jobs

Though different institutions may vary in their ability to maintain the equipment for various reasons, it is simplest to assume that components are on-hand, and maintenance teams are ready. The validity of this assumption depends on the need for the blowout preventer and varies from organization to organization, and from situation to situation.

4. Overall reliability of the BOP system should be kept above a minimum threshold

When performing a risk assessment of a blowout, both the probability of the blowout must be considered. The consequence of the blowout is determined by the specifics of where the drilling rig is installed, and thus the reliability of the blowout preventer can do little to affect it. The probability of the blowout, however, is affected by the reliability of the blowout preventer. Given that all other safeguards preventing the blowout are held constant, it is possible, using fault tree analysis, to determine the probability of a blowout and incorporate it into risk benchmarking methods. Therefore, it is arguable that there is a minimum level of reliability that a blowout preventer must obtain in order for the risk to remain within acceptable or tolerable bounds.

5. Constant failure rate (component reliability decreases exponentially)

It is important to understand that the exponential distribution is valid for constant failure rates. This indicates that the probability of a system failing at a given time is equal to the failure probability after a substantial interval of time, which is referred to as the 'memoryless property' of exponential distribution.

Therefore, this indicates that reliability is not a function of age as per this model. Therefore, this model will be unsuitable for failure mechanisms such as corrosion and erosion as the reliability of equipment prone to these failure mechanisms decreases over time (or with age). However, if the failure mechanism involved are mechanical failure, loss of function, rupture, mechanical damage then the simple exponential model will remain applicable as these failure mechanisms can occur anytime for any given equipment irrespective of its age. In practice, the BOP system must be fit with an appropriate degradation mechanism based upon in-field data.

Table 4, in the supporting documents, lists the most common failure causes for each piece of equipment(Patel *et al.*, 2013). As observed, the failure mechanism for a majority of the components are independent of the age of the component (do not include corrosion and erosion) and therefore the reliability of these components can be modelled as exponential distribution.

In the event that there is a degradation mechanism present, a Weibull distribution, shown in Eq 1, is typically used to measure decreasing or increasing failure rates that result from wear-in or degradation. However, such a distribution does not have the memoryless property, and would require considerably more computation time and complexity than the simple model provided.

$$\mathrm{R(t|T)} == e^{-\left(\frac{t-\tau}{\mu}\right)^{k}} \tag{1}$$

Furthermore, the Big M formulation suffers from an integrality gap in which, at high failure rates, the value of the reliability becomes very small compared to the value of the Big M. Thus, when the reliability is added to M, a rounding error occurs. In the case of the Weibull function, the failure rates are dramatically increased, to the order of the k parameter. A convex hull formulation would replace the Big M formulation to prevent the solvability issues that would result from the increased failure rate. More data would have to be collected that would encompass not just the mean time to failure, but also the age of the blowout preventer at which it would begin to degrade. Such data is not typically available in current RAM analysis, but more thorough RAM analyses should be performed to obtain more accurate failure rate information.

6. Maintenance fully restores component reliability to a reliability value of one

While this assumption is most likely untrue, it is difficult to determine how reliable a component really is after maintenance. This is because of the irreducible uncertainty involved in maintenance projects. Human error can easily result in a maintenance crew failing to notice an issue with equipment. If the maintenance procedure is incomplete, then there may be a systematic error in the detection of issues. Furthermore, if equipment is used to detect failures, then there may be common cause equipment failure in the maintenance procedure. All of these irreducible, unknown uncertainties make it difficult to predict the true reliability after maintenance. Therefore, a sensitivity analysis in which the effectiveness of maintenance is varies should be performed whenever implementing this framework.

7. All components will either fail or work perfectly

Since the BOP system is critical to the safer functionality of a drilling rig, and the loss of function in any component of the BOP results in a loss of production, it is reasonable to say that any failure, even if the BOP can still operate, is a complete failure.

Results and Discussion

As discussed previously, General Algebraic Modelling System (GAMS®) has been used to solve the Mixed Integer Nonlinear Programming problem (MINLP) formulated by the described algorithm. To verify the obtained results from the optimization platform, BARON solvers were utilized(Tawarmalani and Sahinidis, 2005). The computers used were HP systems with 3.2GHz quad Xeon-E3 processors and 8GB RAM running Windows 7. Mean computation time was 26.8 seconds for formulation F2, and 104.3 s for formulation F3. The computation time decreased at the limits of the minimum reliability threshold ($\boldsymbol{R_{low} = 0}$ **and** $\boldsymbol{R_{low} = 1}$). This is because of the increased number of active constraints.

Maintenance schedules were generated from the global optimization solver, such as the ones shown in Table 5, which represent the solutions given at $\boldsymbol{R_{low} = 0.600}$ **and** $\boldsymbol{R_{low} = 0.975}$. This system used two annular preventers, 2 shear ram preventers, and three pipe ram preventers. If a piece of equipment is maintained at the beginning of a job then the square is black, and if it is not, then it is white. The maintenance horizon was set to one year (365 days), and each drilling job was assumed to last for 61 days, except for the first step, which lasted 60 days. The initial reliability of each component was assumed to be one, so no maintenance was needed for the first job.

For all generated maintenance schedules from $\boldsymbol{R_{low} = 0.600}$ to $\boldsymbol{R_{low} = 0.990}$, the UPS (8), rigid conduit & hotline system (10), the control panels (12), and subsea electrical power (15) components were never maintained in this one-year period. With the exception of one instance when $\boldsymbol{R_{low} = 0.960}$, the LMRP stack accumulators (18) were never maintained. To reduce the model, within the specified ranges for the maintenance horizon of one year, each of the listed components can be assumed not to need preventative maintenance.

For all generated maintenance schedules from $\boldsymbol{R_{low} = 0.650}$ to $\boldsymbol{R_{low} = 0.990}$, the choke/kill valves (21) were maintained for every time step. From $\boldsymbol{R_{low} = 0.850}$ to $\boldsymbol{R_{low} = 0.990}$, the choke/kill lines (20) were maintained for every time step. From $\boldsymbol{R_{low} = 0.920}$ to $\boldsymbol{R_{low} = 0.990}$, the 100 HP pumps (11), rig manager control panel (13) and CCC (14) were maintained for every time step. To reduce the model further, within the specified ranges for the maintenance horizon of one year, each of the listed components can be assumed to always be maintained between jobs.

In addition, it is known that hydraulic components are more likely to result in unplanned downtime than electronic components(Patel *et al.*, 2013). In the optimal maintenance schedule generated, hydraulic components such as the 100 HP pumps, choke/kill lines and choke/kill valves are placed at high priority for maintenance. Electronic components such as the UPS, subsea electrical power, and LMRP accumulators were placed at low priority. This suggests a measure of validation of the optimal maintenance schedule and its ability to prevent BOP failure by focusing on the components that show a higher degree of criticality.

The control systems are regarded as the primary cause of unplanned downtime(Patel *et al.*, 2013). However, most of the components of the control systems are left unmaintained. This suggests that there are components within the control systems that are more likely to result in control system failure. The 100 HP pumps, rig manager control panel, and CCC are suggested to be the most frequently maintained, so focusing maintenance efforts on these components are likely to result in higher reliability of the control systems, and therefore the entire BOP.

Table 5: Maintenance Schedule generated for $\boldsymbol{R_{low} = 0.600}$ **(left) and** $\boldsymbol{R_{low} = 0.975}$ **(right)**.

Sr No.	**Job 2**	**Job 3**	**Job 4**	**Job 5**	**Job 6**	**Job 7**
1						
2						■
3		■			■	
4	■		■			
5		■		■		
6		■				■
7						
8						
9		■				■
10						
11	■					
12						
13			■			
14		■			■	
15	■	■	■		■	
16		■				■
17	■					■
18		■			■	■
19			■	■	■	■

Sr No.	**Job 2**	**Job 3**	**Job 4**	**Job 5**	**Job 6**	**Job 7**
1	■			■		
2	■		■	■	■	■
3	■			■		
4					■	
5	■	■	■	■	■	■
6	■	■	■	■	■	■
7		■	■		■	■
8						
9		■	■	■		■
10						
11		■		■		
12						
13	■	■	■	■		■
14		■		■		■
15						
16		■			■	■
17	■			■	■	■
18	■	■	■	■	■	■
19	■	■	■	■	■	■

The reliability of the BOP is plotted against time over the maintenance horizon of one year for each generated maintenance schedule, and two examples are shown in Figure 2. The reliability of the BOP system remains above the minimum reliability threshold, as expected. Furthermore, once the reliability decays to the minimum reliability threshold it does not rise unnecessarily, indicating that maintenance efforts and costs are minimized.

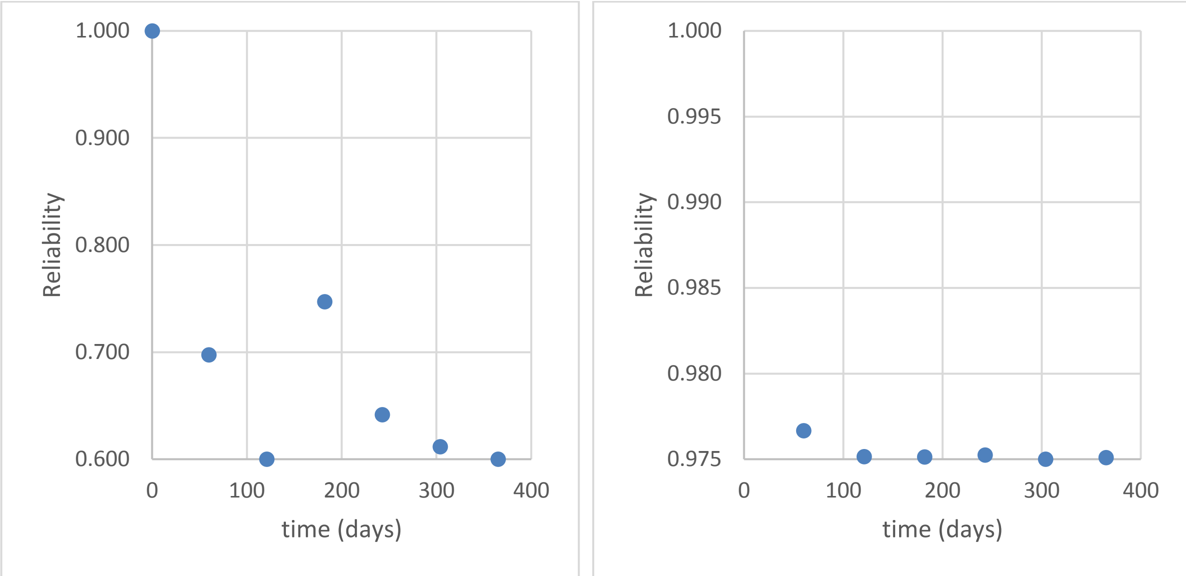

Figure 2. Reliability of the entire BOP system over the maintenance horizon for $\boldsymbol{R_{low} = 0.600}$ **(left) and** $\boldsymbol{R_{low} = 0.975}$ **(right)**.

Apart from maintenance scheduling, the described algorithm can serve as an effective tool for risk-benefit analysis for the required problem of BOP maintenance. A pareto-optimality frontier was plotted by varying the minimum reliability constraint, and is plotted in Figure 3. A minimum reliability threshold is selected and the total cost of maintenance is solved for. The total cost is the cost of all maintained equipment across the year-long maintenance horizon.

It is observed that as the minimum reliability threshold increases, the cost of maintenance increases exponentially, which may be because the reliability decreases exponentially with respect to time, and maintaining the reliability above a certain point thus requires an exponential increase in maintenance efforts.

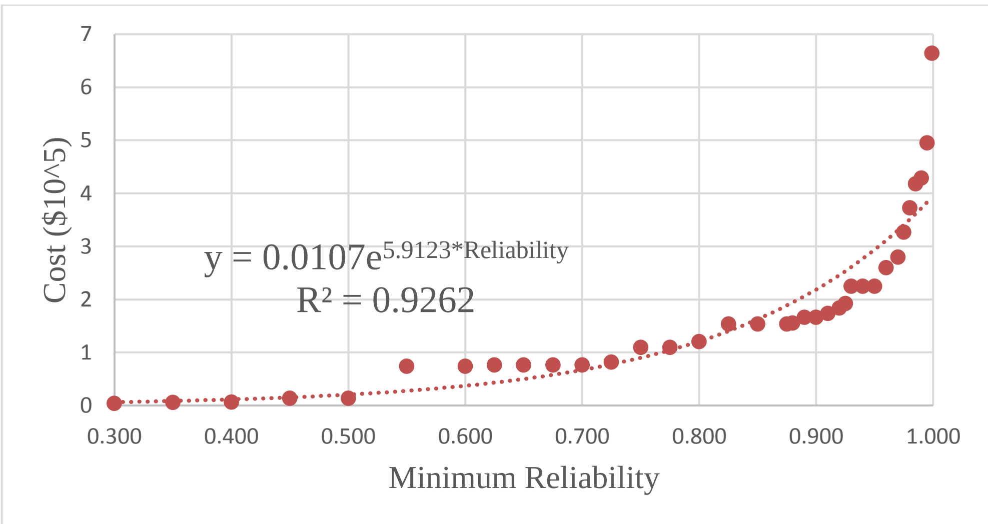

Figure 3: Overall maintenance cost vs R_{low}

The desired maintenance schedule can be selected by analysing the incremental cost for opportunity areas, points of interest where the cost for increasing reliability is low. To clarify this, the incremental cost is plotted in Figure 4. Incremental cost is the rate at which cost increases per unit change in reliability

The incremental cost of increasing reliability increases as the minimum reliability increases. However, below 0.550, from 0.550-0.725, from 0.825 to 0.925, and from 0.930-0.950, the cost to increase the minimum reliability is negligible, and so cost-effective minimum reliability values lie at the higher end of these opportunity areas.

This is especially useful for risk-based decision-making. A tolerable region of risk can be determined through methods such as risk matrices and ALARP(CCPS, 2009). Potentially acceptable values of reliability can be determined in order to keep the risk within the tolerable levels. Given a range of tolerable reliability, Figure 4 can be used to determine if raising or lowering the minimum reliability is cost-effective, and Figure 3 can be used to determine the total cost at each given minimum reliability value.

For example, if the tolerable range of reliability is between 0.750 and 0.950, then Figure 4 demonstrates that the cost of increasing the reliability from 0.750 and 0.800, and from 0.825 to 0.925 is relatively stable, but that there is a small jump in incremental cost at 0.725 and a large jump at 0.925. Therefore, raising the minimum reliability from 0.925 to 0.930 is cost-ineffective compared to raising the minimum reliability to 0.750 to 0.800 or from 0.800 to 0.925. The increase in safety may be worth investing in within ranges of low incremental reliability.

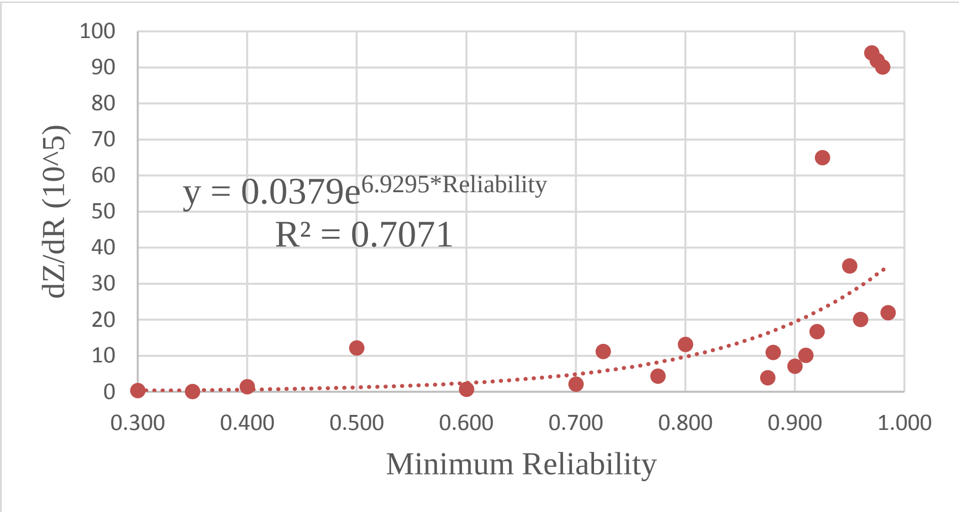

Figure 4: Change in incremental cost for each R_{low}. Incremental cost below $R_{low} = \mathbf{0.600}$ is negligible.

One major source of uncertainty in determining the reliability of a BOP system is that the failure rate is very difficult to accurately measure due to a lack of understanding of the numerous failure mechanisms that could possibly cause failure, a lack of sufficient available data, a potential for misreporting the data, and the potential for degradation within the BOP system that may lead to an increasing failure rate. To account for the uncertainty in the data, a sensitivity analysis was performed, in which the failure rate of each component was increased and decreased by the 90% confidence interval of the failure of the entire BOP, or thirty percent(Holand, 2001). Results are plotted in Figure 5. Although there is a difference in cost based upon failure rate, at higher levels of reliability, this difference becomes very low. Therefore, although the reliability of the optimal maintenance schedule may not be perfect given the potential for uncertainty, it provides a reasonable degree of confidence that can be used to optimize higher reliability BOP systems with high degrees of certainty.

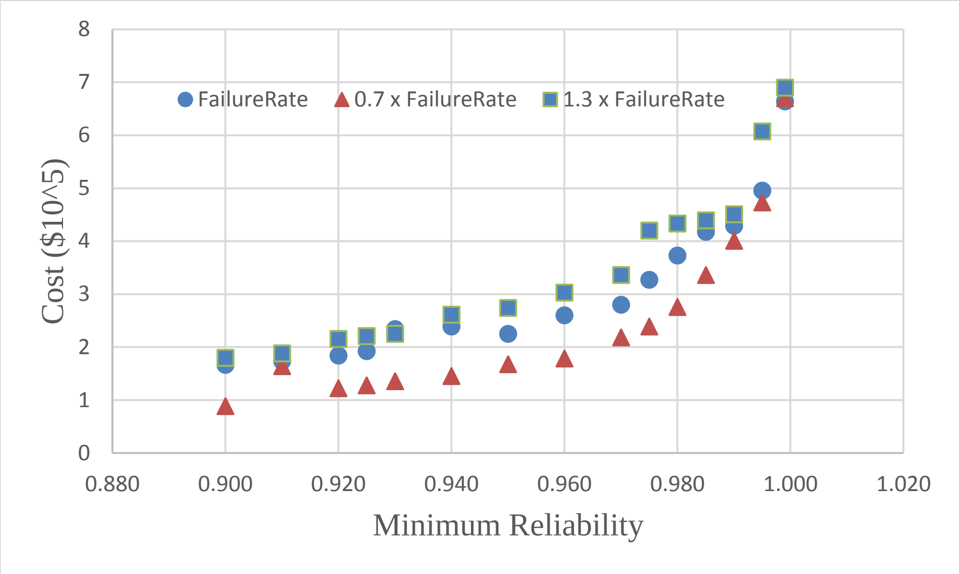

Figure 5. Sensitivity analysis of cost vs deviation in failure rate.

A number of different BOP stack configurations were tested. The number of annular preventers, shear rams, and pipe rams was parametrically varied to determine the most cost-optimal configuration with each reliability constraint. A comparison of some different BOP configurations is shown in Figure 6 and Figure 7. The cost decrease from the previously considered case shown in Figure 3 and the parametrically optimal configuration is 15 ± 8%. This shows definite cost savings when using an optimal BOP configuration using this method.

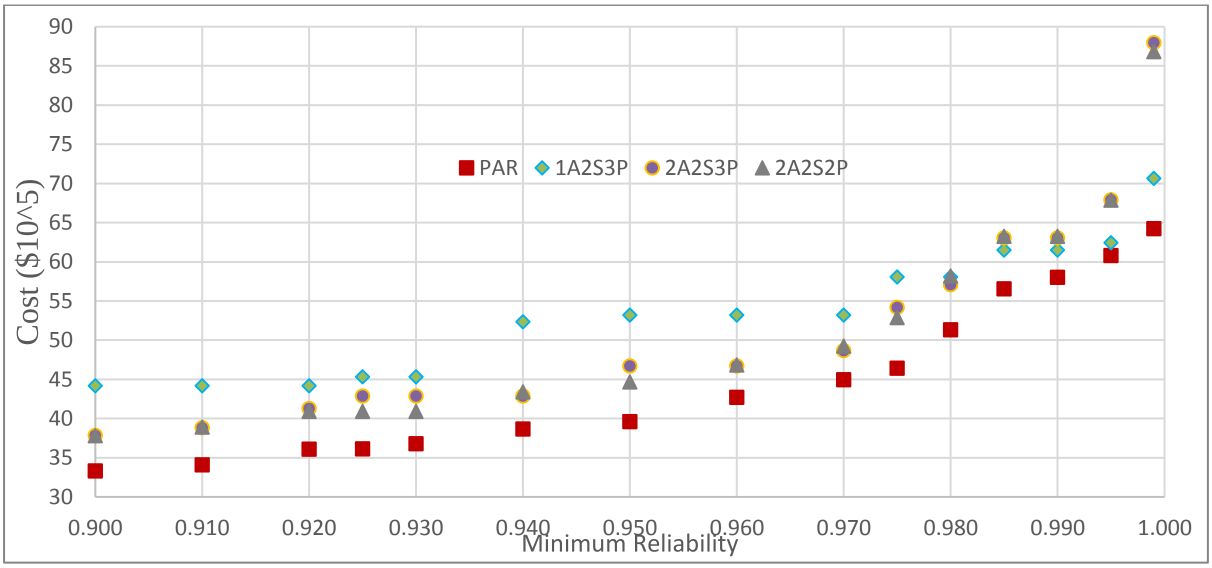

Figure 6. Optimal reliability of blowout preventers with different configurations. (PAR) Parametrically determined optimal configuration (iAjSkP) i annular preventers, j shear rams, k pipe rams

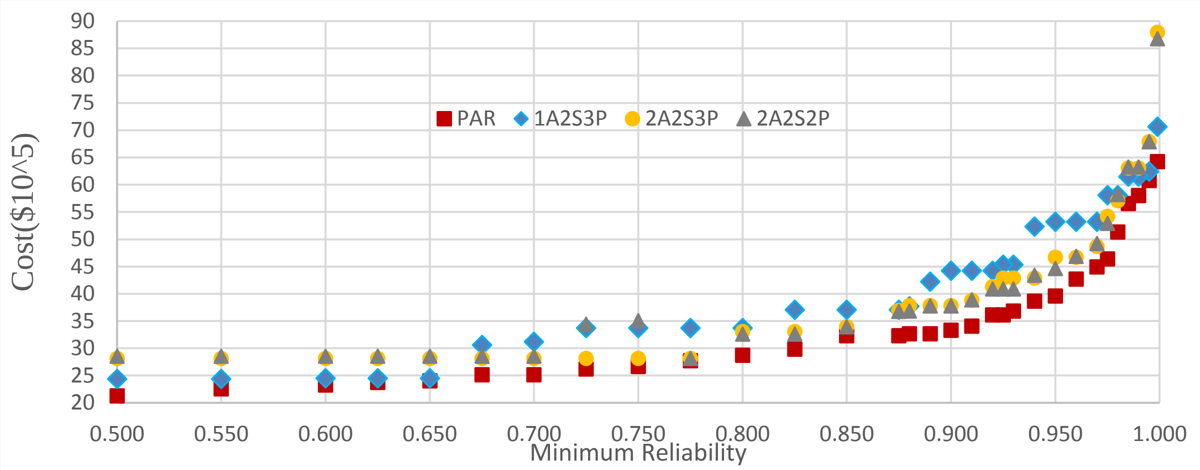

Figure 7. Optimal reliability of blowout preventers with different configurations at higher reliability constraints.

Figure 8 plots the percentage that capital cost resulting from adding more redundant components to the blowout preventer and the preventative maintenance cost play relative to the sum of both. At higher reliability, relatively more preventative maintenance is needed to maintain a higher reliability than the capital cost of implementing redundant systems can sustain. However, as the minimum reliability increases, more redundant systems are necessary.

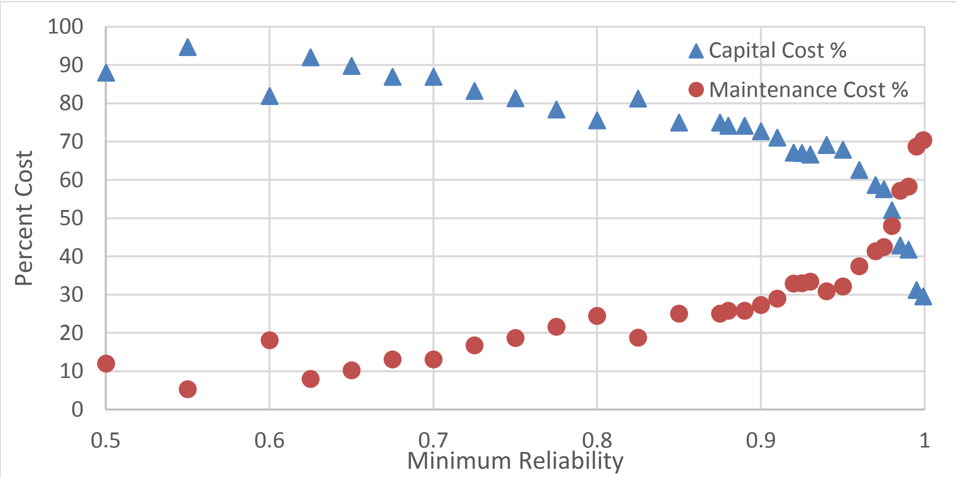

Figure 8. Percent of total cost allocated to capital/maintenance cost

Conclusion

A global, multi-objective MINLP optimization formulation has been developed for the maintenance scheduling of a BOP that can minimize the overall BOP maintenance cost while simultaneously maintaining the reliability above a required threshold. Maintenance schedules were generated from the global optimization solver for a maintenance horizon of one year. A number of assumptions were made, and the validity of each of these assumptions was addressed. Components were identified that were either always required to undergo maintenance or never undergo maintenance. These components could be removed from the model to reduce it. Hydraulic components were found to be more likely to require maintenance, and electrical components were less likely to. A pareto-optimality frontier was created to allow decision-makers to determine the optimal maintenance schedule based on the cost and the minimum reliability. Incremental cost was shown to allow decision-makers to determine the cost-effectiveness of changing minimum reliability. Sensitivity analysis was performed on the failure rate based and showed that, while the data does show some degree of sensitivity, the results largely have a reasonable degree of confidence. The effect of the configuration of the BOP stack on the total cost was tested and found to be significant. Finally, the capital cost of installing was found to play a decreasing role in the total cost of maintenance relative to the preventative maintenance cost as the minimum reliability increases.

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