

A Signal Detection Model to Interpret Safety Tests in Offshore Oil Drilling

Maryam Tabibzadeh^{a,*}, Detlof von Winterfeldt^b, and Najmedin Meshkati^b

^aCalifornia State University, Northridge, Northridge, USA

^bUniversity 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) was not only specific to the Macondo well operations; rather it 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 uses signal detection theory and proposes a model to provide responses to warning signals in offshore drilling and, in particular, to optimally respond to the findings of NPTs. The structure and generic parametric equations of this model enable oil and gas practitioners to calculate a cut-off point value, as a threshold to accept or reject an implemented NPT, which is crucial in the interpretation of this test.

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

1. INTRODUCTION

Large-scale accidents occur because many complex technological systems use operations that are tightly coupled and interactively interdependent [1]. Of particular interest are low probability, high-consequence events such as nuclear power plant accidents, explosions in chemical factories, and massive oil blowouts.

The oil and gas drilling industry, especially offshore and deep-water drilling, is one of such complex systems in which large-scale accidents occur. Major issues, such as high operational pressures and temperatures, large seismological uncertainties, difficult formations, and very complex casing programs, associated with deep-water drilling make this type of drilling very risky [2].

While risky, offshore and deep-water drilling plays a major role in today’s oil production. According to the International Energy Agency (IEA) [3], a third of the world oil production came from offshore drilling in 2010, which will inevitably increase in the future. Fig. 1 shows the number of wells drilled versus water depth in the Gulf of Mexico from 1940 to 2010. In the past few decades alone, offshore and deep-water drilling has increased exponentially.

Considering the stated trade-off between the high risk of offshore and deep-water 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 suitable risk analysis practices into their operations. Risk assessment frameworks enable oil companies to analyze the increasing risks of offshore and deep-water drilling and develop appropriate contingency and mitigation plans for risk reduction. The main intention of developing such frameworks is to prevent accidents like the Deepwater Horizon blowout, which occurred in the Gulf of Mexico on April 20, 2010, in the future.

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

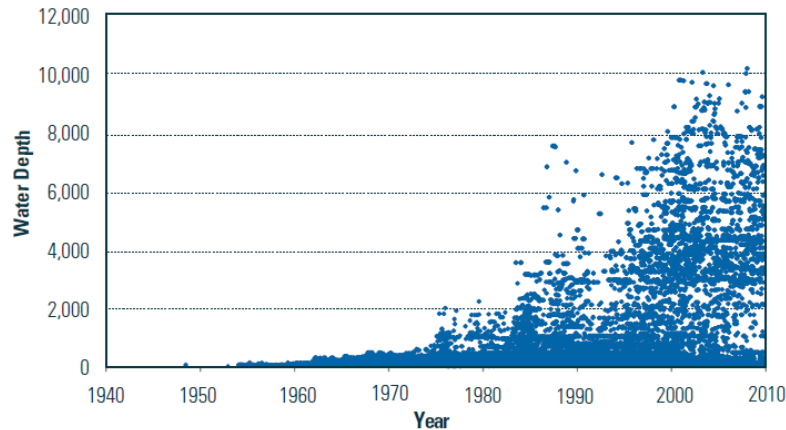


Fig. 1. Wells drilled in the Gulf of Mexico by water depth from 1940 to 2010 [4, page 41]

Formal investigations of the Deepwater Horizon accident indicate that the misinterpretation of a critical procedure called negative pressure test was a major contributing cause of the loss of well control and the subsequent blowout on the DWH rig [5-9]. NPTs are currently the primary way to test cement integrity at the bottom of a well [7]. They are used to indicate whether a cement barrier and other flow barriers can isolate the well and prevent the hydrocarbon influx as part of temporary abandonment [8].

Several petroleum engineering and well design experts share the view that the misinterpretation of the NPT was a major contributing cause of the DWH accident. According to those experts, one single item that could have saved the day for the DWH was the correct interpretation of the negative pressure test conducted by the DWH crew on the day of the accident. For instance, the Honorable Dr. Donald Winter, the chairman of the National Academy of Engineering/National Research Council committee on the DWH accident, stated in his interview with Platts that the blowout was precipitated “not by a piece of hardware, but by the decision to proceed to temporary abandonment in spite of the fact that the negative pressure test had not been passed” [10]. The findings of the United States District Court on the DWH case, in September 2014, corroborate this conclusion. According to those findings, “the misinterpretation of the negative pressure test was a substantial cause of the blowout, explosion, fire, and oil spill” [11].

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. 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 have developed a decision-making model using Signal Detection Theory (SDT) as the foundation to analyze and respond to the results of a negative pressure test. This model provides guidelines to decision makers; e.g. the crew, who conduct and interpret negative pressure tests, and as part of an integrated risk analysis methodology [12], contributes to reducing the risk of misinterpreting future conducted NPTs.

Signal detection theory is a means to quantify the ability to distinguish a signal or a stimulus, as a piece of information, from random patterns of distraction; noise. In addition to science and engineering applications, SDT has been used in psychology and psychophysics for many decades; e.g. [13]. Some of the recent applications of this theory are in image analysis; e.g. [14], and diagnosis and prognosis; e.g. [15]. However, the concept of decision processes in the signal detection theory has neither been used in the oil and gas industry nor in any risk analysis applications.

Following this overview, the general skeleton and structure of our proposed SDT model is introduced in section 2 of this paper. Section 3 describes the SDT model based on the foundation of the introduced structure in section 2. This description includes the explanation of possible scenarios and

variables states in section 3.1, the overview of general principles of decision processes in signal detection theory in section 3.2, and the development of general formulas and equations of the model for its quantification and analysis in section 3.3. Finally, section 4 provides some concluding remarks.

2. NEGATIVE PRESSURE TEST INTERPRETATION

The general structure of our proposed model to analyze and interpret a negative pressure test is shown in Fig. 2. The components of this model have been selected based on the most influential elements in conducting and interpreting an NPT. The main component of the illustrated structure is the target variable, which is the pressure deviation between the observed pressure in the second main phase of conducting a negative pressure test and the expected pressure for that specific phase.

Generally, implementing a negative pressure test consists of two main phases. Phase I is the process of displacing drilling mud with seawater inside drill pipe, closing the annular preventer on the Blowout Preventer (BOP), and measuring the pressure from the installed gauge in the cement unit on the surface. And, phase II includes bleeding off more fluid from the well through drill pipe in order to reduce the pressure to zero and watching for any pressure built-up in the system. (For the detailed process of conducting a negative pressure test, refer to [12] and [16].)

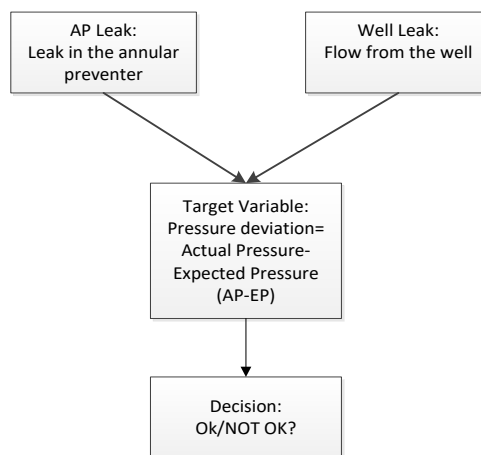


Fig. 2. Structure of the proposed model to interpret an NPT

Pressure deviation, as explained above, is one of the main criteria for evaluating the success or failure of a negative pressure test. In each stage of conducting such test, crew is able to measure the pressure inside the well on the drill pipe and compare it with their expected pressure value. In theory, the ideal value for the stated target variable; pressure deviation, is zero. This means that in an ideal situation, crew expects to see no pressure deviation between the measured pressure from the well in either phase I or phase II of implementing an NPT and what they expected to observe at that stage.

In our signal detection model, we considered the value of pressure deviation in the second phase of conducting a negative pressure test. However, this does not mean that crew does not record the value of pressure in the first phase of conducting the test. This will be an additional piece of data for further analysis of test results.

In the second of phase of performing a negative pressure test, the expected observed pressure is zero since crew bled off enough fluid from the well to reduce the pressure to zero. Hence, measured pressure from the well, which will be in the form of pressure built-up, is equivalent to the pressure deviation as our target variable. It is needed to state that we have used the terms of pressure deviation and pressure built-up interchangeably in the remaining of this paper.

There are two main factors influencing the explained target variable in our proposed model. These two variables, which affect the value of measured pressure from the gauge, are: 1) AP (Annular Preventer)

Leak; leak in the annular preventer on the BOP stack and 2) Well Leak; flow from the well. If there is any leaking in the annular preventer, which is installed on the BOP (Fig. 3), this can cause pressure built-up inside the well due to allowing heavier fluid to be present in the annulus below the BOP stack.

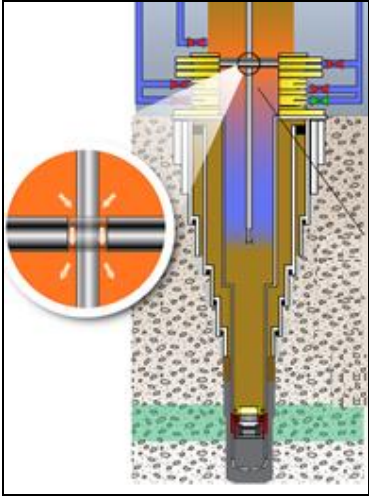


Fig. 3. Leak in the BOP annular preventer (Source of image: [7], page 154)

Another source of pressure built-up during a negative pressure test implementation is having flow from the well, which is equivalent to the existence of well integrity issues. Flow from the well can be due to different potential issues in well integrity such as cementing issues or leaking in wellhead seal, liner-top seal, well casing, and float equipment. Any of the aforementioned issues can cause a well to flow meaning that the hydrocarbon inside the reservoir enters the well and leads to pressure built-up in both the stated phases of conducting a negative pressure test. Fig. 4 shows some of the possible flow paths for hydrocarbon. The left hand side figure illustrates hydrocarbon traveling up the annulus and through the seal assembly and the figure in the right hand side demonstrates the entrance of hydrocarbon inside the production casing and its migration through different possible flow paths.

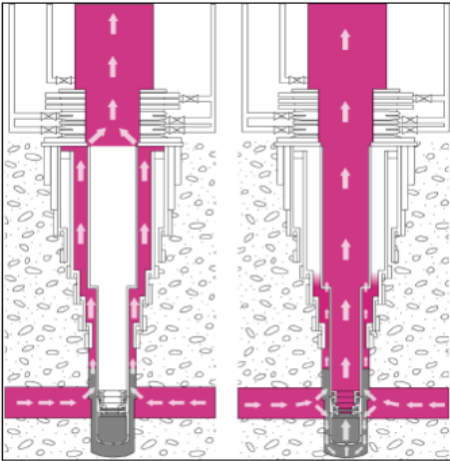


Fig. 4. Possible flow paths for hydrocarbon (Source of image: [7], page 39)

There is a third element in addition to the two aforementioned factors that can affect the value of the target variable; pressure deviation. This element is having part of spacer; a fluid which is pumped between seawater and drilling mud to prevent the contamination of the drilling mud, or mud, which was planned to be circulated above the BOP stack in the displacement process, below the blowout preventer. This issue can cause higher observed pressure than expected in the first phase of conducting NPT since spacer or mud is heavier than seawater. Therefore, this can be a source of pressure deviation in phase I. However, in phase II, this factor will have no impact on the observed pressure from the gauge since crew already bled off enough fluid from the well, which caused zero pressure. Nevertheless, as stated before, crew needs to record pressure deviation in both phases I and II and analyze the results based on all their recorded data. These sets of data will enable them to better

interpret the test results. For instance, if crew observes some pressure deviation in the first phase of performing NPT while there is no pressure built-up in the second phase, they can conclude that the main source of the observed pressure deviation in phase I was having part of spacer or heavier mud below the BOP stack. Therefore, there is no leaking in the annular preventer or flow from the well. This is because if either AP Leak or Well Leak was present, then crew would have observed some pressure built-up in the second phase as well.

In addition to pressure recording, another important criterion that can assist the crew in better interpretation of NPT results is the actual versus expected number of barrels of bled-off fluid from a well in the second phase of conducting the test. For instance, if crew realizes that the stated actual number of barrels is higher than what they expected to observe, this can be due to the presence of either of those three stated influencing factors, which were part of spacer or mud remained below the BOP stack, leaking in the annular preventer, and flow from the well. However, if there is no pressure built-up in the second phase of implementing NPT, then crew can conclude that the higher observed number of bled-off fluid was due to having part of spacer or heavier mud below the BOP stack during the displacement process.

We selected pressure deviation as the target variable for our proposed model rather than comparing the actual number of bled-off fluid with the expected amount since there is smaller measurement error associated with observing pressure from a gauge rather than tracking the number of barrels of bled-off fluid from a well through the trip-tank system. In addition, pressure reading and pressure recording is more commonly used as part of negative pressure test procedure for most oil companies.

We contacted several experts in the area of drilling and well-design to make sure that the structure and the selected variables in our proposed model are logical. All these experts kindly helped us in validating the structure of our model and among them, four contributed in quantifying the results. Some of these experts were retired drilling managers, drilling engineers as well as superintendents of major oil companies such as ExxonMobil and BP. In addition, there were well-known drilling and well-design professors among these experts.

The fourth and the last element in our proposed model, in Fig. 2, is a decision node to whether accept or reject the conducted negative pressure test by crew. For making such decision, the other three components of the model need to be quantified, and based on that quantification, a cut-off point value for pressure deviation has to be calculated and be used as a threshold. Such analysis and calculation enables crew to reject any negative pressure test with an observed pressure deviation higher than the determined cut-off point. This prevents next step investigations for interpreting the test results in the described situation, which provides some cost saving. Of course, crew needs to investigate and identify the contributing causes of an unsuccessful NPT, resolve those identified causes, and re-conduct the test.

On the other hand, if the observed pressure deviation is less than the determined cut-off point value but more than zero, crew still needs to conduct more investigations to evaluate whether the conducted NPT is successful. For this purpose, they have to open the well and watch for flow for several hours. For a successful negative pressure test, there has to be either no flow from the well or a decreasing flow rate which stops within the period of watch for flow. It is noteworthy that we ideally expect to see no flow from the well at this stage. However, there might be some flow due to phenomena such as thermal effect and compressibility of fluid, which both cause fluid expansion [17,18].

In addition, as explained before, taking into account the number of barrels of measured versus expected bled-off fluid from the well can be useful in better interpretation of the test. For instance, if the observed pressure deviation is less than the identified cut-off point while the measured number of barrels of bled-off fluid from the well exceeds the expected amount, this indicates an abnormal result for a negative pressure test. Therefore, crew needs to perform the aforementioned watch for flow process for final conclusion about the test results.

It is noteworthy that some of the existing procedures for NPT do not allow the entrance of spacer or seawater inside the annulus. (Refer to [12] and [16] for the details of a negative pressure test procedure.) In such case, the two stated influencing variables in our model are still valid as contributing causes of pressure deviation. However, the factor of remained spacer or mud below the BOP stack does not exist anymore and that cannot be a source of pressure deviation in phase I of conducting NPT, as we explained before. Nevertheless, there is another factor as an additional source of pressure deviation in phase I and that is pumping different amount of seawater inside the well during the displacement process. This is equivalent to existence of less or more amount of mud inside drill pipe, which causes pressure deviation from what crew expected to observe. Similar to the factor of having part of spacer or mud remained below the BOP stack, this factor only contributes to pressure deviation in the first phase of conducting a negative pressure test and it has no impact on phase II possible pressure built-up.

Furthermore, using a packer during NPT implementation is possible [12,16]. Using a packer rather than conducting a negative pressure test through the annular preventer on the BOP stack does not change the main variables of the discussed model in Fig. 2. The only change will be in having the first variable as leaking in the packer seal and not the annular preventer seal.

3. THE SIGNAL DETECTION MODEL FOR THE NEGATIVE PRESSURE TEST

3.1 Possible Scenarios and States of Model Variables

At this stage, we further discuss different possible scenarios for the variables in the proposed signal detection model and explain the process of calculating the cut-off values on the negative pressure differential that would lead to the conclusion that there is an unsafe condition. However, exact formulas and numbers for determining the cut-off point value will be described in the next sections.

As we explained, we have two influencing variables of leaking in the annular preventer (AP Leak) and flow from the well (Well Leak). Each of these two variables can have two states of yes (Y) and no (N) showing their presence. To be more specific, “AP Leak=Y” is equivalent to having leakage in the BOP annular preventer, and “Well Leak=Y” means that the well in which an NPT is conducted is flowing. The combination of yes and no for each of these two variables constructs four different states or scenarios as follows:

- 1) NN: There is neither any leaking in the annular preventer nor any flow from the well.
- 2) YN: There is leaking in the annular preventer but there is no flow from the well.
- 3) NY: There is no leaking in the annular preventer but there is flow from the well.
- 4) YY: There is both leaking in the annular preventer and flow from the well.

Any of the aforementioned states or scenarios affects the behavior of the target variable; pressure deviation, differently. For instance, there is a much higher chance of having pressure built-up in the well if the state “YY” is present comparing to the “NN” situation.

AP Leak and Well Leak as well as the target variable in the model are probabilistic. The first two variables in this model are discrete binary elements while the target variable is continuous. Therefore, we need to determine two discrete probability values of $P(APLeak = Y)$ and $P(WellLeak = Y)$ as well as four different probability distributions for the pressure deviation, as the target variable, for the four aforementioned states.

Finally, we have the decision node in the model to whether accept or reject the test based on the observed pressure deviation. In order to make the stated decision, there is a need for calculating the described cut-off point. For this purpose, the concept of decision processes in the signal detection theory has been used to choose a decision; accepting or rejecting the conducted test, with a higher Expected Value (EV). In this regard, we first describe some preliminary concepts of decision

processes in signal detection theory in section 3.2 and then in section 3.3, we explain our extensive equations and formulas for quantifying our proposed model using that theory.

3.2. Decision Processes in Signal Detection Theory

The signal detection theory is a computational framework to discern signal from noise, while taking into account other influencing factors such as biases within this distinction process. Fig. 5 illustrates the main components of the theory of decision processes in detection.

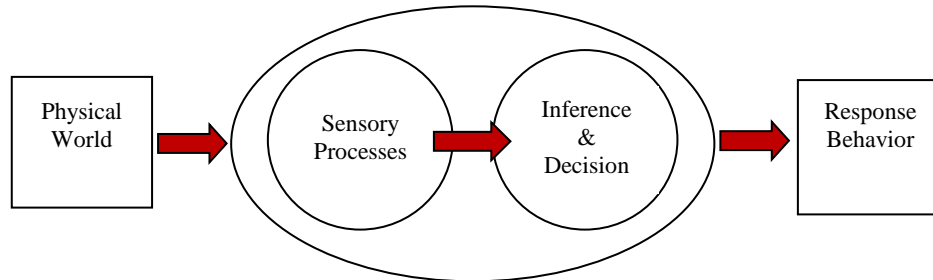


Fig. 5. Signal detection theory and decision processes [19]

Based on this theory, we can have “m” different states of the world; h_1, h_2, \dots, h_m , and “m” different judgments or response alternatives associated to each state; H_1, H_2, \dots, H_m . In this case, each state has a prior probability of $P(h_i)$; $i=0, 1, \dots, m$. In addition, there exists $P(H_j|h_i)$ as the probability of having H_j as the judgment or decision when the state of system is h_i [20].

There will be a pay-off value associated to the combination of each state and judgment; e.g. V_{ij} as the pay-off value for the judgment H_j while the state is h_i . The best judgment for the state h_i will be H_i with zero associated cost; $V_{ii}=0$.

Now, if we assume that there exist only two states and two judgments; $m=2$, there will be only four outcomes as illustrated in the matrix in Fig. 6. In this case, there will be four pay-off values each associated to one of the stated possible outcomes. These four values are:

- 1) V_{00} : value associated with a correct choice of H_0
- 2) V_{01} : value (cost) associated with an incorrect choice of H_1 (when, in fact, H_0 is the correct judgment)
- 3) V_{10} : value (cost) associated with an incorrect choice of H_0 (when, in fact, H_1 is the correct judgment)
- 4) V_{11} : value associated with a correct choice of H_1

Based upon availability of any new data or observation from a studied system, the value of prior probability for each state can be updated to what is known as posterior probability. In addition, decision makers can choose either H_0 or H_1 as their possible judgments.

		States of the World		
		h_0	h_1	
Decisions	H_0	$P(H_0 h_0)$	$P(H_0 h_1)$	$P(H_0)$
	H_1	$P(H_1 h_0)$	$P(H_1 h_1)$	$P(H_1)$
		$P(h_0)$	$P(h_1)$	

Fig. 6. Matrix representing possible outcomes for a binary decision

Based on a specific goal set by decisions makers, choosing either H_0 or H_1 can be more appropriate. If maximum expected value is the decision goal; which is what we have considered as the objective for our signal detection model, then the decision maker has to say H_0 if and only if the inequality (1) holds.

$$EV(H_0 | d) \geq EV(H_1 | d) \quad (1)$$

Where, $EV(H_i | d)$ is the expected value for saying or judging H_i after observing the value “d” from the system for our target variable.

Equation (1) can be simplified to:

$$P(h_0 | d) * V_{00} + P(h_1 | d) * V_{10} \geq P(h_0 | d) * V_{01} + P(h_1 | d) * V_{11} \quad (2)$$

Therefore:

$$P(h_0 | d) * [V_{00} - V_{01}] \geq P(h_1 | d) * [V_{11} - V_{10}] \Rightarrow \frac{P(h_0 | d)}{P(h_1 | d)} \geq \frac{V_{11} - V_{10}}{V_{00} - V_{01}} \quad (3)$$

Note: V_{01} is non-positive since it is the pay-off value associated with misinterpretation of the state “ h_0 ”. Therefore, the value of “ $V_{00} - V_{01}$ ” is non-negative, and diving both sides of the above inequality by that value does not change the direction of the inequality.

We know that $\Omega_1 = \frac{P(h_0 | d)}{P(h_1 | d)}$ is the posterior odd and it is equal to:

$$\Omega_1 = \frac{P(h_0 | d)}{P(h_1 | d)} = \frac{f(d | h_0)}{f(d | h_1)} * \frac{P(h_0)}{P(h_1)} = \beta * \Omega_0 \quad (4)$$

Where:

$f(d | h_i)$ is the conditional probability of the target variable being equal to “d” knowing that “ h_i ” is the state of system,

$\beta = \frac{f(d | h_0)}{f(d | h_1)}$ is the likelihood ratio, and

$\Omega_0 = \frac{P(h_0)}{P(h_1)}$ is the prior odd.

If we substitute equation (4) in the inequality (3), we will have:

$$\frac{f(d | h_0)}{f(d | h_1)} * \frac{P(h_0)}{P(h_1)} \geq \frac{V_{11} - V_{10}}{V_{00} - V_{01}} \Rightarrow \frac{f(d | h_0)}{f(d | h_1)} \geq \frac{(V_{11} - V_{10})}{(V_{00} - V_{01}) * \Omega_0} \Rightarrow \beta \geq \frac{(V_{11} - V_{10})}{(V_{00} - V_{01}) * \Omega_0} \quad (5)$$

Based on the inequality (5), we can calculate a cut-off point value for our target variable which holds in that inequality.

The introduced theory in this section is the foundation for deriving the required equations for our quantitative decision-making model. However, since our proposed model deals with four different states based on the combination of AP Leak and Well Leak, we need to extend the described process in this section in order to cover a four-state situation rather than 2 scenarios. This process has been described in the next section.

3.3. Generalization of the Parametric Signal Detection Model

In this section, we derive a generalized formula for our described model based on the stated theory and equations in section 3.2. As we explained before, there are four different scenarios in our signal detection model based on the combination of states for AP Leak and Well Leak. We name these four scenarios as follows:

- 1) h_0 : NN: There is neither any leaking in the annular preventer nor any flow from the well.
- 2) h_1 : YN: There is leaking in the annular preventer but there is no flow from the well.
- 3) h_2 : NY: There is no leaking in the annular preventer but there is flow from the well.
- 4) h_3 : YY: There is both leaking in the annular preventer and flow from the well.

Based on the general theory, there is a need for four judgments as well. However, we have considered only two judgments for our model since interpreting a conducted NPT can be defined as an acceptance or a rejection decision (H_0 : accept or say OK and H_1 : reject or say NOT OK). Based on this definition, there exist four states and two judgments in this model.

The derived formulas in the previous section describe a two-state, two-judgment situation. Therefore, we need to generalize those formulas for the scope of our model. As we explained in section 3.2, judgment H_0 is selected if and only if the expected value for that judgment based on the observed amount; “d”, for the target variable in the studied system is more than the expected value when H_1 is chosen. In our model, the target variable is the pressure deviation (Actual Pressure (AP)-Expected Pressure (EP)). Therefore, the value for “d” will be a pressure deviation observed from the installed gauge in the cement unit on the surface while conducting negative pressure test. Based on this explanation, there is a need to choose H_0 if and only if:

$$EV(H_0 | d) \geq EV(H_1 | d) \tag{6}$$

Since there are four states in our model, as described above, we can extend equation (6) as follows:

$$P(h_0 | d) * V_{00} + P(h_1 | d) * V_{10} + P(h_2 | d) * V_{20} + P(h_3 | d) * V_{30} \geq P(h_0 | d) * V_{01} + P(h_1 | d) * V_{11} + P(h_2 | d) * V_{21} + P(h_3 | d) * V_{31} \tag{7}$$

Fig. 7 shows the decision tree associated with the above decision-making process to either accept or reject a conducted negative pressure test based on the observed pressure deviation “d”.

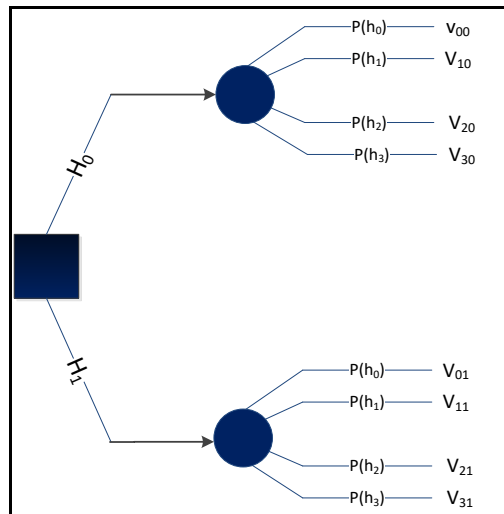


Fig. 7. A decision tree for accepting or rejecting a NPT

Also, we can define the prior and posterior odds and the likelihood ratio for each state “ h_i ”; $i=1,2,3$, by comparing that state with the normal state, which is “ h_0 ” or “NN” (no leaking in the annular preventer and no flow from the well). Based on this logic, we will have:

$$\Omega_{0i} = \frac{P(h_0 | d)}{P(h_i | d)} : \text{Posterior odd for the state “}h_i\text{” comparing to “}h_0\text{”} \quad (8)$$

$$\beta_{0i} = \frac{f(d | h_0)}{f(d | h_i)} : \text{Likelihood ratio for the state “}h_i\text{” comparing to “}h_0\text{”} \quad (9)$$

$$\Omega_{0i} = \frac{P(h_0)}{P(h_i)} : \text{Prior odd for the state “}h_i\text{” comparing to “}h_0\text{”} \quad (10)$$

According to the equation (4), we can extend the equation (8) into:

$$\Omega_{0i} = \frac{P(h_0 | d)}{P(h_i | d)} = \frac{f(d | h_0)}{f(d | h_i)} * \frac{P(h_0)}{P(h_i)} = \beta_{0i} * \Omega_{0i} \quad (11)$$

Therefore, the defined posterior odd for each state is the product of the likelihood ratio and the prior odd for that state comparing to the state “ h_0 ”.

Equivalently, equation (11) can be written down as follows:

$$P(h_i | d) = \frac{P(h_0 | d)}{\beta_{0i} * \Omega_{0i}} \quad (12)$$

If we substitute (12) in the inequality (7), we will have:

$$P(h_0 | d) * V_{00} + \frac{P(h_0 | d)}{\beta_{01} * \Omega_{01}} * V_{10} + \frac{P(h_0 | d)}{\beta_{02} * \Omega_{02}} * V_{20} + \frac{P(h_0 | d)}{\beta_{03} * \Omega_{03}} * V_{30} \geq \quad (13)$$

$$P(h_0 | d) * V_{01} + \frac{P(h_0 | d)}{\beta_{01} * \Omega_{01}} * V_{11} + \frac{P(h_0 | d)}{\beta_{02} * \Omega_{02}} * V_{21} + \frac{P(h_0 | d)}{\beta_{03} * \Omega_{03}} * V_{31}$$

By simplifying (13), we get the following:

$$\frac{(V_{10} - V_{11})}{\beta_{01} * \Omega_{01}} + \frac{(V_{20} - V_{21})}{\beta_{02} * \Omega_{02}} + \frac{(V_{30} - V_{31})}{\beta_{03} * \Omega_{03}} \geq (V_{01} - V_{00}) \Rightarrow \sum_{i=1}^3 \frac{(V_{i0} - V_{i1})}{\beta_{0i} * \Omega_{0i}} \geq (V_{01} - V_{00}) \quad (14)$$

Based on the derived inequality (14), we can determine a cut-off point value “ e ” for our target variable which holds in that inequality. In another word, we can calculate a threshold for the observed pressure deviation in the second phase of conducting a negative pressure test that for any pressure deviation more than that, crew ought to reject the test (say H_1).

In this specific case of conducting a negative pressure test, all associated pay-off values to each combination of states and judgments are costs with negative values. Therefore, we can substitute V_{ij} with C_{ij} ; as a positive value for cost and change the direction of the inequality (14):

$$\sum_{i=1}^3 \frac{(C_{i0} - C_{i1})}{\beta_{0i} * \Omega_{0i}} \leq (C_{01} - C_{00}) \quad (15)$$

For calculating the described cut-off point value using the above equation, there is a need for three main sets of data:

- 1) $P(h_i)$; prior probability of the state “ h_i ”; $i=0,1,2,3$
- 2) $f(x|h_i)$; conditional probability of the pressure deviation being equal to “ d ” knowing that the state of system is “ h_i ” (x =pressure deviation or “AP-EP”)
- 3) C_{ij} ; Cost of saying “ H_j ”; $j=0,1$, while the state of system is “ h_i ”; $i=0,1,2,3$

Upon availability of data for the three above-mentioned categories of probabilities and costs associated with different judgement-state cases, the needed values in equation (15) can be calculated. Based on that, the described cut-off point value can be determined; by entering all the data in Microsoft Excel and solving the stated equation using the “what-if analyses >- goal seek”. It is however noteworthy that the proposed signal detection model in this paper is a generic parametric framework that enables oil and gas drilling practitioners to calculate the discussed cut-off point value for their own specific case based on the characteristics of their operations. In addition, they can update their calculations upon availability of new information.

There are different sources for data gathering to quantify the described signal detection model in this paper. One of these sources is expert judgment elicitation. We have used this source of data collection, quantified the proposed model for a conducted negative pressure test, and calculated a cut-off point value based on the characteristics of a well similar to the Macondo in the DWH case. This case study analysis has been provided in another paper (the second paper in the sequence in this proceedings) due to the page limitation to include both the generic model development and the case study in one paper.

4. CONCLUSION

In this paper, a signal detection model was proposed in order to analyze and correctly interpret the results of a conducted negative pressure test, as a primary procedure to ascertain well integrity in offshore drilling. This model, which utilizes the signal detection theory as the foundation, provides a structure and generic parametric equations that enable oil and gas practitioners to calculate a cut-off point value, as a threshold for accepting or rejecting an implemented NPT, associated with their own specific situation. In addition, the cut-point value calculation can be updated upon availability of additional information or modification of previous collected data.

The described cut-point value is related to the target variable of our model, which is the pressure built-up in the second phase of implementing an NPT, when crew bleeds off enough fluid from the well to reduce the pressure to zero.

It is noteworthy that although the proposed model in this paper has been utilized for negative pressure test interpretation, it can be generalized and used in other decision-making applications in complex technological systems and industries.

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