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The use of Bayesian network modelling for maintenance planning in a manufacturing industry

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ABSTRACT

This paper has been written in order to apply Bayesian network modelling to a maintenance and inspection department. The primary aim of this paper is to establish and model the various parameters responsible for the failure rate of a system, using Bayesian network modelling, in order to apply it to a delay-time analysis study. The use of Bayesian network modelling allows certain influencing events to be considered which can affect parameters relating to the failure rate of a system. Bayesian network modelling also allows these influencing events to change and update depending on the influencing data available at any given time, thus changing the failure rate or probability of failure. A methodology has been developed and applied to a case study in order to demonstrate the process involved.

1. Introduction

When using delay-time analysis to develop a maintenance or inspection model, the need for both relevant and accurate data is vital to the success of the task [1]. The information required in order to carry out such a modelling exercise is gathered from historical data and/or from expert judgement. This information is used to calculate the variables needed to apply delay-time analysis. The variables include:

- average downtime due to inspection, d;
- average downtime for a breakdown repair, d_b;
- arrival rate of defects per unit time, k_f;
- failure rate λ (1/MTBF);
- inspection period, T.

Downtime due to inspection, d is the amount of time, on average, an inspection will take to complete and return the equipment to production. The average downtime due to a breakdown and subsequent repair of the equipment d_b is the time it takes on average to return the equipment to production. The units of both downtime inspection and breakdown repair downtime must be identical but can be measured in hours, days or months depending on the equipment under investigation. The arrival rate of a defect, k_f is the average time a defect arises over a period of time, calculated by the number of defects divided by the total operating time of the equipment under investigation. Failure rate λ is the reciprocal of mean time between failure (MTBF) where MTBF is the mean operating time between failures of a component or piece of equipment. MTBF, however, should not be confused with the delay-time h of a component or piece of equipment. The delay-time h is the time from an initial telltale sign of failure to actual failure, both being dependant on the inspection interval, T.

Given the above information, an expected downtime per unit time function $D(T)$ can be obtained as follows [2,3]:

$$D(T)=\left\{\frac{d+k_f T[(1/T)\int_0^T (T-h)\lambda e^{-\lambda h}dh]d_b}{T+d}\right\} \tag{1}$$

Looking at the variable failure rate λ (1/MTBF), the information required to populate this is based on statistical averages. For example, if a machine or piece of equipment has experienced 10 breakdowns over a period of 1 year this would result in a failure rate of 0.027 failures/day (MTBF 37 days). To further expand on this example, suppose 70% of the breakdowns occurred during the first 3 months of operation, with only 1 breakdown experienced during the last 2 months of operation. Calculating these figures into failure rates highlights the inadequacy of relying on averages when gathering data of this type [4]. Specifically, the failure rate for the first 3 months is that of 0.077 failures/day (MTBF 13 days) but the failure rate for the last 2 months is 0.016 failures/day (MTBF 63 days). Although the average failure rate of 0.027 failures/day (MTBF 37 days) is correct for average breakdowns it may not be adequate to portray the actual situation. Continuing with

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this example, there may be a number of influencing factors that have been responsible for the varying failure rates over the 12-month period. For example, poor reliability of equipment may be encountered due to incorrect installation. Conversely, improvements in the design of the equipment may improve the reliability of the equipment. Other typical influencing factors for this example might include [3]:

- poor initial implementation of equipment;
- improvements in inspection procedure;
- improvements in maintenance personnel training;
- renewal of key components;
- changes to inspection intervals.

A modelling technique capable of appreciating the differing influencing factors, which could affect an event or variable is that of Bayesian network modelling. Bayesian network modelling is a simple mathematical formula for calculating conditional and marginal probabilities of a random event. Conditional probability is the probability of an event given the occurrence of an influencing event, whereas marginal probability is the unconditional probability of an event. Bayesian network modelling can also deal with subjective probability, which may represent the degree of belief from an expert, and apply it in a precise and relevant manner.

2. Applications of Bayesian network modelling

Bayesian network modelling is an artificial intelligence tool used to model uncertainty in a domain or system [5]. Bayesian network modelling can help in identifying the relationships between variables, given uncertainty, in a system. The identification of critical variables whilst taking into account other influencing factors is also a valuable feature of Bayesian modelling. Uncertainty in any system can be due to factors such as

- inadequate understanding of the system;
- incomplete knowledge of the system at a point in time;
- the system or parts of the system behaving in a random manner.

The use of Bayesian network modelling is wide-ranging, covering a multitude of industries and applications. The nature of Bayesian network modelling offers a flexible solution to problems, allowing incremental adjustments to influencing variables and probabilities. This section will examine several relevant case studies in order to demonstrate the varying uses and applications, highlighting both the benefits as well as the drawbacks when using Bayesian network modelling.

The use of oil tankers in the shipping industry is common, where safety is of paramount importance. One of the main risks is that of collisions between tankers and floating production storage and offloading (FPSO) vessels. FPSOs are used when an oil platform is in a remote or deepwater location where seabed pipelines are not cost effective. The process involves pumping oil from the oil rig, transferring it to the FPSO then onto an oil tanker. Numerous collisions between FPSOs and oil tankers have occurred in the North Sea in recent years [6]. A study was carried out examining system safety of FPSOs using Bayesian network modelling techniques [7,8]. The study examined the transfer of oil from an FPSO to an oil tanker. Collision rates were established relating to the varying ways a collision may occur. A fault tree analysis (FTA) was carried out in order to estimate the frequency of collisions for an FPSO, with additional information gathered from statistical reports. A Bayesian network model was then created to model the scenario using *Hugin* software [19]. The model developed gave two influencing nodes: ‘shuttle tanker’ and ‘support vessel’ with one influenced node ‘collision FPSO’, with both influencing nodes connecting to the node ‘collision FPSO’. The model was run, giving figures of 5% probability of ‘impact’ and a 95% probability of ‘no-impact’ for ‘collision FPSO’. Given the flexible nature of Bayesian network modelling, a scenario was then initiated in the model whereby the probability of impact was increased to 100%. The probability of loss of shuttle tanker went up from 7% to 50% with the support vessel failure probability rising from 24% to 65%. Given this scenario, several nodes were added including oil spillage, explosion and human injury. The importance of this is that given a certain event happening (100% probability) other factors either influencing or influenced by the event can be considered in the overall risk analysis. For this example these may include weather conditions, oil spillage, flooding and human error, although human error may be considered to have an influencing effect on most industries in one way or another.

An important aspect to consider when developing Bayesian network models is the complexity of the model. The model can describe complex problems by generating information about their structure, giving an understanding of the system structure [9]. Given this, an important attribute of Bayesian network modelling is its ability of coping with a system of high complexity through modularity. This is achieved by splitting the problem into smaller problem network models, which are solved separately helping to acquire solutions to the larger problem [10]. The use of Bayesian network modelling for optimising preventative maintenance modelling was developed to a limited amount in a petrochemical case study [11]. Preventative maintenance is a maintenance activity aimed at reducing the occurrence and/or severity of failure in a system. In contrast to preventative maintenance is that of corrective maintenance. With corrective maintenance repairs are carried out only after failure has taken place in the system. This study looked at analysing the renewal process with exponential distribution times to failure using Bayesian modelling. The use of Bayesian modelling allowed the prediction of the probability distribution for downtime and the amount of corrective repairs necessary, which ultimately gave a cost per unit time. There was no comparison drawn between this study and that of traditional methods to establish a failure probability distribution. It did however highlight the need for inclusion of prior knowledge using a Bayesian methodology in order to derive probability distributions. This served to reduce the reliance on estimation of parameters which traditionally takes place, allowing optimal decisions regarding maintenance intervals to be established. Several assumptions were made in this study including: each maintenance activity having the same downtime duration and each corrective repair having the same downtime duration. These assumptions may be too restrictive in reality but this example illustrates the use of applying Bayesian network modelling to establish a probability distribution to enhance another maintenance modelling exercise.

A case study looking at reliability assessment during equipment development of a weapon system using a Bayesian approach has also been carried out [12]. This paper looked at an integrated Bayesian approach to assess equipment reliability during the development cycle. The integration process took information relating to the engineering knowledge available and integrated this with statistical results gathered from the testing program giving a true quantitative viewpoint. Bayes’ theorem was applied to evaluate the reliability achieved by updating the prior distribution, showing the current reliability. This information was used to assess and evaluate the effectiveness of design