Application of Bayesian Based Risk Analysis for Overcoming Current Limitations of Traditional Deep Blowout QRA

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1. INTRODUCTION

Offshore drilling is an activity inherent to the oil and gas industry as it is essential in confirming the economic feasibility of hydrocarbon reservoirs. However, risks related to uncertainties, i.e: lack of knowledge about risk influence factors (RIF) and, risks inherent to typical major accident hazards (MAH), are directly associated with this activity, where, in accordance with [1], blowouts are assumed to be one of the major contributors to such risk.

The risks inherent to drilling projects have to be assessed prior to and during the operations, as in any other hazardous industry. Risk assessment studies are part of the regulatory framework of many countries and are a critical document for the permitting process of drilling activities. For instance, the UK Health and Safety Executive (UK) [2], states that the primary objectives of risk assessment in this context are to identify and rank the risks so that they can be adequately managed and to examine associated risk reduction measures to determine those most suitable for implementation.

After the Macondo accident, the Oil Industry's concern about the quality of the risk assessment studies has increased. According to the National Commission on the BP Deepwater Horizon Oil Spill and Offshore Drilling [3], the Macondo blowout requires a reassessment of the risks associated with offshore drilling.

In addition, in some new frontiers, most exploratory blocks and potential reservoirs are located in deep waters and unknown environments. This requires specific wells to be designed and constructed under complex, hazard conditions and with higher degree of uncertainty, leading one to conclude that the risk of blowout in such conditions will also increase.

Nevertheless, it is an oil & gas industry practice to assess the risks of complex drilling projects based on the same traditional methods that are applied to common drilling projects, with low degree of complexity and uncertainty, i.e.: where wells have standard designs and are located in environments where geological and geophysical (G&G) information is readily available. For complex projects, this approach yields risk assessments that do not reflect the specificities of the project and, consequently, do not play their essential role of communicating the risk, in order to direct risk management efforts and risk-based decision making during the project's life cycle.

Most specifically, the limitations identified in standard risk assessment studies for blowout during offshore drilling are related with the generalization of the risk model. This generalization is related with the adoption of generic fault tree and event tree models and with the direct adoption of data gathered from failure and accident data banks. This approach may be suitable for projects with standard well designs, usual topside systems and areas with geological and geophysical (G&G) information quite available.

This paper presents the causes of such presumptions and proposes a Bayesian based risk analysis framework capable of reflecting the specifics of the project. The proposed method was developed considering: (i) concepts of drilling engineering, more specifically those related to the causes of deep blowouts; (ii) review of blowout accident precursors and risk influence factors (RIF), including human and organizational factors (HOF); (iii) review of state of the art risk assessment techniques applied in the hydrocarbon industry; (iv) application of methods for incorporating expert judgment and new observations in quantitative risk analysis; and (v) application of Bayesian Network in risk assessment. The application of Bayesian Network to model the risk allows to address some specificities inherent to blowout phenomenon that are not properly captured by usual methods, i.e: dependability, uncertainty and dynamism.

Drilling engineering, causes of blowout and traditional quantitative risk analysis methods (fault tree and event tree) are not addressed in this paper.

2. OBJECTIVES

The objective of this paper is to present the main problems found in current deep blowout quantitative risk analysis and present the potential advantages of modeling such risk in Bayesian Network. The specific objectives are to:

- Present the main problems inherent to traditional deep blowout quantitative risk analyses and their impact on the quality of these studies;
- Identify potential solutions to address these problems and outline a proposed Bayesian based method for blowout risk analysis;
- Illustrate with a micro scale example the basis of an Bayesian based method to assess blowout risks during drilling operations;

3. LIMITATIONS OF CURRENT DEEP BLOWOUT QRA

The challenge in modeling a blowout hazard is to conduct an analysis which reflects the actual equipment and procedures that are used. The models that are often utilized are generic, unable to distinguish between different platforms, systems and operators [4]. In addition, as it will be presented, the models used for quantification are not suitable to deal with significant levels of uncertainty and changes which are inherent to some drilling projects. This combination leads to generic risk analyses that, in most cases, fail to reflect the specifics of the project.

The findings presented throughout this section result from a review of works developed by several authors, mainly Refs ([3]-[10]) and are in line with author's own professional experience, which includes revision of blowout QRAs, mainly for the purpose of planning and executing risk based audits for drilling projects.

The **Table 1** presented next summarizes the aspects that affect the quality of the blowout QRAs and, for each of them, addresses improvement suggestions, which were taken into consideration to develop the proposed Bayesian network framework for blowout risk analysis.

Table 1: Summary of the main aspects that affect quality of deep blowout QRA and proposed solutions.

#	Aspects of Blowout QRA	Problems	Proposed Solutions
1	Failure to consider customized Risk Influence Factors (RIF) into the QRA mainly the ones related to Human and Organizational Factors (HOF).	Operation's specific RIF are not taken into consideration.	Risk model must consider specifics of: well design, equipment/ systems, procedures and location.
		HOF are not incorporated.	Include human barrier elements and relevant barrier indicators in the model;
2	Uncertainty is not considered as a component of the risk.	Blowout accident data banks and equipment failure data banks are extensively used as basis for estimating the blowout frequency;	Address uncertainty inherent to this system by integrating expert judgment into Bayesian Network (BT);
		Adoption of a safety factor when uncertainty is recognized as a risk factor.	
3	Failure to address: redundant failures, common cause failures; or mutually exclusive primary events.	Fault Tree / Event Tree	Model blowout fault/ event trees into Bayesian Network (BT).
4	Blowout QRAs are static, i.e: the risk is not updated according to new evidence.	Blowout models do not treat dynamics and changes in operational parameters.	Design and implement a risk-based monitoring program for risk updating, integrated with the Bayesian Network Model.

a. Risk Influencing Factors (RIF) and Human and Organizational Factors(HOF)

There have been parallel efforts to develop methods for the formal inclusion of human and organizational factors into QRA. Examples from nuclear and airline industries include Model of Accident Causation using Hierarchical Influence Network (MACHINE), the Work Process Analysis Model (WPAM), System-Action-Management (SAM), Omega Factor Model, I-RISK, Integrated Safety Model (ISM) and Causal Modeling of Air Safety. With respect to the QRA in the offshore industry, Organizational Risk Influence Model (ORIM), Barrier and Operational Risk Analysis (BORA) and Operational Conditional Safety (OTC) are relevant [3].

Also, some research on incorporation of HOF into Offshore QRA was developed by (OGP, 2010) "Human Factors in QRA" [11]. However, not much has been evidenced to specifically incorporate HOF into deep blowout QRA.

From all these methods, the BORA and OTC were developed with a focus on the oil and gas industry. More specifically, BORA-Release analyzes the effect of safety barriers introduced to prevent hydrocarbon releases, and how platform specific conditions of technical, human, operational, and organizational risk influencing factors influence the barrier performance. The method allows analysis of the effect on the hydrocarbon release frequency of safety barriers introduced to prevent release, and at what degree platforms' specific conditions of technical, human, operational, and organizational RIFs influence the barrier performance [12].

BORA-Release comprises of the following main steps: (1) development of a basic risk model including release scenarios, (2) modeling the performance of safety barriers, (3) assignment of industry average probabilities/frequencies and risk quantification based on these probabilities/frequencies, (4) development of risk influence diagrams, (5) scoring of risk influencing factors, (6) weighting of risk influencing factors, (7) adjustment of industry average probabilities/frequencies, and (8) recalculation of the risk in order to determine the platform specific risk related to hydrocarbon release. These various steps in BORA-Release are presented and discussed in specific bibliography (Ref [12] – [14]).

Other relevant work that suggests similar steps as the ones presented by BORA was developed by SINTEF (2012) [15]. The main steps of the method are: (1) Identify possible critical events that may lead to environmental releases, (2) Select critical scenario and identify initiating events, (3) Establish a simplified event tree to identify likely event sequences and the associated barrier functions, (4) Perform an analysis of the relevant barrier functions to identify weaknesses and an estimation of reliability, (5) Assess relative performance of the barrier functions by performing an event tree analysis, and (6) Propose barrier indicators based on findings from the above, i.e: risk influence factors.

It should be noted that a barrier function is any function planned to prevent, control, or mitigate undesired events or accidents. Barrier functions describe the purpose of safety barriers or what the safety barriers shall do in order to prevent, control, or mitigate undesired events or accidents, for example: "close flow" and "stop engine". A function that has at most an indirect effect is not classified as a barrier function, but as a Risk Influencing Factor/Function [16].

Therefore, both methods are based on accident precursors and present an effective process for identifying barriers, barriers functions and RIF (including HOF) that should be considered in a QRA. The transparent processes allow the possibility of performing statistical adjustments of these variables based on expert opinions. Thus, the application of these methods in blowout QRA is suitable for addressing the problem related to the incorporation of relevant technical RIF and HOF in QRA. This is the first solution required in order to implement the second and final step of this research paper which is to test the application of advanced statistical methods, i.e: Bayesian Networks.

Presented next are the problems directly related to the statistical and mathematical framework usually adopted in blowout QRA studies, which are in items 2, 3 and 4 of **Table 1**.

b. Traditional Statistical Approaches and Mathematic Framework to Estimate Accidental Frequencies

This subsection will discuss the negative impacts caused by the extensive application of traditional statistical methods in the quality of the blowout QRAs. For the purpose of this paper, traditional statistical methods are characterized by: (i) probability estimations that are limited to the consultation of historical data banks (accidental frequencies data banks and/or equipment failure data banks); and (ii) the probability 'P' of an accidental event 'A' is modeled based on a set of event trees (ET) and fault trees (FT).

Accident probability estimation is a common and central step to all quantitative risk assessment methods and with Blowout QRA it is not different. However, the current blowout QRAs are developed based on blowout accidental frequency data banks that are generally normalized for the unit "per well drilled or per operation" and separated by operation and category (as presented in
Table **2**), which summarizes the approach presented by the Blowout Frequencies Report 434 (OGP, 2010) [17].

Table 2: Example of the presentation of blowout frequency data bank, developed based on [17].

Operations	Categories
• Exploration drilling shallow gas; • Development drilling shallow gas; • Exploration drilling , deep (normal wells); • Exploration drilling , deep (HPHT wells); • Development drilling , deep (normal wells); • Development drilling , deep (HPHT wells); • Completion; • Wirelining; • Coiled Tubing; • Snubbing; • Workover; • Producing wells; • Gas injection wells; • Water injection wells;	• Top side blowout; • Diverted well release; • Well release; • Subsea blowout;

Therefore, the blowout frequency is traditionally defined based on the combination of the specific operation and different potential categories that the analysis intends to cover. These statistics can also be adjusted based on elements that can contribute the blowout, as suggested by the BlowFAM initiative [18] which suggests an evaluation of top side equipment, procedures safety culture, management system and organization. This step of adjustment is performed through a comparison of specific sites aspects against a standard operation relevant for generic blowout frequency.

In an even more traditional assessment approach, reliability data are directly applied and not always adjusted for any differences between the basis of the kick frequency (i.e. well operation practices, management, etc.) and site specific conditions.

As highlighted by [15], historical data banks and reports are investigated to identify information about reliability performance. Since historic data are seldom broken down to a sufficient detailed component level, it is not possible to suggest that the reliability estimates are more than "rough estimates", averaged over a number of possible demand conditions. Normally, reports and historical data do not provide information that can be used to adjust barrier performance to the specific scenario in question.

The blowout RIF (or elements that can impact the risk of a blowout) may have a significant degree of uncertainty, mainly during the design phase of an exploration campaign. Some examples of potential blowout RIF with a significant degree of uncertainty are: pore pressure gradient, fracture pressure gradient, kick detection time, reservoir pressure, mud weight, available kick tolerance and volume of drilling fluid into the well.

Therefore, fault tree (FT) and event trees (ET) may be sufficient in some cases but it is not suitable for analyzing complex and dynamic socio-technical systems that present one or more of the following characteristics: necessity for probability updating, redundant failures, common cause failures; or mutually exclusive primary events [7].

The following characteristics usually available in drilling projects, mainly exploratory projects, suggest that the traditional statistical approach is not suitable for calculating blowout occurrence probability: (a) no statistical meaningful data are available, (b) in some cases, a complete new system is to be designed (in this specific case: a well), (c) involves high reliability systems where few failure data are available, (d) its dynamics, for example: changes in control/ inspection parameters as well as in G&G information.

Terje Aven & Bjørnar Heide [5] for instance, investigated to what extent risk analysis meets scientific quality requirements of reliability and validity by comparing traditional statistical methods, strongly dependent on historical data banks and Bayesian approaches, concluding that traditional statistical methods meet the reliability and validity criteria only if a large amount of relevant data is available.

Also, more specifically, as stated by [19], the dynamic nature of blowout accidents, resulting from both rapidly changing physical parameters and time-dependent failure of barriers, necessitates techniques capable of considering time dependencies and changes during the lifetime of a well. The combination of having an uncertain scenario in the design phase, together with the acquisition of great amount of new information during the operational phase, which is also very dynamic (changes often occur), generates an appropriate situation for a Bayesian approach. Therefore, the Bayesian network method provides greater value than the bow-tie model (based on fault tree and event tree) since it can consider common cause failures and conditional dependencies along with performing probability updating and sequential learning using accident precursors.

4. APPLICATION OF BAYESIAN NETWORK ON DEEP BLOWOUT RISK ANALYSIS

Bayesian network (BN) takes advantage of Bayes' theorem to update the prior probabilities of variables given new observations, called evidence 'E', rendering the updated or posterior probabilities [19].

The Bayesian network (BN) is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). The Bayesian Network (BN) relies on the Bayes' theorem.

Bayes' theorem expresses the conditional probability, or 'posterior probability', of an event A after B is observed in terms of the 'prior probability' of A, prior probability of B, and the conditional probability of B given A, denoted as B | A. Bayes' theorem is valid in all common interpretations of probability [20].

Bayes' theorem provides an expression for the conditional probability of A given B, which is equal to:

$$\boldsymbol{P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}} \quad \textbf{(1)}$$

Where:

- P(A) and P(B) are the probabilities of A and B independent of each other.
- P(A|B), a conditional probability, is the probability of A given that B is true.
- P(B|A), is the probability of B given that A is true.

In Bayesian Network, the usual way of representing such influences is by a diagram of nodes and arrows, connecting influencing variables (parent variables) to influenced variables (child variables) [21].

The model below illustrates the influences between variables.

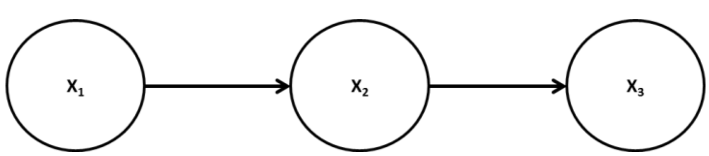

Figure 1: Representation of influences between variables.

The graph structure in Figure 1 can be represented by Equation 2 presented below.

$$P(X_1, X_2, X_3) = P(X_1)\, P(X_2|X_1)\, P(X_3|X_2) \quad (2)$$

Which can be re-written in the following form [21]:

$$P(X_1, X_2, X_3) = P(X_1|\text{parents}(X_1))P(X_2|\text{parents}(X_2))P(X_3|\text{parents}(X_3)) \quad (3)$$

Therefore, for "n" random variables X1, X2, …, Xn, a direct acyclic graph is associated with the Xj variable. Then, the graph is a Bayesian network, representing the variables X1, X2, …, Xn, if:

$$\boldsymbol{P}(\mathbf{X1}, \mathbf{X2}, \dots, \mathbf{Xn}) = \prod_{j=1}^{n} \boldsymbol{P}(\boldsymbol{X}_j\, |\boldsymbol{parents}(\boldsymbol{X}_j)) \quad (4)$$

Where: parents (Xj) denotes the set of all variables Xi, such that there is an arc from node I to node j in a traditional acyclic graph [21].

Therefore, a stochastic matrix can be developed by defining the proper level of dependability between the variables of the blowout risk model, including: direct and probabilistic cause and effect relationship between safety barriers and barriers functions and systems as well as impact of risk influencing factors (RIF) in the system.

4.1 Development of Bayesian Network for Analyzing Risk of Deep Blowout – A Micro Scale Example

The figure below presents the flowchart with the main steps that are required to develop a Bayesian Based risk model capable of overcoming the current limitations of the deep blowout risk analysis already mentioned in previews sections.

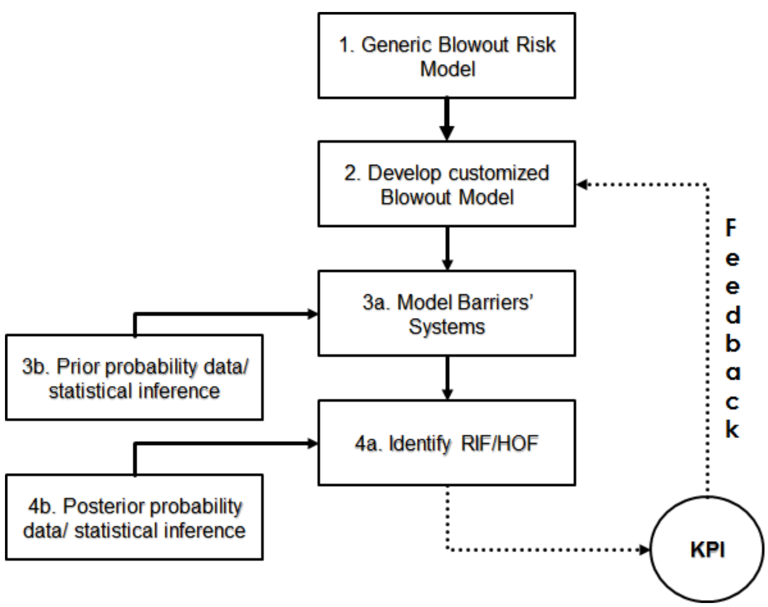

Figure 2: Flowchart presenting the milestones and method of the research.

The specific blowout risk model (customized model) is modeled based on a generic blowout risk model, represented by Item 1 presented at **Figure 2**. In this model, the kick is the top event of the blowout and its basic cause the loos of primary barrier (hydrostatic pressure) assuming that proper G&G conditions are available, i.e: permeability and pressure in reservoir.

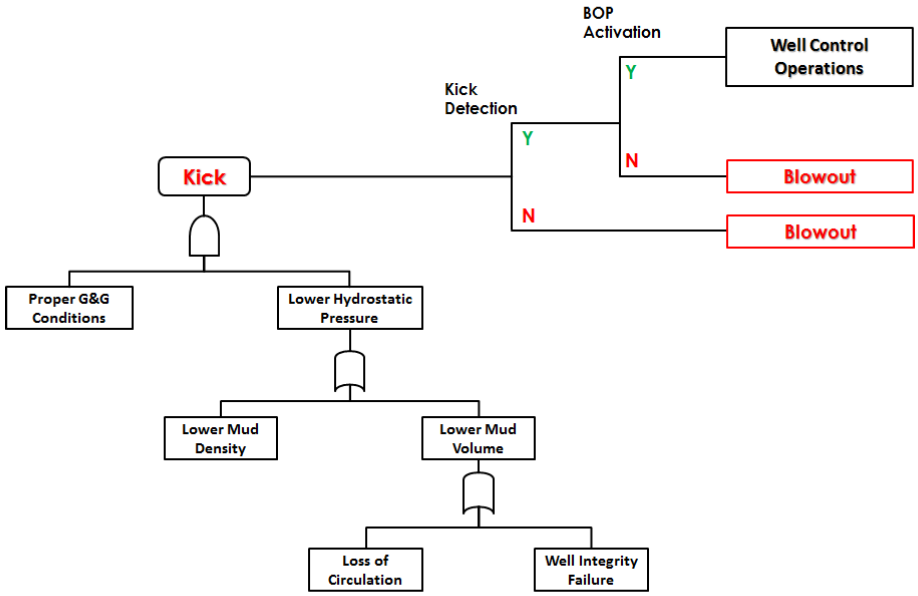

Figure 3: Generic blowout bow-tie model.

The blowout model is developed translated into DAG using Bayesian Network (BN) software as demonstrated by **Figure 4**.

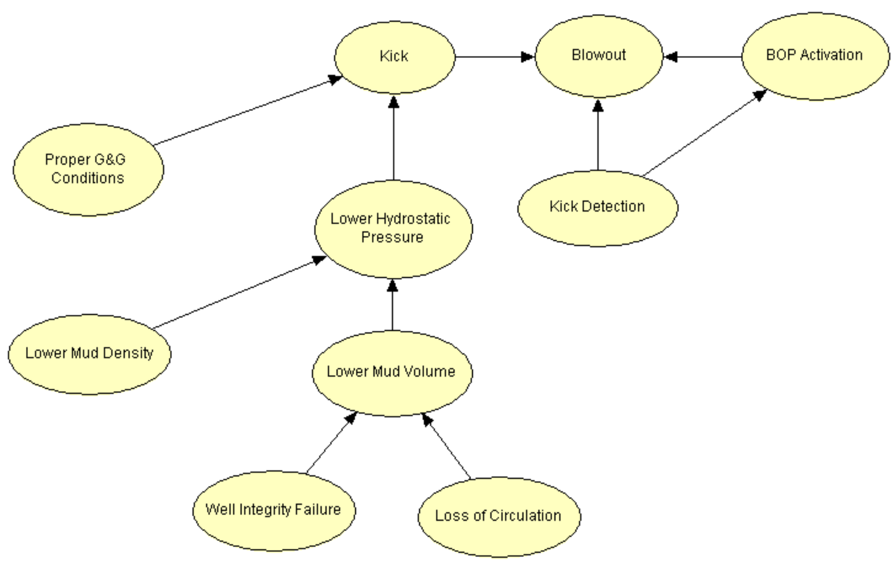

Figure 4: Generic blowout BN model.

Once the generic model is defined a detailed assessment on the performance of safety barriers can be performed based on is systems and RIF. The performance of the barriers' functions is assessed by evaluating their failure probabilities in a BN framework in order to capture potential dependability. This assessment must be performed based on the specific risk influence factors (RIF) of the installation, organization and well design. Another advantage of performing this step in a BN framework is the possibility of incorporating expert judgment in the analysis.

This assessment also allows the identification of safety indicators associated with the performance of the safety barriers. The term indicator can be used in various contexts, for example performance indicators, safety indicators, safety performance indicators, direct performance indicators, indirect programmatic performance indicators and risk indicators [22]. In this work the definition will be of safety indicator or simply KPI.

Systematic feedback on blowout risk is an important means of prevention. Safety management of industrial systems like deep water drilling therefore requires monitoring of safety performance, including the use of safety indicators. The main purposes of safety indicators are to monitor the level of safety in a system, to motivate action, and to provide necessary information for decision makers about where and how to [10]. This feedback process also allows the risk to be updated during the operational phase where new evidence can be considered.

The **Figure 5** presents a micro scale example of hypothetical detailed assessment of the safety barrier kick detection which function is to detect the well flow before it reaches the blowout preventer (BOP). The barrier system related with the performance of this barrier function is presented in form of block diagram and, one level below, the risk influencing factors that may affect the performance of the system. The **Figure 6** presented in sequence presents its mapping into BN.

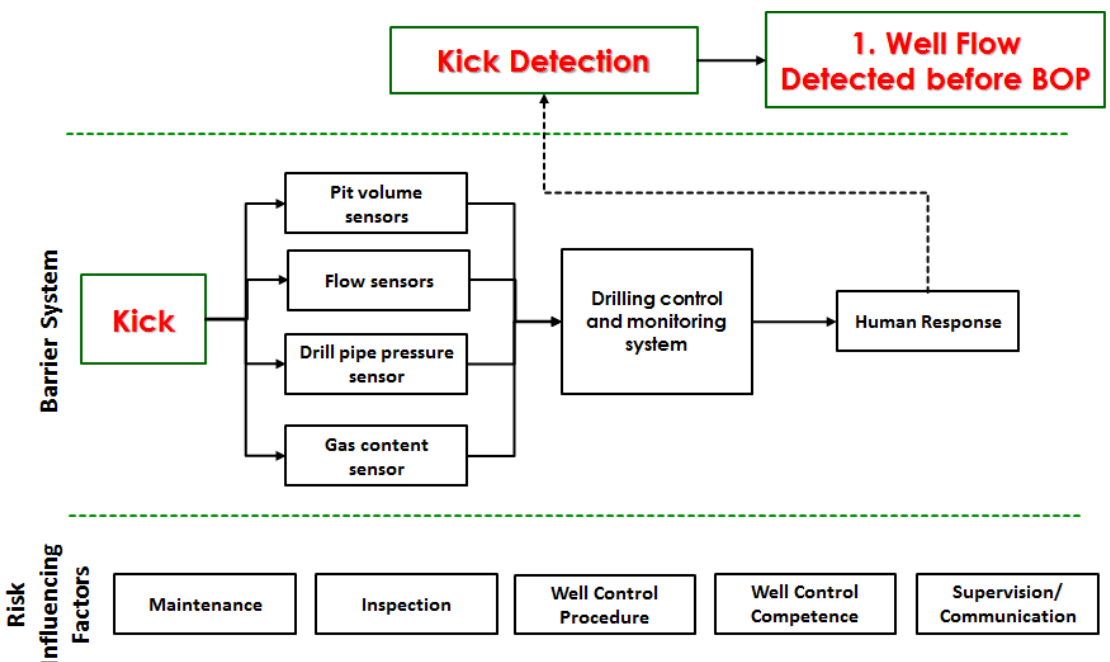

Figure 5: Safety barrier performance assessment (kick detection) in block diagram.

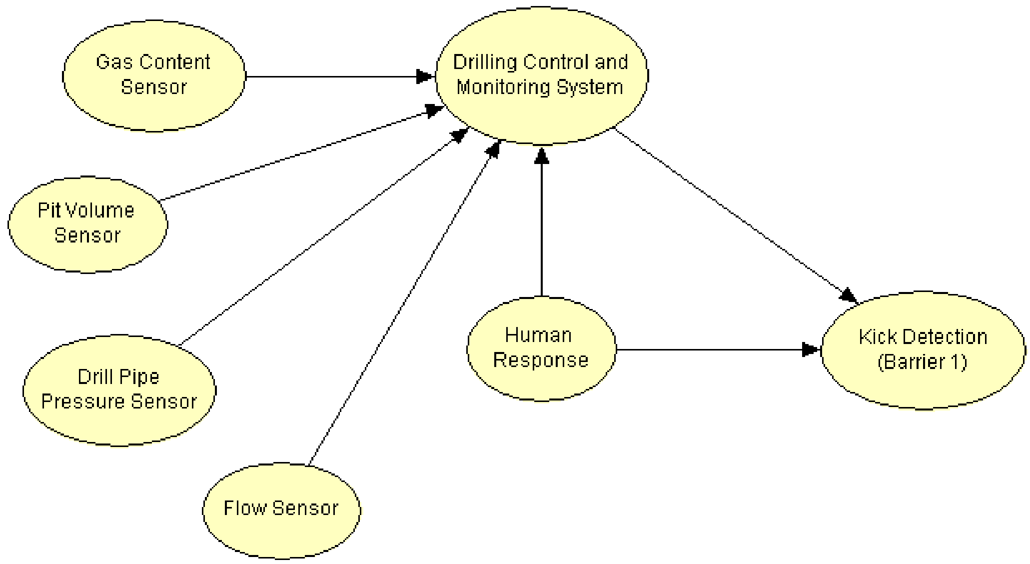

Figure 6: Safety barrier performance assessment (kick detection) in BN.

After modelling the system in BN is necessary to identify the risk influencing factors and KPI that will allow the effective customization of the model for the current operational reality of each rig as well as incorporation of human and organizational factors. The table below provides examples of RIF and KPI that are applicable to the barrier elements of the selected barrier system.

Table 3: Risk influencing factors and KPIs.

RIF	KPI or direct observation of evidences	KPI - States of the variable (measurement)
Maintenance of drilling instrumentation	Preventive maintenance system	% Accomplishment against manufacturer standards.
Inspection/ testing of drilling instrumentation	Monitor recent/ current failures in elements of the system (sensors)	Evidence (Failed / Operational)
Adequacy of well control procedure	Audit on the adequacy of the procedure to rig systems and knowledge of operators (expert judgment)	Audit result: Poor, Medium or Good.
Well control competence	Audit on compliance with Well Control Competence by current crew.	% Accomplishment
Kick drills performance	Record of drills	% of satisfactory results given company's policy.
Supervision/ Communication	Compartmental audit based on stress level caused for management pressure or multiple operations including workers fatigue.	Audit result: Poor, Medium or Good.

The update of the KPIs allows the prior probabilities to be initially adjusted in order to reflect the rig specifics and, during the operation, its update allows the implementation of a dynamic risk management system, i.e: updated over time in function of new evidences.

It was create a simple Bayesian network that allows determining the numerical implications of the expert's opinion on the operator's expectation of the reliability of the BOP. The expert's opinion will be based upon evidences of the effectiveness of the preventive maintenance routine of the BOP and will be divided into three variables: poor practice, normal and good.

Table 4: Encoded experts' judgment for success/ failure of BOP based upon evidences of preventive maintenance effectiveness.

Implementation of Maintenance Practices	**Success in Activation**	**Failure in Activation**
Good	0.5	0.1
Moderate	0.4	0.3
Poor	0.1	0.6

The **Table 4** encodes the conditional probabilities of different expert forecasts for all possible actual situations of the maintenance practices. The first column encodes our knowledge that if the maintenance is being well implemented the BOP is more likely to be activate. The expert will designate it as Good with chance 0.5 (50%), as Moderate with chance 0.4 (40%) and as Poor with a chance 0.1 (10%). Similarly, the second column encodes our knowledge that the expert will designate an eventually failing as Good, Moderate, and Poor 10%, 30%, and 60% of the time it is requested the activation. The figure below shows the BN for the proposed model correlating the prior probability (BOP Failure) with the conditional table (experts forecast).

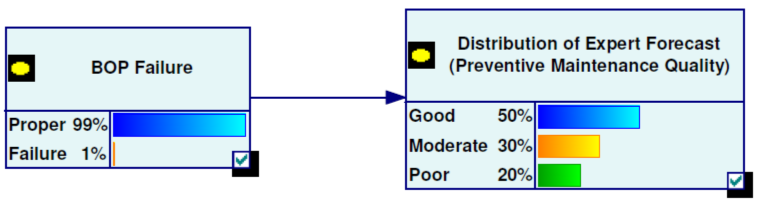

Figure 7: BN diagram for probability distribution over statements made by the expert.

Finally, both the structure and the numerical probabilities can be a combination of expert judgment, measurements and failure frequency data. To model this relationship it is required to set the variable maintenance evidences in their different states (poor, moderate and good) and define a prior failure probability for the BOP which was calculated based on MTTF data (Ref [24]; [25]) which equals to $\mathbf{8.26 \times 10^{-3}}$.

Now it is possible to answer the question "What is the failure probability of the BOP if we have evidence that good/ regular or poor preventive maintenance practices are being implemented? The answers are given in **Figure 8**.

Figure 8: Differed failure rates/ reliability for the three states of the variable maintenance effectiveness.

The integration of RIF and experts' judgment in the BN framework can be used to assess the different barrier functions of the blowout model as well as to monitor impact of changes of operational parameters in the blowout risk model. The approach will be the same. However, special attention must be given for the method of eliciting expert's judgment into probability. It is important to highlight that the assessment presented by this section was an example on how to integrate experts' belief into a BN model and not on the elicitation process.

A formal methodology, as presented by Walls [26], shall be adopted for building prior distributions based upon expert judgment. Such a methodology provides a basis for formally combining the observed failure times that are regarded as realizations of the underlying stochastic model of reliability growth (in our specific case blowout accident precursors), with expert judgment, that is represented by a prior distribution reflecting the subjective engineering uncertainty about the parameters of the growth process [26].

As stated by [27], in the field of human reliability, human errors are seldom collected and registered in any error data bases. So in various fields like nuclear energy, process industry, offshore oil/ gas industry and aerospace the reliability/risk analysts often have to utilize expert judgment as input to quantitative analysis.

5. CONCLUSIONS AND FINAL COMMENTS

Most of deep blowout QRAs are unreliable once they: (i) do not reflect appropriately the RIF of the project; (ii) do not incorporate uncertainty factors; (iii) are static and not updated on the risk when new evidence become available; and (iv) fails in addressing redundant failures, common cause failures, or mutually exclusive primary events. This paper aimed to propose a Bayesian accident precursor-based risk analysis approach to address all these problems.

The main purpose of this method is to reflect the specific risk of a drilling project, considering its specifics, uncertainty and eventual changes over time during the operational phase. More specifically, the method aims to achieve the following objectives:

- Assure that blowout modeling reflects the specific risk influence factors (RIF) of a drilling project;
- Incorporates human and organizational factors (HOF) as RIF; and
- Move from a traditional statistical approach to a Bayesian Network (BN) in order to address uncertainty and dependability;
- Establish key performance indicators (KPI) to allow risk updates due to new observations / evidence;

This paper presented the major steps to develop an accident precursor Bayesian based risk model for analyzing risk of deep blowout. A micro scale example focused in kick detection and BOP activation was presented in order to better illustrate its applicability. However, improvements and further efforts are required in order to implement this model in a real scale drilling project:

- Customize all basic causes of the generic blowout model to a real project's scale once this work was limited to customize only the kick detection;
- Develop the conditional probability tables including understand specific situations of common cause failures;
- Understand the applicability and limitations of incorporating expert judgment into the model to quantify the RIF mainly the ones related with HOF;

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