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BAYESIAN NETWORK FOR DECISION AID IN MAINTENANCE

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This paper aims to deal with uncertainties occurring in preventive maintenance strategies. After analysing the corrective maintenance data, a decision model that integrates the most important maintenance indicators and their probability distributions is provided. A case study illustrating the proposed methodology that utilizes Bayesian Networks is presented in the final part of the paper.

Key words: maintenance, decision aid, bayesian networks.

1. INTRODUCTION

Most companies register a large quantity of information in their maintenance data bases, but this is often poorly exploited. An efficient valorization of a maintenance history can improve future maintenance strategies. In maintenance optimisation, four general types of maintenance strategies are taken into account such as: a) corrective, b) preventive, c) predictive, and d) reliability centered maintenance. In this paper, a decision aid tool and a model for preventive maintenance are proposed.

Preventive maintenance (PM) is an important component of the maintenance activity. Within a maintenance organization it usually accounts for a major proportion of the total maintenance effort. PM may be described as the care and servicing activities carried-out by maintenance people to keep equipment/facilities in satisfactory operational state by providing for systematic inspection, detection, and correction of incipient failures either prior to their occurrence or prior to their development into major failure. To develop an effective PM program, the availability of a number of machines is necessary

Corrective maintenance (CM) may be defined as the set of remedial actions carried out due to failure or deficiencies discovered during preventive maintenance, to repair an equipment/item to restore its operational state. Usually, corrective maintenance is an unscheduled maintenance activity, basically composed of unpredictable maintenance actions that cannot be pre-planned or programmed.

The aim of present work is to give a solution in developing probabilistic models for decision aid in preventive maintenance strategies starting from corrective maintenance data. The paper is organized as it follows: first, the main maintenance indicators and are reviewed. Having made a survey of the significant results presented in the literature, probabilistic models are proposed and Bayesian dynamic networks are used in a case study to illustrate the methodology.

2. MAINTENANCE INDICATORS

2.1. Availability

Availability is a performance criterion for repairable systems that accounts for both the reliability and maintainability properties of a component or system. It is defined as "a percentage measure of the degree to which machinery or equipment is in an operable and committable state at the point in time when it is needed" [1]. *Instantaneous availability* is the probability that a system will be operational at any random time, *t*.

This is very similar to the reliability function in that gives the probability that a system will function at the given time, *t*. Unlike reliability, the instantaneous availability measure incorporates maintainability information.

The *steady state availability* of the system is the limit of the instantaneous availability function as time approaches infinity. *Inherent availability* is the steady state availability when considering only the corrective downtime of the system. It is defined as the expected level of availability for the performance of corrective maintenance only. Inherent availability is determined purely by the design of the equipment. It assumes that spare parts and manpower are 100% available with no delays. It excludes logistics time, waiting or administrative downtime, and preventive maintenance downtime. It includes corrective maintenance downtime. For a single component the inherent availability is given by the well-known formula:

$$A_I = \text{MTTF}/\left(\text{MTTF+MTTR}\right), \tag{1}$$

where MTTF = Mean Time To Failure; MTTR = Mean Time To Repair.

2.2. Maintainability

Maintainability is a design objective that meant to reduce the repairing time of a system or of equipment and to maximize the equipment availability [2]. Maintainability measure is usually expressed as the probability that a machine can be retained in or restored to its specified operable condition within a specified interval of time, when maintenance is performed in accordance with performed procedures.

Various measures are used in maintainability analysis: *mean time to repair* (MTTR), *mean preventive maintenance time*, and *mean maintenance downtime*. Maintainability functions are used to predict the probability that a repair operation which is started at time $t_0 = 0$, will be completed in a time *t*. Mean time to repair is probably the most widely used maintainability measure. Mean time to repair measures the elapsed time required to perform a given maintenance activity [2]:

$$\text{MTTR} = \left(\sum_{i=1}^{k} \lambda_i CMT_i\right) / \sum_{i=1}^{k} \lambda_i, \tag{2}$$

where: k = number of units or parts; λ_i = failure rate of unit/part *i*, for $i = 1, 2, 3, \ldots, k$; CMT_i = corrective maintenance/repair time required to repair the unit/part *i*, for $i = 1, 2, 3\ldots, k$.

Usually, MTTR follows exponential, lognormal, or normal probability distributions.

2.3. Cost

Maintenance cost is simply described as the labor and materials expense needed to maintain equipment/items in satisfactory operational state. Costs associated with maintenance are classified into four areas such as: a) direct costs, b) lost production costs, c) degradation costs, and d) standby costs.

Direct costs are associated with keeping the equipment operable and include costs of periodic inspection and preventive maintenance, repair cost, overhaul cost, and servicing cost. *Lost production costs* are associated with loss of production due to primary equipment breakdown and unavailability of standby equipment. *Degradation costs* are associated with deterioration in the equipment life due to unsatisfactory/poor quality maintenance. *Standby costs* are associated with operating and maintaining standby equipment. A standby equipment is used when primary facilities are either under maintenance or inoperable. Management decides the type of cost data the maintenance section or department should collect by keeping in mind its future applications.

In our approach, total maintenance cost is calculated by the formula:

$$c_m = c_{MOE} + c_f + c_c + c_{ext}, \tag{3}$$

where

c_m = maintenance cost;

c_{MOE} = labor cost;

c_f = fixed cost of maintenance service;

c_c = spare parts or supplies cost;

c_{ext} = external service cost.

3. LITERATURE REVIEW

The maintenance strategy is defined as a set of rules that establish the sequence of maintenance actions [3]. A strategic allocation for the maintenance actions has to be discussed. Thus, from a critical state of preventive maintenance, actions are undertaken to return the system to an operational state (nominal or degraded one) with a threshold of predetermined performance. Four approaches are generally used: (a) Stochastic (Markov-chain) [4] (b) Monte Carlo simulation [5] (c) functional approach [6] (d) Universal Moment Generating Function [7].

A method for modeling complex dynamic maintenance systems is presented in [8]. The approach allows the calculation of maintenance indicators such as frequency of maintenance or costs. In [9] authors present a strategy for integrating uncertainties in the multi-objective optimization of chemical process. They make an analysis of the uncertain parameters by stochastic programming. In [10], François et al., present maintenance strategies for prevention of rails rupture. They are modeling the state evolution of the rail over time by the formalism of dynamic Bayesian networks and Markovian chains. The modular model is divided into interconnected sub-models to describe the process of detection of the broken rail. Borgia et al., investigate in [11] the use of a Dynamic Bayesian Network in modeling the causal relationships between degradation-cause-consequence and use a probabilistic model to obtain these dependences.

Recently, in [12], a model to assess availability, production rate and reliability functions of multi-state degraded systems subject to minimal repair and to imperfect preventive maintenance is proposed. A Markov model of the performance rate is associated to each system state. The aim is that the rate of performance of the system at time *t* exceeds the customer's request. However in reality the customers demand is constant and so the method is not applicable.

4. PROBABILISTIC MODELS

4.1. Preventive maintenance model

This mathematical model represents a system that can either fail completely or undergo periodic PM. The failed system is to be repaired. The model is useful to predict system availability, probability of shutting down system for PM, and probability of system failure.

The following notations are used:

$j =$ system state;

$j = 0$ system operating normally;

$j = 1$ system failed;

$j = p$ system down for PM

$P_j(t) =$ probability that the system is in the state *j* at the time *t*;

$\lambda =$ system failure rate;

$\mu =$ system repair rate;

$\lambda_p =$ rate of system down for PM;

$\mu_p =$ rate of system PM performance.

Differential equations of the PM model are:

$$\frac{\mathrm{d}P_0(t)}{\mathrm{d}t} + (\lambda + \lambda_p) = \mu P_1(t) + \mu_p P_p(t),$$
$$\frac{\mathrm{d}P_p(t)}{\mathrm{d}t} + \mu_p P_p(t) = \lambda_p P_0(t), \tag{4}$$
$$\frac{\mathrm{d}P_1(t)}{\mathrm{d}t} + \mu P_1(t) = \lambda P_0(t).$$

At time $t = 0$, $P_0(0) = 1$ and $P_p(0) = P_1(0) = 0$. Solving these equations we obtain the *system steady state availability*

$$\mathrm{AV}_{\mathrm{ss}} = \frac{\mu\mu_p}{\mu_p\mu + \lambda_p\mu + \lambda\mu_p}. \tag{5}$$

4.2. Corrective maintenance model

The mathematical model of CM represents a system that can either be operating normally, operating in degradation mode, or failed completely. Corrective maintenance is initiated from degradation and completely failed modes of the system to repair failed parts. This model is subjected to the following assumptions:

- System complete failure, partial failure, and corrective maintenance rates are constant in time.
- The operating system can either fail fully or partially. The partially failure can determine stopping the operation.
- All system failures are statistically independent.
- The repaired system is as good as a new one.

The following notations are associated with the model:

$i =$ system state;

$i = 0$ system is operating normally;

$i = 1$ system operation in its degradation mode;

$i = 2$ system failed;

$P_i(t) =$ probability that system is in the i state at time t for i=0, 1, 2;

$\mu_{c_i} =$ system corrective maintenance rate;

where:

i=1 from state 1 to state 0;

i=2 from state 2 to state 0;

i=3 from state 2 to state 1.

Differential equations of the CM model are:

$$\begin{aligned}
&\frac{\mathrm{d}P_0(t)}{\mathrm{d}t} + (\lambda_1 + \lambda_2) P_0(t) = \mu_{c_1} P_1(t) + \mu_{c_2} P_2(t), \\
&\frac{\mathrm{d}P_1(t)}{\mathrm{d}t} + (\mu_{c_1} + \lambda_3) P_1(t) = \mu_{c_2} P_2(t) + \lambda_1 P_0(t), \\
&\frac{\mathrm{d}P_2(t)}{\mathrm{d}t} + (\mu_{c_2} + \mu_{c_3}) P_2(t) = \lambda_3 P_1(t) + \lambda_2 P_0(t).
\end{aligned} \tag{6}$$

At time $t = 0$, $P_0(0) = 1$ and $P_1(0) = P_2(0) = 0$. Having solved equations (6), we obtain the full *steady state availability* of the system:

$$A_{st} = P_0 = \frac{\mu_{c_1}\mu_{c_2} + \lambda_3\mu_{c_2} + \mu_{c_1}\mu_{c_3}}{K_1 K_2}, \tag{7}$$

where:

$$K_1 K_2 = \frac{-D \pm \left(D^2 - 4F\right)^{1/2}}{2}; \quad D = \mu_{c_1} + \mu_{c_2} + \mu_{c_3} + \lambda_1 + \lambda_2 + \lambda_3; \quad F = K_1 K_2.$$

5. BAYESIAN NETWORKS

Probabilistic graphical models are based on directed acyclic graphs. Within the cognitive science and artificial intelligence such models are known as *Bayesian Networks* (BN). A BN is a directed acyclic graph whose nodes represent random variables and links define probabilistic dependences between variables. Bayesian networks achieve compactness by factoring the joint distribution into local, conditional distributions for each variable given its parents. If x_i denotes some value of the variable X_i and pa_i denotes some set of values for the parents of X_i, then $P(x_i \mid pa_i)$ denotes this conditional distribution.

The global semantics of Bayesian networks specifies that the full joint distribution is given by the product

$$P(x_1 \ldots x_n) = \prod_i P(x_i \mid pa_i). \tag{8}$$

To capture the temporal evolution of modeled system one can use a *Dynamic Bayesian Network* (DBN). These networks introduce relevant temporal dependencies that capture the dynamic behaviors of the system at different moments.

The advantage of DBN over Markov chains is that DBN models temporal evolution using only two times slices t and t+1. When a first order Markov process assumption holds the future slice at time t +1, it is conditionally independent of the past ones given the present slice at time t. In this case, it is sufficient to represent two consecutive time slices called the anterior and the ulterior layer respectively to represent the network.

Bayesian networks learn the probabilistic semantic by using different inference algorithms. The most used inference algorithm is the *Junction Tree Algorithm* [14]. The conditional probabilities of a given structure can be estimated from data by using the maximum likelihood approach. They can also be updated continuously from observational data by using gradient-base methods that use just local information derived from inference.

For system modelling, a graphical tool that allows defining, modifying, using and learning models based on Bayesian networks have been used: *Bayesia Lab*®[1] software. This is a decision aid instrument since it allows introducing decision and utility nodes.

The qualitative data in Bayesia Lab is represented by the structure of the BN graph (nodes and arcs), and the quantitative information by the conditional probability tables and databases. Bayesia Lab is also able to seize degrees of events probabilities in addition to observations.

Once validated, probabilities are used jointly with the probability distribution for giving a new probability distribution. Bayesia Lab allows the temporal dimension integration in a Bayesian Network so as a BN can be easily transformed into a DBN. Temporal nodes at instants t and t+1 can be represented and connected by temporal arcs. The parameters evolution of the DBN nodes can be so followed in time [15].

6. CASE STUDY

According to the analysis and evaluation of failures, maintenance action plans are proposed to impact the targeted machines. A case study made on a line served by four fixed workstations and a mobile shuttle has been carried -out. Relevant maintenance information on a horizon of two years is given in Table 1.

Table 1

Maintenance information

Machine	No interventions	MTTR	Cost	Priority ranking
M1	217	95588	10021	3
M2	237	18092	7821	5
M3	340	93300	11445	1
M4	349	17279	11384	4
Shuttle	73	86135	35889	2
Total	1216	310394	76560	-

The aim is to develop a decision aid model to support decision making in developing maintenance strategies. Cross analysis will be used to evaluate the maintenance indicators and their evolution during the policy maintenance. The machine criticality level can be determined in terms of maintenance costs, availability, and maintainability

The following steps are made in the analysis process:

1. Identifying the critical machines via a cross-analysis of maintenance indicators
2. Developing a model and a priority ranking according to the previous analysis
3. Simulation of machines behavior
4. Proposing action plans through maintenance procedure.

Forward, a probabilistic graphical model for decision aid in preventive maintenance strategies is conceived (Fig. 1).

[1] http://www.bayesia.com/en/products/bayesialab.php

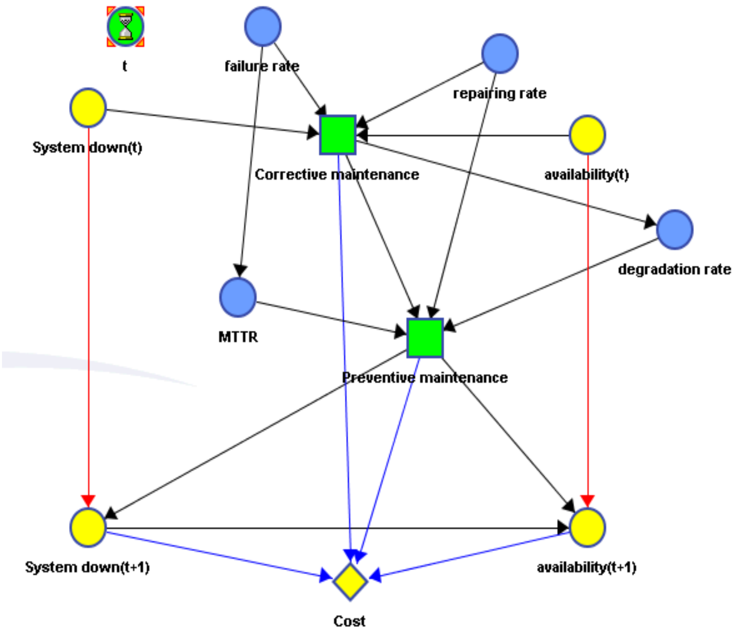


Fig. 1 – Dynamic Bayesian network model.

Data from critical machines is introduced for simulation. Equations (2), (3), (5–7) are used behind the nodes of the graphical model. In Fig. 1, variable states subject to uncertainties are represented by circular nodes and the square nodes are decisions to take. Utility (gain) is represented by the rhomboidal node.

In the worst case scenario, repairing rate has a lognormal distribution, and MTTR has an exponential distribution (Figs. 2 and 3).

The case showed that the proposed model can be a useful decision aid tool in establishing the rate of intervention in preventive maintenance using probabilistic data from corrective maintenance. Figures 4 and 5 present simulation's results.

If at the moment *t*, the availability of the machine was low and the rate of failure was high, taking into account the failure rate, repair rate, MTTR values and degradation rate, one can plan preventive maintenance intervention so as the availability at the moment *t*+1 to be higher than at the moment *t*. Therefore, machine performance increases and total maintenance costs are reduced with 30%.

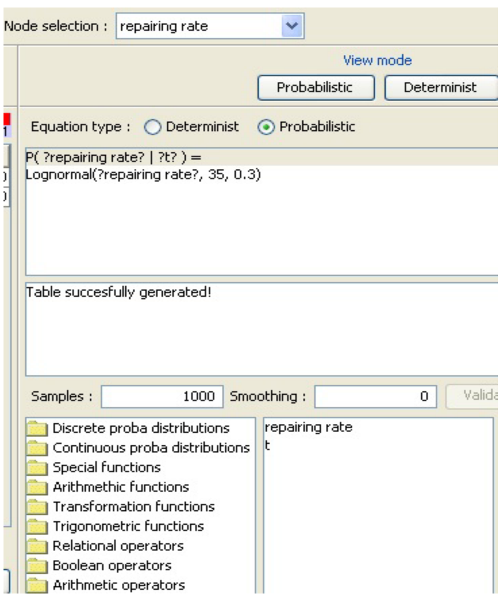


Fig. 2 – Repairing rate probability distribution.

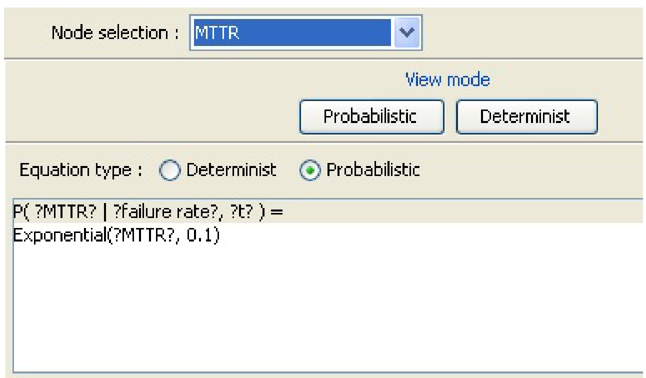
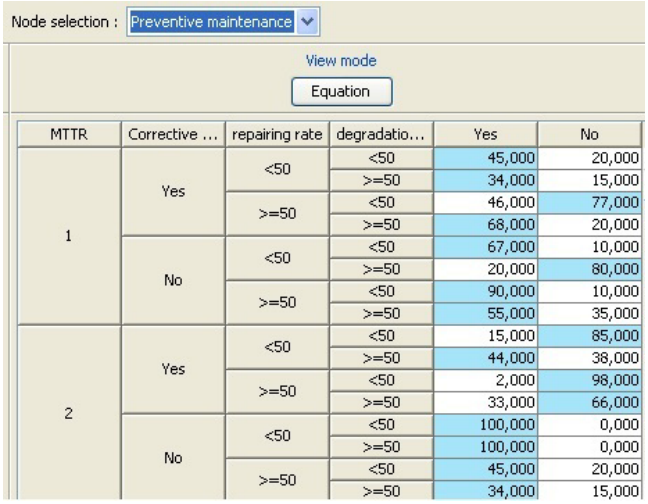


Fig. 3 – MTTR probability distribution.



MTTR	Corrective ...	repairing rate	degradatio...	Yes	No
1	Yes	<50	<50	45,000	20,000
			>=50	34,000	15,000
		>=50	<50	46,000	77,000
			>=50	68,000	20,000
	No	<50	<50	67,000	10,000
			>=50	20,000	80,000
		>=50	<50	90,000	10,000
			>=50	55,000	35,000
2	Yes	<50	<50	15,000	85,000
			>=50	44,000	38,000
		>=50	<50	2,000	98,000
			>=50	33,000	66,000
	No	<50	<50	100,000	0,000
			>=50	100,000	0,000
		>=50	<50	45,000	20,000
			>=50	34,000	15,000

Fig. 4 – Values determining preventive maintenance interventions.

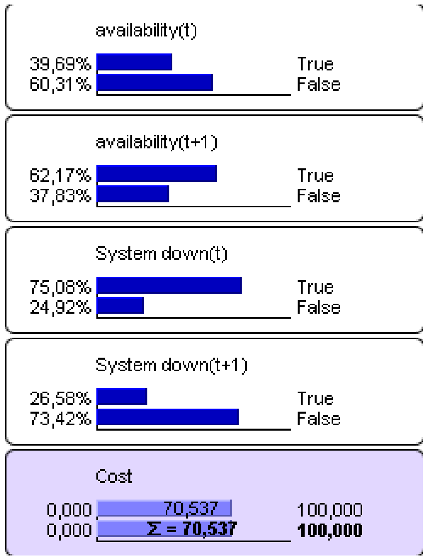


Fig. 5 – Variations of maintenance indicators.

7. CONCLUSIONS

A method to improve maintenance strategies of multi-state degraded systems was proposed. Having made an analysis on a corrective maintenance data base, probabilistic model was developed for aid in decision-making in preventive maintenance. Availability, maintainability and maintenance costs were the analyzed indicators.

The method was implemented on a real industrial case, according to the priorities ranking of a machine fleet. The possibility that the machine returns to its initial non degraded state was not taken into account in our model. Efforts have been made to embed the model in practical Decision Support Systems (DSS) [16, 17]. Future studies will take into account separately corrective maintenance and preventive maintenance indicators.

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