Journal of Hazardous Materials A108 (2004) 147–159

Journal of Hazardous Materials

www.elsevier.com/locate/jhazmat

Risk-based maintenance of ethylene oxide production facilities

Faisal I. Khan*, Mahmoud R. Haddara

Faculty of Engineering & Applied Science, Memorial University of Newfoundland, St. John's, NL, Canada A1B 3X5

Received 8 August 2003; received in revised form 22 January 2004; accepted 23 January 2004

Abstract

This paper discusses a methodology for the design of an optimum inspection and maintenance program. The methodology, called risk-based maintenance (RBM) is based on integrating a reliability approach and a risk assessment strategy to obtain an optimum maintenance schedule. First, the likely equipment failure scenarios are formulated. Out of many likely failure scenarios, the ones, which are most probable, are subjected to a detailed study. Detailed consequence analysis is done for the selected scenarios. Subsequently, these failure scenarios are subjected to a fault tree analysis to determine their probabilities. Finally, risk is computed by combining the results of the consequence and the probability analyses. The calculated risk is compared against known acceptable criteria. The frequencies of the maintenance tasks are obtained by minimizing the estimated risk.

A case study involving an ethylene oxide production facility is presented. Out of the five most hazardous units considered, the pipeline used for the transportation of the ethylene is found to have the highest risk. Using available failure data and a lognormal reliability distribution function human health risk factors are calculated. Both societal risk factors and individual risk factors exceeded the acceptable risk criteria. To determine an optimal maintenance interval, a reverse fault tree analysis was used. The maintenance interval was determined such that the original high risk is brought down to an acceptable level. A sensitivity analysis is also undertaken to study the impact of changing the distribution of the reliability model as well as the error in the distribution parameters on the maintenance interval.

Keywords: Risk-based maintenance; Maintenance planning; Risk assessment; Reliability optimization; Acceptable risk

1. Introduction

Over the past few decades, maintenance strategies progressed from the primitive breakdown maintenance to the more sophisticated strategies like condition monitoring and reliability centered maintenance. The paradigm shift was partly motivated by the sharp increase in the degree of mechanization, automation, and complexity of industrial equipment, and partly by the need to implement new maintenance strategies which would increase the effectiveness and profitability of the business. Another link in this chain of progress has been recently added by the introduction of a risk-based approach to maintenance. This approach has been suggested as a new vision for asset integrity management [1,14,15,17,18]. Risk-based maintenance strategies have been developed to provide a basis for not only taking the reliability of a system into consideration when making decisions regarding the type and the time for maintenance actions, but also to be able to take into consideration the risk that would result as a consequence of an unexpected failure [e.g. 2-5,14,19].

The problem of optimal maintenance is an old problem which has been discussed extensively in the literature. The difficulty with maintenance optimization lies in the fact that it is not only sufficient to model the problem accurately but it is also important to have the accurate data. Accurate data are not always available, therefore, we can only strive towards an optimal maintenance strategy. Several authors have endeavored to develop risk-based optimal maintenance strategies (e.g. [6,16,20–22]). Most of these strategies are based on prioritization schemes.

This paper has two main objectives: (i) to present a risk-based maintenance methodology that has a maintenance interval optimization model, and (ii) to demonstrate an application of the discussed methodology. To solve for the optimal maintenance interval, an objective function is

* Corresponding author. Tel.: +1-709-737-8939; fax: +1-709-737-4042.
E-mail address: fkhan@engr.mun.ca (F.I. Khan).

0304-3894/$ – see front matter
doi:10.1016/j.jhazmat.2004.01.011

formulated and minimized. The independent variables in the objective function represent the differential gain in the reliability of the different system components. The coefficients of the independent variables represent the cost of increasing the reliability of the components as a result of effecting more frequent maintenance actions. The reliability function of each component is calculated based on a maintenance cycle that minimizes the risk that would result as a consequence of an unexpected failure. Thus, by maximizing the objective function, one identifies the longest maintenance cycle that maximizes the reliability for an acceptable level of risk. The novel feature of this method is that it provides a mathematical model for the maintenance cycle optimization based on risk. Using this method, one can then determine a maintenance strategy that minimizes the cost for an acceptable level of risk. The risk-based methodology along with the model is discussed in the first half of the paper and the application of the methodology to an EO production plant is discussed in the second half of the paper.

2. Risk assessment

Risk assessment is a technique for identifying, characterizing, quantifying, and evaluating the loss caused by an event. Risk assessment integrates reliability and consequence analysis at the various stages of the analysis, and attempts to answer the following questions [4]:

- What can go wrong that could lead to a system failure?
- How can it go wrong?
- How likely is its occurrence?
- What would be its consequences?

In the present context risk is defined as the product of failure probability and its consequence. Risk assessment can be quantitative or qualitative. Quantitative risk assessment requires a great deal of data both for the assessment of probabilities and the assessment of consequences. Source, release, and impact models are used for consequence assessment, while fault tree analysis is used to determine the probability of sequence of events which results in a defined consequence. Quantitative risk values are measured in units of loss ($, downtime, human life, damage area) per unit time.

3. Risk-based maintenance (RBM)

Recently, Khan and Haddara [4,5] introduced a risk-based maintenance methodology. This methodology aims at reducing the overall risk that may result as a consequence of unexpected failures of operating facilities. By assessing the level of risk caused by the failure of each component, one can prioritize the maintenance tasks for the components of the system. This means that high risk items will be given more attention than low risk items. Using RBM one can determine the duration between two consecutive inspections for a piece of equipment to minimize the total risk as a result of the incidence of failure. The implementation of RBM reduces the likelihood of an unexpected failure. The quantitative value of risk is the basis for prioritization of inspection and maintenance activities.

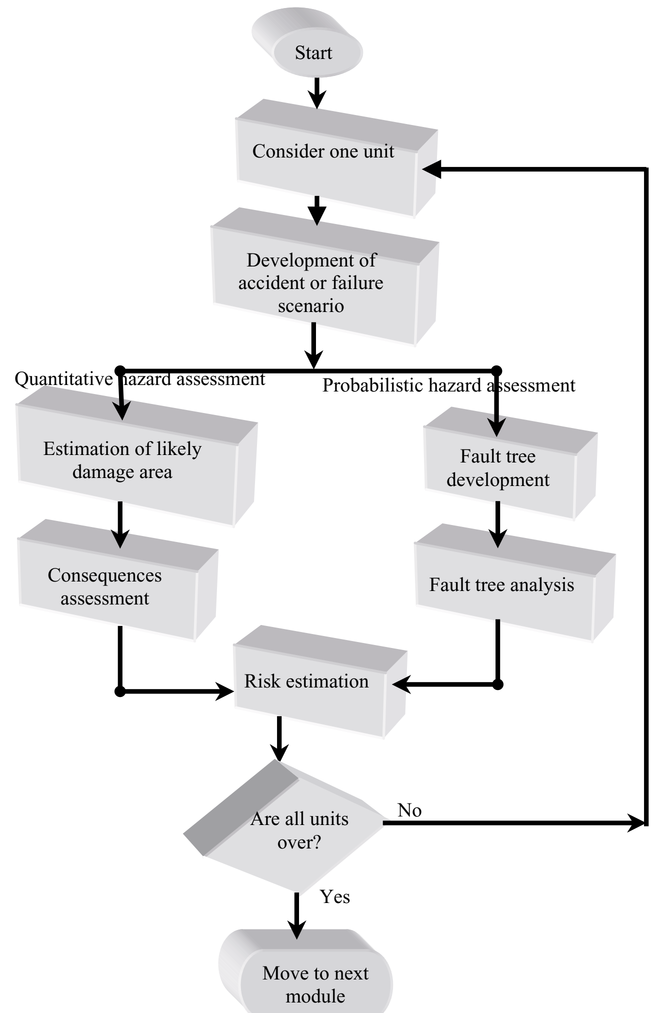

Fig. 1. Description of risk estimation module.

The RBM methodology is comprised of three modules, which are interactively linked. The RBM starts with dividing the complete system under study in small manageable units. Each unit is subjected to the different steps shown in Figs. 1–3. The risk, computed for a specific failure scenario(s) of a unit, is compared against the acceptance criteria. If the risk exceeds the criteria, the failure scenario is reevaluated for optimal maintenance/inspection duration that would bring down the exceeded risk to an acceptable level. This process is repeated for each unit. Results obtained for all units are combined to develop an overall maintenance plan for the system. Detailed description of each step of RBM methodology is detailed in following sections.

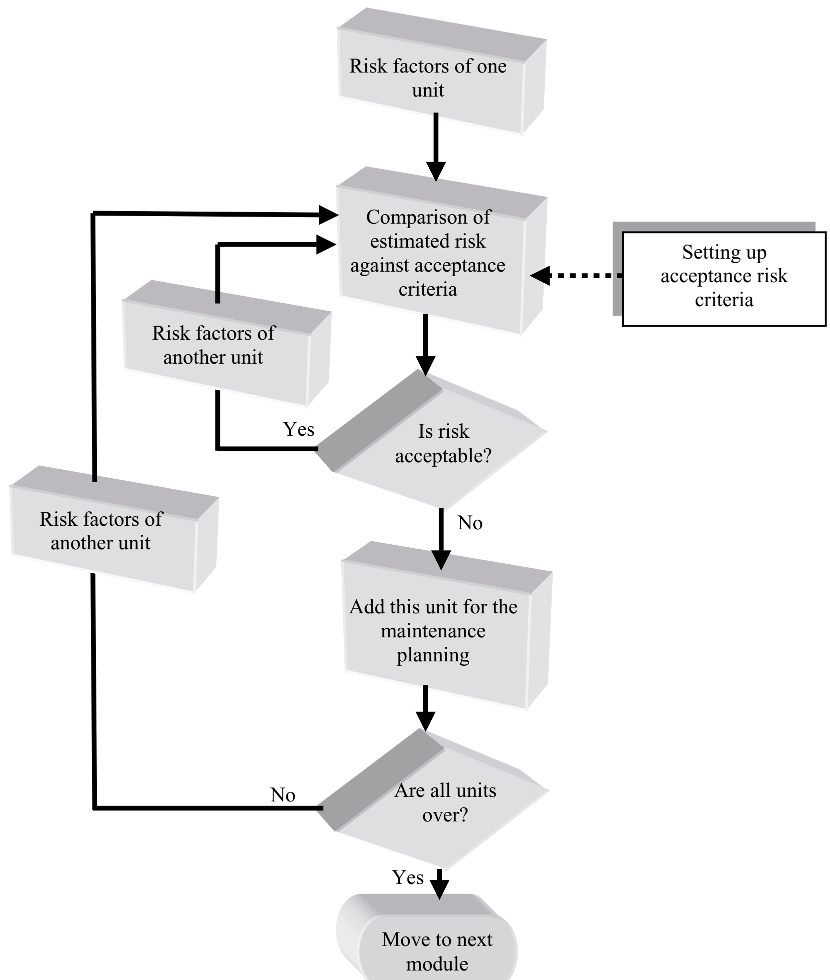

Fig. 2. Description of risk evaluation module.

3.1. Module I: risk estimation

This module is comprised of four steps, which are logically linked as shown Fig. 1. A brief description of each step is presented below.

3.1.1. Step I.1: failure scenario development

A failure scenario is a description of a series of events which leads to a failure event. It may contain a single event or a combination of sequential events. It is well evident from the past case studies that a failure occurs as a result of interacting sequence of events. The expectation of a scenario does not mean it will indeed occur, but that there is a reasonable probability that it would occur. A scenario is neither a specific situation nor a specific event, but a description of a typical situation that covers a set of possible events or situations. It is the basis of risk study; it tells us what may happen so that we can devise ways and means of preventing or minimizing the possibility of its occurrence. Failure scenarios are generated based on the operational characteristics of the system, physical conditions under which operation occur, geometry of the system, and safety arrangements. Recently, Khan [7] has proposed a systematic procedure—maximum credible accident scenario (MCAS)—to evaluate failure (accident) scenarios in a process system. It advocates consideration of maximum credible scenarios rather than worst-case accident scenarios as recommended by many regulatory agencies.

The developed failure scenarios may be screened to shortlist the ones that are more relevant for the scope of the study. This approach reduces the effort required without incurring a significant effect on the accuracy of the overall result of the study. It is advisable to consider one or two most appropriate failure scenario for each unit. MCAS may be used as a tool to shortlist (screen unimportant scenarios) failure scenarios.

3.1.2. Step I.2: consequence assessment

The objective here is to quantify the potential consequences of the total functional failure, which represents a credible scenario. In this analysis, the failure mode and function failure types are not considered. The analysis involves assessment of likely consequences if a failure scenario does materialize. Initially, consequences are quantified in terms

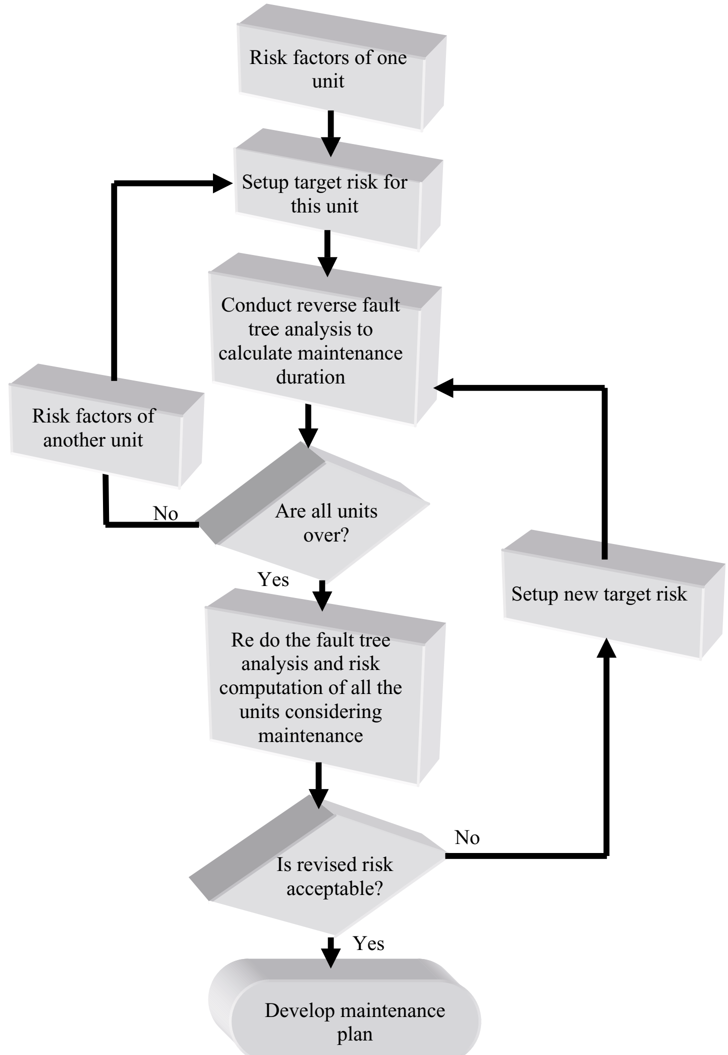

Fig. 3. Description of maintenance planning module.

of damage radii (the radius of the area in which the damage would readily occur), damage to property and toxic effects (chronic/acute toxicity). The calculated damage radii are later used to assess human health, environmental and production losses (in terms of dollars). This allows one to distinguish between prioritization performed on each category. It is of great practical benefit to separate the consequences of failure analysis from the consequences of failure mode analysis.

The assessment of consequences involves a wide variety of mathematical models. For example, source models are used to predict the rate of release of hazardous material, the degree of flashing, and the rate of evaporation. Models for explosions and fires are used to predict the characteristics of explosions and fires. The impact intensity models are used to predict the damage zones due to fires, explosion and toxic load. Lastly toxic gas models are used to predict human response to different levels of exposures to toxic chemicals. There are many computational tools available to conduct this step such as SAFETI, MAXCRED, RISKIT, etc. [8]. MAXCRED is one of the recent ones that uses the latest models of fires, explosions and toxic release and dispersion [8].

The total consequences assessment is a combination of four major categories of consequences: (i) system performance loss, (ii) financial loss, (iii) human health loss, and (iv) environment and/or ecological loss. The method of quantification of these four categories may change according to the scope of the study undertaken. Khan and Haddara [4] have defined quantification of these four parameters in the context of process operation. In present study same formulation is used.

3.1.3. Step I.3: probabilistic failure analysis

Probabilistic failure analysis is conducted using fault tree analysis (FTA). FTA is an analytical tool that uses deductive reasoning to determine the occurrence of an undesired event. One can use a fault tree analysis along with component failure data and human reliability data to determine the frequency of occurrence of an event.

In this step of RBM, fault trees are constructed for various likely initiating events, which may eventually lead to the 'top' event or the failure scenario. In order to develop probabilistic fault trees and analyze them swiftly Khan and Abbasi [9] have developed a methodology termed as 'analytical simulation'. A computer automated tool called PROFAT (PRObabilistic FAult Tree analysis [10]) was also developed to perform analytical simulations. The key features of this tool are: (i) fault tree development, (ii) Boolean matrix creation, (iii) finding of minimum cutsets and optimization, (iv) probability analysis, (v) improvement index estimation (see [9,10] for details). There are many other software commercially available, which can be used for this application, such as Fault Tree by (Relax Software Corporation), Fault Tree+ (Isograph Direct Inc.), and Fault Tree (Item Software Inc.).

3.1.4. Step I.4: risk estimation

Based on the results of the consequence analysis and probabilistic failure analysis, the risk posed by each unit was estimated. The consequence analysis encompasses the fatality, the economic, the environment and the system performance losses. Thus, the level of risk calculated reflects the total risk for the system. The computed risk will be evaluated against the acceptance criteria in the next module.

3.2. Module II: risk evaluation

This module of RBM is aimed to evaluate the earlier computed risk through the algorithm shown in Fig. 2. This module comprises of two steps as detailed below.

3.2.1. Step II.1: setting up acceptance criteria

As acceptance of risk may be different from one organization to another and from one system to another, the authors have suggested an open-ended methodology. In this step, the user sets up risk acceptance criteria, which depend on the scope of the study, the criticality of the system, and the policy or strategy of the organization. Some of the commonly used risk acceptance criteria are ALARP (as low as reasonably possible), Dutch acceptance criteria, and USEPA acceptance criteria.

3.2.2. Step II.2: risk comparison against acceptance criteria

Risk computed in Module I is compared with the risk acceptance criteria set-up earlier. A unit/component whose risk exceeds the acceptance criteria is marked for further analysis to reduce its risk. It is repeated for all the units/components of the system. The marked units are subsequently processed in Module III for maintenance planning.

3.3. Module III: maintenance planning

Units marked in Module II are studied in detail to reduce the risk through optimal maintenance planning. This module consists of two steps, which are logically linked, as shown in Fig. 3. A brief account of each step is discussed below.

3.3.1. Step III.1: estimation and optimization of maintenance duration

Units whose risk exceeds the acceptance criteria are each subjected to detailed investigation. The investigation includes identification of basic causes of failure and their functions. Using these details a maintenance optimization model is developed. The developed model is solved along with reverse fault tree analysis for a targeted value of top event (component failure probability/rate). This analysis gives optimal maintenance times for the component under study. This process is repeated for all units/components in this category. A maintenance plan can then be developed based on maintenance times arrived at in the previous step.

3.3.2. Step III.2: re-estimation and re-evaluation of risk

This is an optional step and it is aimed at verifying that the maintenance plan developed will produce an accepted risk level for the complete system. In this step, step 4 of Module I and step 2 of Module II are repeated using revised values for the failure probabilities. The result of this step will clearly determine whether the developed maintenance plan is effective in the managing risk or not.

4. Maintenance optimization model

Minimize the cost function, Z given as

$$Z = \sum_{i=1}^{n} c_i x_i^p \tag{1}$$

subjected to

$$f(R_i + x_i) \geq R^*, \quad 0 < (R + x_i) \leq B_i < 1 \tag{2}$$

where i is the component number $i = 1, 2, 3 \ldots, n$; n the total number components; p the power of reliability growth cost function. The quadratic cost function ($p = 2$) is the simplest non-linear cost function. Since it is convex, it shows reliability growth cost increasing at an increasing rate, which is commonly observed situation [11]. x_i is the incremental change in the reliability of ith component to meet the accepted risk level; c_i the corresponding cost of achieving this incremental change in the reliability of ith component (corresponding to target risk); R^* the target reliability of the system based on an acceptable risk; R_i the initial reliability of ith component; and B_i an upper bound on the attainable component reliability.

The solution of the optimization problem will yield values for the optimized values of incremental change in the reliability (x_i), the optimal maintenance interval is calculated using:

$$R_i + x_i = R_i(T) \tag{3}$$

where T is the optimal maintenance interval.

5. Case study: optimum RBM strategy for an ethylene oxide production facility

5.1. Process summary

Ethylene oxide (EO) is produced by the oxidation of ethylene with pure oxygen. Ethylene and oxygen are reacted at 10–30 atm and 400–500 °F in a fixed bed catalytic reactor. The catalyst beds consist of large bundles of tubes that contain supported silver catalyst spheres or rings. The tubes are 6–12 m long and 20–50 mm in diameter. The reactor off-gas is fed to CO_2 scrubbers, then to EO scrubbers, which absorb the EO into the liquid phase. The EO is recovered from the liquid in a desorber and distilled to remove water. EO purity is typically greater than 99.5%:

$$C_2H_4 + 0.5O_2 \rightarrow C_2H_4O \quad (4)$$

$$C_2H_4O + 2.5O_2 \rightarrow 2CO_2 + 2H_2O \quad (5)$$

$$C_2H_4 + 3O_2 \rightarrow 2CO_2 + 2H_2O \quad (6)$$

Catalyst pellets are designed to favor selective oxidation (epoxidation, Eq. (1)) over total oxidation (Eqs. (2) and (3)) by limiting the availability of active sites. Silver is supported on pure aluminum oxide having pore diameters ranging from 0.5 to 50 μm and a specific surface area less than 2 m^2/g. The effluent from the reactor passes through the absorber, in which the EO and some of the carbon dioxide, hydrocarbons, and aldehydes dissolve in the water. Most of the unabsorbed gas that leaves the top of the absorber is cooled and becomes the recycle ethylene stream. Gaseous impurities from the oxygen feed, such as argon, are purged from the recycle gas stream through the main process vent. Because there are fewer impurities in the oxygen feed, the purge stream is totally recycled. Thus, there is a build-up of by-product CO_2 that could reduce catalytic selectivity to EO at high levels if not removed from the system. A portion of the overhead gas from the absorber passes through a CO_2 absorber which uses potassium carbonate as an absorbent, then joins the recycle to the reactor. The spent CO_2 absorbent is reactivated in the CO_2 desorber, and then recycled to the CO_2 absorber. The CO_2 is vented from the CO_2 desorber. The dilute aqueous solutions of EO, CO_2, and other volatile organic compounds from the absorbers are combined and fed to the desorber where the EO and dissolved inerts are distilled under reduced pressure. The desorber water, virtually free of EO, is re-circulated to the absorbers. The crude EO from the desorber is sent to a stripper for the removal of CO_2 and inert gases and then sent to a final refining column (distillation column). Light gases separated in the stripper are vented overhead. The final product, 99.5 mol% EO, is stored under a nitrogen atmosphere in pressurized tanks.

Khan et al. [12] have conducted a detailed risk assessment study of the EO production plant. Table 1 summaries hazard identification results of this study. The study identified five units to be of serious concerns. They are: the reaction unit, EO storage unit, ethylene transportation line, ethylene EO distillation column, and ethylene reboiler. These units need a further detailed assessment of risk and accordingly safety measures designed and maintenance plan in action to counter these escalated risks. Authors have applied the RBM methodology to develop the maintenance plan for all the five units mentioned above. To illustrate the methodology the results of ethylene transportation line are presented below.

5.2. Module I: risk estimation

5.2.1. Failure scenario development for transportation of ethylene

Ethylene has been transported from the storage area located in remote vicinity to the reaction unit through pipeline. A fraction of the pipeline runs along the road. The most credible accident scenario envisaged for this unit is the release of ethylene either through a leak or rupture, causing the development of a vapor cloud which on meeting ignition source, cause a fireball.

5.2.2. Consequence assessment

The consequence assessment results for a fireball are presented in Table 2. The vapor cloud generated by instantaneous/continuous release on ignition would cause a fireball, which would generate a heat radiation effect. It is clear from Table 2 that an area of ∼90 m radius faces a 50%

Table 1
Summarized results of hazard identification in ethylene oxide production plant[a]

Units	Chemical of concern	Type of major hazard	Fire and explosion damage index (FEDI)	Toxic damage index (TDI)	Hazard control index (HCI)	SWeHI = maximum (FEDI or TDI)/HCI
Ethylene transportation line	Ethylene	Fire and explosion	440.3	145.5	39.3	11.2 (H)
Reaction unit	Ethylene and ethylene oxide	Fire and explosion	575.4	177.5	35.0	16.5 (HH)
Ethylene oxide distillation column	Ethylene oxide	Fire and explosion	380.5	135.0	33.1	11.5 (H)
Reboiler	Ethylene oxide	Fire and explosion	281.7	106.5	26.8	10.5 (H)
Ethylene oxide storage	Ethylene oxide	Fire and explosion	541.5	165.7	30.9	17.5 (HH)

EH: extremely hazardous: HH: highly hazardous, H: hazardous, MH: moderately hazardous, LH: less hazardous, NH: not hazardous.
[a] See [11] for details.

Table 2
Results of maximum credible accident analysis for the ethylene transportation line

Parameters	Values
Fire: fireball	
Radius of the fireball (m)	50.00
Duration of the fireball (s)	21.00
Energy released by fireball (kJ)	9.20E+05
Radiation heat flux (kJ/m^2)	1406.00
Damage radii (DR) due to thermal load	
DR for 100% fatality/damage (m)	50
DR for 50% fatality/damage (m)	88
DR for 100% third degree of burn (m)	139
DR for 50% third degree of burn (m)	181

probability of being damaged due to heat load. The heat radiation may cause a fatality as well as second-order accidents by seriously damaging other units/accessories. The worse affected would be the ethylene oxide reactor and its accessories.

5.2.3. Probabilistic failure analysis

5.2.3.1. Fault tree development. The top event was identified as a release causing the formation of a vapor cloud, which on meeting an ignition source would lead to a fireball. The developed fault tree is shown in Fig. 4. There are 25 basic events which contribute directly and indirectly to the accident scenario. These events with their frequency of failure (lognormally distributed) are given in Table 3. Most of the data are obtained from the specific industry; however, the values of some parameters were obtained from the literature [13], as industry-specific data was not available for these events. These failure frequencies are converted to failure probabilities using following expression:

$$F(t) = \Phi\left(\frac{1}{s}\ln\frac{t}{t_{\text{median}}}\right) \tag{7}$$

where $F(t)$ is the cumulative failure probability at time t; t_{median} the median failure time; s the shape parameter; and ϕ the normalized probability function give as $\Phi(z) = \int_{-\infty}^{z}(1/2\Pi)\,\mathrm{e}^{-y^2/2}\,\mathrm{d}y$

5.2.3.2. Fault tree analysis. The result of fault tree analysis is presented in Table 4. The probability of occurrence of the undesired event when all initiating events occur is estimated as 6.08E−03 per year. The right most column of Table 4 depicts the improvement factor for each component. Improvement index denotes percent contribution of an event in causing the scenario (occurrence of the top event). The improvement factor analysis suggests that events 1, 4, 5, 6, 11, and 12 have the significant contribution (about 75%) to the probability of the eventual accident. Table 4, which summarizes the results of the improvement analysis, indicates

Table 3
Elements of the fault tree developed for the most credible accident in the ethylene transportation line

Components number referred in Fig. 4, Tables 4 and 5	Elements	Median time (t_{median}) (year)	Shape factor (s)
1	Flammable gas detector fail	1.1043	0.817
2	Gas out of run	0.332	0.088
3	Inert gas release mechanism failed	1.437	1
4	Flame arrestor A failed	2.976	1
5	Flame arrestor B failed	2.976	1
6	Ignition source present	2.402	1
7	Mechanical failure due to corrosion	16.877	1
8	Leak from valves (two valves)	1.325	1
9	Leak from bends (four bends)	1.693	1
10	Leak from joints (10 joints)	0.868	0.557
11	Flow sensor failed	1.022	0.728
12	Pressure sensor failed	1.421	1
13	Pipeline chocked	16.902	1
14	Valve chocked	10.771	1
15	High inlet flow	1.437	1
16	High inlet pressure	1.437	1
17	Pressure controller/trip failed	1.738	1
18	High inlet temperature	0.490	0.191
19	External heat source present	4.997	1
20	Side reaction	2.300	1
21	Temperature controller/trip failed	1.738	1
22	Phase change	4.997	1
23	Valves fails open (two valves)	3.964	1
24	Corrosion	3.535	1
25	Mechanical damage	7.469	1

t_{median} and s are median time and shape factor as used in Eq. (7). These are obtained using failure data from industry and also from [13].

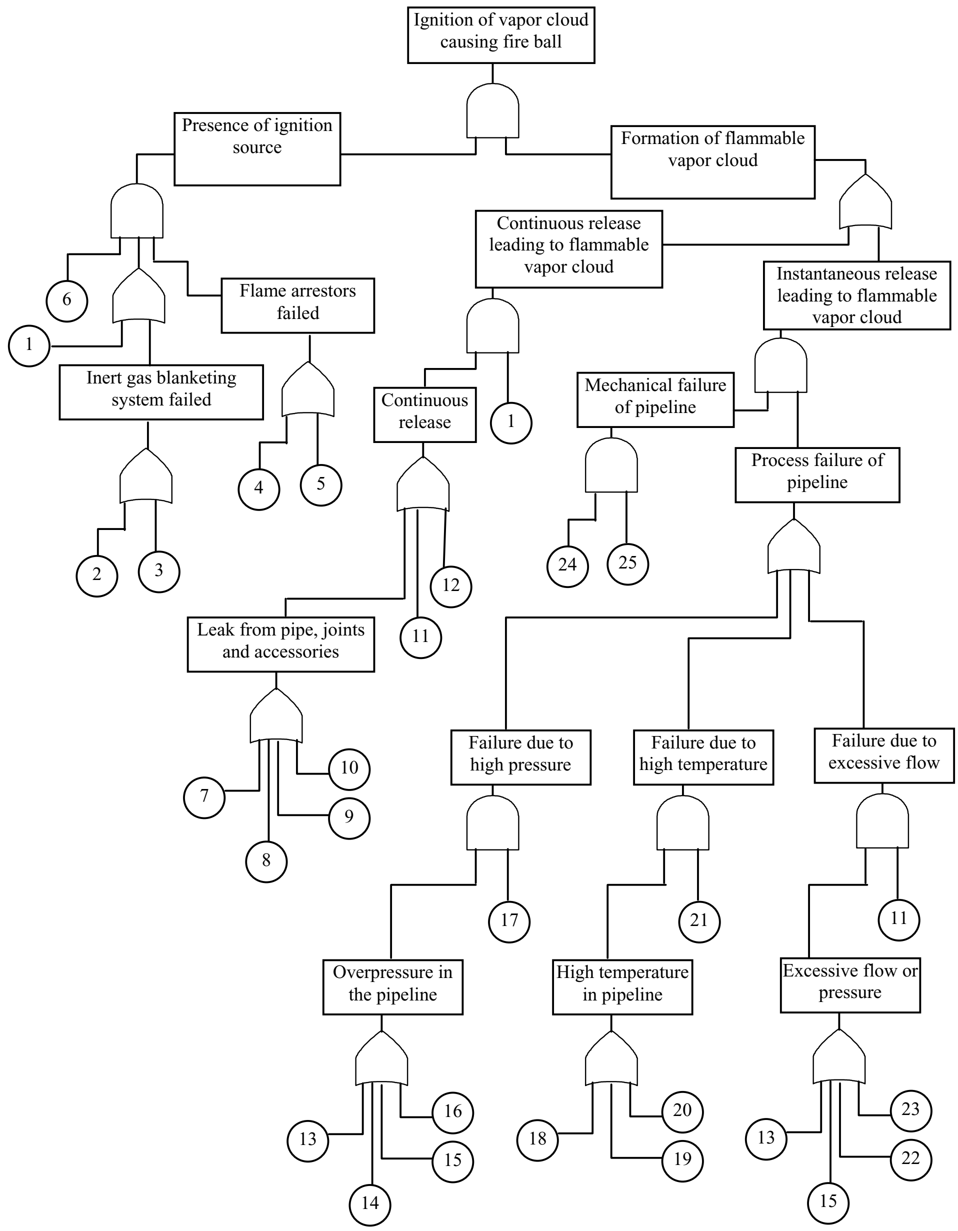

Fig. 4. Fault tree for failure maximum credible accident in ethylene transportation line.

that events which would have the lowest contribution towards the undesired event are 13, 14, 19, and 22 (see Table 3 for the details of these numbers). The study concludes that particular attention must be paid to events 1–6 and 8–12, which are most likely to cause the eventual accident (top event).

5.2.3.3. Risk quantification. Using the results of steps 2 and 3, individual risk for (1 year duration) has been computed as 3.15E−04. In present study, human health loss is the major source of risk as it dominates over other consequences factors such as system performance loss, assets loss, and environmental and ecology damage.

5.3. Module II: risk evaluation

5.3.1. Risk comparison against acceptance criteria

In present study both societal risk and individual risk factors are considered. In case of societal risk, Dutch frequency-number of fatality (FN) acceptance criteria is used as shown in Fig. 5. The FN curve for ethylene transportation line is plotted in Fig. 5. It is evident from the figure that current FN curve far exceed the acceptance criteria. Thus, there is need for developing maintenance plan or extra safety measures to bring this elevated risk to an acceptable level.

Similarly, comparing the calculated individual risk factor (3.15E−05) with acceptance risk criteria (1.0E−06), it is

Table 4
Results of PROFAT for the most credible accident scenario in the ethylene transportation line

Event not occurring	Probability	Improvement	Improvement index
0	6.0869E−03	0.000E+00	0.000
1	7.2389E−05	2.405E−02	12.902
2	3.1266E−03	1.184E−02	6.350
3	5.0299E−03	4.227E−03	2.267
4	0.0000E+00	2.434E−02	13.057
5	0.0000E+00	2.434E−02	13.057
6	0.0000E+00	2.434E−02	13.057
7	6.0774E−03	3.779E−05	0.020
8	4.2906E−03	7.185E−03	3.853
9	4.7057E−03	5.524E−03	2.962
10	3.3138E−03	1.109E−02	5.948
11	6.7800E−05	2.407E−02	12.911
12	9.6455E−05	2.396E−02	12.850
13	6.0865E−03	1.556E−06	0.000
14	6.0864E−03	1.974E−06	0.001
15	6.0543E−03	1.303E−04	0.069
16	6.0746E−03	4.917E−05	0.026
17	6.0622E−03	9.871E−05	0.052
18	6.0530E−03	1.355E−04	0.072
19	6.0848E−03	8.167E−06	0.004
20	6.0798E−03	2.825E−05	0.015
21	6.0444E−03	1.699E−04	0.091
22	6.0836E−03	1.318E−05	0.007
23	6.0819E−03	2.003E−05	0.010
24	5.9917E−03	3.806E−04	0.204
25	5.9917E−03	3.806E−04	0.204

Refer Table 3 for detail of these events.

observed that the current individual risk is far exceeding the acceptance criteria.

As in present study focus is on maintenance planning, a target reliability which will satisfy the risk acceptance criteria is estimated. The value is 0.99999795.

5.4. Module III: maintenance planning

5.4.1. Estimation and optimization of maintenance duration

As a first step, a maintenance cost model is developed based on the available information. The developed cost model is minimized for the set of important basic components (components short listed based on the results of importance factor calculation, components 1–6, and 8–12):

$$Z = \sum_{i=1}^{6}(c_i x_i^2) + \sum_{i=8}^{12}(c_i x_i^2) \tag{8}$$

subject to

$$f(R_i + x_i) \geq 0.99999795, \quad 0 < (R_i + x_i) \leq 1 \tag{9}$$

where i denote the important basic components (1–6 and 8–12).

The input data and results of above model are shown in Table 5. It is clear from the results that among 11 important components, components 1, 2, 10, 11, and 12 need extra attention and improvement in their reliability. This improvement in the reliability is achieved through inspection and preventive maintenance. Considering above results optimal preventive maintenance time is calculated using following model:

$$R_{\text{latest}} = (R_i + x_i) = 1 - \Phi\left[\frac{1}{s}\ln\frac{T}{t_{\text{median}}}\right] \tag{10}$$

The results of this step are presented in Table 5. Using the latest value of failure probabilities of different components (after considering preventive maintenance strategy) fault tree analysis is conducted again. The revised failure probability is calculated as 1.244E−06 and individual risk factor is 6.07E−07 (Table 5). FN curve for the revised condition (after revising the failure probability considering preventive

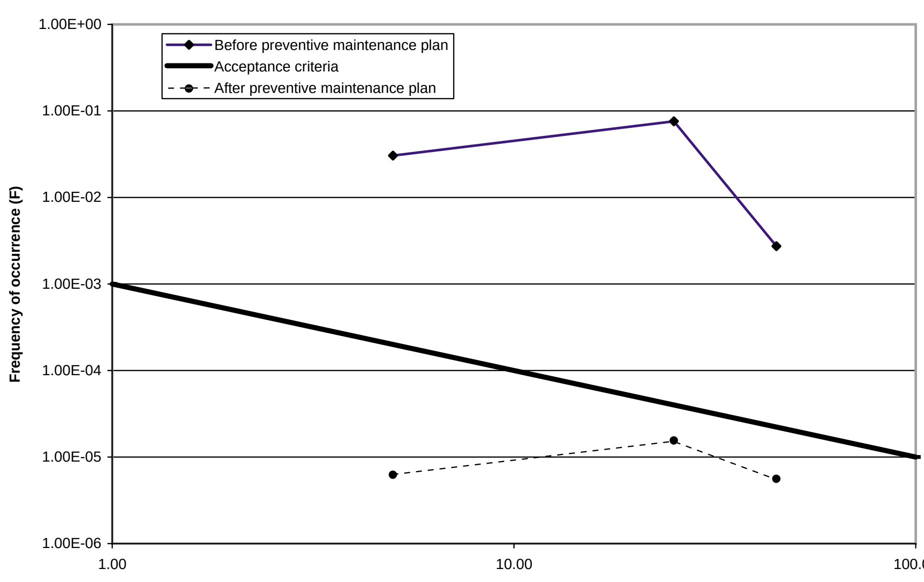

Fig. 5. FN curves for an ethylene transportation pipeline.

Table 5
Average individual risk factor before and after add-on safety measures have been decided

Components[a]	Cost ($/improvement in reliability)	Improvement in reliability (x_i)	Revised failure probability (R_{latest})	Preventive maintenance interval (year)
1	15	2.81E−01	0.1704	0.506
2	20	4.18E−01	0.5817	0.0338
3	20	2.06E−01	0.1519	0.514
4	150	2.63E−02	0.1114	0.879
5	150	2.63E−02	0.1114	0.879
6	60	6.66E−02	0.1238	0.756
8	20	2.13E−01	0.1766	0.789
9	30	1.39E−01	0.1605	0.821
10	20	2.64E−01	0.3361	0.568
11	15	2.91E−01	0.1971	0.436
12	15	2.60E−01	0.1025	0.400

Revised occurrence probability of accident scenario: 1.24E−06; revised individual risk factor: 6.07E−07. x_i is the optimal improvement in the reliability of ith component calculated using the model given in Eqs. (8) and (9). R_{latest} is the revised reliability calculated using Eq. (10).
[a] Refer Table 3 for detail of these components.

maintenance strategy) is depicted in Fig. 5. It is evident from the figure that revised risk profile (FN) is staying well within the acceptability criteria.

A reverse fault tree analysis is conducted to ascertain that the calculated preventive maintenance intervals (using above models) are optimal and able to bring the risk to an acceptable level (see Table 5). This analysis further supports that the calculated intervals are optimal.

5.5. Sensitivity analysis

A detailed sensitivity analysis is conducted to study the effect of the use of different reliability distribution models on the maintenance intervals. The effect of the uncertainty in the parameters of the models on the maintenance interval has also been investigated.

5.5.1. Selection of reliability distribution model

In addition to the lognormal distribution model three other reliability models were studied. These are: Weibull distribution with $\beta = 2$, Weibull distribution with $\beta = 3$, and a constant failure rate model. The results are presented in Fig. 6. It is evident from the figure that the maximum effect on the maintenance interval occurs when the constant failure rate model is used. The sensitivity of the maintenance interval is the same for both the Weibull model with $\beta = 3$ and the lognormal distribution model. The Weibull with $\beta = 2$ shows comparatively more robust results. It may be concluded from this study that the proper selection of a reliability model is very important. The two-parameter Weibull model ($3 > \beta > 1$) shows more consistent results followed by lognormal distribution.

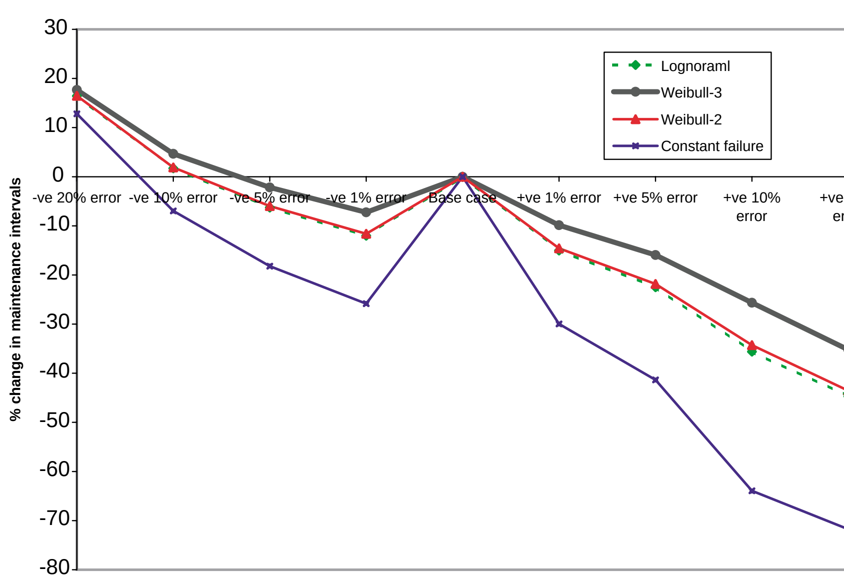

Fig. 6. Sensitivity analysis for different reliability models.

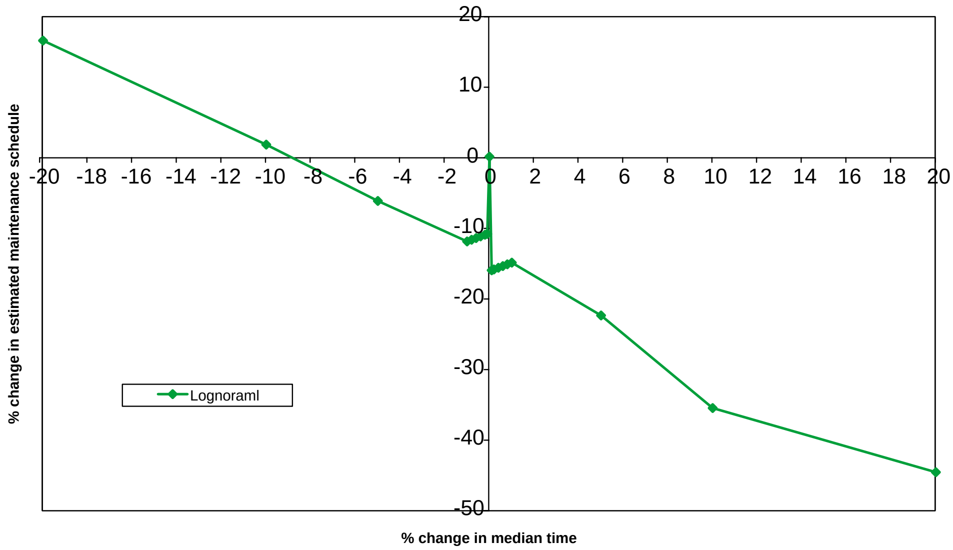

Fig. 7. Sensitivity analysis results for median time.

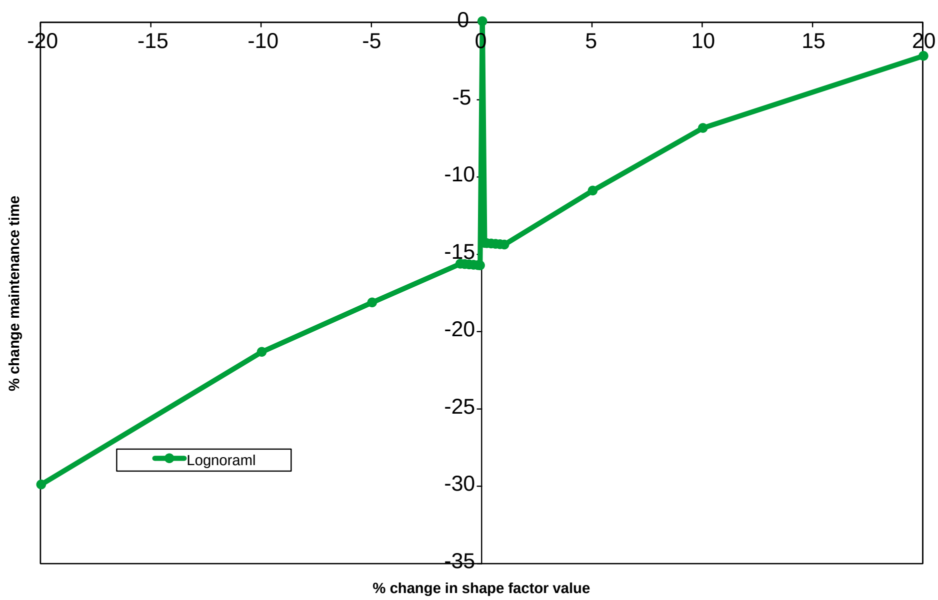

Fig. 8. Sensitivity analysis results for change in shape factor.

5.5.2. *Uncertainty in the reliability distribution model*

A sensitivity study is conducted to study the impact of the uncertainty in the values of the parameters (t_{median} and s) of the distribution model. The results are plotted in Figs. 7 and 8. Fig. 7 shows the sensitivity results related to median time change. It is evident from the figure that the estimated preventive maintenance interval is sensitive to the median time. Results are more sensitive for positive errors in the median time (higher than the base value) as compared to negative errors (lower than the base value). A positive error of about 20% in the median time may underestimate the maintenance time interval by 44%, whereas a negative error of the same magnitude will overestimate the maintenance interval by 15%. Thus, it is evident from this study that a conservative value of the median time should be avoided.

Fig. 8 shows the sensitivity results to the shape factor (s). The results show that the maintenance interval is more sensitive when there is a negative change in the shape factor as compared to a positive change. A negative error of 20% in the shape factor may underestimate the maintenance interval by 30%, whereas positive error of same magnitude may underestimate maintenance interval just by 4%. It is therefore advisable to use a conservative value of shape factor.

6. Discussion and conclusions

Risk assessment integrates reliability analysis with safety and environmental issues. Risk-based maintenance answers to the five following questions in developing an optimum maintenance strategy:

- What can cause the system to fail?
- How can it cause the system to fail?
- What would be the consequences, if it fails?
- How probable is the occurrence?
- How can we prioritize inspection/maintenance actions?
- What is the optimum frequency of inspection/maintenance tasks?

Such a maintenance planning approach is expected to provide a cost effective maintenance program and it also minimizes the consequences (related to safety, economics, and the environment) of a system's outage/failure. This will, in turn, result in a better asset and capital utilization. An optimum risk-based maintenance plan is superior to existing classical maintenance plans because it strives towards the minimization of cost as well as risk.

The failure of a system is rarely the result of a single cause, but rather the result of a combination of a series of interacting events. As a result, risk-based maintenance must not be perceived as a static exercise to be performed only once. It is a dynamic process, which must be continuously updated as additional information become available.

In this paper, we have introduced a methodology to develop an optimum risk-based maintenance strategy. The methodology is more comprehensive and quantitative than available methodologies. It comprises three main modules: (i) a risk estimation module, (ii) a risk evaluation module, and (iii) a maintenance optimization module.

A case study was considered to illustrate the methodology. Out of the five most hazardous units in the ethylene production facility considered, the ethylene transportation pipeline is the unit that has the highest risk. Human health risk factors were calculated using available failure data, which fits best a lognormal distribution model. Original calculations indicated that both societal risk factors and individual risk factors exceed the acceptable risk criteria. Subsequently, optimal maintenance intervals were calculated using the maintenance model and a reverse fault tree analysis. It is further verified that the implementation of the suggested maintenance and inspection strategy would bring the risks to acceptable levels.

A sensitivity analysis was also undertaken to study the impact of changing the shape of the reliability distribution on the results. The sensitivity of the model to errors in the reliability distribution parameters was also investigated. It is observed that the Weibull model is more robust than the other models, whereas the constant failure rate model is the most sensitive to changes in the parameters. In the case of the lognormal distribution, one must avoid using conservative values for the median time as it causes negative impact on the maintenance schedule.

Acknowledgements

Authors thankfully acknowledge the financial support of Natural Science and Engineering Research Council (NSERC) under Discovery grant.

References

[1] R.L. Montgomery, C. Serratella, Risk-based maintenance: a new vision for asset integrity management, Press. Vess. Piping 444 (2002) 151–165.
[2] S. Apeland, T. Aven, Risk based maintenance optimization: foundation issues, Reliab. Eng. Syst. Safety 67 (2000) 285–292.
[3] M.A. Nessim, M.J. Stephens, T.J.E. Zimmerman, Risk based maintenance planning for offshore pipelines, in: Proceedings of the Annual Offshore Technology Conference, vol. 2, 2000, pp. 791–800.
[4] F.I. Khan, M. Haddara, RBM: a new approach for process plant inspection and maintenance, in: Proceedings of AIChE's Loss Prevention Conference, April 1–3, 2003, New Orleans, LA.
[5] F.I. Khan, M. Haddara, Risk-based maintenance (RBM): a quantitative approach for maintenance/inspection scheduling and planning, J. Loss Prev. Process Ind. 16 (2003) 561–573.
[6] J.K. Vaurio, Optimization of test and maintenance intervals based on risk and cost, Reliab. Eng. Syst. Safety 49 (1995) 23–36.
[7] F.I. Khan, Maximum credible accident scenario for realistic and reliable risk assessment, Chem. Eng. Prog. 97 (11) (2001) 55–67.
[8] F.I. Khan, S.A. Abbasi, MAXCRED—a new software package for rapid risk assessment in chemical process industries, Environ. Model. Software 14 (1999) 11–25.
[9] F.I. Khan, S.A. Abbasi, Analytical simulation and PROFAT II: a new methodology and a computer automated tool for fault tree analysis in chemical process industries, J. Hazard. Mater. 75 (2000) 1–27.
[10] F.I. Khan, S.A. Abbasi, PROFAT: a user-friendly system for probabilistic fault tree analysis, Process Safety Prog. 18 (1) (1999) 42–49.
[11] C. Ebeling, Introduction to Reliability and Maintainability Engineering, McGraw-Hill, Boston, 1997.
[12] F.I. Khan, T. Husain, S.A. Abbasi, Design and evaluation of safety measures using a newly proposed methodology "SCAP", J. Loss Prev. Process Ind. 15 (2002) 129–146.
[13] RAC, Non-electric Components Reliability Data, Center for Reliability Assessment, New York, 2002.
[14] American Society of Mechanical Engineers Code Committee SC6000, Hazardous Release Protection, ASME, New York, NY, 2000.
[15] F. Backlund, J. Hannu, Can we make maintenance decisions on risk analysis? J. Qual. Maint. Eng. 8 (1) (2002) 77–91.
[16] R. Dekker, Applications of maintenance optimization models: a review and analysis, Reliab. Eng. Syst. Safety 51 (1996) 229–240.
[17] J.A. Farquharson, F. Choquette, Using QRA to make maintenance trade-off decisions, Press. Vess. Piping 444 (2002) 129–134.
[18] J.A. Harnly, Risk-based prioritization of maintenance repair work, Process Safety Prog. 17 (1) (1998) 32–38.
[19] U. Kumar, Maintenance strategies for mechanized and automated mining systems: a reliability and risk analysis based approach, J. Mines Met. Fuels 46 (11–12) (1998) 343–347.
[20] J. Vatn, P. Hokstad, L. Bodsberg, An overall model for maintenance optimization, Reliab. Eng. Syst. Safety 51 (1996) 241–257.
[21] W.E. Vesely, M. Belhadj, J.T. Rezos, PRA importance measures for maintenance prioritization applications, Reliability Engineering and System Safety 43 (1994) 307–318.
[22] L.J. Perryman, N.A.S. Foster, D.R. Nicholls, Using PRA in support of maintenance optimization, Int. J. Pres. Ves. & Piping 61 (1995) 593–608.

Further reading

[23] T. Aven, K. Porn, Expressing and interpreting the results of quantitative risk analyses: review and discussion, Reliab. Eng. Syst. Safety 62 (1998) 3–10.

[24] S.J. Brown, I.L. May, Risk-based hazardous release prevention by inspection (maintenance), J. Press. Vess. Technol. 122 (8) (2000) 362–367.

[25] C.A. Clarotti, A. Lannoy, H. Procaccia, Probabilistic risk analysis of ageing components which fail in demand a Bayesian model: application to maintenance optimization of diesel engine linings, in: Proceedings of the Conference on Aging Materials and Methods for the Assessment of Lifetime Engineering Plants, Cape Town, 1997, pp. 85–94.

[26] J. Grievink, K. Smith, R. Dekker, C.F.H. van Rijn, Managing reliability and maintenance in the process industry, in: Proceedings of the Foundations of Computer Aided Process Operations, Crested Butte, CO, 1993.

[27] A. Knoll, P.K. Samanta, W.E. Vesely, Risk based optimization of the frequency of EDG on-line maintenance at Hope Creek, in: Proceedings of probabilistic Safety Assessment, Park City, 1996, pp. 378–384.

[28] S. Martorell, A. Sanchez, S. Carlos, V. Serradell, Comparing effectiveness and efficiency in technical specifications and maintenance optimization, Reliab. Eng. Syst. Safety 77 (3) (2002) 281–289.

[29] W. Pyjadas, A.A. Chen, A reliability centered maintenance strategy for a discrete part manufacturing facility, Comput. Ind. Eng. 31 (1/2) (1996) 241–244.

[30] S.K. Stefanis, E.N. Pistikopoulos, Methodology for environmental risk assessment of industrial non-routine release, Ind. Eng. Chem. Res. 36 (1997) 3694–3707.

[31] J.S. Tan, M.A. Kramer, A general framework for preventive maintenance optimization in chemical engineering operations, Comput. Chem. Eng. 21 (12) (1997) 1451–1469.

[32] S.G. Vassiliadis, E.N. Pistikopoulos, Maintenance-based strategies for environmental risk minimization in the process industries, J. Hazard. Mater. 71 (1) (2000) 481–501.