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Developing a Quantitative Risk-based Methodology for Maintenance Scheduling Using Bayesian Network

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The main objective of the maintenance process is to increase equipment's life while maintaining the safety and reliability of the process systems. The maintenance planning concerns identification of what and how to inspect, how often to inspect, and what maintenance actions to be taken. Even though the maintenance may be used as an effective means for controlling the degradation of systems, the procedures may also have considerable impact on the operation. It results in direct and indirect economic consequences in terms of shutdowns and unavailability of systems. Therefore, it is necessary to plan maintenance such that a balance is achieved between the expected benefit and the corresponding economic consequences implied by these activities. The objective of this research is to integrate predictive and preventive maintenance strategies in an optimal way to maintain the desired availability and safety integrity level while minimizing the maintenance intervals. The outcome of this work would help to conserve resources while maintaining overall system availability and the safety. The results showed that the risk-based methodology developed using Bayesian Network increases the reliability of the equipment and also optimizes the cost of maintenance. Application of the developed methodology is demonstrated on the maintenance of a power plant as a case study.

1. Introduction

Plant safety in process industry is associated with the reliability of the system and hassles free operation. The robust maintenance/inspection program can increase the overall reliability of systems. The complexity and demand of the safety and integrity of assets require an advance approach to extend equipment's life and reduce the probability of failure. To develop an appropriate maintenance strategy, it is required to estimate the impact of maintenance on assets and determine the relationships between likelihood of the undesirable events and the possible consequences. The probabilistic risk assessment methods are one of the effective tools to determine the likelihood of hazard and associated consequences (Yang, 2004). This risk-based maintenance strategy identifies critical equipment based on risk evaluation (Sarkar and Behera, 2012). Instead of corrective maintenance, planned preventive maintenance, and condition-based maintenance, the application of risk-based maintenance/inspection procedures have improved the system reliability in the past few decades (Arunraj and Maiti, 2007). Several researchers (Khan and Haddara, 2004b; Bertolini et al., 2009; Suwanasri et al., 2014) demonstrated the application of risk-based maintenance strategies. Most of the aforementioned researchers stated that an optimal risk-based maintenance strategy minimizes the plant's overall risk resulting from breakdowns and failures. This also reduces maintenance costs and the expense associated with failures in a plant.
Thermal power plants have one of the most challenging processes for engineering professional. In thermal power plants, water is transformed to steam which turns turbine generator and produces electricity. Although thermal power plants are one of the primary sources of environmental emissions, they are still a major source of producing electricity in many countries. The availability and productivity of the complex systems, such as a thermal power plant, is directly associated with the reliability of different components (units) and their

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maintenance policy. In order to guarantee a power plant operational performance, a risk-based strategy can be applied to define an appropriate maintenance policy. The objectives of the present study are to develop a dynamic risk-based methodology for maintenance/inspection scheduling, and demonstrate the application of the developed methodology on the maintenance of a power plant.

2. Risk Assessment

Risk analysis is a technique used to identify the possible events that can occur, assessing how likely they can happen, and evaluating the potential consequences. As a result, risk can be estimated qualitatively or quantitatively for a particular failure scenario.

Risk = Likelihood of failures x Consequence of the failure (1)

There are many different approaches in quantitative risk analysis to assess the probabilities of failures and the associated consequences. Fault tree (FT) and event tree (ET) analysis has been used extensively in accident modelling to estimate the causation probability and consequences (Khan and Abbasi, 2000; Ferdous et al., 2011). To update the probabilities and reduce the uncertainty of parameters used in FT, researchers combined FT with other methods such as condition monitoring, fuzzy theory and evidence theory (Ferdous et al., 2009; Markowski et al., 2009). However, these integrated techniques are implemented under specific conditions only and have limited applications (Khakzad et al., 2011). On the other side, Bayesian Network (BN) is another approach used for estimating causation probability. Application of BN in accident modelling has been previously explained by different researchers (Simoncic, 2004; Khakzad et al., 2013). Some of priorities of using BN in comparison with the conventional methods such as FT and ET analysis are the ability to model complex systems, reducing parameter uncertainty by having new evidences, and being user-friendly by applying a compact graphical approach (Khan and Haddara, 2004a; Weber et al., 2012). A brief description of the fundamentals of BN for mapping the possible events that may cause an accident and the potential consequences is presented in section 2.1. The BN model used to estimate the risk of failure in the proposed risk-based maintenance strategy is discussed in section 2.2. In section 3, a developed methodology is implemented to a scenario of thermal power plant maintenance. The conclusion of this study is presented in the final section.

2.1 Bayesian networks

Applications of BN in risk management and safety analysis have received increasing attention in past few years (Weber et al., 2012; Yuan et al., 2015). A BN represents a graph with a set of probability tables. Each node in BN depicts an uncertain variable and an arc demonstrates the causal relationship between two variables. A conditional probability table (CPT) provides the probabilities of each state of the variable considering each combination of parent states. As shown in Figure 1, in the BN structure for risk analysis, RN represents the root nodes (similar to primary events in FT), IN represents the intermediate nodes (similar to intermediate events in FT), and PN represents the pivot node (similar to top event in FT). Moreover, C denotes the possible consequences resulting from a failure.

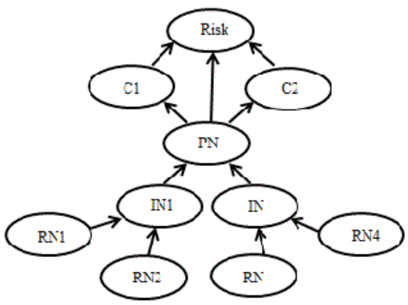

Figure 1: Bayesian network structure for risk analysis

Considering the conditional interdependence and chain rule, a BN represents the joint distribution of variables U = {A_1, A_2… A_n}, P (U) in the network according to Equation 2 (Jensen and Nielsen, 2007).

$$P(U) = \prod_{i=1}^{n} P(A_i \backslash Pa(A_i))) \quad (2)$$

Pa (A_i) = Parents of A_i in a BN

In a BN, Bayes theorem is used to update the prior probabilities of events when given new information called evidence (E). The new information is achieved in operational life cycle of a process.

$$P(U\backslash E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \tag{3}$$

2.2 Risk-based maintenance

The risk-based procedure developed in this study includes five different linked steps as demonstrated in Figure 2. In the first step, an undesired event is defined to develop a failure scenario. The undesired event is resolved into its immediate causes and the resolution of events is continued until the basic causes are identified. The developed scenario does not determine that an accident will indeed occur, however, there is a reasonable probability for an accident to occur.

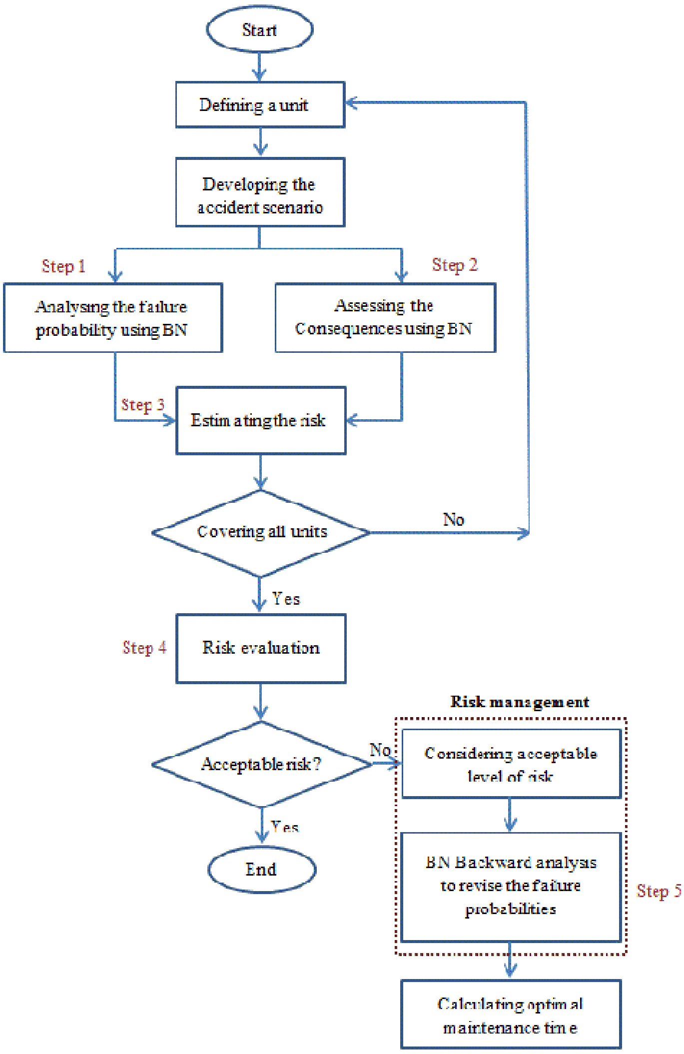

Figure 2: Risk assessment and management for maintenance scheduling of a plant

A BN-based risk analysis model is developed by considering the failure scenarios and all relevant failure causes. In the second step, the consequence analysis is considered to assess the potential consequences if a failure scenario does occur. Four major categories can be considered in the consequence assessment; however some of these categories can be ignored depending on the nature of the accident. These categories are human health loss, economic loss, environmental loss and system performance loss. These categories are very well described by Khan and Haddara (2003). The consequences can be quantified and divided into different states by decision makers according to a particular scenario. The pivot node in the developed BN is connected to each consequence node, which takes into account the effect of the occurrence of the final failures on the individual consequence. In third step, the risk is estimated by the network considering the failure probabilities and the relevant consequences. Three different states of low, medium and high are considered for the risk node. At this stage, the risk is estimated and assessed. Ultimately, the main objective of the developed methodology is to reduce the level of risk through scheduling a better maintenance plan. The risk computed in this section must be compared against the risk acceptable criteria (Fourth step). Whenever the estimated risk exceeds the acceptable criteria, further analysis is warranted to reduce the risk using risk management plan. It should be noted that the acceptable risk value can be altered for different organizations and systems (Khan and Haddara, 2004a). In fifth step, the backward inference on the BN is employed (Fung and Favero, 1994). Considering the minimum potential risk (low), the backward analysis is carried out to determine the required value of the probability of failures for the root nodes. Consequently, after considering the revised probability for failures, the optimal maintenance time for the component can be estimated. At this stage, the maintenance plan can be developed for an optimal maintenance times. This task can be carried out by determining the particular failure function (distribution), defining the probability and then calculating the maintenance time.

3. Risk-based strategy for maintenance of power plant: case study

The present case study deals with the analysis of a power supply failure in a thermal power plant and development of an efficient and failure free maintenance plan. As illustrated in Figure 3, the failure of boiler starting system (F1), the failure of power generation system (F2), the failure of water supply system (F3), and the failure of steam generation (F4) may individually lead to a power supply failure. The failure of subsystem/equipment in each section may lead to the failure of that section (e.g. the failures of X1 to X3 may lead to the failure of F1). A BN is developed for the envisaged failure scenarios of different sections and a final unit. Two potential consequences of power plant failure, economic loss (C1) and system performance loss (C2) are considered in the developed BN. The failure probability for each section of this unit is calculated using cumulative failure probability function demonstrated in the Equation 4.

$$F(t) = 1 - e^{(\frac{t}{\theta})^{\beta}} \qquad (4)$$

Assigning the prior probabilities given in Table 1, the BN is analysed using GeNIe. The probability of power supply failure (PN in this BN) is calculated as 0.024. The results of failure probabilistic analysis and the consequence assessment are combined in the BN to quantify the risk. Three different states; low, medium and high risks are considered in this study. Considering the current condition for each of the units, and their failure probabilities, the risk value is calculated and given in Table 2.

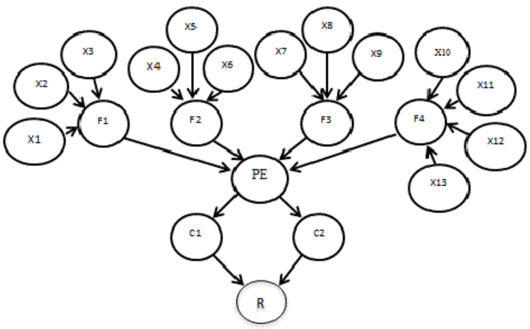

Figure 3. Generic BN for risk analysis of thermal power plant

Whenever the risk value is higher than the acceptable level, the probability of failure for different units should be decreased. This is can be done by assigning 100% probability (Table 2) to low risk state as an evidence and then performing backward analysis to re-calculate the failure probabilities. After considering the updated probabilities and the particular failure function (distribution), the time intervals between the consecutive maintenance tasks are calculated, as demonstrated in Table 1. Having the maintenance interval of different subsystems/equipment, the minimum length of the maintenance interval can then be assigned to the unit, which is 256 days in the considered unit in this case. Although some of the equipment may be over maintained using this method, the acceptable value of risk and reducing the downtime necessary for maintenance justify the value of the developed methodology. The methodology developed in this study provides a dynamic tool to schedule maintenance according to the existing condition of different units. This methodology will help to lower the failure risk to meet the acceptable criterion by continuous monitoring the new evidences on failure probabilities of individual subsystem/equipment in a unit.

Table 1: Components of BN and their probabilities

Subsystem/equipment failures	Symbol	Failure Probability	Revised failure probability	Optimal time (t) (days)
Fuel supply failed	X1	0.00192	0.00029	260
Air supply failed	X2	0.00186	0.00028	257
Water supply failed	X3	0.00182	0.00027	256
Generator failed	X4	0.001878	0.00028	258
Turbine failed	X5	0.00182	0.00028	258
Turbine system supply failed	X6	0.00182	0.00027	256
HP water system failed	X7	0.00182	0.00027	256
Condenser failed	X8	0.00183	0.00027	257
LP water system failed	X9	0.00182	0.00027	256
Air and flue gas system failed	X10	0.00182	0.00027	256
Steam generator failed	X11	0.00183	0.00027	256
Fuel oil system failed	X12	0.00185	0.00027	257
Instrument and service system failed	X13	0.00192	0.00028	260

Table 2: The current and assigned risk values

State	Probability	Set evidence
High	0.241	0
Medium	0.482	0
Low	0.276	100%

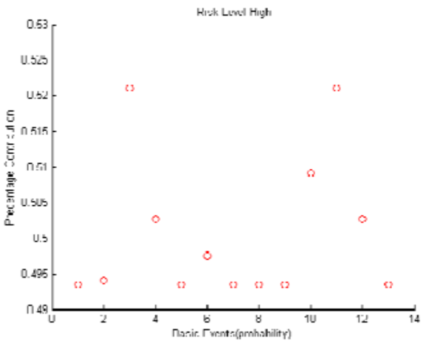

Figure 4: Contribution of different factors to the basic events

The developed methodology in this study has advantages in comparison with the previous risk-based methodologies for maintenance scheduling using conventional techniques such as FT and ET (Khan and Haddara, 2003). Considering the complex dependencies among the components and dynamic modelling of risk analysis using the existing conditions of components are some of these advantages. Moreover, a sensitivity analysis is also carried out to identify critical equipment based on risk values.

This is conducted by considering the zero probability for individual primary failures. Thereby, the developed BN model calculates the percentage contribution by comparing the respective case with the base case. As illustrated in Figure 4, the failure of water supply system and the steam generator has the most significant effects on the power plant.

4. Conclusion

To reduce the risk of failures and minimize the cost of maintenance including the cost of failure, a new risk-based methodology employing Bayesian Network is developed. The failure analysis of different subsystems/equipment and the consequence assessment are considered in a single network. This methodology provides useful information on the causes of:

Failures for different units;

The probable consequences on different subsystem failures in a unit;

The risk of a unit failure;

The frequency of required maintenance to retain the acceptable level of risk.

Application of the developed methodology for the maintenance scheduling of a power supply system in a thermal power plant demonstrated that preventive maintenance time of 256 days is needed for this unit. This maintenance time minimizes the risk of equipment failures in this unit to an acceptable level. The developed methodology is also capable of prioritizing the critical components that have significant contributions to the final risk value. In the considered case study, the water supply system and the steam generator are the most two critical components that have the significant contributions to the power supply risk.

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