Estimating BOP Failure Probability Through Bayesian FTA

Milton George Fonseca Kämpffe[1]
Fernanda Abizethe De Carvalho Duim[1]
Pauli Adriano De Almada Garcia[1,2]
Carlos Magno Couto Jacinto[2, 3]
Helton Luiz Santana Oliveira[1, 3]

[1]*Fluminense Federal University, Post Graduate Program in Production Engineering, Niterói - RJ, Brazil*
[2]*Fluminense Federal University, Post Graduate Program in Business Administration, Volta Redonda - RJ, Brazil*
[3]*Petrobras, Rio de Janeiro-RJ, Brazil*

Abstract: Most deepwater oil prospection activities are carried out by dynamic positioning rigs. Due to the risks of such activities, these rigs are more often subject to emergency disconnections and, therefore, the blowout preventer (BOP), which is a safety equipment, must have high reliability level. Hence, BOP is used to ensure the safety of well drilling process and become one of the most important safety device available, and its reliability becomes even more critical, specifically its kill and choke line, which are especially important for well control. Considering the non-homogeneity of failure data available from BOP system, the main issue for reliability estimates is based on Bayesian inference. Due to the above-mentioned limitation, the present paper will present a simplified application considering a Bayesian fault tree approach for a typical BOP kill line failure probability. The results showed some advantages of considering a methodological approach that make possible to combine different information sources for reliability measures.

1. INTRODUCTION

Most deepwater oil prospection activities are carried out by dynamic positioning (DP) rigs. Due to the risk aspects of such activities, these rigs are more often subject to emergency disconnections and, therefore, the blowout preventer (BOP) safety equipment requires better reliability towards the well's integrity preservation.

The scope of this article is centered on the BOP used for safety purpose in offshore well construction, excluding the injection ones.

Subsea BOP stack plays an important role in providing safe working conditions for the drilling activities in 10,000 ft ultra-deep-water region and its failure can cause catastrophic accidents [1]. A typical arrangement of a BOP adapted from [2] is represented in the figure 1.

As a regulatory requirement of the Brazilian National Petroleum Agency (ANP), under certain circumstances, a BOP must be an integral part of solidary barriers assembly and in others it is not. According to [3], a well barrier schematic (WBS) represents the union of one or more elements with the objective of preventing the unintentional flow of fluids from the formation to the external environment and between intervals in the well, considering all the paths possible.

In [4], a barrier is an envelope of one or several well barrier elements (WBE) preventing fluids from flowing unintentionally from the formation into the wellbore, into another formation or to the external environment.

The oil and gas exploration and production operations involve a lot of issues regarding the worker’s safety and the environment’s health. It is essential that the risks regarding these operations are optimized to a minimum, through the maintenance and control over the pressures and types of fluids involved [5].

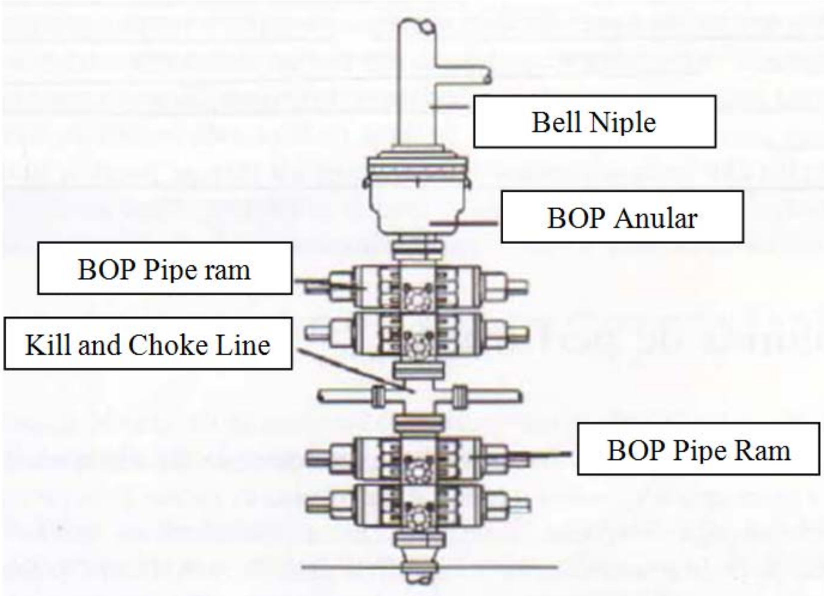

Figure 1 -Typical arrangement of a BOP set - Adapted from [2]

1.1 BOP Kill Line

One of the main components of the well control system is the kill line, which is a high pressure line through which the high density mud is introduced into the well to balance the pressure of the hydrostatic column with that of the bottom of the well, after the occurrence of a kick. The detection of a kick during drilling operations is performed with the aid of a flow indicator or mud volume indicator, which detects an increase in the flow of sludge returning from the well over the one being circulated by the pump. Failure of the well control system can lead to an eruption [6].

Choke and kill lines are critical during well control operations. Its function is to access the well and circulate kick fluids out of the well in a controlled manner. The kill line is generally used to pump heavier drilling fluid into the well during well control operations. This line is connected directly to the high-power pumps of the drilling rig [7].

The kill line is a high-pressure line responsible for connecting the BOP to the pumping equipment. It is where drilling fluids with the proper weight are injected into the well during the control of a kick, to dampen the well or even "kill" [8].

This subsystem should be able to close the well in case of kick or blowout. It is called kick an undesirable flow of fluids from the formation into the well, which may turn into a blowout which is the uncontrolled flow of the well [6].

In conventional overbalanced drilling, a loss of well control occurs when the pressure of formation fluids exceeds the pressure exerted by the column of drilling fluid on the bottom of the wellbore. Thus, a kick – an undesired rush of formation fluids into the wellbore – occurs. If not quickly detected and properly suppressed via kill operations, a kick can give rise to a number of outcomes among which a blowout is considered the most unwanted and feared [9].

The loss of one of the BOP lines, choke or kill, results in loss of well monitoring. The combat is restricted to another active line, considering half (50%) of chance to circulate the well successfully. To improve the circulation of a kick and consequently increase the safety of the well, it is necessary to use as many side outlets as possible on the BOP stack for the choke and kill lines [7].

In that regard, this paper aims to present a study specifically about the kill line, one of the many aspects involved in the oil well control system.

Focusing on the effectiveness of this article as measured by the achievement of the main and specific objectives described below, this was organized in seven sections and appendices sequenced and interconnected in a manner similar to logic adopted in scientific research.

The remainder of the article is organized as follows. The research objectives are presented in the next section, the background is exposed in section three, the methodology is formulated in section four, the description of this research is report in section five, the simplified application of the methodology considering a Bayesian net approach for failure modeling allied with Bayesian inference for failure parameter to the top event (TE) and results obtained are shown in section six, conclusions are stated and commented besides a future work is proposed in section seven.

2. RESEARCH OBJECTIVES

The main objective of this research is to present a simplified application considering a Bayesian fault tree approach for failure modeling and estimates for the BOP kill line a posteriori failure probability.

Specific objectives include:

(i) the modeling of the Kill line FT (Appendix I) via WinBUGS software script(Appendix II);

(ii) the obtaining of global uncertainty for the BOP failure parameter - kill line, which will be represented by the a posteriori probability density function of occurrence of the top event in the system of the kill line with DP drilling rig. Based on the a posteriori, one can make decision based on its statistical values of percentiles and confidence intervals;

(iii) the analysis of the probability value of failure of the conventional BOP kill line reported by [10] through a comparison with the values obtained in (ii), keeping in mind that there must always be a balance between the points of view of safety and the financial viability of the business for an oil company to be profitable.

2.1 Research Justification

Given the non-homogeneity of information, i.e., not independent and identically distributed (iid) data, as well as its scarcity, the main issue for reliability analysis for BOP systems is the use of a Bayesian based framework.

It contemplates all relevant information and propagates their respective uncertainties to the estimation of the top event of interest and therefore becomes an approach that can more effectively support the decision making process related to well safety.

3. BACKGROUND

3.1 Fault Tree

The basis of many traditional probabilistic risk analysis (PRA) is event tree and fault tree models, which logically relate the occurrence of low-level events to a higher-level event (e.g., an initiating event followed by multiple safety system failure events may lead to an undesired outcome). The occurrence of initiating events and system failures (or just ‘‘events’’) in the fault trees and event trees are modeled probabilistically, and the associated probabilistic models each contain one or more parameters, whose values are known only with uncertainty. The application of Bayesian methods to estimate these parameters, with associated uncertainty, can uses all available information, leading to informed decisions based upon the applicable information at hand [11].

Since the Kill line FT (Appendix I) is not a trivial system, in [12] the author claims that dynamic situations cannot be modeled by conventional methods such as cut sets. He supposes that conventional methods means to calculate a system failure-rate or failure-probability derived from a

Boolean function whose terms are the minimal cuts obtained from a fault tree, and the input data are the failure rates or failure-probabilities for the basic components.

Solving a fault tree using conventional (cut set) method approach is helpful only in solving trivial systems. More complex and realistic systems would likely result in very complex basic events with associated probability expressions that are difficult to handle [12].

In the most extreme case, the approach results in a fault tree with exactly one basic event. That is precisely what is done when a dynamic fault tree is converted to a Markov chain for solution. The solution of the equivalent Markov chain yields the probability expression for the one basic event in an equivalent fault tree [12].

3.2 Bayesian Inference

This technique supports the quantification and estimation of parameters for the basic events and the propagation of uncertainties for the top event of the BOP kill line.

Because Bayesian posterior distributions are true probability statements about unknown parameters, they may be easily propagated through complex system models, such as fault trees, event trees, and other logic models [13].

In [14] the authors mentioned the Bayesian approach that has been applied facilitates quantitative updating of generic probabilities of discharge of hazardous substances from shipwrecks.

The approach allows for mathematically correct handling of uncertainties in input data and formal integration of expert judgement regarding hazardous activities with available data on the intensities of such activities at the wreck. It also improves the potential to make risk estimations in a similar and objective way for different wrecks

Bayesian statistical inference relies upon Bayes' Theorem to make coherent inferences about the plausibility of a hypothesis. Observable data is included in the inference process. In addition, other information about the hypothesis is included in the inference. Consequently, in the Bayesian inference approach, probability quantifies a state of knowledge and represents the plausibility of an event, where ''plausibility'' implies apparent validity. Bayesian inference uses probability distributions to encode information, where the encoding metric is a probability (on an absolute scale from 0 to 1) [11].

In the Bayesian inference for failure parameters it was considered the exposure data of operating experience from different rigs as prior information prediction.

By considering that the prior state-of-knowledge about $\underline{\theta}$ is represented by the probability distribution $\pi_0(\underline{\theta})$, and given the available evidence E, the Bayes' theorem can be used to find the posterior probability distribution over $\underline{\theta}$ [15, 16].

$$\pi(\underline{\theta}|E) = \frac{L(E|\underline{\theta})\pi_0(\underline{\theta}|E)}{\int L(E|\underline{\theta})\pi_0(\underline{\theta}|E)d\underline{\theta}}$$

(1)

In Equation (1) $\underline{\theta}$ is the unknown parameter of interest, E is the exposure data, where $\pi(\underline{\theta}|E)$ is the a posteriori distribution of the hyper-parameters and the likelihood function is $L(E|\underline{\theta})$.

In a late study, [17] suggested that a Bayesian Network main application in accident analysis is an inference engine for updating the prior occurrence probability of events given new information, called evidence. The new information is usually operational data including occurrence or non-occurrence of the accident or primary events

A recent research from [18] proposed an analysis of a hybrid Bayesian-Importance model for system designers to improve the quality of services. The proposed model is based on two factors:

failure probability measure of different service components and, an expert defined degree of importance that each component holds for the success of the corresponding service. (1)

3.2.1 The Choice of a Priori Distribution

This choice and the values for its respective parameters for high level information, top event failure, are of fundamental importance in the study of reliability and availability.

In [19], the authors claim that probability models are typically introduced to represent aleatory uncertainty and constitute the basis for the statistical analysis of the data and information available on a system, and are considered essential for assessing these uncertainties and drawing useful insights on its random behavior. They are also capable of updating the probability values, as new data and information on the system become available.

In this framework, the standard procedure for constructing probability models of random events and variables is as follows: (i) observe the process of interest over a finite period, (ii) collect data about the phenomenon, (iii) perform statistical analyses to identify the probability model (i.e., distribution) that best captures the variability in the available data, and (iv) estimate the internal parameters of the selected probability model [19].

According to [20 - 22], the probabilities that the experts produce, from previous knowledge, assume characteristics of lognormal distributions.

And conforming to [21] and [23, 24], in the case of lognormal distributions, intuitive estimates of the mode (value of the observation that occurs most frequently) or the median (measure of central tendency) of the distributions are quite accurate, while mean estimates are partially biased towards the median. The median is a measure more representative of the central tendency of the distribution and is highlighted as a "better" estimate, besides being conservative.

Also [20] consider the median value of the lognormal distribution as the most recommended for use to obtain better estimates.

It is also highlighted by [21] and [24] an error factor (EF) of the produced distribution. This factor is obtained from the ratio between the highest value of the estimate (percentile 95%) and the lowest value (percentile 5%) of a lognormal distribution.

4. METHODOLOGY

Focusing on the effectiveness of this article as measured by the achievement of the main and specific objectives described in section two, this structured methodology was employed to describe the three stages developed and the procedures used in this research to obtain the results contained in section six.

4.1 Classification of This Research

The author [25] mentions that a research can be classified according to two basic criteria: As to the purposes and means.

Regarding to the purposes, the present research is characterized as exploratory and methodological. Exploratory because the title of this article, "Estimating BOP Failure Probability Through Bayesian FTA" is related to an area with little accumulated and systematized knowledge.

Methodological because it is a research that refers to instruments of capture of reality and associates procedures to achieve a purpose.

As for the means, this research is characterized as documentary only, since it uses material accessible to the general public, via physical or electronic media.

This would be considered as a field research if an empirical investigation had been carried out in the place where the operations related to the BOP occur and that it had elements to explain them. Also would include interviews and questionnaires (survey) to the participants (named specialists).

4.2 Developed Research Stages

After defining the three specific objectives contained in section two, the first stage was to carry out a bibliographic search through the [26].

Recent articles (e.g. year 2017) [14] and [18, 19] that represented the state of the art in topics related to this article were selected for study. The result of this search is contained in the item references.

The second stage consisted of: (i) getting of the failure rates and probabilities of failure of the basic components used in KillLine FT ([10] and Appendix I); (ii) the choice of a priori distribution for BE of FT and the a priori probability of TE (Item 4.3); (iii) the modeling of FT (Appendix I) via WinBUGS software script (Appendix II).

In the third stage was obtained the global uncertainty for the BOP failure parameter, which was represented by the a posteriori probability density function of occurrence of the top event in the system of the kill line with DP drilling rig (Section six).

The fourth stage was the analyses of the probability value of failure of the conventional BOP kill line reported by [10] through a comparison with the values obtained in the third stage and conclusions were stated and commented (Section seven).

4.3 The Choice of a Lognormal A Priori Distribution and its Mu and Tau Parameters

According to what was exposed in item 3.2 of this article, this choice and the values for its respective parameters for high level information, top event failure (p.TE.pred), are of fundamental importance. This choice is related to BE of FT and the a priori probability of TE.

4.3.1 Basic Events (BE)

Due to the best adaptation to the modeling of fourteen BE (from one to eight and from eleven to sixteen) contained in the Appendix I, the lognormal distribution was used in these events. For the basic events nine and ten an exponential distribution was used (the time values (24 and 48 hours) were provided by [10]), with their lambda values modeled by a lognormal. For all BEs an error factor (EF) of 10 was used.

4.3.2 A Priori Probability for TE

It was employed a lognormal a priori distribution p.TE.pred ~ dlnorm(mu.TE, tau.TE) for the estimation of probability of occurrence of TE using different values (2.5, 5.0 and 10.0) of EF for both parameters mu.TE and tau.TE.

After running the model encoded via winbugs script (Appendix II) using a combination of values of EF for mu.TE and tau.TE, nine a posteriori values (97.5%) of p.TE.pred were obtained and are represented in Table 1.

Table 1 - A posteriori values (97.5%) of p.TE.pred represented by a predictive lognormal
Source - The authors (2017)

		tau (EF)		
		2.5	5.0	10.0
mu (EF)	2.5	0.8084	0.8722	0.8832
	5.0	0.6771	0.8101	0.8485
	10.0	0.4453	0.6745	0.7836

From the observation of table 1, the value 0.8832 for p.TE.pred is the most conservative and was selected, which corresponds to the values of EF 2.5 and 10.0, respectively, for mu.TE and tau.TE.

The WinBUGS script conducting a two-stage Bayesian analysis and using these values is shown in the Appendix II of this article.

4.3.3 Others A Priori Distributions Besides Lognormal

The beta, uniform, gamma, exponential and normal predictive distributions were employed for p.TE.pred in the Appendix II script. All resulting values obtained from p.TE.pred were approximately 0.98 and the use of these predictive distributions were discarded.

5. DESCRIPTION OF THE RESEARCH

The fault tree proposed by [10] has a top event (TE) “Failure in the kill line system, Conventional BOP, with dynamic positioning (DP) drilling rig”. This system fault tree is represented in the Appendix I.

Through qualitative and quantitative approaches, an analysis of the risks involved in the activities related to the TE by [10] will be performed and the reliability of the BOP stack kill line configuration will be quantified in terms of the ability to pump fluid of drilling heavier into the well during well control operations and thus contain undesirable (kick) inflow.

Based on the probability density functions a posteriori, one can make decision based on its statistical values of percentiles and confidence intervals.

This analysis will be useful so that preventive tests can be carried out on high cost and risky equipment, thus minimizing the probability of failure and financial expenses for an oil company.

In addition, it is possible to identify which activities are most likely to occur and to relate them to those with the highest repair and control costs, but the analysis criteria used are limited to non-financial severity effects and, therefore, are not part of the scope of this article.

The Kill line FT (Appendix I) was coded in the WinBUGS software [27] based on MCMC sampling algorithm. WinBUGS allows encoding a model via scripts (Appendix II) or doodles (graphical tool to illustrate a model in the form of a Directed Acyclic Graph (DAG)).

It has three branches: P1) Failure to open (lower valve failure), Control system failure to open one of the lower valves and P2) External leaks in kill line extensions.

The sixteen basic events (by some being distinct), just as the branches and OR and AND logic gates were numbered. Among several elements in the FT, valves, pods (yellow and blue) and the possibility of occurrence of clogs and leaks were considered.

To clarify the visualization, this script (Appendix II) was split into the modeling the TE, modeling the gates of FT, modeling the priors on BE parameters and the data of BE.

Considering the exposure data of operating experience from different rigs as prior information predictions and using the relationships given in Equation (1), the a posteriori probability for TE can be estimated.

6. RESULTS OBTAINED

In this section the simplified application of the methodology formulated in section four is made considering a Bayesian net approach for failure modeling allied with Bayesian inference for failure parameter to the top event (TE) and results were obtained.

After running the model encoded via winbugs script (Appendix II)for 49,500 iterations, thea posteriori density distribution for the occurrence rate of the kill line system failure (Figure 2) wasobtained for the corresponding statistical values of mean, SD, median, 2.5% and 97.5%

percentiles (95% confidence interval) (Table 2). It was observed that the values of percentiles obtained for 10,000 and 49,500 iterations did not present a significant difference.

From Table 2 it can be stated that, with 97.5% of confidence, that the probability of failure of the kill line will be less than 0.8832 and, with 2.5%, it will be higher.

The assigned a posteriori failure probability for the top event presented in Table 2 was determined over the period of the operation specified by [10].

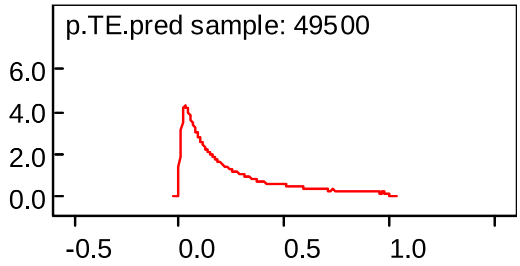

Figure 2 - A posteriori distribution of the kill line system failure
Source - The authors (2017)

Table 2 -A posteriori failure probability for the TOP EVENT of the kill line system failure
Source - The authors (2017)

Node	Mean	SD	2.5%	Median	97.5%
p.TE.pred	0.2522	0.2407	0.0103	0.1654	0.8832

Based on the a posteriori distribution, one can make decision based on its statistical values of percentiles and confidence interval (Table 2).

The value of the probability of failure of the conventional BOP kill line ($p \approx 0.8981$) reported by [10] was obtained assuming that their basic events metrics had no uncertainties.

From a comparison of this value with the results contained in table 2, it is observed that this is close to and above the 97.5% percentile (0.8832), proving to be a very conservative value.

This value (0.8832) refers only to one of the integral parts of conventional BOP, its kill line, and if we consider all the components of BOP, the value of the probability of failure will certainly be higher, resulting in a possibility of making the business unfeasible.

It is important that always should be a balance between the points of view of safety and the financial viability of the business for an oil company.

Using the predictive a posteriori distributions, it is also possible to predict the number of events for a specific time interval, for example, year 2017 in this study. This can be done in WinBUGS via the trick ofmissing data (www.WinBUGS.info).

7. CONCLUSIONS

Focusing on the effectiveness of this article as measured by the achievement of the main and specific objectives described in section two, this was organized in seven sections and appendices sequenced and interconnected in a manner like logic adopted in scientific research.

As a final result, we obtain the global uncertainty for the kill line system with dynamic positioning (DP) rigs, which is represented by an *a posteriori* density (Figure 2). Based on the *a posteriori*, one can make decision based on its statistical values of percentiles and confidence intervals for the top event (Table 2).

The present study has illustrated an application of precursor-based hierarchical Bayesian analysis to probability estimation and risk analysis of kill line. Considering blowouts as major accidents, we used a fault tree diagram to decompose the kill line to its components.

Since these accidents precursors are much likely to be collected from a variety of data sources with different physical and operational characteristics, we adopted a two-stage Bayesian analysis to model the source to source uncertainty.

The results obtained in section six were consistent with the theoretical basis contained in section three, considering that the basic events uncertainties propagation for the TE of the BOP kill line provided a very close probability value of failure when assumed that their basic events metrics had no uncertainties.

The value of the probability of failure of the conventional BOP kill line reported by [10] was proved to be a very conservative value, resulting in a possibility of making the business unfeasible.

It is important to keep in mind that there must always be a balance between the points of view of safety and the financial viability of the business for an oil company to be profitable.

From the satisfactory value obtained in the calculation of the probability of failure of the kill line and based in the methodology described in section 4, it is possible to conclude that the modeling of the Kill line FT can be considered reliable; the research undertaken reached the main and the three specific objectives and therefore can be considered conclusive.

The aim of this article is to show what is gained from the applicability of its methodology and the potential results that can be obtained by the fact that the associated information uncertainties are being treated and the possibility of updating the parameters of interest as support for decision making.

In addition, for future work it is proposed to consider high-level data (e.g. system failures) and intermediate-level data (e.g. subsystem failures) to update the initial estimates of the FT events and, consequently, the BOP kill line failure probability. Other initiatives are to take a totally Bayesian approach to include other intervening factors such as common cause failures (CCF), human reliability and preventive maintenance effects.

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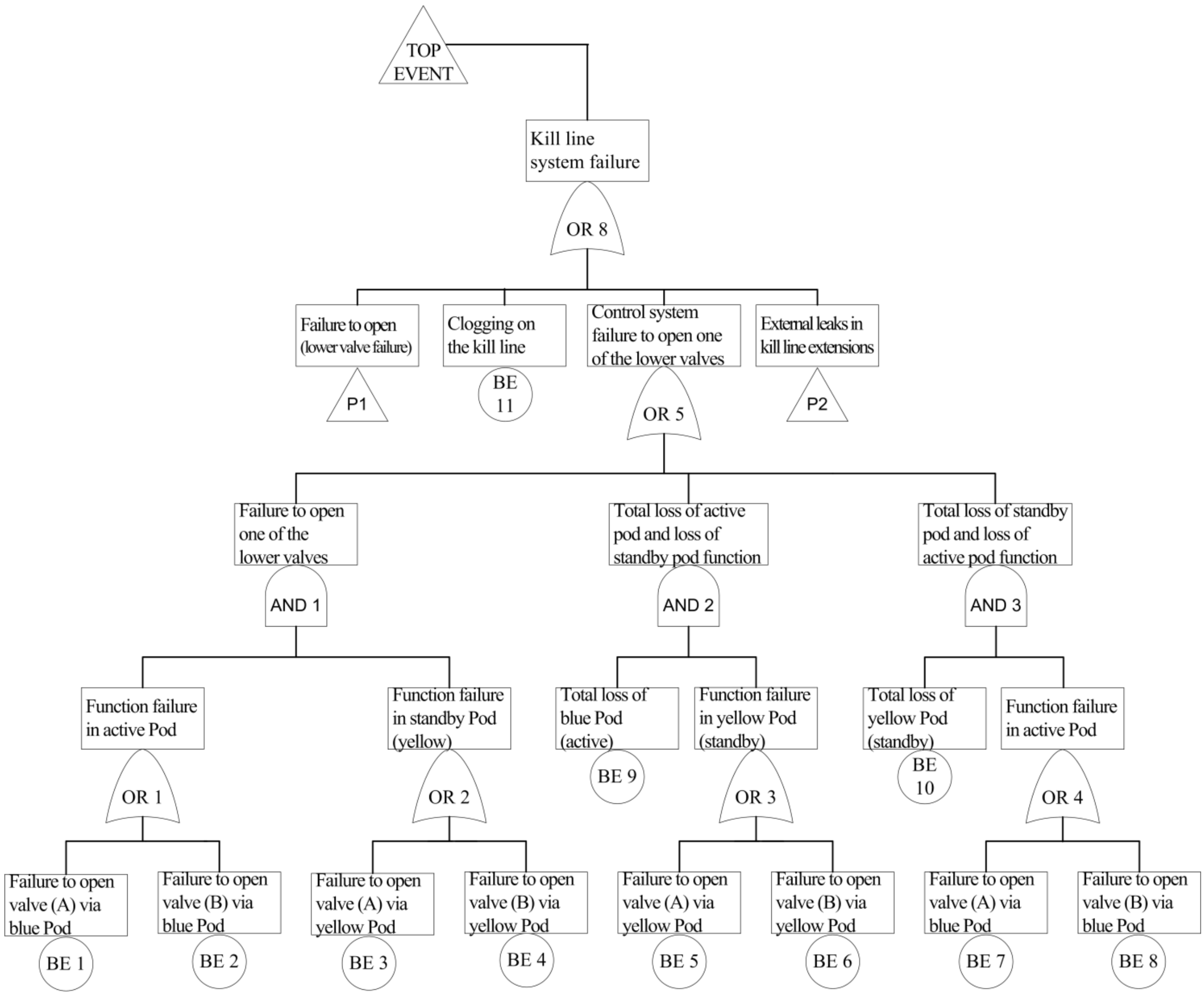
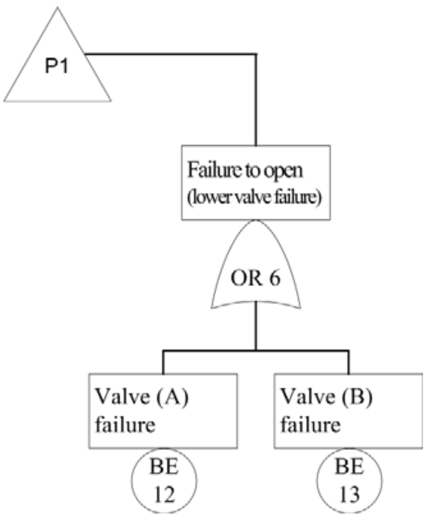
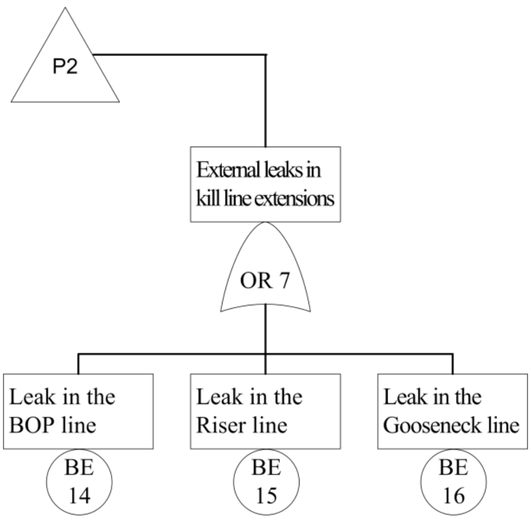
APPENDIX I

FAULT TREE REPRESENTATION OF THE FAILURE IN THE KILL LINE SYSTEM







APPENDIX II

MODEL ENCODED VIA WINBUGS SCRIPT

```
model {
# KILL LINESystem Failure

# This is a system (fault tree TOP EVENT) predictive distribution

p.TE.pred ~ dlnorm(mu.TE, tau.TE)|(,1)
mu.TE<- log(p.TE)-pow(log(2.5)/1.645, 2)/2
tau.TE<- pow(log(10)/1.645, -2)
```

WinBUGS script for modeling the TOP EVENT

```
# Probability of TOP EVENT (Gate OR8)
p.TE<- p.P1 + p.basic11 + p.OR5 + p.P2
- p.P1*p.basic11 - p.P1*p.OR5 - p.P1*p.P2
- p.basic11*p.OR5 - p.basic11*p.P2
- p.OR5*p.P2 + p.P1*p.basic11*p.OR5*p.P2
```

WinBUGS script for modeling the gates of FT

```
# Probability of Gate P1 (Gate OR6)
p.P1 <- p.basic12 + p.basic13 - p.basic12*p.basic13

# Probability of Gate OR5
p.OR5 <- p.AND1 + p.AND2 + p.AND3
- p.AND1*p.AND2 - p.AND1*p.AND3 -
p.AND2*p.AND3
+ p.AND1*p.AND2*p.AND3

# Probability of Gate P2 (Gate OR7)
p.P2 <- p.basic14 + p.basic15 + p.basic16 -
p.basic14*p.basic15
- p.basic14*p.basic16 - p.basic15*p.basic16 +
p.basic14*p.basic15*p.basic16

# Probability of Gate AND1
p.AND1 <- p.OR1*p.OR2

# Probability of Gate AND2
p.AND2 <- p.basic9*p.OR3

# Probability of Gate AND3
p.AND3 <- p.basic10*p.OR4

# Probability of Gate OR1
p.OR1 <- p.basic1 + p.basic2 - p.basic1*p.basic2
```

```
# Probability of Gate OR2
p.OR2 <- p.basic3 + p.basic4 - p.basic3*p.basic4

# Probability of Gate OR3
p.OR3 <- p.basic5 + p.basic6 - p.basic5*p.basic6

# Probability of Gate OR4
p.OR4 <- p.basic7 + p.basic8 - p.basic7*p.basic8
```

WinBUGS script for modeling the priors on basic event parameters

```
p.basic12 ~ dlnorm(mu.p.basic12, tau.p.basic12)|(,1)
mu.p.basic12 <- log(mean.p.basic12) -
pow(log(EF.p.basic12)/1.645, 2)/2
tau.p.basic12 <- pow(log(EF.p.basic12)/1.645, -2)

p.basic13 ~ dlnorm(mu.p.basic13, tau.p.basic13)|(,1)
mu.p.basic13 <- log(mean.p.basic13) -
pow(log(EF.p.basic13)/1.645, 2)/2
tau.p.basic13 <- pow(log(EF.p.basic13)/1.645, -2)

p.basic14 ~ dlnorm(mu.p.basic14, tau.p.basic14)|(,1)
mu.p.basic14 <- log(mean.p.basic14) -
pow(log(EF.p.basic14)/1.645, 2)/2
tau.p.basic14 <- pow(log(EF.p.basic14)/1.645, -2)

p.basic15 ~ dlnorm(mu.p.basic15, tau.p.basic15)|(,1)
mu.p.basic15 <- log(mean.p.basic15) -
pow(log(EF.p.basic15)/1.645, 2)/2
tau.p.basic15 <- pow(log(EF.p.basic15)/1.645, -2)

p.basic16 ~ dlnorm(mu.p.basic16, tau.p.basic16)|(,1)
mu.p.basic16  <- log(mean.p.basic16) -
pow(log(EF.p.basic16)/1.645, 2)/2
tau.p.basic16 <- pow(log(EF.p.basic16)/1.645, -2)

p.basic11 ~ dlnorm(mu.p.basic11, tau.p.basic11)|(,1)
mu.p.basic11 <- log(mean.p.basic11) -
pow(log(EF.p.basic11)/1.645, 2)/2
tau.p.basic11 <- pow(log(EF.p.basic11)/1.645, -2)

p.basic1 ~ dlnorm(mu.p.basic1, tau.p.basic1)|(,1)
mu.p.basic1 <- log(mean.p.basic1) -
pow(log(EF.p.basic1)/1.645, 2)/2
tau.p.basic1 <- pow(log(EF.p.basic1)/1.645, -2)

p.basic2 ~ dlnorm(mu.p.basic2, tau.p.basic2)|(,1)
mu.p.basic2 <- log(mean.p.basic2) -
pow(log(EF.p.basic2)/1.645, 2)/2
tau.p.basic2 <- pow(log(EF.p.basic2)/1.645, -2)

p.basic3 ~ dlnorm(mu.p.basic3, tau.p.basic3)|(,1)
mu.p.basic3 <- log(mean.p.basic3) -
pow(log(EF.p.basic3)/1.645, 2)/2
tau.p.basic3 <- pow(log(EF.p.basic3)/1.645, -2)
```

```
p.basic4 ~ dlnorm(mu.p.basic4, tau.p.basic4)|(,1)
mu.p.basic4 <- log(mean.p.basic4) -
pow(log(EF.p.basic4)/1.645, 2)/2
tau.p.basic4 <- pow(log(EF.p.basic4)/1.645, -2)

p.basic5 ~ dlnorm(mu.p.basic5, tau.p.basic5)|(,1)
mu.p.basic5 <- log(mean.p.basic5) -
pow(log(EF.p.basic5)/1.645, 2)/2
tau.p.basic5 <- pow(log(EF.p.basic5)/1.645, -2)

p.basic6 ~ dlnorm(mu.p.basic6, tau.p.basic6)|(,1)
mu.p.basic6 <- log(mean.p.basic6) -
pow(log(EF.p.basic6)/1.645, 2)/2
tau.p.basic6 <- pow(log(EF.p.basic6)/1.645, -2)

p.basic9 <- 1 - exp(-lambda.9*time.9)
lambda.9 ~ dlnorm(mu.p.basic9, tau.p.basic9)
mu.p.basic9 <- log(mean.p.basic9) -
pow(log(EF.p.basic9)/1.645, 2)/2
tau.p.basic9 <- pow(log(EF.p.basic9)/1.645, -2)

p.basic7 ~ dlnorm(mu.p.basic7, tau.p.basic7)|(,1)
mu.p.basic7 <- log(mean.p.basic7) -
pow(log(EF.p.basic7)/1.645, 2)/2
tau.p.basic7 <- pow(log(EF.p.basic7)/1.645, -2)

p.basic8 ~ dlnorm(mu.p.basic8, tau.p.basic8)|(,1)
mu.p.basic8 <- log(mean.p.basic8) -
pow(log(EF.p.basic8)/1.645, 2)/2
tau.p.basic8 <- pow(log(EF.p.basic8)/1.645, -2)

p.basic10 <- 1 - exp(-lambda.10*time.10)
lambda.10 ~ dlnorm(mu.p.basic10, tau.p.basic10)
mu.p.basic10 <- log(mean.p.basic10) -
pow(log(EF.p.basic10)/1.645, 2)/2
tau.p.basic10 <- pow(log(EF.p.basic10)/1.645, -2)
```

```
}
```

WinBUGS script for data of basic events

```
data
list(time.9=24, time.10=48,
mean.p.basic12=0.005, EF.p.basic12=10,
mean.p.basic13=0.005, EF.p.basic13=10,
mean.p.basic14=1.05E-2, EF.p.basic14=10,
mean.p.basic15=1.03E-2, EF.p.basic15=10,
mean.p.basic16=1.03E-2, EF.p.basic16=10,
mean.p.basic11=0.077, EF.p.basic11=10,
mean.p.basic1=0.5, EF.p.basic1=10,
mean.p.basic2=0.5, EF.p.basic2=10,
mean.p.basic3=0.5, EF.p.basic3=10,
mean.p.basic4=0.5, EF.p.basic4=10,
mean.p.basic5=0.5, EF.p.basic5=10,
mean.p.basic6=0.5, EF.p.basic6=10,
```

```
mean.p.basic9=1.67E-3, EF.p.basic9=10,
mean.p.basic7=0.5, EF.p.basic7=10,
mean.p.basic8=0.5, EF.p.basic8=10,
mean.p.basic10=3.34E-3, EF.p.basic10=10)
```

Inits
list()