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Risk-based Interventions for Safer Operation of a Hydrogen Station

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In ensuring safety of plant operation, both the reliability of plant components and human resources are important. Moving towards optimising resources, there is a need to prioritise intervention measures such as maintenance program and review of standard operating procedures. In this paper, a technique known as basic event ranking approach (BERA) is applied to a hydrogen station. BERA examines the relative importance of plant components based on their probability of failure within the realm of fault tree analysis model, and yields values of importance index for each basic event investigated. To incorporate changes in reliability data throughout the plant lifetime, a dynamic extension to BERA is introduced. The vulnerability of plant components and human actions are ranked with respect to the selected top events of fault trees generated from plant functions. The results revealed the potential of BERA to facilitate risk-based intervention initiatives to support process safety.

1. Introduction

Major accidents are characterised by complex causal patterns with many factors influencing the occurrence of such accidents. The efforts to track back various interaction of factors and the causes lead to accident can to be understood by using accident modelling approach to improve safety barriers and can be used as the prediction of future end states (Al-shanini et al., 2014a). Accident causes are not originated from technical aspect only but also from human and organisational deficiencies that could contribute to operational failures (Kidam and Hurme, 2013). Initiatives for process safety management system improvement have been proposed from global survey of process industries from all over the world (Pitblado, 2011). One of well-known organisational deficiencies in industry is perfunctory maintenance activity. Maintenance can keep the integrity of safety barriers and thus improve the prevention of major accidents. 80 from 183 major accidents reports in US and Europe from year 2000 to 2011 was related to inadequate maintenance (Okoh and Haugen, 2014).

Maintenance in CPI is not just for ensuring the healthiness of components but it also plays a crucial role in achieving organisation's goals especially when finance is a concern by ensuring optimum maintenance cost. This goal can be achieved by a systematic strategies of prioritise maintenance according to the hierarchy of vulnerability among the components. The importance measure (IM) techniques of Probabilistic Safety Assessment (PSA) is one of the tools that had broadly been used in many application to identify the relative importance of the component in the plant. It highlights the component that needs most attention to be improved to reduce risk that contribute to system failure or reduce chances of any accident cases. There were several IM techniques that had been established and more explanation about the methods can be find in the overview by Van der Borst and Schoonakker (2001).The latest IM method that had been established and undergo steady development was known as Basic Event Ranking Approach (BERA) (Khalil, 2016).

Unlike other methods, the ranking of vulnerability using the BERA framework depends on several important factors, which are nominal failure probability of basic component, the number and type of gates that are connected to the top event (TE) with basic component x_i, the number of minimal cut sets containing the x_i and

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the order of minimal cut sets that contain basic event. In this paper, further development of this method on dynamic updating by using Markov chain Monte Carlo (MCMC) simulation has been proposed and a simple case study of from Dujin will be used to demonstrate the technique (Kelly and Smith, 2009).

2. Modelling Framework

2.1 BERA

The analysis starts by constructing the fault tree of the system, and based on the fault tree, the contribution of each element (x_i) to the top event (TE) is analysed. The probability of top event, *P(TE)* is determined by the sum of all probability of minimal cut sets in the system, and is shown as Eq(1):

$$P(TE) = \sum_k^N P(MCS_k) \tag{1}$$

Here, $P(MCS_k)$ is the probability of cut set k and N is the total number of cut sets in the system. Using these values, the cut-set importance measure (IMk) can be computed using Eq(2):

$$IMk = P(mk)/P(TE) \tag{2}$$

Where IM_k is the importance measure for cut set k, and m_k is the failure probability of the cut set k. The cut-sets importance measures can then be used to evaluate the importance index of each basic component using the proposed BERA equation, given as in Eq(3):

$$BERA\ (x_i) = P(x_i) * \sum_{J=1}^{L} IM_J \tag{3}$$

Here, $BERA\ (x_i)$ is the importance index for the basic component x_i, L is the number of minimal cut set that contains the basic component i, and IM_j is the minimal cut set's importance measure that contains the basic component i.

2.2 Dynamic BERA

Importance measure has played an important role in identifying component vulnerability and maintaining safety in process industries, it is difficult for static BERA as it fails to capture the variation of risks as deviations or changes of the component condition in the process and plant take place. Further development dynamic updating of BERA methodology has been done by adapting Markov chain Monte Carlo (MCMC) simulation. Software called OpenBUGS is used to generate probability of BERA for every two month in one year (Lunn et al., 2009).

3. Case Study

As a case study, an on-site hydrogen station based on the work of Duijm and Markert (2009) is used. The schematic diagram of the plant is reproduced here as Figure 1.

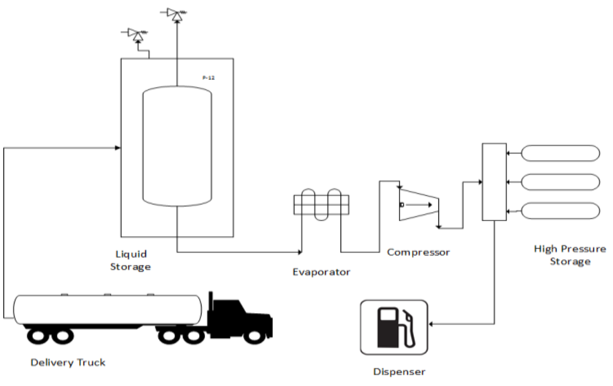

Figure 1: Schematic diagram of on-site hydrogen station (Duijm and Markert, 2009)

The Fault Tree Analysis of the prevention barriers failures from this case study have been developed by Al-Shanini (2014a). Fault tree model of External Ignition Barrier (EIB) failure is used to demonstrate the application of BERA methodology and its dynamic updating ability as shown in Figure 2. To prove the capabilities of this methodology on broader spectra, another fault tree model which is Maintenance Prevention Barrier (MPB) that consists of human error or organisational deficiencies also been used as shown in Figure 3.

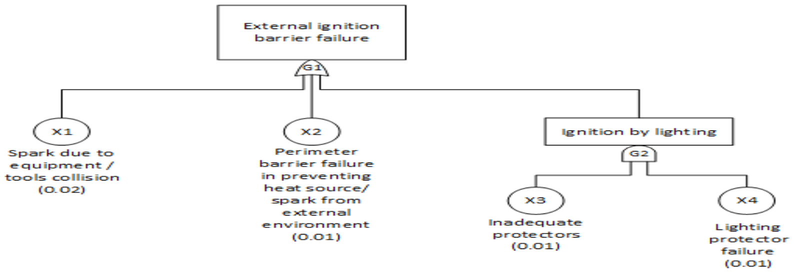

Figure 2: External Ignition Barrier (EIB) Failure (Al-Shanini et al., 2014b)

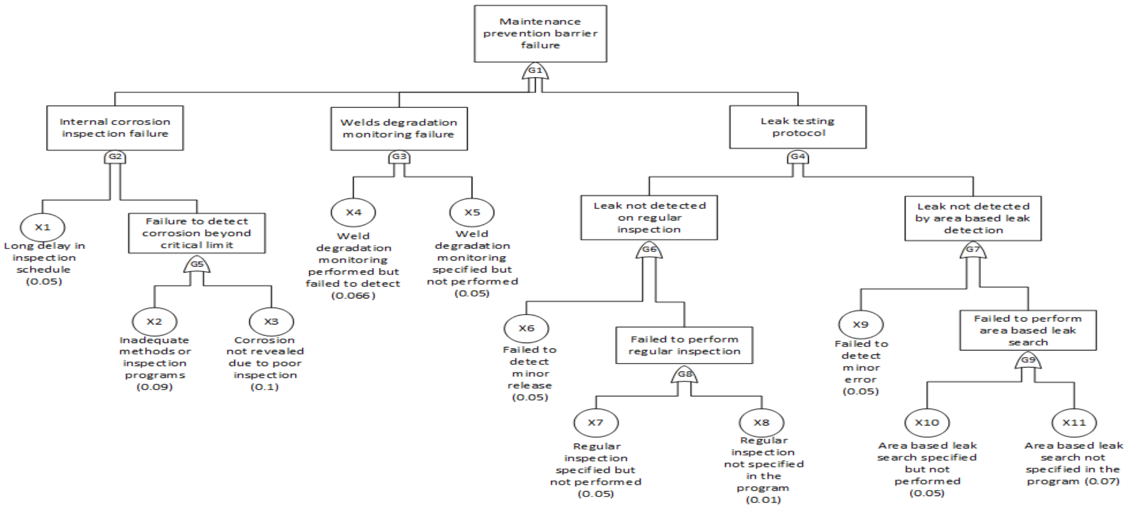

Figure 3: Maintenance prevention barrier (MPB) failure FT model (Al-Shanini et al., 2014b)

In this analysis, hypothetical precursor data of prior parameters of basic events are used to implement the methodology. In cases where real data is available, this should be replaced by real ones. For this case study considered the time interval used is every two months in a year.

4. Result and Discussion

4.1 Ranking Computation Using BERA

Using information from the both fault tree shown in previous section, the number of minimal cut sets can be determined and the top event probability can be computed using Eq(1). Fault tree in EIB giving final value of P(TPB) = 0.0301. Then, the cut set importance index (IM_k) is determined by using Eq(2) and the ranking can be identified using Eq(3). Results obtained shown in Table 1 and Table 2.

Table 1: Importance Measure (IM) of cut sets for EIB failure

No of MCS	MCS element	CS probabilities	Mk	IMk
1	X1	0.02	0.02	2.554×10^{-1}
2	X2	0.01	0.01	1.277×10^{-1}
3	X3,X4	(0.01,0.01)	1.00×10^{-4}	1.277×10^{-3}

Table 2: Ranking of Components' Vulnerability Using BERA for EIB failure

Component	Failure Probability	No. of gates	Gate Type	No. of min. cut sets	Order of cut sets	BERA probability	Ranking
X1	0.02	1	OR	1	1	5.107×10^{-3}	1
X2	0.01	1	OR	1	1	1.277×10^{-3}	2
X3	0.01	2	AND-OR	1	2	1.2768×10^{-5}	3
X4	0.01	2	AND-OR	1	2	1.2768×10^{-5}	3

The ranking is in descending order in terms of vulnerability, with X1 being most vulnerable. The result shows component X1 is the most vulnerable followed by X2, while X3 and X4 in the same rank. The high value of failure probability of component X1 has influence its ranking to be the most vulnerable component. Component X3 and X4 are in the same rank because of its similar prior probability and have been appeared once in the same cut set. This result is consistence with the factors that significantly affect BERA ranking as stated before. Same step in evaluating BERA is applied on MPB failure fault tree. The top event value for MPB failure fault tree is P(TPB) = 0.0315. The result shows in Table 3, basic event X11 is the most vulnerable followed by X3, X1, X6 and X7, X2, X9 and X10, X4 and the least vulnerable is basic event X8. Although the prior failure probability of X3 is higher than X11 but result shows that raking of X11 is higher than X3. This is because X11 has more number of gates and appears in three minimal cut set compare to X3 which has only 3 numbers of gates and appear in only one cut set. This illustrates the effect of other criteria in BERA methodology in influencing the final ranking.

Table 3: Ranking of Components' Vulnerability Using BERA for MPB failure

Basic event	Failure Probability	No. of gates	Gate Type	No. of min. cut sets	Order of cut sets	BERA probability	Ranking
X1	0.05	2	AND-OR	2	2,2	3.241×10^{-3}	3
X2	0.09	3	OR-AND-OR	1	2	2.763×10^{-3}	6
X3	0.1	3	OR-AND-OR	1	2	3.412×10^{-3}	2
X4	0.066	2	AND-OR	1	2	1.486×10^{-3}	9
X5	0.05	2	AND-OR	1	2	1.126×10^{-3}	10
X6	0.05	3	OR-AND-OR	3	2,2,2	2.900×10^{-3}	4
X7	0.05	4	OR-OR-AND-OR	3	2,2,2	2.900×10^{-3}	4
X8	0.01	4	OR-OR-AND-OR	3	2,2,2	1.160×10^{-4}	11
X9	0.05	3	OR-AND-OR	3	2,2,2	1.876×10^{-3}	7
X10	0.05	4	OR-OR-AND-OR	3	2,2,2	1.876×10^{-3}	7
X11	0.07	4	OR-OR-AND-OR	3	2,2,2	3.678×10^{-3}	1

4.2 Dynamic BERA

Dynamic updating technique is carried out for further development on BERA methodology. Table 4 shows the hypothetical Information for hyper prior parameter and frequency failure data in a year to generate dynamic updating for every two month in a year. Table 5 shows the results generate from the simulation. Table 6 and Table 7 show the results of BERA and its ranking. The simplicity of result obtained where component X1 and X2 are in the same rank throughout the year. This is because of both components are involved with only 1 gate and only appear once in a cut set. For component X3 and X4, several changes in ranking can be seen throughout the year because both of them involved with two gates where slightly more than component X1 and X2. Overall, component X1 is the most vulnerable component and need more prioritisation in maintenance compare to other 3 components.

Table 4: The hypothetical information of EIB failure

Component	Prior Probability	Distribution	Hyper - prior parameter		Frequency of failure in one year
			ὰ	ß	
X1	0.02	gamma	1.2 (4,3.333)	60 (3.5,0.058)	C(1,0,0,0,1,0)
X2	0.01	gamma	1.6 (1.28,0.8)	160 (40,0.25)	C(0,0,1,1,0,0)
X3	0.01	gamma	1.8 (2.4,1.333)	180 (90,0.5)	C(0,1,0,0,0,0)
X4	0.01	gamma	1 (3,3)	100(145,0.145)	C(0,1,0,0,1,0)

Table 5: Failure probability for six period of EIB failures

Com-ponent	Frequency of failure in one year	Prior Probability	1st	2nd	3rd	4th	5th	6th
X1	C(1,0,0,0,1,0)	0.02	0.08524	0.04271	0.03853	0.03283	0.07298	0.03739
X2	C(0,0,1,1,0,0)	0.01	0.009992	0.009894	0.0253	0.03029	0.02359	0.0217
X3	C(0,1,0,0,0,0)	0.01	0.00983	0.0199	0.01392	0.01353	0.01331	0.01304
X4	C(0,1,0,0,1,0)	0.01	0.009757	0.02346	0.0127	0.01255	0.02474	0.01521

Table 6: BERA result for every two months in a year of EIB failures

Compo-nent	Prior Probability	1st	2nd	3rd	4th	5th	6th
X1	5.1073×10^{-3}	2.4139×10^{-1}	6.0603×10^{-2}	4.9321×10^{-2}	3.5808×10^{-2}	1.7695×10^{-1}	4.6446×10^{-2}
X2	1.2768×10^{-3}	3.3169×10^{-3}	3.2522×10^{-3}	2.1265×10^{-2}	2.0481×10^{-2}	1.8488×10^{-2}	1.5644×10^{-2}
X3	1.2768×10^{-5}	3.1323×10^{-5}	3.0865×10^{-4}	8.1755×10^{-5}	7.6326×10^{-5}	1.4561×10^{-4}	8.5925×10^{-5}
X4	1.2768×10^{-5}	3.1090×10^{-5}	2.6357×10^{-4}	7.4590×10^{-5}	7.0798×10^{-5}	2.7065×10^{-4}	1.0022×10^{-4}

Table 7: BERA Ranking of EIB failures

Component	Data for one year	Prior	1st	2nd	3rd	4th	5th	6th
X1	C(1,0,0,0,1,0)	1	1	1	1	1	1	1
X2	C(0,0,1,1,0,0)	2	2	2	2	2	2	2
X3	C(0,1,0,0,0,0)	3	3	3	3	3	4	3
X4	C(0,1,0,0,1,0)	3	4	4	4	4	3	4

More discussion can be done if larger network of fault tree with more basic event and gates is used. Therefore for more detail explanation, another fault tree is used to demonstrate dynamic BERA from the same case study but focusing more on human error or organisational deficiencies. Table 8 shows hypothetical data that had been used to generate result of this technique.

Table 8: The hypothetical information of MPB failure

BE	Prior Probability	Distribution	Hyper - prior parameter α	ß	Frequency of failure in one year
X1	0.05	Gamma	5 (2,0.4)	100 (145,0.145)	C(1,0,1,0,1,1)
X2	0.09	Gamma	2.13 (3.0,4.225)	23.666 (3.0,1268)	C(0,1,0,0,0,1)
X3	0.1	Gamma	3 (1.5,0.5)	30 (7.5,0.25)	C(1,2,1,0,0,1)
X4	0.066	Gamma	3 (1.8,0.6)	45.45 (17,0.375)	C(0,1,0,0,0,1)
X5	0.05	Gamma	2.5 (1.5,0.6)	50 (3.5,0.07)	C(1,0,1,1,0,0)
X6	0.05	Gamma	2.3 (2.576,1.12)	46 (2.76,0.06)	C(1,0,0,0,0,1)
X7	0.05	Gamma	2 (2.24,1.12)	40 (5.5,0.1375)	C(2,1,0,0,1,0)
X8	0.01	Gamma	1.6 (1.28,0.8)	160 (40,0.25)	C(0,1,0,1,0,1)
X9	0.05	Gamma	3.55 (1.775,0.5)	71.1 (15,0.211)	C(0,0,0,0,1,2)
X10	0.05	Gamma	2.25 (3.0,1.333)	45 (7.5,0.1666)	C(1,1,0,1,2,0)
X11	0.07	Gamma	1.47 (1.323,0.9)	21 (3,0.143)	C(1,0,0,1,0,1)

Table 9: BERA result every two month in a year of MPB failure

BE	Prior	1st	2nd	3rd	4th	5th	6th
X1	3.2410×10^{-3}	5.7670×10^{-2}	3.0870×10^{-2}	8.0370×10^{-2}	1.7950×10^{-2}	4.4410×10^{-2}	6.6910×10^{-2}
X2	2.7630×10^{-3}	2.5550×10^{-4}	4.2150×10^{-3}	7.3997×10^{-3}	2.8370×10^{-3}	3.4870×10^{-3}	2.3340×10^{-2}
X3	3.4120×10^{-3}	2.8450×10^{-3}	1.3198×10^{-2}	1.4250×10^{-1}	4.2720×10^{-2}	4.7450×10^{-2}	7.0670×10^{-2}
X4	1.4860×10^{-3}	2.2840×10^{-2}	5.0790×10^{-2}	3.6199×10^{-2}	2.8603×10^{-2}	2.3910×10^{-1}	2.3610×10^{-2}
X5	1.1260×10^{-3}	6.4050×10^{-2}	4.5760×10^{-2}	7.2502×10^{-2}	7.0420×10^{-2}	2.3980×10^{-2}	2.2870×10^{-2}
X6	2.8999×10^{-3}	5.1240×10^{-1}	1.1440×10^{-1}	3.9507×10^{-2}	5.1920×10^{-2}	3.0110×10^{-2}	8.7697×10^{-2}
X7	2.8999×10^{-3}	7.7970×10^{-1}	5.3670×10^{-1}	1.1040×10^{-1}	1.4380×10^{-1}	2.5360×10^{-1}	1.0160×10^{-1}
X8	1.1600×10^{-4}	1.2490×10^{-3}	6.0440×10^{-3}	1.8903×10^{-3}	3.2580×10^{-3}	2.3730×10^{-3}	9.0730×10^{-3}
X9	1.8764×10^{-3}	3.4510×10^{-2}	2.5990×10^{-2}	1.2930×10^{-2}	1.2990×10^{-2}	2.6780×10^{-2}	5.6090×10^{-2}
X10	1.8764×10^{-3}	1.8160×10^{-1}	2.0720×10^{-1}	5.1090×10^{-2}	1.1630×10^{-1}	2.5780×10^{-1}	8.2030×10^{-2}
X11	3.6778×10^{-3}	1.0590	2.1280×10^{-1}	4.9670×10^{-2}	1.8570×10^{-1}	5.2340×10^{-2}	1.2550×10^{-1}

Table 9 and Table 10 show the result obtained. In dynamic BERA, another important factor is added for determining the raking which is frequency of failure in a year. Along with other factors mention previously, rank of basic event in certain period is relatively affected by the failure of other basic event in the system. As for example, for basic event X3 in 3rd period, the rank is significantly change from 9 to 1 due to few failure among basic event happen in that period as well as driven by its large prior failure probability. Comparing basic event

X2 and X8, although failure probability of basic event X2 is high compare to X8, both remain in lower rank because basic event X2 involve in few failure throughout the year compare to X8.

Table 10: BERA Ranking of MPB failures

BE	Frequency of failure in one year	Prior	1st	2nd	3rd	4th	5th	6th
X1	C(1,0,1,0,1,1)	3	6	7	3	8	6	6
X2	C(0,1,0,0,0,1)	6	11	11	10	11	10	9
X3	C(1,2,1,0,0,1)	2	9	9	1	6	5	5
X4	C(0,1,0,0,0,1)	9	8	5	8	7	3	8
X5	C(1,0,1,1,0,0)	10	5	6	4	4	9	10
X6	C(1,0,0,0,0,1)	4	3	4	7	5	7	3
X7	C(2,1,0,0,1,0)	4	2	1	2	2	2	2
X8	C(0,1,0,1,0,1)	11	10	10	11	10	11	11
X9	C(0,0,0,0,1,2)	7	7	8	9	9	8	7
X10	C(1,1,0,1,2,0)	7	4	3	5	3	1	4
X11	C(1,0,0,1,0,1)	1	1	2	6	1	4	1

5. Conclusion

A new IM technique called basic event ranking approach (BERA) has been applied to a hydrogen station as a case study. BERA examines the relative importance of plant components based on their probability of failure within the realm of fault tree analysis model, and yields values of importance index for each basic event investigated. Several important factors that affect ranking of vulnerability of BERA which are nominal failure probability of basic event, the number and type of gates that are connected to the top event (TE) with basic event x_i, the number of minimal cut sets containing the x_i and t the order of minimal cut sets that contain basic event. In dynamic updating BERA, frequency of event failure added up the important factors that determine the BERA ranking. Although prior aims of BERA are to find the vulnerability hierarchy among components, this technique can also broaden its application to identify human error or organisational deficiencies that contribute most challenge to practice safety in process industry. BERA is considered potentially useful in assessing the vulnerability of basic component for planning plant maintenance and upgrade process safety activities.

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