Development of a Risk Based Methodology to Consider Influence of Human Failure in Industrial Plants Operation

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Abstract: Human Failures are one of the most unexplored causes in industrial accidents. Since there is still lack of heeds to qualify as well as quantify Human Errors, in this paper the authors attempt to highlight the importance of paying attention to qualitative methods in implementing quantitative risk analyses mainly in the framework of estimating more accurate Human Error Probability (HEP). A key point in evaluating such a risk is considering non-linear socio-technical interaction in system to develop causal network for the accident scenario. An application of qualitative and quantitative Bayesian Network (BN) is therefore presented. The study shows that human performance has the most changes in the light of evidences. The developed methodology applied to a case study of an operation in field of Oil and Gas.

Keywords: Human Error Probability, Risk Assessment, Bayesian Network

1. Introduction

As it has been dramatically demonstrated in many cases, injuries and dangerous occurrences arising from lifting operations account for a significant proportion of the total of those occurring offshore. Many regulators found that it would be beneficial to look at the worldwide picture to review national initiatives and to share best practice in order to improve their effectiveness in regulating these risks; see for example (CAPP, 2013; DNV, 2014; HSE, 2007; OGP, 2006).

Human factors play a pivotal role in process industry. There is no specified, valid and determined on the statistical distribution of the causes to industries accidents owing to the different sort of accident analysis. However, the main group of causes are identified as human errors, technical and mechanical failures (Celik & Cebi, 2009; Akhtar & Utne, 2014).

Recently, BN is used exclusively in a wide range of studies including medical, engineering, economics, business, etc., however implementing HEP in terms of modern-stage probabilistic studies still is not considered as it deserves. Expressing HEP in connection with probabilistic network such as BN will lead up to work out cause and effect interaction between each sub-activities of human performance in more details. Almost all previous methods are based on mutually exclusive assumption without any attention being taken into account on the part of human interactions with technical and organization issues quantitatively. Although, FRAM is supposed to find out these reciprocal interactions qualitatively and consider the flexibility of system to overcome failure conditions based on resilient engineering, still it is derived from a suitable quantitative part to give a reasonable number to each resonance scenarios. BN itself is quantitative and qualitative based probabilistic method with introducing acyclic directed graph for the whole system. Probabilistic network graph obliges risk assessor to couple BN and FRAM. It means Directed Acyclic Graph (DAG) could be constructed by using FRAM qualitative analysis which itself introducing resonance on system.

The objective of this paper is to present a methodology for developing HRA and risk analysis, using qualitative to quantitative risk-based approach for modelling the risk of an operation in oil and gas operation in marine. The methodology applied in this study is described in section 2 and illustrated concisely in Figure 1. A short overview on the case study is given in section 3. Section 4 is devoted to conducting FRAM network while applying methodology to estimate HEP is presented in section 5. Finally, in section 6 the conclusion is presented.

2. Risk-based approach

As illustrated in Fig. 1, we developed an epistemic-based investigation approach to assess the risk of studied operations, including qualitative and quantitative risk assessments, each of which consists of several steps. Qualitative and quantitative risk assessments are presented, respectively, by applying an FRAM and BN. FRAM is applied to analysis human error interacting with different parts of system as well as providing resonance on network to work out an accident scenario qualitatively. Finally, as a beneficial point of executing BN, in the light of new evidence, the influence of variables on each other are investigated.

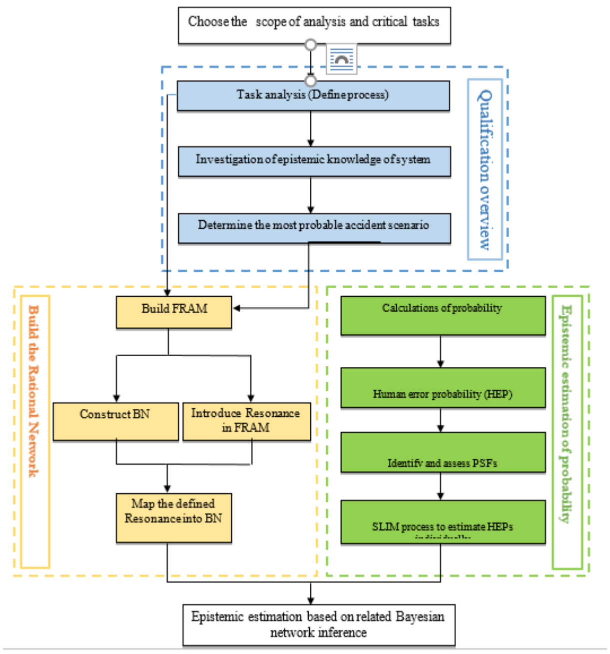

Fig.1. Risk based methodology of present study

3. Application of methodology: Case study

To implement the proposed methodology for making an epistemic estimate of risks in connection with offshore operations and considering human error, we carried out a thorough task analysis of a light-weight lifting operation in the South Pars oil and gas field in the Persian Gulf of Iran. To summarize the related activities, a quick description for each sub-activity is given below.

i. Vessel is positioned in correct coordinate,

ii. Ultra short base line system (USBL) is used for positioning under the water and under water gyro system will be used for object orientation.

iii. Beacons and under water gyro transfers the transitional position of the object to the survey room on board.

iv. Lifting equipment consisting of sling, belt, spreader bar, is ready for lifting support.

v. Carne ready for lifting.

vi. Object lowered down by crane up to 1 m above seabed and checking its orientation by survey team and remote operating vehicle (ROV),

vii. ROV supervisor checks the operation by monitor and takes fix point to validate the position of support installation on seabed and releasing the object on seabed.

4. Functional Resonance Analysis Method (FRAM)

FRAM (Hollnagel, 2004) characterizes socio-technical systems by the functions they perform. Boundaries of systems are thus defined through a description of functions, in accordance with the principles of joint cognitive systems (Hollnagel et al., 2005). It is a risk model reviewing non-linear interactions and it reviews everyday activities when things are working as they should. By describing operations when they are functioning, you can find out how and why something goes wrong in the system. The Functional Resonance Accident Method is one of the new methods focusing on the relations between different functions in the system, and by mapping these, describing outcomes using the idea of resonance arising from the variabilities of normal performance. (Herrera, 2012)

The FRAM network of studied operation is presented in Figure 2. This network is a basis for quantitative analysis of HEP estimation. In the FRAM network of present case study functions with green color are background function which provide a support for foreground function. The functions with blue color are foreground function. Foreground function directly can lead to a failure in lifting process. As it is obvious from FRAM network the process has 14 functions, 7 background and 7 foreground. The functions are coupled with each other via their common aspects. There are some functions with barrier goal such as quality control, winch control and connecting wire/belts and inspection of connection. Lack of functional barriers make some functions of the operation such as under water gyro/beacon, USBL system, lifting support by crane, vulnerable against unpredictable variabilities. It should be noted that since all operation are assumed to be performed at same time, it is not possible to consider the variability and resonance of all functions in an entire accident scenario. Hence, the HEP estimation is conducted for an operation as a specific resonance in the FRAM network. This resonance is based on variabilities of the functions (it is specified by numbers). The resonance is a detectable signal that emerges from the unintended interaction of the variabilities of many functions that together may combine in unexpected ways, leading to consequence that are disproportionally large (Herrera et al., 2010). According to epistemic knowledge gained from accident reports, related research, and expert opinions, the most probable accident scenarios are illustrated in Fig. 2 (by numbers upper the functions from 1 up to 4 and red surrounded color) in which human error may lead to the failure to check the connection between the belt and trunnion. This situation may result in the weight of the support structure not being in accordance with the Safe Working Load (SWL) of the derrick. The inadequate connection of slings may cause breakages in the process of lowering the support. Regardless of the nature of the break, the slamming of the load is a plausible outcome, especially near the surface. Consequently, disconnection of the load and derrick may occur. The Network in Fig. 2 illustrates these potential accident scenarios as a functional resonance in FRAM.

5. Applied methodology for HEP estimation

Human error consideration as a part of risk analysis is inevitable if one wants accuracy to be achieved in the process of risk assessment. In present paper a developed methodology is proposed for HEP estimation. In order to implement the idea of developing HEP a novel methodology presented in 4 parts: 1) Converting FRAM networks into BN, 2) Including provided resonance of FRAM into BN, 3) Computing HEP in each function, 4) Compile BN based on HEP, evidence and max-propagation.

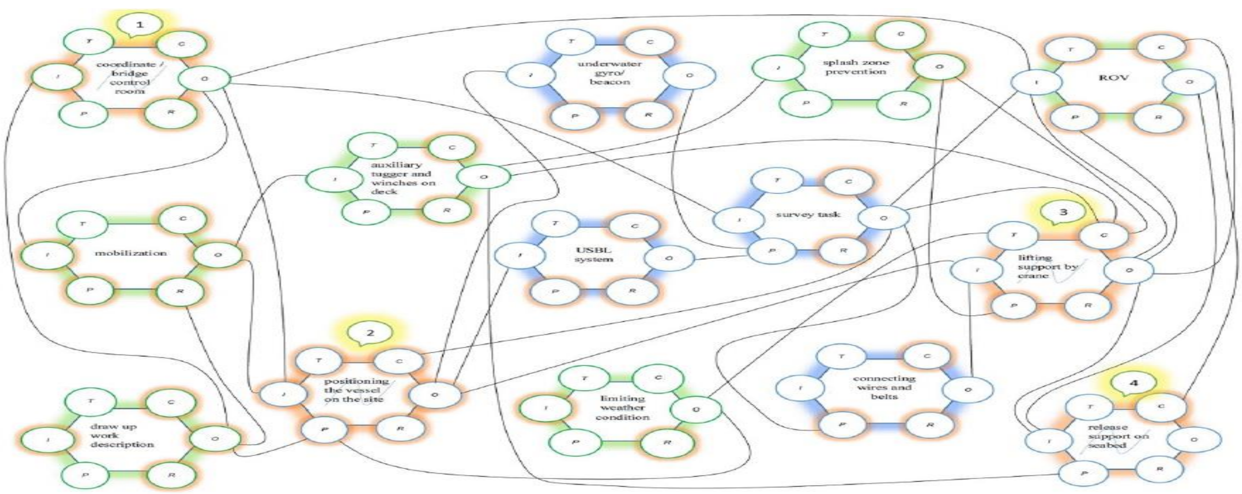

Figure 2: Resonance of human error in the process of fixing the sea fastening of derrick on the vessel

Note: T = Time, C=Control, P=Precondition, R=Requirement, I=Input, O=Outcome

5.1. Converting FRAM network into BN

BN is a graph with a set of probabilities. A Combination of probability theory and graph theory and based on a well-defined Bayes theorem, BN are demonstrated by a DAG, contains nodes representing random variables, arcs as joints among nodes, and Conditional Probability Tables (CPTs) (Chen et al., 2014; Abimbola et al., 2015)

BN provide an elegant mathematical structure for modelling complicated relationships among random variables and inferring the probability of a cause when its effect is observed. It allows scientists to combine new data with their existing knowledge or expertise.

BNs are based on the Bayes theorem, that is, inference of the posterior probability of a hypothesis according to some evidence. Mathematically, the Bayes' rule states,

$$posterior = \frac{likelihood.prior\ probability}{evidence} \quad (1)$$

$$P(\theta|x) = \frac{p(x|\theta)\,p(\theta)}{p(x)}$$

Where P (θ |x) denotes the probability that random variable "θ" with specific value given the evidence "x".

5.2. Including provided resonance of FRAM into BN

There are just two functions that have no impact on the resonance (under water gyro and USBL system) and subsequently there is not any variable related to these function in the BN. Four variables are defined as a resonance in the BN; one, two, three and four (Fig.3.). Related functions of these variable in the FRAM network are coordinate bridge/control room, positioning the vessels on the site, lifting support by crane and release support on seabed respectively.

Each arc in the network is based on both linear and non-linear interactions between variables according to provided resonance. Without considering any resonance there is not any relationship between variables in the BN and as a result human error would be the common and exclusive descendent node of all functions.

5.3. Computing HEP in each function

After mapping the operation into BN based on FRAM, it is needed to find the probability of error for each human related lifting activity. If significant human contributors to the likelihood of major occurring accidents is omitted, then the probability of the occurring event may be seriously underestimated. Conversely, the role of human in enhancing the reliability of a system needs to be taken into account. Although dozens of Quantitative Risk Assessment (QRA) techniques are employed today, most of them suffer from lack of calculation of human error likelihood (Toroody et al., 2016)

The SLIM integrates various Performance Shaping Factors (PSFs) relevant to a task into a single number called a success likelihood index (SLI). The SLI is calculated by the following formula (see Eq.(2)). For numerous sub-activities for each task then SLI should be calculated for each sub-activity separately and consequently the related HEP should be calculated by Eq. (3) in which, "n" is the number of sub-activity and "m" is the number of PSFs to find related SLI for task jth, besides, R and W are the Rate and Weight of each PSF respectively.

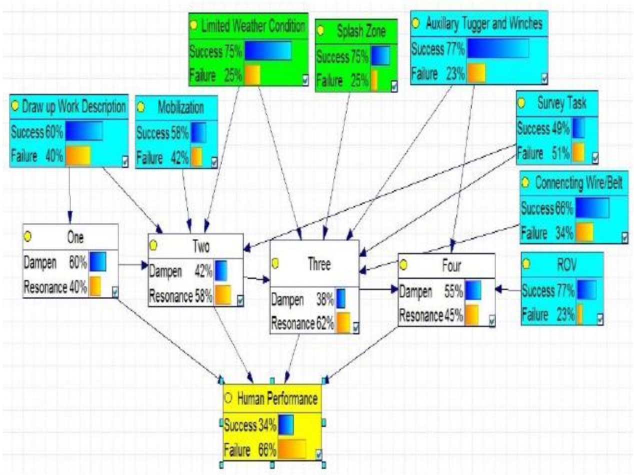

Figure 3: Bayesian Network based on provided resonance through functions 1 to 4 in qualitative FRAM network

$$SLI = \sum_{i=1}^{m} R_i W_i \quad (2)$$

$$SLI_j = \sum_{j=1}^{n} \sum_{i=1}^{m} R_{ij} W_i \quad (3)$$

For a given SLI, the human-error probability (HEP) for a task is estimated by using the Eq. (4) (Noroozi et al., 2013; Noroozi et al., 2014; Abbassi et al., 2015; Toroody et al., 2016; Musharraf et al., 2013):

$$\log(HEP) = a \times SLI + b \quad (4)$$

$$HEP = 10^{a \times SLI + b} \quad (5)$$

Where a and b are constants determined from two or more tasks for which HEPs are known. In this study a and b are considered as -1.95 and 10 E-04, respectively (Toroody et al., 2016).

Identifying PSFs is a substantial step of presenting the SLIM. (Musharraf et al., 2013).

5.3.1 Identification PSFs

Performance shaping factor is provided basis for considering potential influences on human performance and systematically considering them in quantification of Human Error Probabilities (HEPs). PSFs often characterized as internal and external. Internal PSFs are influences that the individual brings to the situation such as mood, fitness, stress level, etc. External PSFs are influences in the situation or environment that affect the individual such as temperature, noise, work practices, etc. Currently there is no standard set of PSFs used in HRA methods, but most sets use PSFs identified in human performance literature. Personal factors include, attention, attitude, personality, fatigue, knowledge, experience, motivation. Additional factors include communication, teams, leadership, safety culture, ergonomics, training, environment, management, time and workload.

Table 1: Rank and weight of PSFs

PSF	Rank	Weight
Experience	*10*	0.21
Skill	9	0.19
Motivation	8	0.17
Stress Level	7	0.15
Work Memory	7	0.15
Time Pressure	6	0.13

5.3.2 PSFs assessment

Determining the weight of PSFs to estimate the SLIs is one of the most pivotal steps. Human performance data with greater detail is difficult to find in real world situations, which requires the use of expert judgment techniques (Musharraf et al., 2013). In this assessment, the PSFs with highest ranks are taken into account as the related PSFs, listed in Table 1 (Toroody et al., 2016). The number in the second column denotes the normalized importance (weight Wi) of a particular PSF for the task under consideration, as determined by experts.

Rating the PSFs is another important step in the SLIM procedure. Participant experts such as technical engineers select rating R, from 0 to 1 for each of PSFs. Each PSF rating has an ideal value of 1 at which human performance is judged to be optimal. These ratings are based on six PSFs demonstrated in Table 1 as the most important ones in lifting of light structures. By applying Eq. (3) SLI were obtained for each activity. Afterward, Eq. (4) and Eq. (5) are used to calculate the HEP of each task. Human Error Probability of activities is presented in Table 2.

the probability of human error, HEP_T, for light structure's lifting in the offshore industry can be calculated using Eq. (6)

$$\boldsymbol{HEP_T = 1 - \prod_{j=1}^{n}\left(1 - HEP_j\right)} \qquad (6)$$

5.4 Compile BN based on HEP, evidence and Max-propagation

In order to find out that how BN helps to have better interpretation about relationship between nodes, the evidence is set on two variable; survey task failure, human performance failure. Also, the results from BN are depicted in Fig.5 and Fig.6. BN illustrated that what variables work most effectively on the others when evidences are set. The maximum changes in both types of Max-propagation analysis for human error, are related to second resonance (two) and third resonance (three) nodes.

In the light of mentioned evidence, the CPTs were changed and shown separately in Table 3. As it has been mentioned previously, the primary HEP value are based on SLIM and subsequently the update process using NOGM are made according to these rates. The differences of methodologies are appeared in probability of resonance nodes (see Table 2). It is necessary to say that two variables in the BN (Splash zone and Limited weather) do not have any value in primary HEP estimation. The reasons are that firstly, mentioned variables are not within the scope of human performance and control and secondly, HEP estimation was carried out based on PSFs, using SLIM.

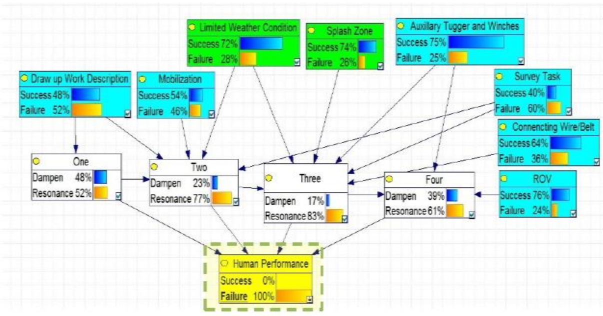

Figure 4: Max-Propagation analysis for human errors based on evidence on Human Performance

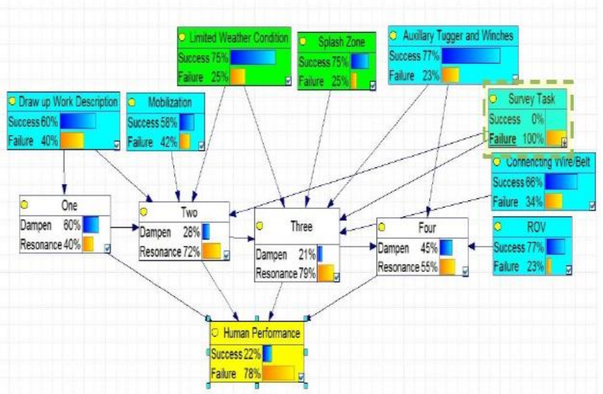

Figure 5: Max-Propagation analysis for human errors based on evidence on Survey Task

6.Conclusion

The First half of the paper was devoted to qualitative analysis of considered case study where FRAM network were drawn and build on this network the BN were conducted qualitatively. The second half of the paper discussed quantitatively in which HEP estimation for each function were assigned. Finally, in the light of new information and to figure out the impact of failure in each nodes on the other nodes, two evidences were set.

The application of the developed methodology to a case study depicted that the proposed coupling of FRAM and BN has made the application of risk assessment more reliable. It is highly recommended to have interdisciplinary studies based on HRA and statistical method to find accurate estimation of human error in terms of hidden cause effects and time dependence. Including the time element in HEP estimation, gives more accurate results. Besides, “Hidden causes effect gap” plays a prominent rule in understanding the accuracy of prior estimation of human error. Since, it means a hidden cause individually contributes to a major means of error, but it could not be realized in reality.

Table 2: Human error (failures) probability comparison of different sub activity using SLIM and BN

Variables	SLIM	BN (Fig. 4)	BN (Fig. 5) Evidence on Human Performance	BN (Fig. 6) Evidence on Survey Task
Draw up work description	40.07%	40.07%	51.85%	40.07%
Mobilization	42.33%	42.33%	46.19%	42.33%
Limited weather	-	25%	27.9%	25%
Splash zone	-	25%	26.49%	25%
Auxiliary tugger and winches	23.03%	23.03%	25.22%	23.03%
Survey task	50.6%	50.6%	60.19%	100 %
Connecting wire and belts	33.59%	33.59%	36.11%	33.59%
ROV	23.11%	23.11%	24.12%	23.11%
First resonance	28.33%	40.07%	51.85%	40.07%
Second resonance	10.5%	57.61%	77.04%	72.07%
Third resonance	47.63%	61.53%	82.66%	78.6%
Forth resonance	13.6%	44.91%	60.89%	54.59%
Human Performance	86%	65.82%	100 %	78.29%

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