Maintenance program of blowout preventer under high-temperature high-pressure conditions

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Abstract: Various techniques have been put forth to analyse blowout preventer (BOP) reliability such as the Petri-net and Markov methods. However, these methods suffer from the drawback of being unable to update the reliability assessment when the failure data is available for the system. This study uses a model based on fault tree analysis and dynamic Bayesian network (DBN) that relates the failure probability of each component to the failure probability of BOP system and provides an optimized preventive maintenance schedule with minimum maintenance cost. The BOP stack are considered as a series-parallel system with subsystems. The different components of the BOP stack are assumed to follow a constant failure rate. When the reliability of the system falls below a specified threshold level, the involved component(s) is repaired such that the maintenance cost for the overall time-period under consideration is minimized. The downtime associated with BOP maintenance has been incorporated in the objective function of overall cost to prevent frequent removal of subsea BOP system which can lead to high downtime, increased maintenance costs and low productivity.

keywords: BOP, maintenance, reliability, dynamic Bayesian network

Introduction

Need for BOP reliability from the perspective of safety and economics

Incidents such as the Deepwater Horizon explosion of 2010, in which poor maintenance of the blowout preventer was one of the causes that lead to 11 fatalities, illustrate the need for a well-designed maintenance schedule based on risk and reliability analysis (Barstow, 2010). A blowout is one of the most catastrophic incidents that can occur in offshore systems because of the extremely high consequence associated with them. Apart from potentially high consequences, likelihood of a blowout occurring in wells operating under high temperature, high pressure (HTHP) conditions is as high as 1.9×10^{-3} per year (SINTEF, 2013), This ultimately leads to high risk associated with wells operating under HTHP conditions. A subsea blowout preventer (BOP) stack is used to seal, control and monitor oil and gas wells, thus preventing blowout incidents and therefore proper maintenance of BOP stack is essential from the perspective of safety. Table 1 shows some of the major blowout incidents and near misses (Vinnem, 2014):

Location	Incidents
UK	Ocean Odyssey,1989
Norway	Ekofisk B, 1977 West Vanguard, 1985 Snorre A, 2004 Gullfaks C, 2010
Brazil	Enchova, 1984 Frade, 2011
South China Sea	Seacrest, 1989
US	Ixtoc, 1979 Macondo, 2010

Table 1: Blowout incidents and near misses

Apart from the perspective of keeping the risk associated with an offshore platform below the required standards, BOPs also play a significant role in the profitability associated with offshore drilling platforms. BOP maintenance requires 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 (Draegebo, 2014). Therefore, BOP maintenance is regarded as one of the most expensive downtime events for an offshore platform (Shanks, 2003). It is observed that around 2% of offshore rig operational time is lost due to BOP failures (Holand, 1987).

Previous work

BOP reliability has always been an area of focus in offshore industry research. Different methods have been utilized for assessing BOP reliability. However, each method has its own advantages and disadvantages. Simpler methods like Fault tree analysis have been successfully implemented to analyse BOP reliability (Holand, 1997). Similarly, the Markov method has been proven to be instrumental in analysing the performance of subsea BOP systems and the effect of stack configuration of BOP and mount type from the perspective of BOP reliability (B. Cai, 2012). The relatively complex stochastic petri-net method has also been applied for evaluation of reliability of subsea BOP systems along with the associated system availability (B. Cai, 2012). Dynamic Bayesian networks have been proved to be effective to evaluate real time reliability of BOP and its associated components (B. Cai, 2015). Dynamic Bayesian networks have been observed to be superior to other methods in the aspect of their ability to update the reliability assessment when failure data is available for the system. Therefore, a dynamic Bayesian network is implemented in this study for BOP reliability evaluation.

BOP stack configuration

BOP stack configurations vary based on the requirements of the offshore rig. The BOP configuration used in this study can be referred to as a conventional stack configuration (Z. Liu, 2015). The conventional BOP stack system consists of 2 upper annular BOPs, 1Lower Marine Riser Package (LMRP) connector,1 blind shear ram BOP, 3 pipe ram BOP and 1 wellhead connector. The 2 upper annular BOPs and 3 pipe ram BOPs are in parallel configuration, the annular BOP parallel system, LMRP connector, blind shear ram BOP, pipe ram BOP parallel system and wellhead connector are in series configuration with respect to reliability. The BOP stack can be represented by Figure 1:

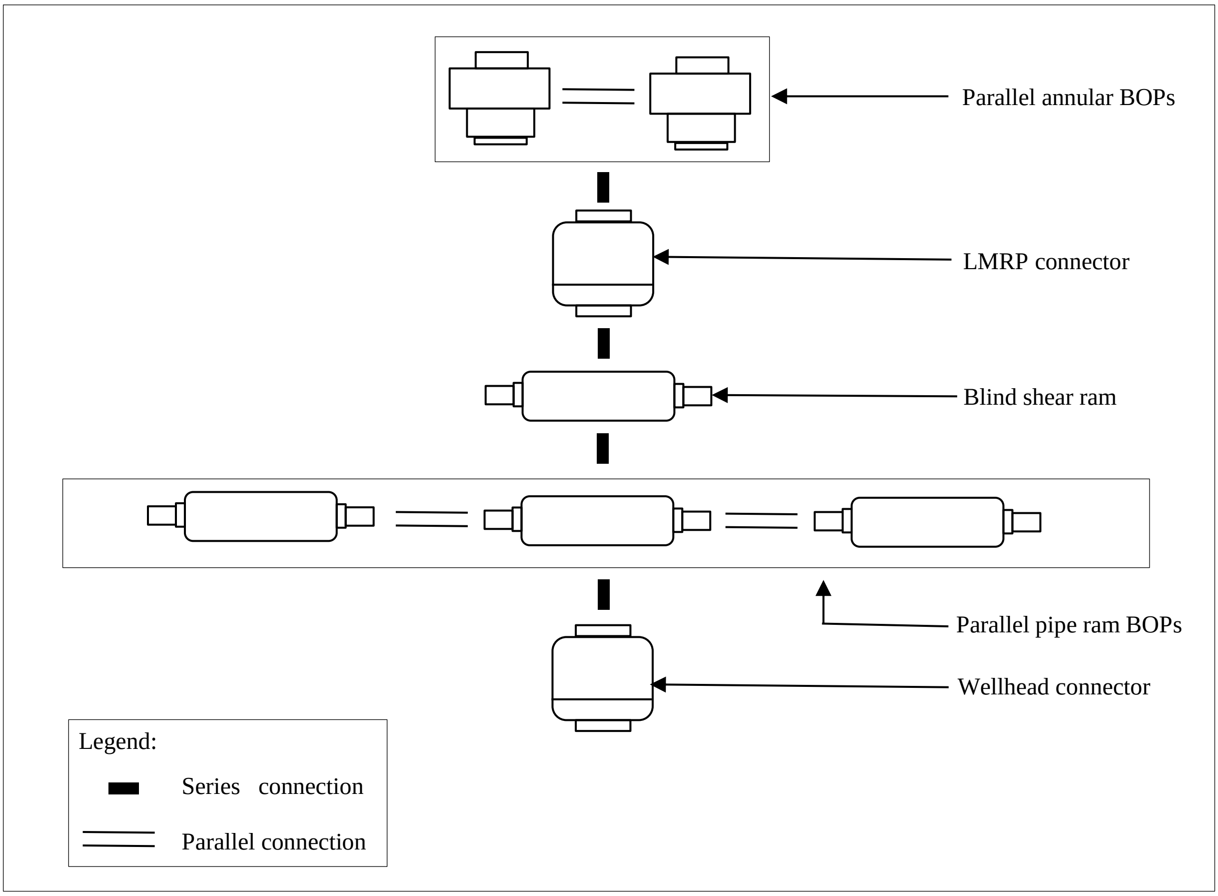

Figure 1: BOP stack configuration

Optimization algorithm

This study utilizes an optimization algorithm that provides a predictive maintenance plan using dynamic Bayesian network (Demet Özgür-Ünlüakin, 2006). The algorithm model is reduced to decrease computational time for the used optimization platform (General Algebraic Modelling System/GAMS). The inputs to the algorithm are the failure rates of BOP stack components, the cost of maintenance and the associated downtime of BOP components and the configuration of the BOP stack. The components are replaced in an optimized manner such that the reliability of the BOP stack system does not fall below a required threshold reliability value, while simultaneously minimizing the overall maintenance cost. The algorithm is described as follows:

Objective function:

$$Z = min\left(\sum_{t=1}^{T}\sum_{i=1}^{n} c_{i,t} * x_{i,t} * j_i + \sum_{t=1}^{T} d_t * y_t\right)$$

subject to the following constraints:

$$R_{i,t} \leq e^{-\lambda_i} R_{i,t-1} + x_{i,t}M \ \ \forall\, i,t$$

$$R_{i,t} \geq e^{-\lambda_i} R_{i,t-1} - x_{i,t}M \ \ \forall\, i,t$$

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

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

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

$$R_{s,t} = \prod_{i=1}^{n} R_{p,i,t} \ \ \forall\, t$$

$$y_t - x_{i,t} \geq 0 \ \ \forall\, i,t$$

$$R_{low} \leq R_{i,t} \leq 1 \ \ \forall\, i,t$$

$$x_{i,t} \in \{0,1\} \ \forall\, i,t \ \&\ y_t \in \{0,1\} \ \forall\, t$$

$$c_{i,t} = \ c_{i,0} * (1.0035)^{m-1}$$

The model sets are defined as follows:

i: Index of component

t: Time-period step (weeks)

j_i: Number of parallel components of component i

The model parameters are defined as follows:

m_i: Number of parallel components of component i

M: Big M formulation constant; M=1+R_{low}

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

d_t: Cost of downtime 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 stack system at time t

R_{low}: Minimum reliability threshold of BOP stack system

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

y_t: Binary variable used to determine if downtime occurs at time t

The following assumptions are made in the described algorithm:

- Overall reliability of the BOP stack system should be kept above a minimum threshold
- Components age at a constant rate (component reliability decreases exponentially)
- It is possible to replace components at any time
- Maintenance restores components fully
- Each component has an exponential failure rate
- All components will either fail or work perfectly
- Components will be replaced on time by the beginning of the next period
- All maintenance causes downtime of one time-period

Required Data for BOP stack

The described algorithm requires the failure rates of components present in the stack. Different databases providing failure rates for BOP stack components are have been put forth. The following failure rates are used for reliability assessment of BOP (American Bureau of Shipping and ABSG Consulting Inc. , 2013):

Component	**Mean time to failure (hrs)**
LMRP connector	76,698
Upper annular ram	40,083
Shear ram	61,358
Pipe ram	40,035
Well head connector	76,698

Table 2: failure rate data of BOP stack components

Apart from failure rate data, the model required the cost of replacing the BOP components and the associated downtime cost during the maintenance of that BOP component. Since, the focus of this study is to provide a methodology for maintenance scheduling of BOP stack based on dynamic Bayesian network, a representative set of cost values have been used. An initial downtime cost of $ 25,000 has been assumed uniformly for all the BOP components. The cost of maintenance is assumed to increase according to a compounding interest formula with 0.35% interest per week. The following are the cost of maintenance of the BOP components used in this study:

Component	**Cost ($)**
LMRP connector	7,000
Upper annular ram	25,000
Shear ram	20,000
Pipe ram	20,000
Well head connector	7,000

Table 3: Initial cost of maintenance of BOP stack components

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 was utilized. It was observed that, the computational time increased rapidly with an increase in minimum reliability threshold for the system.

The following maintenance schedule (Table 4) was obtained by the described algorithm for a time-period step (t) of 1 week for different minimum reliability thresholds ($\mathbf{R_{low}}$) for an overall period of 12 months:

<table>
<tr><td colspan="2">R_{low}</td><td colspan="2">R_{low}</td><td colspan="2">R_{low}</td><td colspan="2">R_{low}</td></tr>
<tr><td colspan="2">0.675</td><td colspan="2">0.700</td><td colspan="2">0.725</td><td colspan="2">0.750</td></tr>
<tr><td>t (weeks)</td><td>Component to be replaced</td><td>t (weeks)</td><td>Component to be replaced</td><td>t (weeks)</td><td>Component to be replaced</td><td>t (weeks)</td><td>Component to be replaced</td></tr>
<tr><td>12</td><td>LMRP connector</td><td>29</td><td>LMRP connector</td><td rowspan="2">23</td><td>LMRP connector</td><td rowspan="2">31</td><td>LMRP connector</td></tr>
<tr><td></td><td></td><td></td><td></td><td>Well head connector</td><td>Well head connector</td></tr>
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<table>
<tr><td colspan="2">R_{low}</td><td colspan="2">R_{low}</td><td colspan="2">R_{low}</td><td colspan="2">R_{low}</td></tr>
<tr><td colspan="2">0.775</td><td colspan="2">0.800</td><td colspan="2">0.825</td><td colspan="2">0.850</td></tr>
<tr><td>t (weeks)</td><td>Component to be replaced</td><td>t (weeks)</td><td>Component to be replaced</td><td>t (weeks)</td><td>Component to be replaced</td><td>t (weeks)</td><td>Component to be replaced</td></tr>
<tr><td rowspan="2">34</td><td>LMRP connector</td><td rowspan="3">29</td><td>LMRP connector</td><td rowspan="3">19</td><td>Upper annular ram</td><td rowspan="2">22</td><td>Shear ram</td></tr>
<tr><td>Shear ram</td><td>Shear ram</td><td>Shear ram</td><td>Pipe ram</td></tr>
<tr><td></td><td></td><td>Well head connector</td><td>Pipe ram</td><td rowspan="2">29</td><td>LMRP connector</td></tr>
<tr><td></td><td></td><td></td><td></td><td rowspan="2">35</td><td>LMRP connector</td><td>Shear ram</td></tr>
<tr><td></td><td></td><td></td><td></td><td>Well head connector</td><td rowspan="3">37</td><td>Upper annular ram</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td>LMRP connector</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td>Well head connector</td></tr>
</table>

Table 4: Maintenance schedule of BOP stack

It is observed that as the minimum reliability threshold decreases, the number of maintenance jobs required decreases. Many of the maintenance jobs that are scheduled at the same time-period to minimize the associated downtime cost.

Apart from maintenance scheduling, the described algorithm can serve as an effective tool for risk-benefit analysis for the required problem of BOP stack maintenance. This effectiveness can be derived by plotting the overall maintenance cost including downtime (objective function) versus the minimum reliability threshold dictated for the BOP stack. The graph obtained (pareto-optimality curve) is as follows:

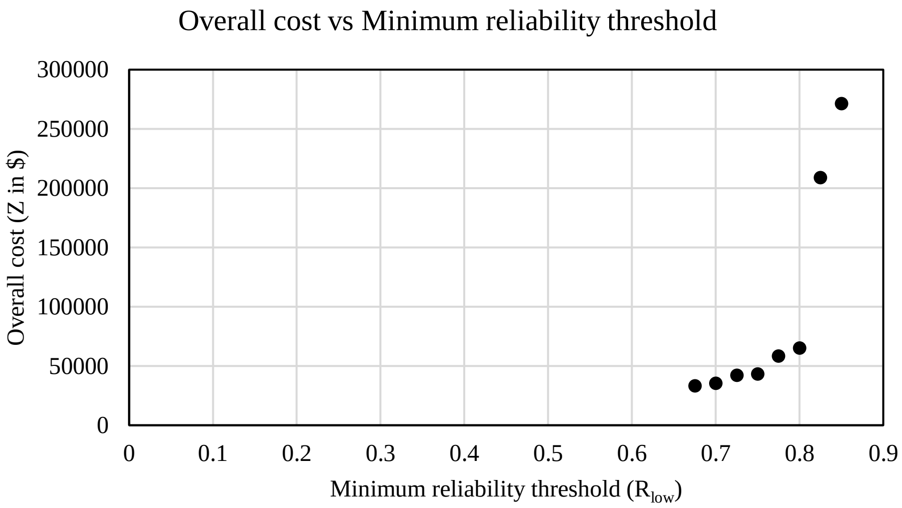

Figure 2: Overall cost vs Minimum reliability threshold

The cost appears to vary exponentially with the minimum reliability threshold, 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.

Conclusion

An optimization model has been developed for maintenance scheduling of BOP stack that can minimize the overall cost associated with BOP maintenance (including maintenance downtime) while simultaneously maintaining the reliability above a required threshold. The model has the capability to consider the subsequent increase in cost of maintenance with respect to time to accurately predict the time-period that requires maintenance, the described model can thus be further improved by incorporating the increase in cost of maintenance as a function of the decrease in the reliability of the BOP component. Also, the model can be effectively utilized for carrying out a risk benefit analysis for the BOP maintenance problem. The problem can be further extended by determining the minimum reliability threshold required to maintain the risk below the required standards by carrying out a detailed risk assessment for the offshore rig. This will be effective in preventing overspending or underspending on BOP stack maintenance.

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