A Case Study to Analyze Negative Pressure Test Interpretation in Offshore Drilling: Utilizing a Signal Detection Model

Maryam Tabibzadeh[a,*], Detlof von Winterfeldt[b], and Najmedin Meshkati[b]
[a] California State University, Northridge, Northridge, USA
[b] University of Southern California, Los Angeles, USA

Abstract: According to the findings of the U.S. District Court on the BP Deepwater Horizon (DWH) case, "the misinterpretation of the negative pressure test was a substantial cause of the blowout, explosion, fire, and oil spill." It is noteworthy that the Negative Pressure Test (NPT) is a critical procedure to ascertain well integrity in offshore drilling in general. Therefore, the correct interpretation of this test and designing optimal responses is crucial for the safety of future offshore drilling.

This paper utilizes our proposed signal detection model for proper interpretation of a conducted negative pressure through identifying warning signals, which was developed in another paper, in the case study of the BP Deepwater Horizon. Results of our model capture the misinterpretation of the conducted NPT by the DWH crew, and we believe that this model will enable decision makers to correctly interpret and respond to future NPTs.

The source of data to quantify the stated signal detection model is expert judgement elicitation. In addition to quantifying the model, some sensitivity analyses have been conducted to understand the impact of different decision-making biases on interpreting NPT results.

Keywords: Rational decision-making, risk assessment, signal detection theory, offshore drilling safety, negative pressure test, BP Deepwater Horizon.

1. INTRODUCTION

Offshore drilling industry is one of the complex technological systems with tightly coupled and interactively complex [1] operations. The nature of operations in this industry makes this industry high-risk. On the other hand, world's oil supply has a vital need to offshore drilling. According to the International Energy Agency (IEA) [2], a third of the world oil production came from offshore drilling in 2010, which will inevitably increase in the future.

Considering the stated trade-off between the high risk of offshore drilling operations and the rising dependence of the oil supply to this type of drilling, there is a growing need for oil companies to incorporate more robust risk analysis practices into their operations. Risk assessment frameworks enable oil companies to analyze the increasing risks of offshore drilling and develop appropriate contingency and mitigation plans for risk reduction and accident prevention.

One of the most catastrophic accidents in the history of the United States and the world is the BP Deepwater Horizon (DWH) blowout, which occurred in the Gulf of Mexico on April 20, 2010. Among different contributing causes of this accident, misinterpretation of a critical procedure called Negative Pressure Test (NPT) was a major contributing cause of the loss of well control and the subsequent blowout on the DWH rig [3-9].

It is noteworthy that the NPT was not only specific to the Macondo well operations, rather it is an important procedural step for temporary abandonment in most offshore drilling. They are used to indicate whether a cement barrier and other flow barriers can isolate the well and prevent the

[*] Corresponding author. Email: Maryam.tabibzadeh@csun.edu

hydrocarbon influx [6]. Therefore, the correct implementation and interpretation of this test is crucial for the safety of future offshore drilling.

Based on the critical role of an NPT in ascertaining well integrity in offshore drilling, we developed the generic parametric equations of a decision-making model using Signal Detection Theory (SDT) as the foundation, in the first paper in the sequence of two papers, to analyze and respond to the results of a negative pressure test [10]. This model provides guidelines to oil and gas drilling practitioners to look for warning signals while conducting an NPT and optimally respond to the findings of the test. In this paper, as the second paper in the sequence, we have applied the described decision-making (signal detection) model to a case study in order to quantify the model. We have also conducted some sensitivity analyses to understand the impact of different decision-making biases in interpreting NPT results.

Following this overview, we have provided the details on data gathering in section 2.1. Model quantification has been provided in section 2.2, and some sensitivity analyses have been conducted in section 2.3. Finally, section 3 provides some concluding remarks.

2. CASE STUDY

2.1. Data Gathering for Model Quantification

In this paper, the developed signal detection model by Tabibzadeh et al. [10], as a decision-making framework to respond to NPT results, has been applied to a case study. The main source of data gathering in this study is expert judgment elicitation. We were not able to access any source of hard data regarding previous conducted negative pressure tests from the literature or the databases of large corporations due to different reasons including privacy issues.

We were fortunate to receive the kind guidance of four main experts in the area of drilling and well-design for validating and quantifying our proposed signal detection model. One of our experts, as an experienced drilling manager, preferred to remain anonymous. The other three experts, who we contacted, are: 1) Mr. Stan A. Christman, retired ExxonMobil executive engineering advisor, 2) Mr. Fred Dupriest, retired ExxonMobil chief drilling engineer and lecturer at the Texas A&M University, and 3) Mr. Roger D. Gatte, BP retired wells superintendent.

Due to the dependence of many of the required sets of data for quantifying our proposed generic signal detection model to different conditions under which a negative pressure test is implemented; e.g. depth, type of used fluids, formation characteristics, and type and age of used annular preventer, we were able to get any generic datasets. In addition, those experts were not willing to give exact numbers for some of the required sets of data, and that seems logical based on the described varying conditions for each drilled well. The strategy to mitigate this challenge will be described later in this section.

What we will state in the remainder of this section is our understanding and interpretation from our personal communication with the aforementioned experts. In the cases that we have the exact numbers received from the experts, we will report them. Additionally, we will do some sensitivity analyses on each of the stated datasets in section 2.3 in order to assess the impact of each of those sets on the final result of the model. This way, we are not limited to one final answer using the derived formulas for the developed signal detection model by Tabibzadeh et al. [10]. It is also noteworthy that upon availability of additional data or more accurate data, our quantitative analysis using the proposed parametric model can be updated.

Tabibzadeh et al.'s proposed signal detection model [10] provided a parametric equations to calculate a cut-off point value for the model target variable, which was the difference between the actual and the expected pressure (pressure deviation) in the second phase of implementing a negative pressure test, when crew bleeds off enough fluid from the well to reduce the pressure to zero (Please refer to [10] for more details). This cut-off point value was a threshold to reject the NPT (say the test is not okay) for any observed pressure higher than that.

To calculate the above-stated cut-off point value, there is a need to gather data for three categories: 1) prior probability of states, 2) conditional probability of the pressure deviation based different states of the system, and 3) cost of judgement for each given state. The collected data for each of these three categories are provided in sections 2.1.1 through 2.1.3.

2.1.1. Prior Probability of the States

At this stage, we start with reporting data for the prior probability of the possible states in the model. In reference [10], we talked about four different possible states of “NN”, “YN”, “NY”, and “YY” based on the combination of “yes” or “no” for each of the two variables “leaking in the BOP annular preventer (AP Leak)” and “flow from the well (Well Leak)”. The formula for the prior probability of each of these states is as follows:

$$P(h_i) = P(APLeak, WellLeak); i = 0,1,2,3 \tag{1}$$

Since AP Leak and Well Leak; leaking in the BOP annular preventer and flow from the well, are independent variables, we can have the equation (2) as follows:

$$P(h_i) = P(APLeak) * P(wellLeak); i = 0,1,2,3 \tag{2}$$

Based on this equation, we will have:

$$P(h_0) = P(NN) = P(APLeak = N) * P(WellLeak = N) \tag{3}$$
$$P(h_1) = P(YN) = P(APLeak = Y) * P(WellLeak = N) \tag{4}$$
$$P(h_2) = P(NY) = P(APLeak = N) * P(WellLeak = Y) \tag{5}$$
$$P(h_3) = P(YY) = P(APLeak = Y) * P(WellLeak = Y) \tag{6}$$

Based on what we derived above, we need two probabilities of $P(APLeak = Y)$ and $P(WellLeak = Y)$. According to Christman [11], there is a higher possibility for well integrity issues and flow from the well rather than leaking in the annular preventer. He also stated that the probability of leaking in the annular preventer $P(APLeak = Y)$, depends on the specifications of the annular; e.g. its manufacturer. Gatte [12] and Dupriest [13] also confirmed the described statement by explaining that the specifications of an annular preventer and its condition; e.g. number of times it has been used in previous operations, influence $P(APLeak = Y)$.

According to Christman [14], the probability of leaking in the annular preventer can be in the range of 0.1% to 1%. Regarding the probability of flow from the well, Dupriest [13] stated that leaks of wellhead seals, liner-top packer, or casing are very rare, and the probability of these events all together can be around 1/3000. He also mentioned that it is, by far, more likely to have leak path in the shoe, which includes the floats in the float collar, floats in the shoe, cement left in the float joints, and cement that is outside casing from the shoe up to the pay zone. This number has been stated to be around 1/300 by Dupriest [13]. As a result, the combination of these two probabilities makes $P(WellLeak = Y)$; or probability of flow from the well, to be around 0.4%.

Based on all the above-stated analysis, we interpreted that $P(APLeak = Y)$ can be around 0.01 and $P(WellLeak = Y)$ is approximately 0.02.

2.1.2. Conditional Probability of Pressure Deviation based on the States

The second essential dataset for quantifying our proposed model is the conditional probability of the target variable; pressure deviation, knowing the state of system. We needed to gather data regarding the behavior of the pressure deviation variable for each of the four explained states in the system. It is needed to state that all the ranges of pressure deviation for each of the four scenarios are based on characteristics of a well like the Macondo in the DWH; in the matter of depth, similarity of the formation type, use of the annular preventer on the BOP to conduct NPT, etc. This is our mitigating strategy to be able to elicit data and quantify the model. All the gathered data in this study and calculations based on them can be adjusted upon the arrival of new information.

The first state is the “NN” situation, which is the normal state of having no leaking in the annular preventer and no flow from the well. Based on the unanimous opinion of all the contacted experts, the most possible value for the pressure deviation in the state “NN” is zero since both major sources of pressure built-up are absent. However, crew might see some pressure deviation in this state due to factors such as thermal effect or fluid compressibility, which can cause fluid expansion. According to our personal communications with the stated experts, pressure built-up due to fluid expansion varies based on different conditions such as depth of the well, temperature of fluid, and fluid hydraulic characteristics. Our interpretation based on those communications was that the pressure deviation for the “NN” state can varies in the range of zero to 400psi. One of the main reasons for such interpretation is based on some elicited data from one of the experts. According to Christman [15], compressibility of fluids under pressure and temperature (mostly for oil-based fluids and not water-based ones) are two of the major sources of change in fluid density. He stated that the actual downhole fluid density can increase around 0.2-0.4ppg (pounds per gallon) due to compressibility effect and around 0.1-0.2ppg due to thermal effect. We interpreted a fluid density change in the range of 0.1-0.4 based on these two factors. Based on this interpretation, if we consider a well as deep as the Macondo with the depth of 18300ft, the pressure deviation due to fluid compressibility and thermal effect can be in the range of 95-380psi, using the following formula:

$$P(psi) = 0.052 * \rho(ppg) * h(ft) \tag{7}$$

Based on all the above-stated analysis, the pressure deviation in the “NN” state can vary from zero to something around 400psi. Since we know that zero is the most probable observed pressure deviation for this state, the probability distribution of the target variable should have the highest value at zero pressure deviation and decrease after that. This characteristic makes the exponential distribution the best alternative for $f(x|h_0)$. The conditional probability distribution that we considered for this state is a $Weibull(\lambda, k)$ with the shape factor (k) of 1, which is actually equivalent to an exponential distribution with parameter $\frac{1}{\lambda}$. We also considered $\lambda = 35$ as the scale parameter for this distribution. Fig.1 illustrates the behavior of the pressure deviation in this state based on the specified λ and k.

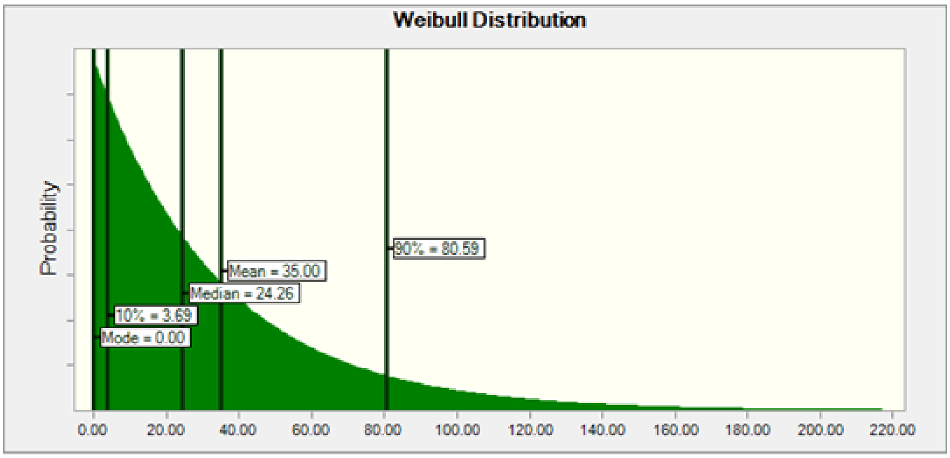

Fig. 1. Probability distrubution for $f(x|h_0)$

The next state is the "YN" situation, which is equivalent to having leaking in the annular preventer on the BOP but no flow from the well. In this situation, leaking in the BOP annular preventer can be a source of pressure built-up in phase II after bleeding off the caused u-tube pressure by the displacement process to zero. This leaking can cause a pressure built-up as much as the whole bled-off u-tube pressure. For a case like the BP DWH, since some heavy spacer with the density of 16ppg was used, leaking in the annular preventer can cause the movement of some part of the spacer below the BOP stack, which can contribute to fairly high pressure built-up. Based on our interpretation, this pressure deviation can be as high as 2900psi. According to Christman [14], in the worst case for the Deepwater Horizon situation, based on the 421bbls of used spacer by the crew, the bottom of the spacer could be at 8367ft and the top at about 3000ft. We also know that there existed mud above the spacer inside the annulus and also the whole drill pipe was full of seawater. Knowing all these components, the pressure difference between the drill pipe and the annulus could be around 2900psi, which is our reference for the pressure deviation upper limit in the "YN" state. The following illustrates the calculation for the 2900psi pressure deviation based on the stated numbers:

$$P(DP) = 0.052 * \rho(ppg) * h(ft) = 0.052 * 8.7 * 8367 = 3742\, psi$$
$$P(annulus) = 0.052 * 14 * 3000 + 0.052 * 16 * (8367 - 3000) = 6649\, psi$$
$$P(difference) = 6649 - 3785 = 2907 \sim 2900\, psi$$

We know that the density of sweater was around 8.55-8.6ppg, and the depth for the displaced drilling mud with seawater in the DWH conducted negative pressure was 8367ft.

Based all the above stated elements, we considered a $Weibull(\lambda, k)$ distribution with the scale factor (λ) of 1400psi and the shape factor of 4. It is right that the range of pressure deviation for this state can vary from zero to 2900 psi. However, there is more possibility of observing high pressure deviations in this state. Therefore, we need a probability distribution which is skewed towards the right tale, and the stated parameter values ensure this behavior. This probability distribution has been shown in Fig. 2.

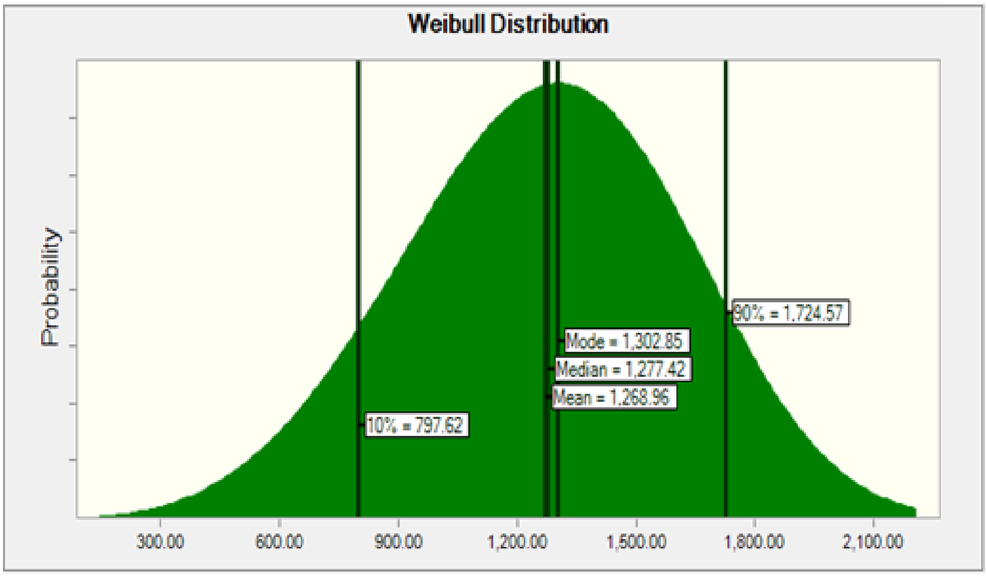

Fig. 2. Probability distrubution for $f(x \mid h_1)$

The next state is "NY", which is equivalent to no leaking in the annular preventer but having flow from the well. In this situation, issues with well integrity can cause entrance of hydrocarbon from reservoir inside the annulus, which contribute to pressure increase inside the well. After bleeding off the pressure inside the well to zero, any pressure built-up due to hydrocarbon influx into the well will be the difference between the formation pressure in the bottom of the well and the hydrostatic head pressure. For a case like the DWH, the upper limit of this number was around 1400-1500psi knowing the characteristics of the formation and the method of conducting the negative pressure test. As stated before, we have considered a well with the characteristics of the Macondo. Therefore, we can consider the range of zero to 1500psi as an interval for the pressure deviation in the state "NY". Again, there is more possibility of observing high pressure deviations within the stated interval. Hence, we need a probability distribution for this situation, which is skewed towards its right tale. We assumed that $f(x|h_2)$ is a $Weibull(\lambda, k)$ distribution with $\lambda = 1000$ and k=8, as illustrated in Fig. 3.

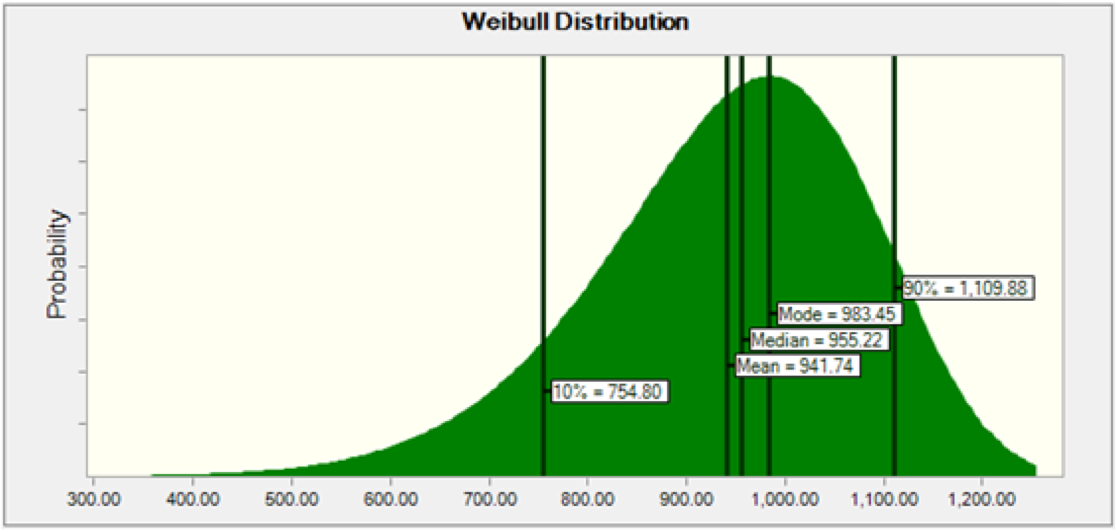

Fig. 3. Probability distrubution for $f(x|h_2)$

The last state is "YY", which is equivalent to both having leaking in the annular preventer and flow from the well. In this state, pressure deviation can increase as much as the u-tube pressure that crew bled off the fluid from to zero, and this value was around 2900psi, as was explained for the "YN" state. Therefore, we will have the range of zero to 2900psi for this state as well. The only main difference between the "YN" and the "YY" states is that in the latter case, pressure can rise up much quicker comparing to the first situation and this is due to the presence of both AP Leak and Well Leak as sources of pressure built-up. Based on this analysis, we have considered the same probability distribution for $f(x|h_3)$ as it was the case for the $f(x|h_1)$.

2.1.3. Pay-off Values (costs) Associated with Pairwise States and Judgements

The last required sets of data are C_{ij}'s or the cost of saying "H_j" to the state "h_i". What we have considered in this regard is some cost ratios, rather than the exact monetary value for each C_{ij}. This way, knowing the exact value of each C_{ij} is not necessary, which is something preferable due to the variable cost of operations based on many factors such as location and daily operation costs. Therefore, we can actually set some initial values for some of the costs and calculate other dependent costs using the stated ratios. In section 2.3, we will also conduct some sensitivity analyses in order to evaluate the impact of changing these ratios on the cut-off point value.

According to Christman [11, 16], if crew misinterprets a successful negative pressure test by rejecting it, it takes several hours, or even one to two days, to investigate and re-conduct the test. This can cause some costs between \$0.5M and \$2M. Therefore, C_{01}= \$0.5M-\$2M.

On the other hand, if crew misinterprets a failed test and accepts the results, this can cause some costs in an average range of \$1B to \$2.5B. This range is the authors' interpretation and it has been deduced based on the given data that disastrous accidents in a scale similar to the DWH blowout occur one in ten years [11]. We know that the DWH approximately caused \$40B. We also know that there might be many other accidents with smaller cost-scale due to misinterpretation of a negative pressure test, and of course, some other series of failure which may contribute to those accidents. In addition, sometimes misinterpreting NPT can cause some kicks in the well, but if crew can control the situation, associated costs can be around $2M-$4M [11]. In general, the following is what we considered to calculate the approximate cost of misinterpreting an abnormal state, as a contributing cause of a failed NPT:

$$0.1 * \$25B + 0.9 * \$4M \sim \$2.5B$$

In the above calculation, 0.1 is the described one big accident in an average of 10 years with an approximate cost of $25B and the rest (0.9) are smaller incidents in which crew can attain control of the well before any big explosion.

If we calculate the ratio between cost of rejecting a normal state and accepting an abnormal situation based on the aforementioned costs, we can have a range of 1000 to 3000. In this model, we have considered the value of 2000 as a basic amount for the described ratio. This value is what we considered for the two ratios of (C_{20}/C_{01}) and (C_{30}/C_{01}). This is because C_{20} and C_{30} are both associated with misinterpretation of an abnormal state in which there is flow from the well as a source of not only pressure built-up but also some possible kicks that eventually can cause a blowout.

It is needed to state that the value of the (C_{20}/C_{01}) and (C_{30}/C_{01}) might be less than 2000 if the estimated probability of 1 big accident in 10 years is overestimated. However, as we discussed before, we will conduct some sensitivity analyses on different influencing factors, including the stated cost ratios, on the cut-off point value in section 2.3. This will assist us to identify how sensitive the cut-off point value is to the described cost ratios.

The considered value for (C_{10}/C_{01}) is zero since although C_{10} is associated with the situation of accepting (saying "H_0") the test results for the abnormal state "h_1", this actually does not cause any cost at the end. The reason for such case is that even if crew does not recognize leaking in the annular preventer and accept the conducted test, there will be no harm; e.g. kick, in this situation since there was no involved well integrity issue in this state.

There is a need to identify three more costs in order to be able to determine all different combinations of C_{ij}. First is C_{00} as the cost associated to correctly accepting NPT while the state is normal. This cost has been considered to be zero in this document. For the second set of data, we assumed that all C_{i1}'s; i=1, 2,3, as the costs of rejecting NPT (saying "H_1") for the abnormal states of "h_1", "h_2", and "h_3" are the same and equal to C_1=$0.5M. We deduced this value based on the fact that if crew concludes that a negative pressure test is inconclusive, they have to investigate the situation, resolve possible issues, and re-conduct the test, and we assumed that this cost does not vary so much based on the presence of leaking in the annular preventer, flow from the well, or both. Lastly, we assumed that C_{01}, as the cost of rejecting NPT while the state is normal ("NN"), is equal to C_{i1}'s; i=1,2,3. This is due to considering the fact that if crew misinterprets a normal state, they need to re-evaluate all the conditions and re-implement the test, which cost them a similar amount as the stated C_{i1}'s.
Based on all the stated numbers, we will have:

State "h_0": C_{00}=0, C_{01}=$0.5M
State "h_1": C_{10}=0, C_{11}=$0.5M
State "h_2": C_{20}=2000*C_{01}=$1B, C_{21}=$0.5M
State "h_3": C_{30}=2000*C_{01}=$1B, C_{31}=$0.5M

The summary of all the considered cost values and cost ratios has been shown in Table 1. This table indicates the probability of each of the states; h_i, as well. The method of calculating these probabilities was discussed in section 2.1.1.

It is noteworthy that although the combination of each state-judgment can have both monetary and non-monetary costs associated with it, the considered cost values in this research have been focused on monetary costs. Expansion of the cost estimation system as an input to the proposed signal detection model is one of the areas of future research.

Table 1. Cost matrix for state-judgment combinations

		Judgment	
		H_0	H_1
State	**$P(h_i)$**		
h_0=NN	0.9702	C_{00}	$C_{01}=C_1$
h_1=YN	0.0098	$C_{10}=C_1$	$C_{11}=C_1$
h_2=NY	0.0198	$C_{20}=2000*C_{01}$	$C_{21}=C_1$
h_3=YY	0.0002	$C_{30}=2000*C_{01}$	$C_{31}=C_1$

2.2. Model Quantification and Analysis

Based on all the three main sets of data, we can calculate the needed amounts to determine the described cut-off point value (See equation (15) in [10]) by entering all the data in Microsoft Excel and solving the stated equation using the "what-if analyses >- goal seek". The calculated cut-off point value based on the stated data in this sections 2.1.1 through 2.1.3 is 247psi. Intuitively, the cut-off point is an intersection of the conditional probabilities $f(x|h_i)$, for different states in the farthest left hand side. As it is shown in Fig. 4, $f(x|h_i)$s have been intersected around 250psi. However, there are more detailed influencing elements, which determine the exact value of the cut-off point.

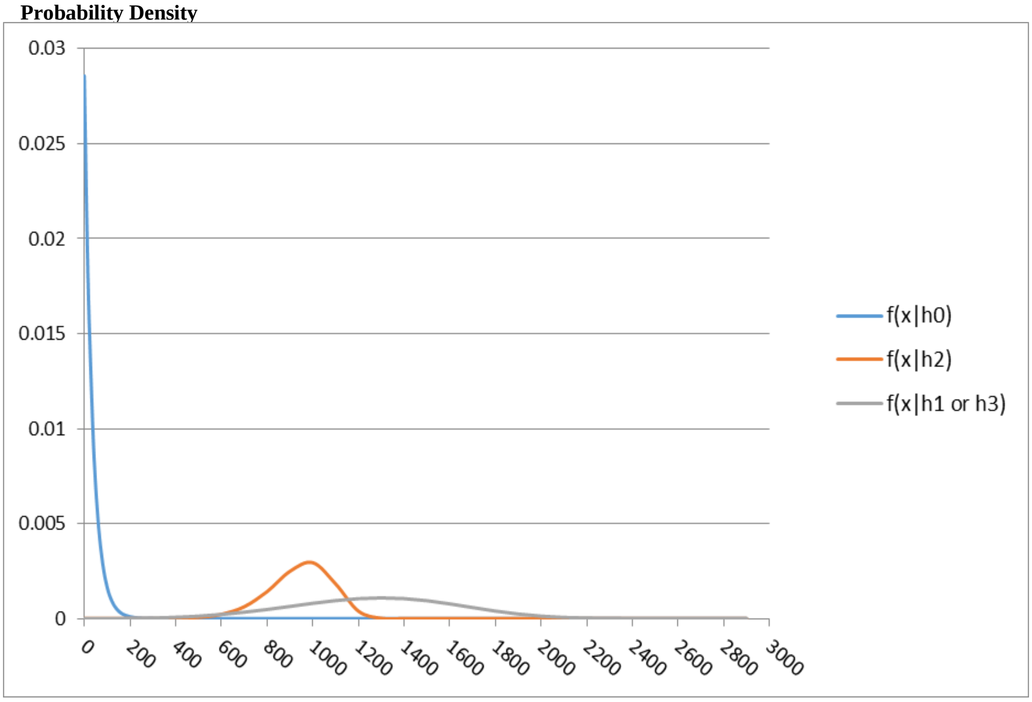

Fig. 4. Joint diagram of all $f(x|h_i)$'s

Determining 247psi as the cut-off point value means that for any observed pressure built-up more than this amount in the second phase of conducting NPT, crew needs to reject the test. However, for any value less than this cut-off point, as long as the observed pressure deviation is more than zero, crew needs to conduct more investigations by taking into account the number of barrels of actual versus expected bled-off fluid from the well to reduce the pressure to zero in phase II and also by watching the well for flow.

As we explained before in this section, our main purpose from this analysis is not to introduce an exact cut-off point value to the practitioners of the oil and gas industry who deal with the implementation of negative pressure tests, but to propose a rational decision-making model consisting of both a structure and some generic parametric equations for it in order to enable them to calculate the described cut-off point value in that model based on data availability. What we explained in this section are just some illustrations for quantifying such model using gathered data from some experts of the field. Of course, all these calculations can be updated based upon the availability of more data. In addition, we will conduct some parametric as well as numeric sensitivity analyses in the next section in order to illustrate the dependence of the model target variable and the described cut-off point value to different explained influencing factors. Moreover, we can describe different biases involved in decision-making, which can affect the final result and interpretation of a conducted negative pressure test.

2.3. Model Sensitivity Analysis

In this section, we conduct both parametric and numeric sensitivity analyses in order to illustrate the dependence level of the cut-off point value to the data inputs in the model. The conducted sensitivity analysis of the prior probability of the states have been provided as an example in this paper. Other categories of conducted sensitivity analyses; i.e. sensitivity analysis of cost ratios and sensitivity analysis of conditional probability of pressure deviation based on the states, have not been provided due to page limitation. For more details on those sensitivity analyses, you can refer to [17].

2.3.1. Sensitivity Analysis for Prior Probability of the States

The first sets of required input or data for our proposed model were the prior probabilities of all four states; "h_i"; i=0,1,2,3. We explained that the product of the two probabilities $P(APLeak)$ and $P(WellLeak)$ constructs those prior probabilities. Therefore, conducting sensitivity analyses on the states prior probability is equivalent to evaluating the impact of $P(APLeak = Y)$ and/ or $P(WellLeak = Y)$ on the cut-off point value.

Based on equations (18) to (21) in [10], increasing the value of either $P(APLeak = Y)$ or $P(WellLeak = Y)$, which are respectively the probability of leaking in the annular preventer and the probability of flow from the well, reduces the prior probability of the normal state "h_0" and at the same time, it increases the prior probability of abnormal states; $P(h_i); i = 1,2,3$. As a result, the prior odd for each of the states "h_i"; i=1,2,3, comparing to the normal state "h_0" will decrease based on the equation (10) in [10]. Subsequently, this reduction contributes to an increase in the left hand side value of the inequality (15), which causes a decrease in the cut-off point value calculated from that inequality.

This analysis shows that increasing the value of $P(APLeak = Y)$ or $P(WellLeak = Y)$ reduces the cut-off point value, and this reduction is equivalent to less possibility of accepting a negative pressure test based on an observed pressure. Reversely, if crew underestimates either $P(APLeak = Y)$ or $P(WellLeak = Y)$, this contributes to an increase in the cut-off point value and subsequently, higher possibility of accepting a conducted NPT even for abnormal states, which is something undesirable. This underestimation is a bias that negatively influences the outcomes of our proposed signal detection model.

Analyzing the contributing causes of such underestimation connects this bias to some root organizational factors, which were the subject of our analysis in other studies [17-21]. Some of the main contributing organizational factors in this regard are as follows:

- Economic pressure; if personnel are under the pressure of completing operations faster in order to save time and cost (most drilling operations have very high daily costs associated with them, so even saving hours is critical to drilling teams), then there is a high possibility of underestimating the probability of leaking in the annular preventer or/and the probability of flow from the well.

- Personnel management issues; if personnel are not well trained or do not have enough related experience regarding negative pressure testing and its influencing factors, they might not be able to estimate the stated probabilities correctly.
- Issues in communication and processing of uncertainties and also lack of an integrated, informed management; if there is no effective communication between personnel regarding the importance and associated risks of conducting and interpreting negative pressure tests, there is a high possibility for inaccurate estimation of the stated probabilities. In addition, existence of no management system to emphasize the importance of NPT or to provide insight and feedback regarding personnel's estimations and interpretations of this test contributes to misestimating $P(APLeak = Y)$ or/and $P(WellLeak = Y)$.

Our numerical analysis based on the entered data in the model confirms the described interdependency between the probabilities $P(APLeak = Y)$ and $P(WellLeak = Y)$ and the cut-off point value. As Fig. 5 indicates, decreasing the probability of leaking in the BOP annular preventer increases the cut-off point value. We also highlighted the behavior of the $P(APLeak = Y)$ within the interval [0,0.1] using a logarithmic scale for the horizontal axis in Fig. 6. Based on both these figures, we can see that decreasing $P(APLeak = Y)$ can increase the cut-off point value as high as 252psi.

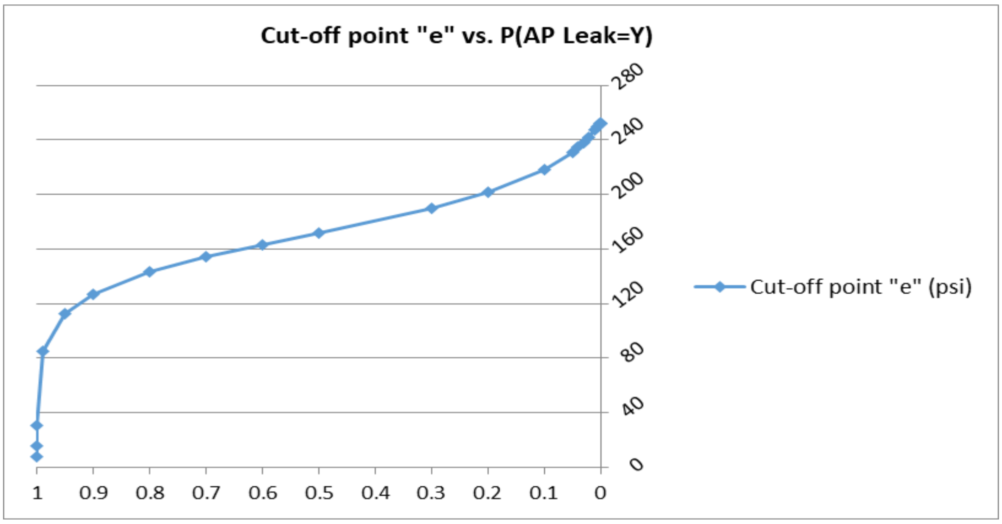

Fig. 5. Sensitivity analaysis of the cut-off point value based on $P(APLeak = Y)$

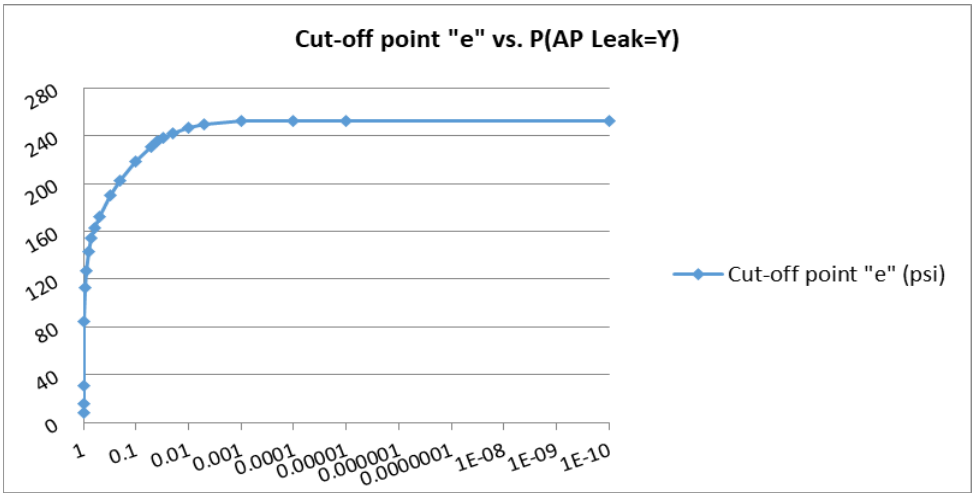

Fig. 6. Sensitivity analaysis of the cut-off point value based on $P(APLeak = Y)$ with the highlighted interval [0,0.1]

Fig. 7 and 8 illustrate the dependence of the cut-off point value to $P(WellLeak = Y)$. This trend is similar to the interdependence between the cut-off point value and $P(APLeak = Y)$. However, in this case, if $P(WellLeak = Y)$ becomes less than or equal to 0.000001, the cut-off point will increase to infinity meaning that any observed pressure deviation, no matter how high it is, is acceptable. It is needed to state that we represented the infinity value for the cut-off point with a large amount; i.e. 2000psi, in both Fig. 7 and 8.

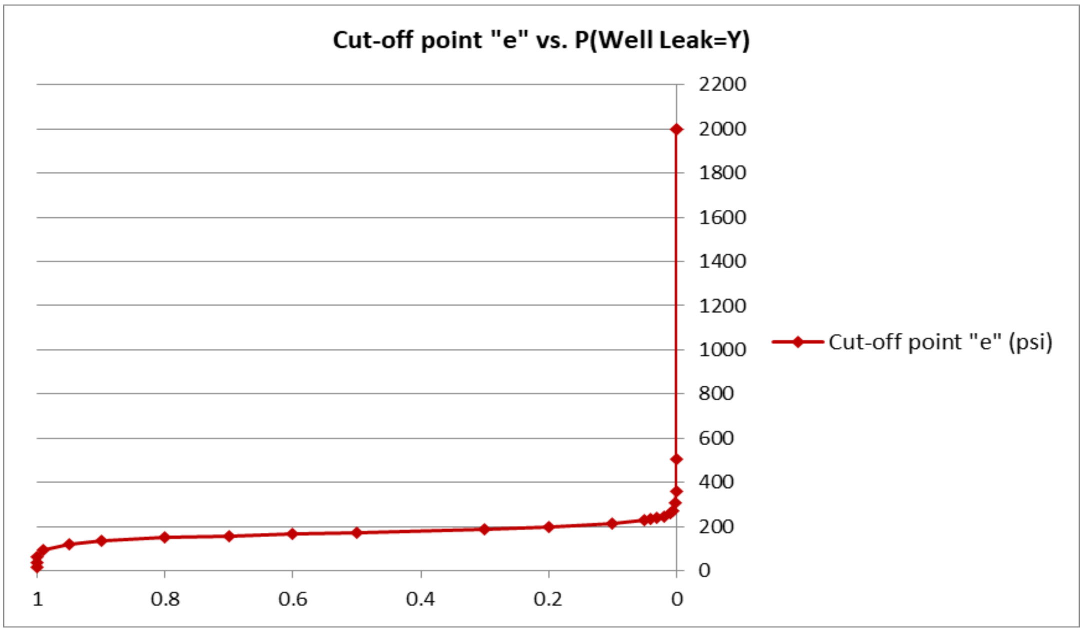

Fig. 7. Sensitivity analaysis of the cut-off point value based on $P(WellLeak = Y)$

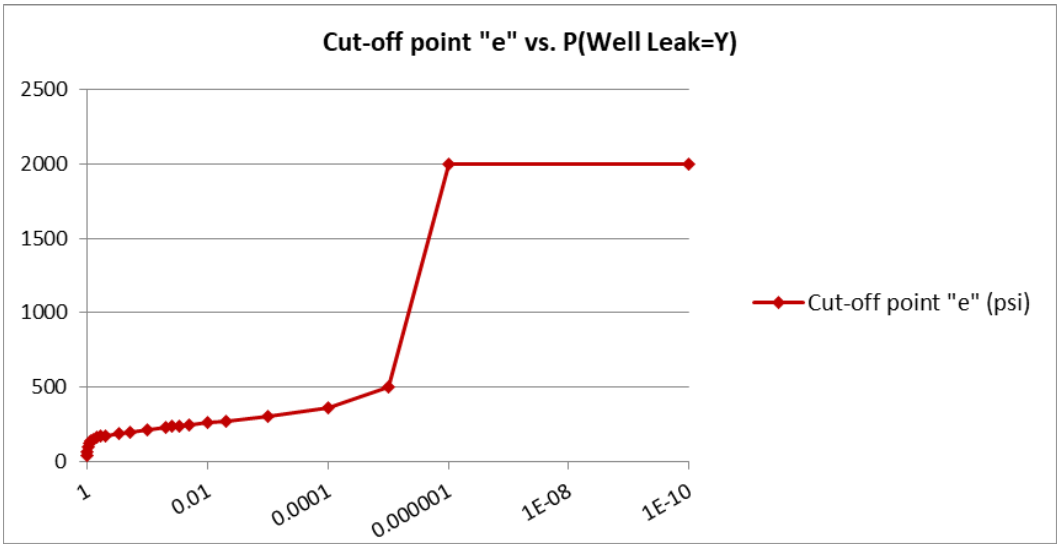

Fig. 8. Sensitivity analaysis of the cut-off point value based on $P(WellLeak = Y)$ with the highlighted interval [0,0.1]

Similar to this category of sensitvity analysis, other types of sensitivity analysis can be conducted to investigate the impact of different invloved factors on the discussed cut-off point and to understand the effect of different decision-making biases in interpreting NPT results.

Based on all these analyses, it seems that accepting a pressure built-up as high as 1400psi by the DWH crew was something irrational. Based on our analysis, it is almost impossible to reach a cut-off point value as high as 1400psi, for a well with characteristics similar to the Macondo well, in the scope of our proposed signal detection model. This also indicates that most probably, there were some other involved biases and issues in the process of interpreting the conducted negative pressure test in the DWH. One example which was highlighted by the Deepwater Horizon Study Group (DHSG) Report#3 [22, Appendix B, Page 10] is the DWH crew's confirmation bias in interpreting the NPT results. Justifying the observed 1400psi pressure built-up on the drill pipe as a phenomenon called "bladder effect", which could not exist for the DWH situation, is one instance of the existence of the confirmation bias in the negative pressure test interpretation.

Similar to other stated biases, there are some main organizational factors as the root contributing causes of the aforementioned confirmation bias. These organizational factors are: economic pressure, personnel management issues, and issues in communication and processing of uncertainties. It is noteworthy that previous studies corroborate this finding that organizational factors are the root causes of accumulated errors and questionable decision-making made by personnel and management; e.g. [23-26].

3. CONCLUDING REMARKS

In this paper, the proposed parametric signal detection model by Tabibzadeh et al. [10] was quantified and applied to a case study to determine a cut-off point value. This value indicates a threshold to reject a conducted negative pressure test if the observed pressure deviation in the second phase of implementing the test, when crew bleeds off enough fluid from the well to reduce the pressure to zero, is more than it. Based on the gathered data for the case analysis, which resembled the characteristics of a well similar to the Macondo, the calculated cut-off point value was 247psi, which is much lower than the observed 1400psi pressure difference in the case of the BP DWH. The use of such a model would have indicated the failure in the conducted test.

It is noteworthy that this paper only provided a case study to illustrate the capabilities of the developed signal detection model by Tabibzadeh et al. [10]. That model can be quantified based on any sets of collected data for any conducted negative pressure test, which is and will be a critical procedure to ascertain well integrity in offshore drilling. In addition, the calculations of the model can be updated upon availability of more (accurate) data. Finally, the conducted model sensitivity analyses in this paper contributed to better understanding of the impact of different decision-making biases on interpreting NPT results.

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