APPLICATION OF RISK ASSESSMENT APPROACH ON A HYDROGEN REFULLING STATION

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ABSTRACT

An accident modelling approach is used to assess the safety of a hydrogen station as part of a ground transportation network. The method incorporates prevention barriers associated to human factors, management and organizational failures in a risk assessment framework. Failure probabilities of these barriers and end-states events are predicted using Fault Tree Analysis and Event Tree Analysis respectively. Results from the case study considered revealed the capability of the proposed method in estimating the likelihood of various outcomes as well as predicting the future probability. In addition, the scheme offers opportunity to provide dynamic adjustment by updating the failure probability with actual plant data. Results from the analysis can be used to plan maintenance and management of change as required by the plant condition.

1.0 INTRODUCTION

Hydrogen is a promising energy for the future as it is available in abundance, renewable and sustainable [1]. It is also an efficient source that offers higher combustion energy with 142 MJ/kg compared to 45 MJ/kg for the case of gasoline. Recent estimation shows that by the year of 2050 there will be a hydrogen demand of over 42 million metric tons gasoline equivalent (GGE) in the United States of America alone, which can fuel up 342 million light-duty vehicles 8.2×10^{12} km travel per year [2]. This is however, not without challenges, and safety remains as one of the main concerns.

To realize hydrogen as the future source of energy and the subsequent hydrogen economy, safety issues must be thoroughly addressed. While hydrogen is not toxic, it has a wide flammability range and can easily be ignited to cause fire and explosion when combined with oxygen. Although safety records of hydrogen processing in the process industry are generally good, the combined risks associated with production, storage, transportation and use on the widespread scale to replace hydrocarbons will undoubtedly bring incidents [3]. To reduce the risk, reliable risk analysis methodology is required so that appropriate control measures can be planned and required safety standards can be established. This is particularly important especially when the population at large is involved such as in the case of hydrogen refuelling stations [4].

This concern has initiated works on the safety of hydrogen refuelling stations. In particular, a number of reports have been published recently on the risk assessment of hydrogen stations. Duijm and Markert [5] applied a graphical tool known as safety-barrier diagram to represents possible accident scenario and to assess the safety for an offsite hydrogen refuelling station. The method can be effectively used along with other hazard identification methods such as HAZOP and FMEA as it provides complementary technique for documenting accident scenarios and safety measures. Kikukawa and co-workers applied quantitative risk assessment (QRA) methodology to hydrogen refuelling stations [6] and [7] and based on the outcome of these studies, they proposed typical safety measures needed for the stations including some general guidelines as well as specific features for protecting the liquid hydrogen storage tank, hydrogen dispenser and the vent line. Zhiyong *at al.* [8] also used QRA to assess risks associated with gaseous hydrogen refuelling station and concluded that a compressor leak would be the most contributing factor in increasing risk of the three parties considered, i.e., workers, customers, and third party.

While the use of QRA has been generally accepted as a standard for risk assessment in process industries, it is a static methodology and the results are therefore valid based on the conditions used and information incorporated during the assessment. Since it is an elaborate procedure and time consuming, it is perhaps a better strategy to include some mechanisms to accommodate changes in process conditions so that an update of the assessment can be generated without the need of a repeat full-blown QRA. This approach falls in the realm of dynamic risk assessments (DRA). In this paper, DRA methodology is applied to a hydrogen refuelling station. The scheme estimates the likelihood of hazard conditions by considering all scenarios that may lead to hazardous event including potential failures associated to the process itself as well as influences from the surroundings such as the users, management as well as natural phenomena.

2.0 CASE STUDY: HYDROGEN FILLING STATION

Generally, there are two types of hydrogen refuelling stations, i.e., offsite and stations. In the offsite station, hydrogen is brought by trucks; whereas in onsite it is produced adjacent to the station or as part of the station itself [5]. Within the station, hydrogen is either stored in liquefied cryogenic or pressurized gas forms. The liquid H2 station is simpler in construction and requires less number of equipment compared to the pressurized counterpart. However, the handlings of liquefied H2 at cryogenic temperature requires additional safety measures such as a storage tanks with vacuum double-wall configuration, along with its associated piping and dispensing hoses. Fig. 1 shows the process flow diagram, which consists of unloading facility, H_2 storage tank, evaporator, compressor, small high-pressure storage tank, and the refuelling facility.

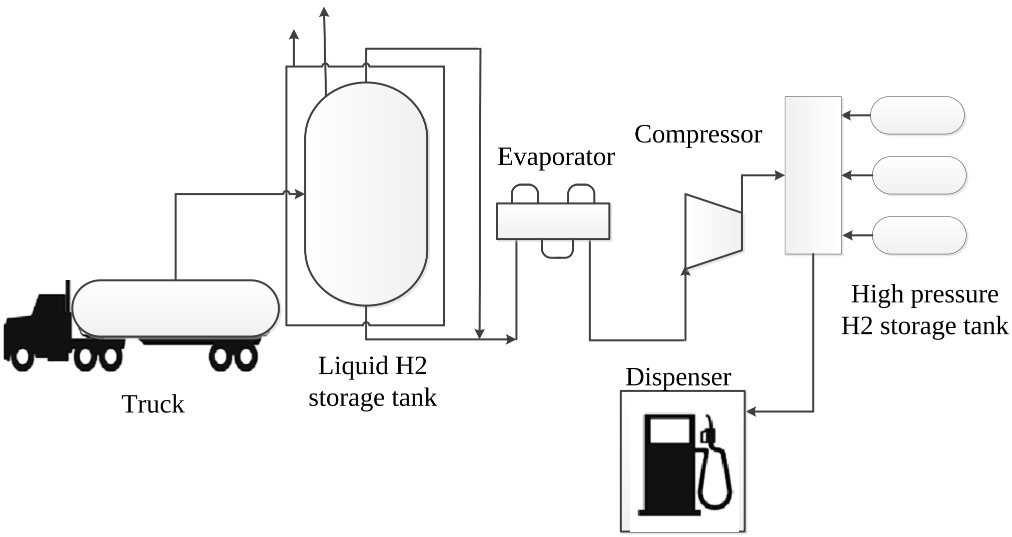


Figure 1: Process diagram of offsite liquefied H2 refuelling station [5].

3.0 RISK ASSESSMENT FRAMEWORK

In this article, DRA is applied to support risk-based decisions for better inherent safety. The model used is based on SHIPP methodology developed by Rathnayaka *et al*. [9]. SHIPP represents accidents as the propagation of deviations through prevention and mitigation barriers that include process (operational, maintenance, and technical), human, and management and organizational barriers. As shown in Fig. 2, the framework is founded upon a series of prevention barriers, which are release prevention (RPB), dispersion (DPB), ignition (IPB), escalation (EPB), and damage control and emergency management (DC&EMB) barriers. These are typical layers of protection normally employed in process industries, in addition to plant operation facilities such as process control, alarm and interlocks. A release that is triggered by the failure of the RPB will be protected by the DPB, which will then be protected by the IPB, EPB and DC&EMB. Note that all these barriers are also affected by human and management & organizational barriers.

In SHIPP, the failure of these prevention barriers is modelled using Fault Tree (FT) models as top events, whereas the propagation of deviation through the prevention barriers are modelled using Event Tree (ET) model. The release of material (toxic or/and flammable) or /and energy is the initiating abnormal events that could propagate to produce accident if not properly mitigated by the prevention barriers.

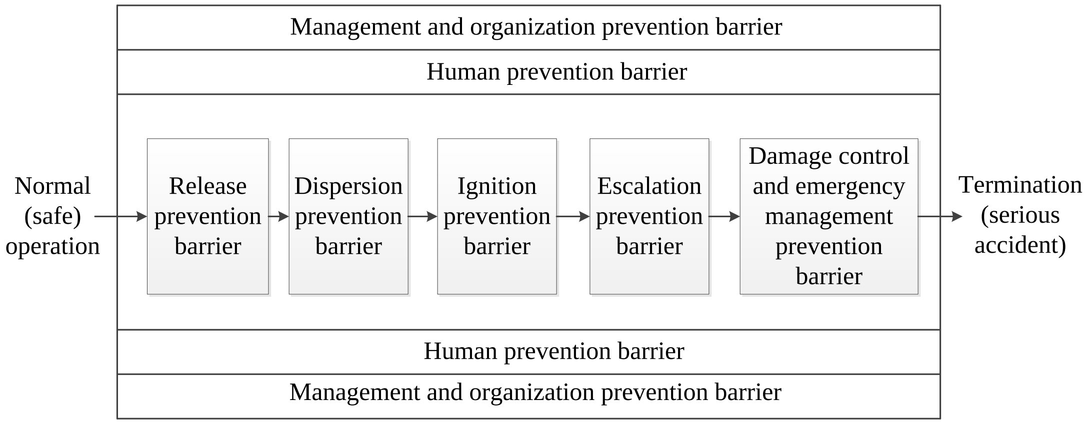


Figure 2: SHIPP methodology

3.1 Prevention Barriers

Prevention barriers play mitigating roles to eliminate or reduce the impact of the release scenario. To estimate the failure probability for each of these barriers, Fault Tree (FT) model is constructed based on process understanding of the off-site hydrogen refuelling station. Using the FT model, the overall failure probability for each barrier is computed based on failure probabilities of the base elements obtained from failure databases.

Prevention barriers FT models for the hydrogen refuelling station considered in this study are developed and are as shown in Fig. 3, Fig. 4, Fig. 5, Fig. 6 and Fig. 7. In addition to the technical and management aspects, two types of natural events, i.e., earthquake and lighting are considered as causes of barriers failure. For example, the RPB failed due to the failure of one of the prevention barriers of operational error, H_2 containment equipment/components, earthquake/lightning, or maintenance; each of these sub-systems failed due to reasons that all constructed to model the RPB causal reasons of failure and same way for other prevention barriers. The reliability data used in FT models are adopted from what are normally used for natural gas industry, other chemical process industries, as well as expert opinion, on occasion where data is not available. This is due to the scarcity of reliability data for basic events failure probabilities related to hydrogen refuelling station. The source this data are [10 - 14]. Using the FTA, prevention barriers failure probabilities are computed and the results are shown in table (1).

Table 1: Prevention barriers prior failure probabilities

Prevention barrier	Failure probability
RPB	0.1458
DPB	0.0740
IPB	0.0488

EPB	0.0774
DC&EMB	0.0139

3.2 Consequence Scenario

Release of hydrogen is the unwanted event that could be initiated from the process and/or external events, which can then propagate to accident if not mitigated. The consequence scenario of this initiating event is modelled using Event Tree (ET). Based on this analysis, six end-state events (C1, C2, C3, C4, C5, and C6) are plausible depending on the failure or success of the barriers, as shown in Fig. 8. These end-state events are safe, near-miss, mishap, incident, accident, and serious accident respectively. Note that for a serious accident to occur, all prevention barriers must fail.

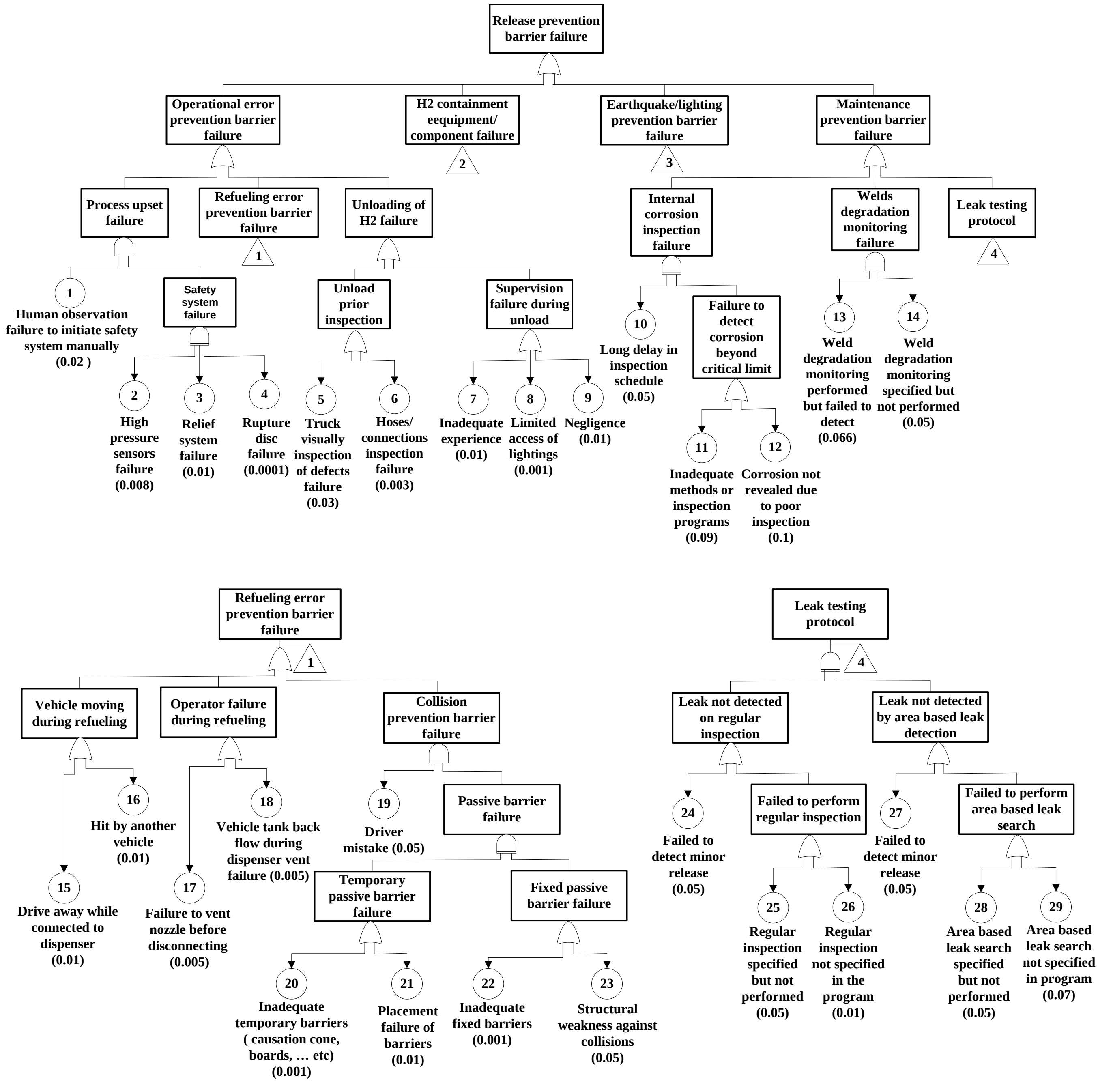
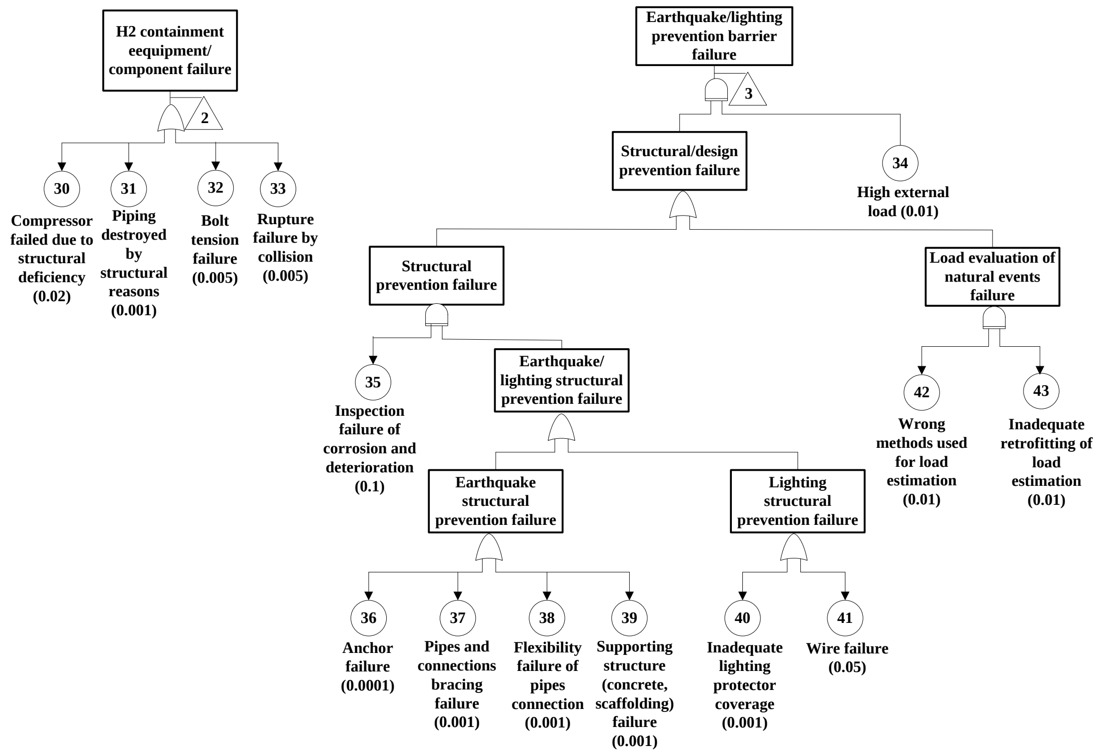


Figure 3: RPB failure FT model



(Continue) Figure 3: RPB failure FT model

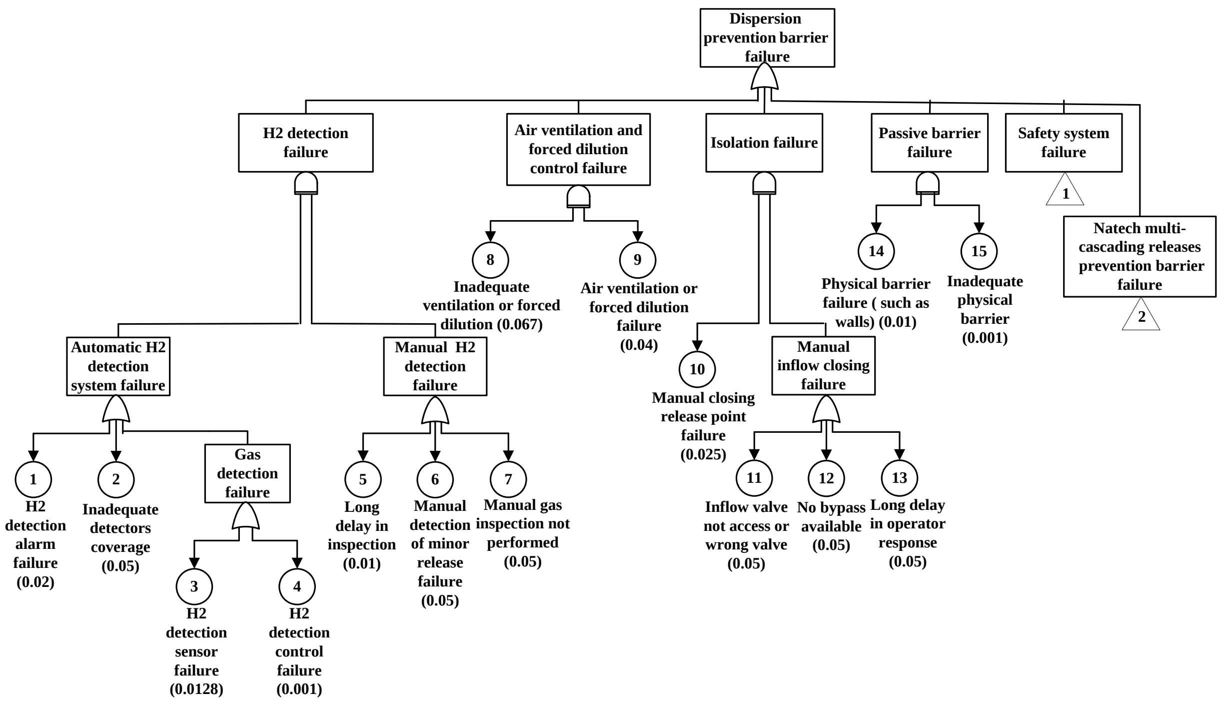
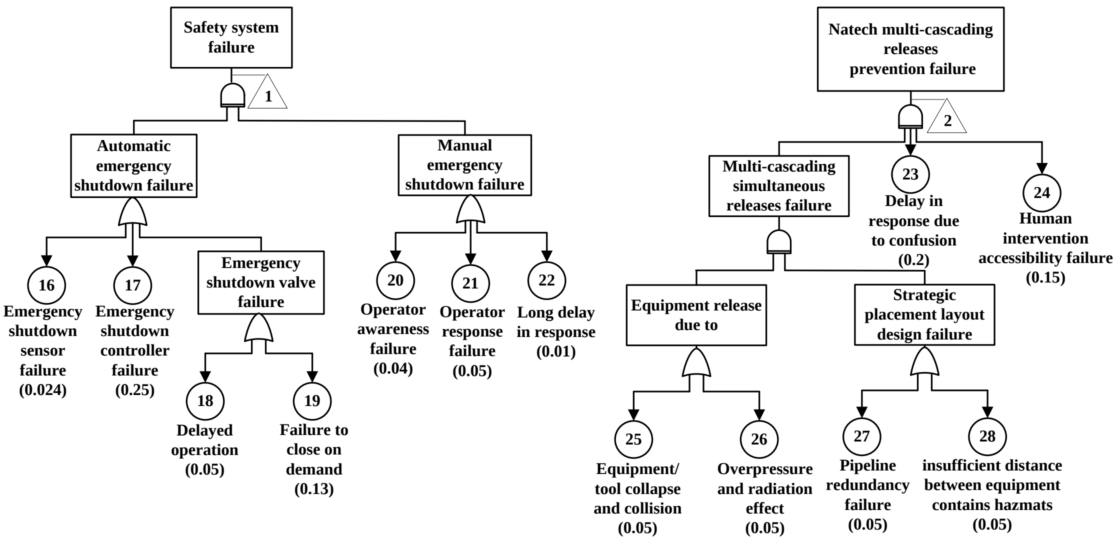


Figure 4: DPB failure FT model



(Continue) Figure 4: DPB failure FT model

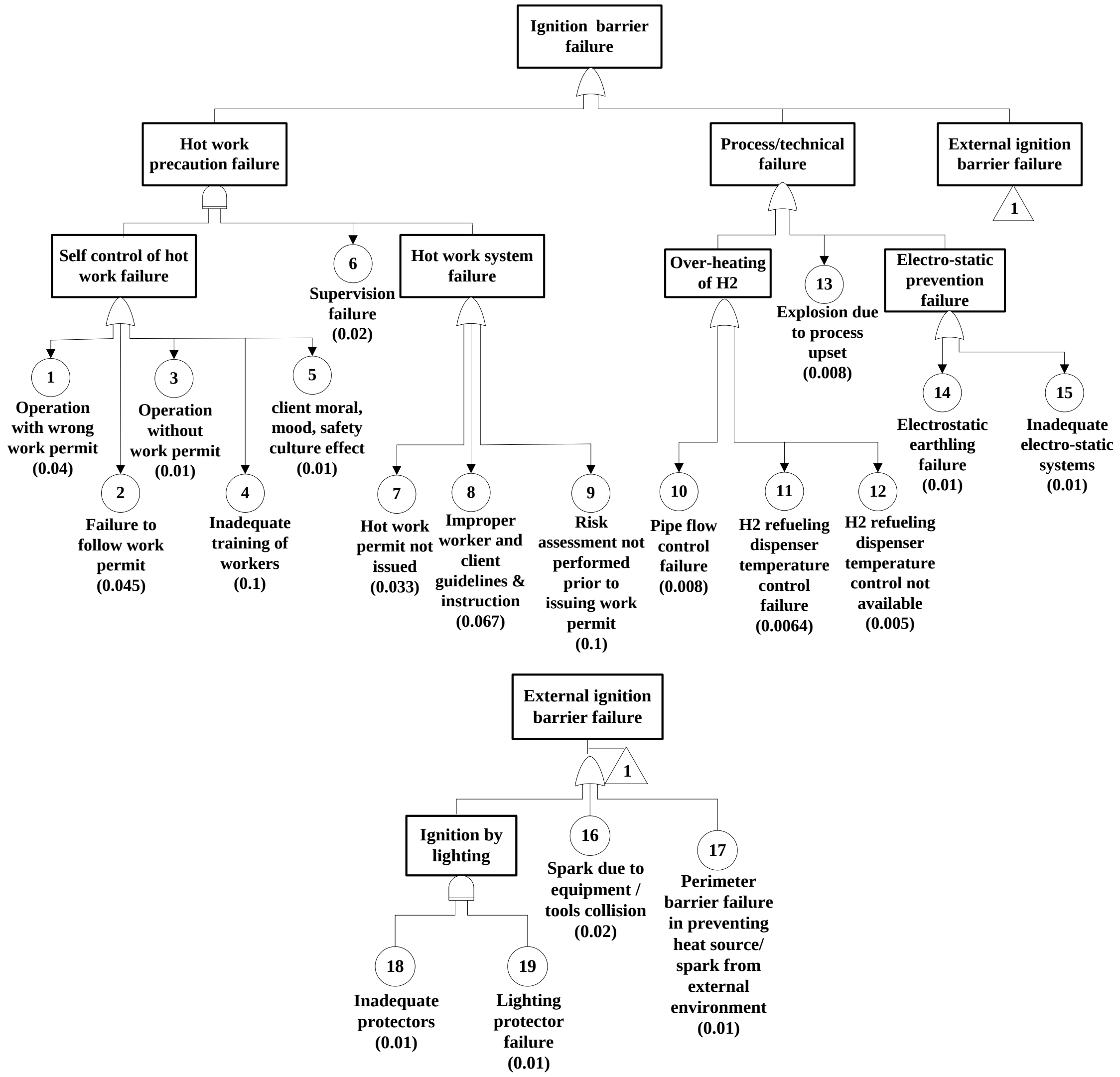


Figure 5: IPB failure FT model

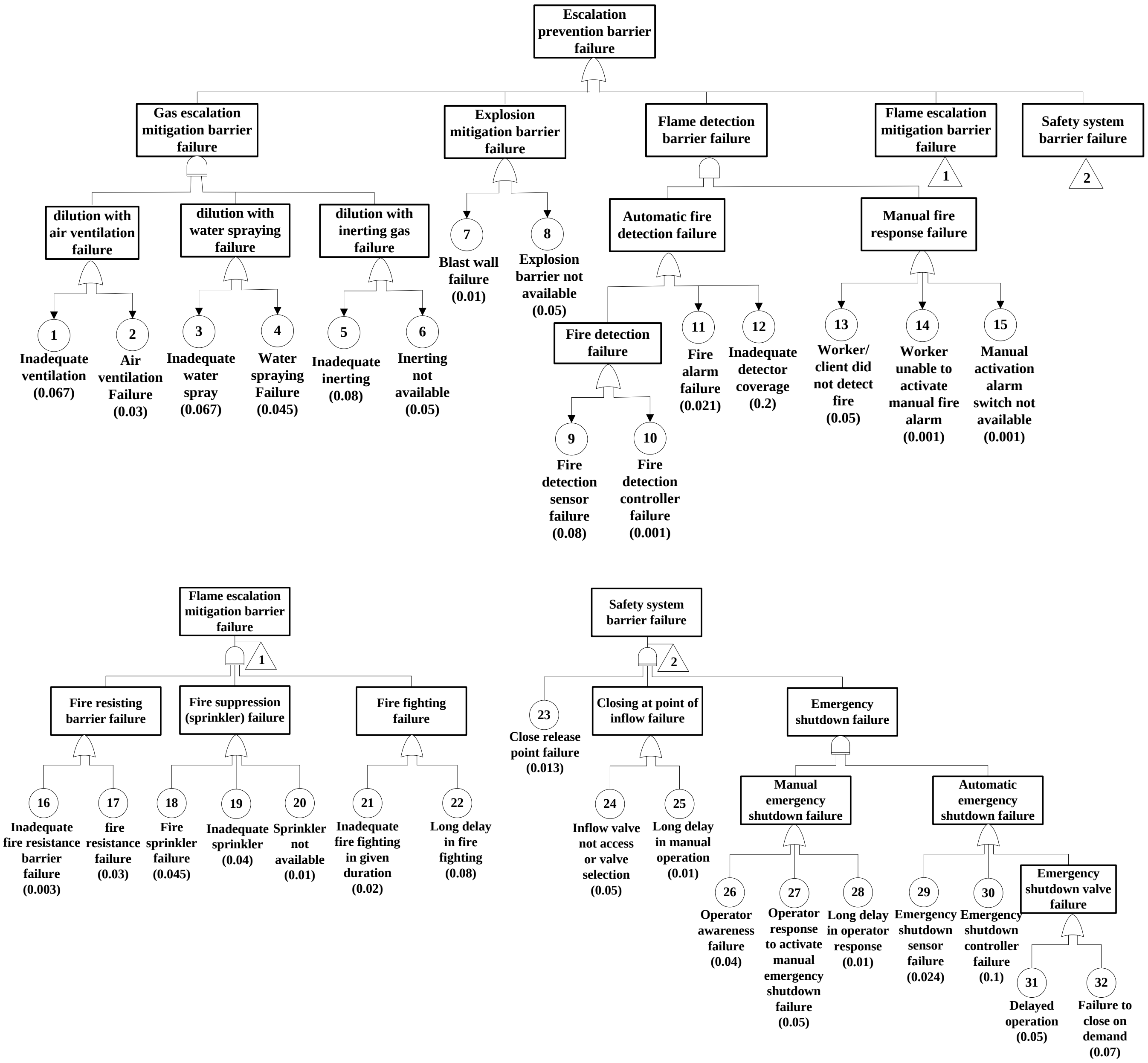


Figure 6: EPB failure FT model

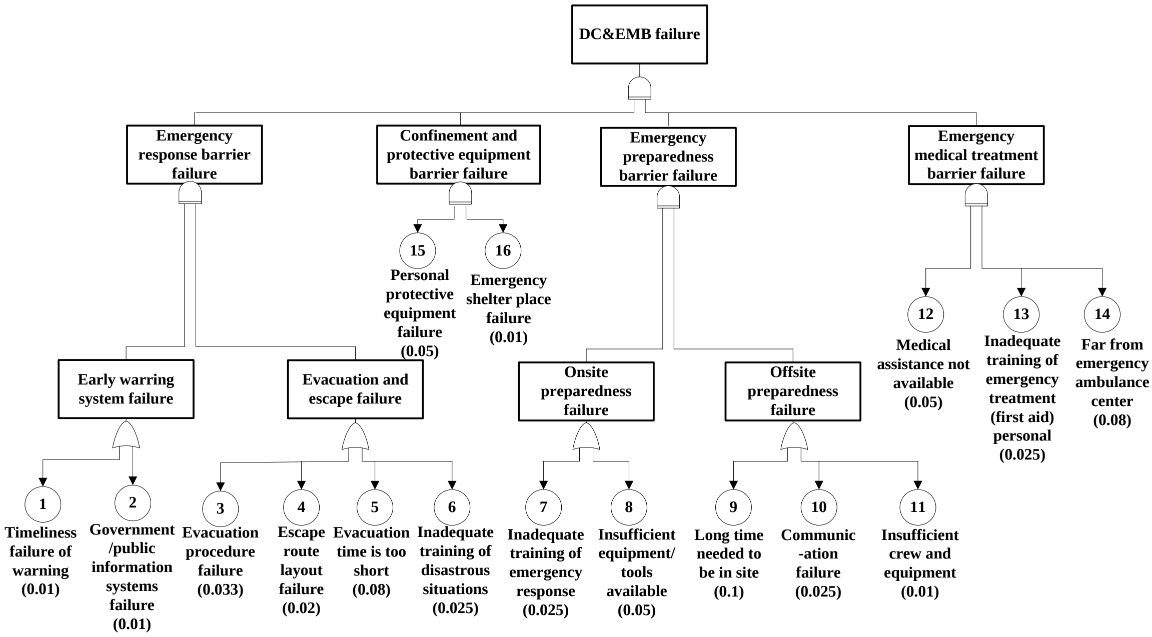


Figure 7: DC&EMB failure FT model

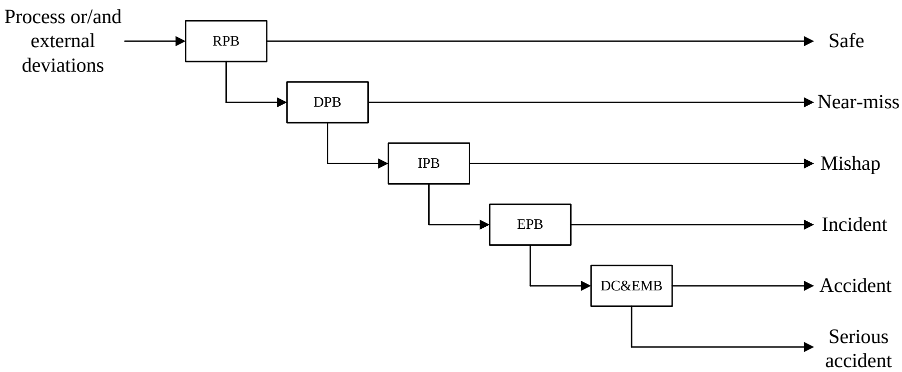


Figure 8: Accident model ET consequence analysis model

Within this modelling framework, the probability of each real time incident data is utilized to update the failure probabilities for all prevention barriers. This provides dynamic capability to the risk assessment approach, which can be implemented periodically, based on the availability of data updates and the nature of the process being considered. The outcome would facilitate risk based decision and helps in preventing accident through prioritizing facility's safety, maintenance, and management of change plans.

3.3 Barrier and End-state Events Failure Probability Updating

DRA is applied to update failure probabilities of the prevention barriers and end-state events through the use of precursor data - as likelihood function - and Bayesian theory. The accumulative discrete precursor data of end-state events in ET model is provided at each time interval. This data is extracted to formulate the likelihood function as the number of successes and failures for each safety barrier (j) at each time interval (t). Each (j) in the ET has two branches, i.e., success (upper branch) or fail (lower branch), in which the number of successes (s) is the summation of end-state events occurrence that branched from the success branch. Similarly, the number of failures (f) is the summation of end-state events that are branched from the fail branch of that safety barrier (j) at a particular time interval. This is applied for all (j) as shown in Eq. 1.

$$s_j = \sum m(j)_{sb} \quad , \quad f_j = \sum m(j)_{fb} \ , \ j = 1, 2, 3, ...N \tag{1}$$

Here, *sb*, and *fb* — denote success branch and fail branch of a particular safety barrier *(j)* respectively; *m(j)* — the number of occurrence of end-state events that are branched from success or fail branches of safety barriers *(j)* each time interval.

Then, the prior failure probabilities obtained from FTs are updated using Bayesian theory as represented by Eq. 2 below:

$$f(x \setminus data) = \frac{f(x)\, f(data \setminus x)}{\sum f(x)\, f(data \setminus x)} \alpha\ f(x)\, f(data \setminus x) \tag{2}$$

Here, *f(x\data)* — the posterior failure probability; *f(x)* — the prior failure probability; *f(data\x)* — the likelihood function; and $\sum f(x)\, f(data \setminus x)$ — the normalization factor.

In this analysis, hypothetical precursor data of end state events are used to implement the methodology. In cases where real data is available, this should be replaced by real ones. For the hydrogen filling station considered, the hypothetical data assumed is as shown in Table (2), and the time interval used is six months.

Table 2: Hydrogen station hypothetical accumulated precursor data

Time interval	Safe C1	Near-miss C2	Mishap C3	Incident C4	Accident C5	Serious accident C6
1	2	0	0	0	0	0
2	4	0	0	0	0	0
3	6	1	0	0	0	0
4	8	2	0	0	0	0
5	8	3	0	0	0	0
6	10	3	1	0	0	0
7	11	4	1	0	0	0
8	13	4	2	0	0	0
9	15	4	2	1	0	0
10	17	5	3	1	0	0

3.4 Deviations Prediction Model

An additional feature of the proposed framework is that it can be used to predict the number of expected abnormal events for next time interval. This is built upon the latest available information on accumulative precursor data and can be employed in prioritizing plans in preventing deviations prior to occurrence. The general formula for stochastic prediction model of random variable z is as represented in Eq. 3 below [15]:

$$p(z \setminus \pi) = \int_0^1 p(z \setminus \theta)\, p(\theta \setminus \pi)\ \partial\theta \tag{3}$$

Here, θ — the unknown parameter; *p(θ \π)* — the posterior distribution of the unknown parameter based on data π; and *p(z\θ)* — the sampling distribution function of *z* given θ. By integrating the sampling distribution *p(z\θ)* of the unknown parameter θ over the posterior distribution, it averages over the uncertainty in the parameter. That the predictive distribution can provides a full account for the uncertainty of the unknown parameter. By applying Eq. 3 to discrete random variable, the number of abnormal events in the next time interval given the precursor data, $p(y_{t+1} \backslash data)$ can be computed as follows:

$$p(y_{t+1} \backslash data) = \sum_{all\,\lambda} p(y_{t+1} \backslash \lambda)\, p(\lambda \backslash data) \tag{4}$$

Note that the number of abnormal events is assumed independent and random, where *data = (y1, y2, y3... yt)* – the observed end-state events data for each time *t = (1, 2, 3… t)*; and λ – the average number of abnormal events.

To determine the $p(\lambda \backslash data)$, the prior distribution for the number of abnormal events is computed. Typically, it is in the form of gamma distribution with a probability density as in the following:

$$p(\lambda \backslash \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma\alpha} \lambda^{\alpha-1} e^{-\beta\lambda} \tag{5}$$

Here, α and β – the shaping parameters of gamma distribution. To produce the posterior distribution, the prior is multiplied with suitable conjugate likelihood function. For a gamma prior distribution, the conjugate likelihood function would be a Poisson distribution as shown in Eq. 6:

$$p(data \backslash \lambda) = \frac{\lambda \sum_{i=0}^{n} y^{n}\, e^{-n\lambda}}{\prod (y_n!)} \tag{6}$$

By applying Bayesian updating through multiplying Eq. 5 with Eq. 6, the posterior probability of the number of abnormal events can be obtained. Nevertheless, the value of interests is actually the mean of the posterior, which is given by Eq. (7) below:

$$\lambda_{posterior} = E(\lambda \backslash data) = \frac{\alpha + \sum_{i=0}^{n} y_n}{\beta + n} \tag{7}$$

Here, $\sum y_n$ – the total number of end-state events (abnormal events); and n – the time interval. The posterior of abnormal events occurrence follows Gamma distribution with shaping parameters as following [15]:

$$\left.\begin{aligned} \alpha_{posterior} &= \alpha + \sum_{i=0}^{n} y_n \\ \beta_{\ posterior} &= \beta + n \end{aligned}\right\} \tag{8}$$

Based on the pervious hypotheses, and since the number of events occurrence is a non-negative integer value, then the predictive system is considered to follow the Poisson process and Eq. 4 will be as [16] and [9] which represents Poisson-Gamma prediction model:

$$p(y_{t+1} \backslash data) = \frac{\left(\lambda_{posterior}\right)^{y_{t+1}} e^{-\lambda_{posterior}}}{y_{t+1}!} \tag{9}$$

4.0 RESULTS AND DISCUSSION

Assuming the frequency of the initiating abnormal event in ET is unity, the estimated posterior failure probabilities of the prevention barriers in each of the ten time intervals are as illustrated in Fig. 8. Based on these posterior probabilities it can be observed that all prevention barriers show good performance with probabilities lower than their priors. However, the failure probabilities of the RPB and DPB are increasing after the second time interval. This has to be taken into the consideration by the management and a study is therefore needed to determine the cause of this trend.

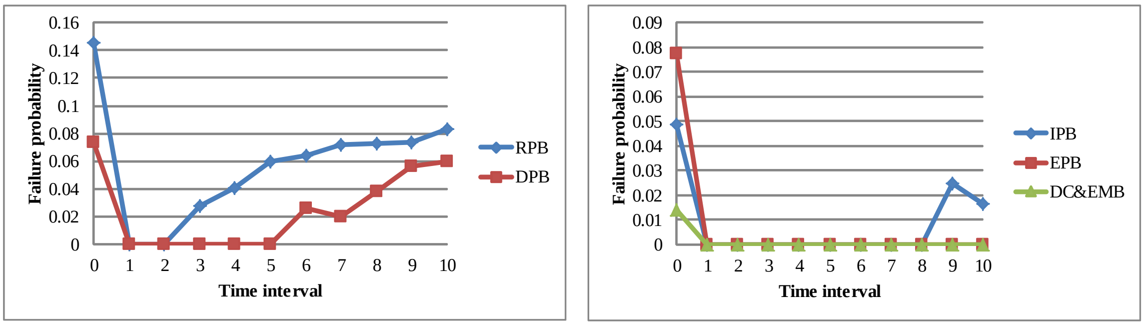


Figure 8: Prevention barriers posterior failure probability

Fig. 9 displays the prior and posterior estimation of end-state events probability. The results conclude that all end-state events probabilities, except for C1 (safe), are lower than their priors.

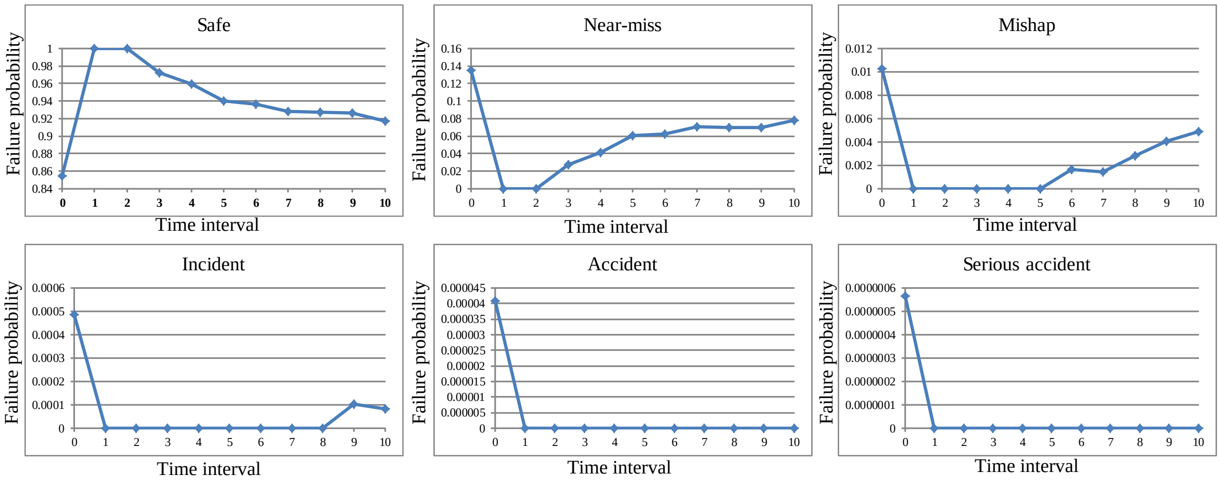


Figure 9: End-state events posterior failure probability

The predictive model results show reasonably good validation with the actual system. Fig. 10 displays the variation between the actual and the predicted number of initiating abnormal events. The biggest variation between predicted and actual numbers occurs at the tenth time interval. Note that at interval, the number of abnormal events is high and this increases the likelihood function to unexpected values, leading to poor prediction. The absolute error value in the tenth interval is 55%, whereas for other intervals the values are in the range of (0% - 43%).

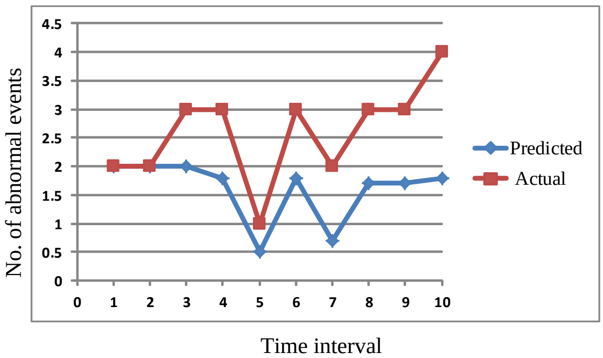


Figure 10: Prediction of abnormal events in next time interval

5.0 CONCLUSION

The DRA methodology provides a systematic procedure for accident modelling of the hydrogen refuelling station. It has assessed and predicted risks, and provided indications on the need to improve the plant where it matters. The results obtained in this study have proved the appropriateness and ability of this approach in supporting risk-based decisions to facilitate the management in prioritizing prevention plans so that safer conditions are established.

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