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An integrated framework for condition-informed probabilistic risk assessment

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ABSTRACT: Traditional Probabilistic Risk Assessment (PRA) is based on techniques like Event Tree Analysis (ETA) and Fault Tree Analysis (FTA), which are considered static, i.e., the failure probabilities of the safety barriers do not take into account the system evolution in time, e.g., due to various degradation mechanisms, like fatigue, wear, corrosion, etc. On the other hand, condition-monitoring data are available in practice and can be used, possibly even for real-time updating. In this paper, we develop an integrated framework for condition-informed risk analysis. A conventional event tree model is used, in which some safety barriers are subject to degradation mechanisms and their failure probabilities are treated as time-dependent. Particle Filtering (PF) is used to update the failure probabilities of the safety barriers in real-time, based on the collected condition-monitoring data. The updated failure probabilities are, then, used in the event tree model. The developed framework also allows predicting the scenario probabilities in the future. To do this, the failure probabilities are updated and predicted by PF and, then integrated in the event tree. The developed framework is applied for condition-informed risk assessment of a high-level alarm equipment from literature.

1 INTRODUCTION

Safety barriers of industrial plants are frequently subject to degradation processes, such as wear (Compare et al. 2016, Zeng et al. 2016), fatigue (Zeng et al. 2014, Chiacío et al. 2016), crack growth (Kim et al. 2015), material degradation (Zeng et al. 2013), etc. As a result, the reliability of safety barriers degrades over time. Besides, as a system lives, its operating environment is subject to changes, which might affect its time-dependent behavior with respect to risk (Liu et al. 2015).

Traditional Probabilistic Risk Assessment (PRA) techniques do not consider these time-dependent aspects (Khan et al. 2015, Siu, 1994). To deal with this, Dynamic Risk Assessment (DRA) methods are being developed. For example, a dynamic event tree has been proposed to model dynamic scenarios (Swaminathan & Smidts 1999). Bayesian network has been used by Khakzad & Amyotte (2013) to make use of observed statistical failure counting evidence and updating the failure probability of the basic events. Khakzad et al. (2012) has developed a DRA method by updating the probabilities of the initial events in a bow-tie model using a physical reliability model. In Podofillini et al. (2010), a possibility clustering approach has been used to generate the stochastic scenarios of the potential system states for DRA. The Go-flow method has been used by Yang et al. (2014) for real-time calculation of risk indexes. However, most of the existing works only consider statistical failure counting data, which come from a population of similar systems and do not fully reflect the degradation conditions of the system of interest.

Condition-monitoring data have been used by Kim et al. (2015) for DRA to capture system-specific degradation behaviors. However, their work does not consider the noise in the observed degradation data. Particle filtering (PF) has been applied by Wang et al. (2016) to filter the process noise and estimate the true degradation states in DRA. However, their work has not considered consequence analysis models, e.g. Event Tree (ET), Bayesian Network (BN), etc. for risk calculations. Rather, the risk indexes have been assessed directly from the monitored degradation variables by considering the affected performance due to the degradation. Besides, prediction of future risk is not considered in these works.

In this paper, we develop an integrated framework to update and predict the system risk based on observed degradation data subject to noise. For this, ET is combined with PF for risk updating and risk prognostics. The remainder of the paper is organized as follows. In section 2, the developed framework is presented. In section 3, we apply the developed framework to a safety system from literature. The paper is concluded with some discussions of future works in Section 4.

2 METHODS

2.1 *Problem description*

We consider a generic ET in Figure 1 (for illustration, we just consider two safety barriers), where *IE* represents the initial event, $SB_i, i = 1,2,\cdots,n(n=2)$ represent the safety barriers and $C_1, C_2,\cdots,C_m (m=3)$ represent the consequences caused by *IE*. To integrate condition monitoring data in the event tree analysis, the following assumptions are made:

1. At time t, the i-th safety barrier fails with probability $1 - R_{SB,i}(t), i = 1,2,\cdots,n$, where $R_{SB,i}(t)$ is the reliability of SB_i at t.
2. Time-dependent $R_{SB,i}(t)$, $i = 1,2,\cdots,n$ are estimated based on condition monitoring data on their degradation while $R_{SB,i}(t)$, $i = q+1,\cdots n$, are constant and estimated based on historical data;
3. Degradation of $SB_1, SB_2,\cdots,SB_q$ is monitored at n_o predefined observation times, $t_1, t_2,\cdots,t_{n_o}$. The condition monitoring data collected are $z_{k,i}, i = 1,2,\cdots,q, k = t_1, t_2,\cdots,t_{n_0}$.

We consider the conditional probability of each scenario consequence, given *IE*:

$$p_{C_i} = \Pr\{C_i \mid IE\}, i = 1,2,\cdots,m \tag{1}$$

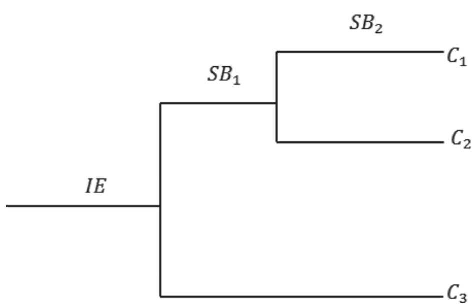

Figure 1. An illustrative ET model.

This probability is determined by the reliabilities of the safety barriers. The vector, $\boldsymbol{p}_C(t) = \left[p_{C_1}(t), p_{C_2}(t),\ldots, p_{C_m}(t)\right]$, contains the conditional probabilities of all possible consequences.

In conventional ETA, the probabilities are estimated before the system comes into operation, based on an initial estimate of the $R_{SB,i}(t), i = 1,2,\cdots,n$ from historical data or expert judgments. When condition monitoring data become available, these estimates should be updated to reflect the actual condition of the SB_i. Here, we extend the conventional ETA to make use of the condition monitoring data. In particular, two tasks are considered:

1. Update: suppose new condition monitoring data are collected at time t_o. Update the estimated conditional probabilities at the current time, i.e., $\boldsymbol{p}_C(t_o)$, based on the condition monitoring data $z_{k,i}, i = 1,2,\cdots,q, k = t_1, t_2,\cdots,t_o$;
2. Prognostics: suppose we have the condition monitoring data up to time t_o. Predict the values of $\boldsymbol{p}_C(t_f)$ at a future time t_f, based on the condition monitoring data $z_{k,i}, i = 1,2,\cdots,q, k = t_1, t_2,\cdots,t_o$.

2.2 *Update*

PF is used in this paper for updating. For this, it is assumed that the degradation of the safety barriers can be described by a state space model:

$$\begin{cases} \mathbf{x}_{k,i} = g\left(\mathbf{x}_{k-1,i}\right) + \varepsilon \\ \mathbf{z}_{k,i} = h\left(\mathbf{x}_{k,i}\right) + \sigma \end{cases} \tag{2}$$

where $g(\cdot)$ and $h(\cdot)$ are the state and observation equations, respectively, and are determined based on knowledge on the associated degradation processes; ε is the process noise and σ is the observation noise. Furthermore, the failure threshold for SB_i is $z_{th,i}$, i.e., SB_i fails when $h\left(\boldsymbol{x}_{k,i}\right) \le z_{th,i}$.

Suppose we have the degradation monitoring data $z_{k,i}, k = t_1, t_2,\cdots,t_{o-1}$ and at $t = t_o$, a new observation becomes available. PF recursively estimates the posterior density of the true degradation states based on sequential Monte Carlo simulation and Bayesian theorem, as shown in Algorithm 1. For details of Algorithm 1, readers might refer to Arulampalam et al. (2002) and Hu et al. (2016). The posterior density function (PDF) of $z_{k,i}$, can, then, be approximated using the particles and their weights:

$$p(\mathbf{x}_k \left|\mathbf{z}_{1:k}\right.) \approx \sum_{k=1}^{N_s} \omega_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i) \tag{3}$$

where $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ is the estimated PDF of $\mathbf{x}_k$, δ is the Dirac Delta function, $x_k^j, j=1,2,\cdots,N_s$ are the particles used to approximate the posterior distribution, and N_s is the number of particles.

Algorithm 1: Procedures of PF
For $i=1:N_s$
Sample $x_{t_k}^i \sim p(x_{t_k}^i|z_{t_1:t_{k-1}})$;
Assign the particle weight:

$$\omega_k^i = \omega_{k-1}^i L(z_k|x_k^i) / \sum_{i=1}^{n} L(z_k|x_k^i)$$

End For
Calculate the state estimation and the posterior PDF:

$$\hat{\mathbf{x}}_k = \sum_{i=1}^{N_s} \omega_k^i \cdot x_k^i,\ p(\mathbf{x}_k \mid \mathbf{z}_{1:k}) \approx \sum_{i=1}^{N_s} \omega_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i)$$

Calculate N_e according to (4)
If $N_e \le N_s$
Resample with $p(x_k^{i*} = x_k^j) = \omega_k^j$
End if

where $p(x_{t_k}^i|z_{t_1:t_{k-1}})$ is determined by the output of PF at $t=t_{o-1}$, $L(z_k|x_k^i)$ is the likelihood of measurement z_k given the particle x_k^j, which can be obtained from the measurement equation in (2). N_e can be estimated by

$$N_e \approx 1/\sum_{j=1}^{N_s} (\omega_k^j)^2 \tag{4}$$

At each t_o, the reliability of the safety barriers can be updated:

$$R_{SB,i}(t_o) = \sum_{j=1}^{N_s} \omega_{k,i}^j \cdot \mathbf{1}\left(h(x_{m,i}^j) \ge z_{th,i}\right) \tag{5}$$

where $R_{SB,i}(t_o)$ is the reliability of SB_i at $t=t_o$ and $\mathbf{1}\left(h(x_{m,i}^j) \ge z_{th,i}\right)$ is an indicator function, which equals to 1 when $h(x_{m,i}^j) \ge z_{th,i}$ and 0 otherwise.

The updated reliabilities are, then, combined with the reliabilities for $SB_{q+1}, SB_{q+2}, \cdots, SB_n$ to update the risk index $\boldsymbol{p}_C(t_m)$. Algorithm 2 summarizes the procedures for updating $\boldsymbol{p}_C(t_m)$:

Algorithm 2: Procedures for updating $p_C(t_m)$
Use Algorithm 1 to update $x_{k,i}^j$ and $\omega_{k,i}^j$.
Update the reliability using Eq. (5).
Update $\boldsymbol{p}_C(t_m)$ based on the updated reliability and the ET.

2.3 *Prognostics*

To predict p_c at a future time t_f, the reliabilities of $SB_1, SB_2, \cdots, SB_q$ at time t_f are predicted first using PF, as shown in Algorithm 3.

Algorithm 3: Prediction of $R_{SB,i}\left(t_f \mid z_{t_1,i}, z_{t_2,i}, \cdots, z_{t_{n0},i}\right)$
Use Algorithm 1 to update $x_{k,i}^{(j)}$ and $\omega_{k,i}^j$.
$F=0$;
For j=1 to N_s;
For $t=t_o:\Delta t:t_f$
Update the particles using the state equation in (2).
Update $z_{k,i}^j$: $z_{k,i}^j = h\left(x_{k,i}^j\right)$.
If $z_{t,i}^j > z_{th,i}$;
$F = F + w_{t,i}^j$;
break;
End If
End For
End For
$R_{SB,i}\left(t_f \mid z_{t_1,i}, z_{t_2,i}, \cdots, z_{t_k,i}\right) = 1 - F.$

The predicted reliabilities are, then, used in the ET to predict p_c. We define Remaining Time to Critical Event (RTCE) as an index for risk prognostics: RTCE is defined as the remaining time before a critical event occurs. This occurrence is determined by comparing with predefined threshold values. For example, the system safe operation dropping below a predefined threshold can define a critical event. Also, a certain consequence exceeding a predefined threshold can define a critical event.

Suppose we consider a critical event defined by $p_{C_i} < p_{th,i}$. Then, its RTCE can be calculated by

$$\text{RTCE} = \inf_t \left\{ p_{C_i}\left(t \mid z_{t_1}, z_{t_2}, \cdots, z_{t_n}\right) < p_{th,i} \right\} - t_o, \tag{6}$$

where $t_1, \cdots, t_o$ are observed points and the prediction is made at t_f. Equation (6) can be solved based on Algorithm 4.

Algorithm 4: Numerical evaluation of RTCE
Set $t_M, \Delta t, t = t_o$.
While $t < t_M$
$t = t + \Delta t$.
Predict the reliability of the safety barrier at t, based on Algorithm 3.
Update the $p_C(t)$ based on the predicted reliability.
If $p_C(t) < p_{th}$
RTCE = $t - t_o$
Break;
End If
End While

3 CASE STUDY

3.1 *System description*

In this section, we apply the developed methods to a tank safety system from literature (Kalantarnia et al. 2009), as shown in Figure 2. The safety system is intended to protect the tank system from the initial event of overflow. There are five safety barriers in the safety system: Basic process control (BPC), Bypass line, High level alarm (HLA), Pressure safety valve (PSV) and Manual Valve (MV).

In theory, overflow entering the system should be detected by BPC, which could in turn open the bypass valve and release the overflow. If the BPC fails to operate, the HLA will be triggered and alarm the operator to close the manual valve to prevent more flow from entering the tank. If, for some reasons, the operator fails to close the manual valve, the PSV will be activated and the excess flow will be released through it. The worst scenario is that if the PSV fails to operate, high pressure gas will be present in the tank, which might cause severe consequences, such as fire or explosion. ET depicts the possible scenarios, as shown in Figure 3.

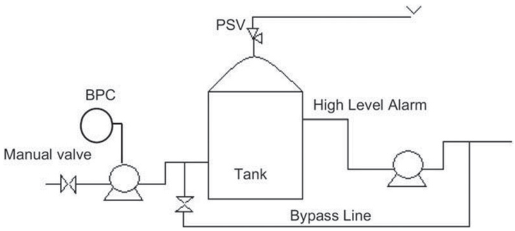

Figure 2. Tank safety system (Kalantarnia, 2009).

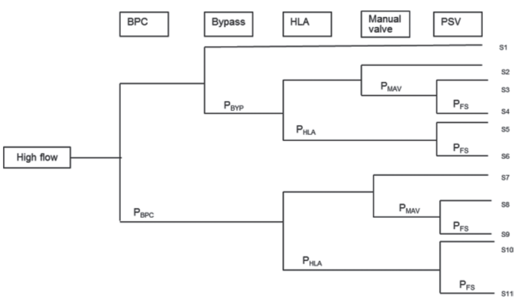

Figure 3. Event tree for tank overflow scenarios.

Occurrence probabilities of different scenarios are given in Table 1. According to the impact of each scenario, the consequences are grouped into 3 classes: C_1 represents that the initial event occurs, but does not affect the normal operation of the system; C_2 represents that there are material losses but not severe; C_3 is the most serious consequence, which represents that all safety barriers fail and large amounts of hazardous materials are released.

3.2 *Condition-monitoring data*

For illustrative purposes, we consider monitoring of the degradation of only one component: the HLA. It is supposed that the degradation of the HLA is caused by the Lithium battery, which provides the electricity needed for its operation. According to Hu et al. (2016), the degradation of Lithium batteries can be described by a state-space model:

$$\begin{cases} x_{k,1} = x_{k-1,1} + \varepsilon_1 \\ x_{k,2} = x_{k-1,2} + \varepsilon_2 \\ x_{k,3} = x_{k-1,3} + \varepsilon_3 \\ x_{k,4} = x_{k-1,4} + \varepsilon_4 \end{cases} \tag{7}$$

$$z_k = x_{k,1}\exp(x_{k,2}) + x_{k,3}\exp(x_{k,4}) + \sigma \tag{8}$$

where $x_{k,i}, i = 1,2,3,4$ are state variables; z_k is the capacity of the Lithium battery at time k, which determines its degradation state; $\varepsilon_i, i = 1,2,3,4$

Table 1. The probabilities of the scenarios.

Scenarios	Probability	Consequence	Description
S_1, S_2, S_7	$p_{\mathrm{hf}} R_{\mathrm{BPC}}$ $p_{\mathrm{hf}}(1-R_{\mathrm{BPC}})R_{\mathrm{HLA}}R_{\mathrm{MAV}}$ $p_{\mathrm{hf}} R_{\mathrm{BPC}}(1-R_{\mathrm{BYP}})R_{\mathrm{HLA}}R_{\mathrm{MAV}}$	C_1	High level occurring, no lost (near miss)
S_3, S_5, S_8, S_{10}	$p_{hf} R_{\mathrm{BPC}}(1-R_{\mathrm{BYP}})R_{\mathrm{HLA}}(1-R_{\mathrm{MAV}})R_{\mathrm{PSV}}$ $p_{hf} R_{\mathrm{BPC}}R_{\mathrm{BYP}}(1-R_{\mathrm{HLA}})R_{\mathrm{PSV}}$ $p_{hf}(1-R_{\mathrm{BPC}})R_{\mathrm{HLA}}R_{\mathrm{MAV}}R_{\mathrm{PSV}}$ $p_{hf}(1-R_{\mathrm{BPC}})(1-R_{\mathrm{HLA}})$	C_2	Little amount of materials loss
S_4, S_6, S_9, S_{11}	$p_{hf} R_{BPC}(1-R_{BYP})R_{HLA}(1-R_{MAV})(1-R_{PSV})$ $p_{hf} R_{\mathrm{BPC}}R_{\mathrm{BYP}}(1-R_{\mathrm{HLA}})(1-R_{\mathrm{PSV}})$ $p_{hf}(1-R_{\mathrm{BPC}})R_{\mathrm{HLA}}R_{\mathrm{MAV}}(1-R_{\mathrm{PSV}})$ $p_{hf}(1-R_{\mathrm{BYP}})(1-R_{\mathrm{HLA}})(1-R_{\mathrm{PSV}})$	C_3	Large amount of materials loss

Table 2. Parameters of normal distribution.

Parameter	Mean	Variance
ε_1	0	$1e-4$
ε_2	0	$1e-5$
ε_3	0	$1e-5$
ε_4	0	$1e-4$
σ	0	$5e-3$

Table 3. Initial values of state model parameters.

Parameter	Value
x_{11}	$8.87e{-}1$
x_{12}	$-8.86e{-}4$
x_{13}	$-2.32e{-}4$
x_{14}	$4.58e{-}2$

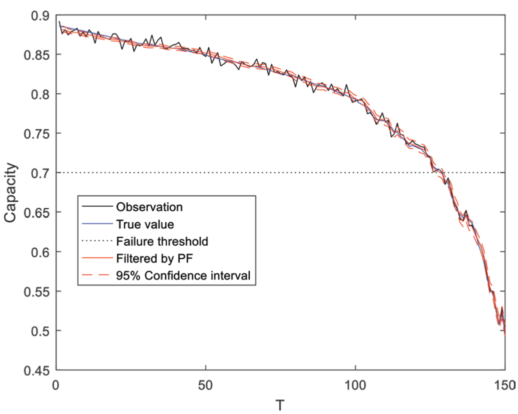

Figure 3. Trajectory of the HLA degradation.

and σ are the process and observation noises, respectively.

In this paper, we generate the degradation path of the HLA using (7) and (8), with the parameters values in Tables 2–3. The generated degradation path is given in Figure 3. The failure threshold of the HLA is assumed to be 0.7.

The true degradation state of the HLA is estimated by PF using Algorithm 1. The result is also given in Figure 3. It can be observed that, in general, PF can estimate and predict the degradation of HLA rather satisfactorily.

3.3 *Updating*

Algorithm 2 is used for updating. The failure probabilities of the other components are given in Table 2. Each time new monitoring data is available, the reliability of HLA is updated using Algorithm 1. Then, p_{c_i} can be updated using Algorithm 2, with the data in Table 4.

For illustrative purposes, we present the update at three time points, $t = 124, t = 127, t = 130$ in arbitrary units of time (Figures 4–6). It can be seen that the probabilities of occurrence of the different consequences are changing with the degradation in time of the HLA. Also, as shown in Figure 3,

Table 4. Failure probabilities of different safety measures.

Safety barrier	Failure probability
Basic process control (BPC)	$f_{BPC} = 0.025$
Bypass line (BYP)	$f_{RYP} = 0.150$
High level alarm (HLA)	Updated using PF
Manual valve (MV)	$f_{MAV} = 0.015$
Pressure safety valve (PSV)	$f_{PSV} = 0.045$

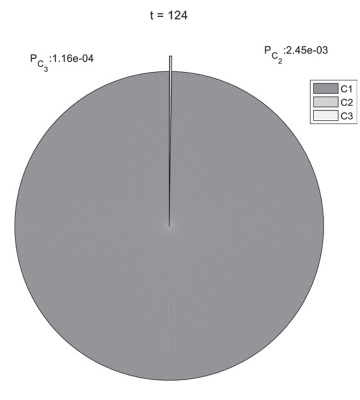

Figure 4. Probability of consequences C_1, C_2, C_3 at $t = 124$.

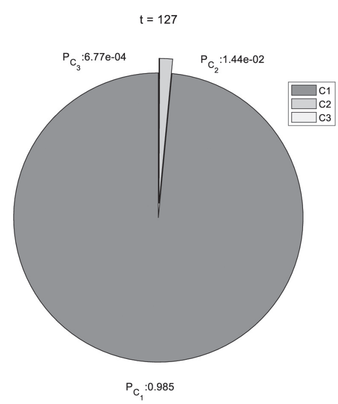

Figure 5. Probability of consequences C_1, C_2, C_3 at $t = 127$.

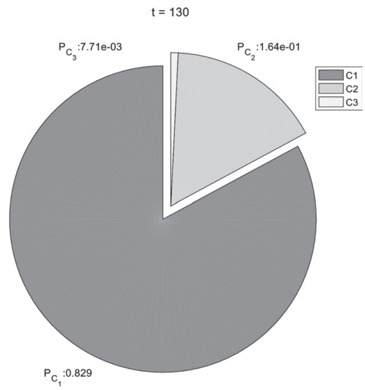

Figure 6. Probability of consequences C_1, C_2, C_3 at $t = 130$.

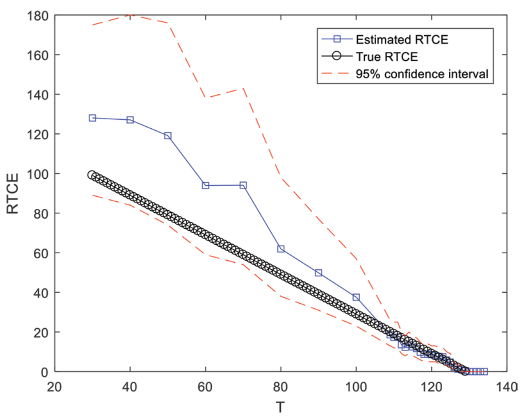

Figure 7. RTCE of the C_1 at different time points.

the failure time of the HLA is $\mathrm{TTF} = 130$, which causes the big change in the probabilities in Figure 6. Figures 4 and 5 show that by using the condition monitoring data, we can be alerted before such changes take place.

3.4 *Prognostics*

In this section, we use Algorithms 3 and 4 for prognostics. As an illustration, we consider the prediction of the RTCE when C_1 reaches a critical value. We assume that the $p_{th,1} = 0.9$, which means that a critical event is defined by $p_{C_1} \le p_{th,1} = 0.9$. The RTCE of C_1 predicted at different time points is illustrated in Figure 7. It can be seen that as monitoring data become available, the predicted RTCE is more and more accurate, as expected.

4 CONCLUSION

In this paper, we propose an integrated framework for DRA. Event tree and particle filtering are integrated for online updating and prediction based on condition-monitoring data. A case study on a tank safety system is carried out for demonstration proposes. The results show that the developed framework can support a condition-informed DRA.

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