Modelling Manila Rail Transit Reliability With Dynamic Bayesian Networks

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Abstract: Reliability has been an important issue in modern transportation systems, such as the Manila Rail Transit (MRT) Line 3. In the aim of modelling the reliability of the MRT 3 (TATRA RH8D5M), ten of its components were modeled after a renewable and repairable indices based on exponential reliability models. The relationship of future and past component reliability were then represented as a vector autoregressive (VAR) process with a dynamic Bayesian network without the need of a fault tree analysis or reliability block design. To gather further knowledge of the correlation between components, an incremental association structural learning algorithm was applied between the reliabilities of each component, where the association between reliabilities of components learned from this algorithm is represented with an undirected graph together with the represented VAR process in the dynamic Bayesian network. To further the possible inference, a maximum likelihood estimation parameter learning algorithm was used to derive the conditional probabilities of the reliabilities of the component and the overall system. Resulting component reliabilities demonstrates varying reliabilities based on component age, where concepts based on life mortality may apply. This is present on component reliabilities such the bogie of the TATRA RH8D5M, where it can be expected to have high number of failures of components aged less than 50, and aged more than 200. The resulting structure from the dynamic Bayesian network representation of the VAR process and the incremental learning demonstrates expected relationships among component reliabilities, but the strength of these relationships which is derived from the MLE-based parameter learning presented strong cases of failures due to failures of other expected components.

Key Words: Reliability Engineering; Bayesian Networks; Vector Autoregressive

1. INTRODUCTION

The purpose of this research is the reliability modelling of the Manila Metro Rail Transit. It is suggested that graphical methods such as the Reliability Block Diagram (RBD) or Fault Tree (FT) Analysis would provide a comprehensive insight into the reliability of the system (Conradie et al., 2015). To consider the influence of time and exogenous variables on the wearing out effect of a system, and the interdependencies among the the usage of a Dynamic Bayesian Networks (DBN), which are derived from Bayesian Networks (BN), graphical models of probabilistic relationships between variables in a domain of knowledge (Murphy, 2002), is an efficient methodology in modelling the reliability of the system.

Recent developments in this field are the use of an event-based approach in modelling reliability with a BN (Marquez, Neil, and Fenton 2009). This makes use of dynamic discretization that allows the representation of dynamic fault trees and Boolean constructs. Another recent development is in multistate reliability modelling with DBN (Li et al, 2018), a methodology in reliability modelling of a multi-state element with the use of a DBNs. The study assumes that an element contains many levels of degradation and that there are constant state transition rates. Following these assumptions, Li, et al. (2018) was able to device the DBN representation of a component changing from a perfectly functioning state, to a useful state, to a pseudo-fault state, and finally a faulty state.

2. METHODOLOGY

2.1 Reliability Estimation

Calculation of the mean time between repairs (MTBR) is through acquiring the length of time between occurrences of a component within the rolling stock maintenance logs, this is then divided by the number of occurrences. The repair rate (μ) is estimated with the given formula by (Ushakov and Harrison, 1994)

$$\mu = \frac{1}{MTBR}$$

The reliability function is given as

$$R(t) = 1 - ke^{\lambda_i t}, i = 1, \ldots, 13 \qquad \text{where, } k = \left(1 - \frac{\lambda_t}{\mu}\right)^{-1}$$

2.2 Structural Learning

A DBN is defined to be a pair $(B_1, B_{\rightarrow})$, where B_1 is a BN and $B_{\rightarrow}$ 2TBN (Murphy, 2002), the structure of a DBN can be divided in two parts. The structure of the BN was learned using the *iamb* function of the bnlearn package. The structure of the 2TBN was learned using the *VAR* function of vars package.

Structure learning for a BN can be divided into two, namely constraint-based algorithms and score-based algorithms (Scutari, 2010). The *iamb* function of bnlearn is an example of a constraint-based algorithm. All constraint-based algorithms can be divided into three steps (Nagarajan, Scutari, and Lèbre, 2013). First, nodes that are connected by an undirected arc are identified. Second, v-structures among all nonadjacent nodes A and B with common neighbor C are identified. And third, directions of arcs are identified recursively to obtain a completed partially DAG (CPDAG).

According to (Nagarajan, Scutari, and Lèbre, 2013), it is commonly assumed that dependence relationships of DBN's are represented by a VAR process. Consider a VAR process of order 1 with 3 variables.

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_p \end{bmatrix} + \begin{bmatrix} \phi_{11,i} & \phi_{12,i} & \phi_{13,i} \\ \phi_{21,i} & \phi_{22,i} & \phi_{23,i} \\ \phi_{31,i} & \phi_{32,i} & \phi_{33,i} \end{bmatrix} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix}$$

Every arc is defined between two successive time points. The nonzero coefficients in A, that is the element a_{ij}, $i \neq j$ which is not zero, is an arc from $X_i(t-1)$ to $X_j(t)$. Figure 1 shows us a VAR process in graphical form. The variables are represented as nodes in the model. Nodes that belong to the same time period or time slice are placed inside a dotted box with a time t as seen in Figure 1.

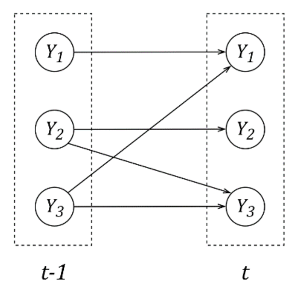

Fig. 1. VAR Process in graphical Form

According to Nagarajan, Scutari, and Lèbre (2013), vars package is a useful R package for analysing time series as a VAR processes, making it optimal for the structure learning of the DBN.

2.3 Parameter Learning

The function *bn.fit* was used for the parameter learning. It requires an object of class bn and the data frame containing the variables in the model as parameters. The bn object was based on the structure that was produced after the structure learning. The *bn.fit* function can either be set to use maximum likelihood parameter estimation (MLE) or Bayesian parameter estimation for the method of estimation (Scutari & Ness, 2018). The latter is only implemented for discrete data. Since the data that was used are continuous, MLE was used.

3. RESULTS AND DISCUSSION

Resulting models of the repairable component reliabilities are illustrated in Fig 2, which are simulated densities of component time to failure based on the component reliabilities. Observe that the time to failures are bimodal in general, which appeals to the nature of component failures, where early failure rates are decreasing. This is analogous to infant mortality, where components are more liable to failure due to manufacturing issues. The mid area of the figure has the lowest failure rates, this phenomenon is referred to as the useful life. At this area, the probability of failure of a component is independent of the age. After the useful life of the component, the failures start an increase, hence the start of the wear out period where aging failures becomes dominant. Components during this period often experience corrosion, embrittlement, fatigue cracking, and diffusion of material.

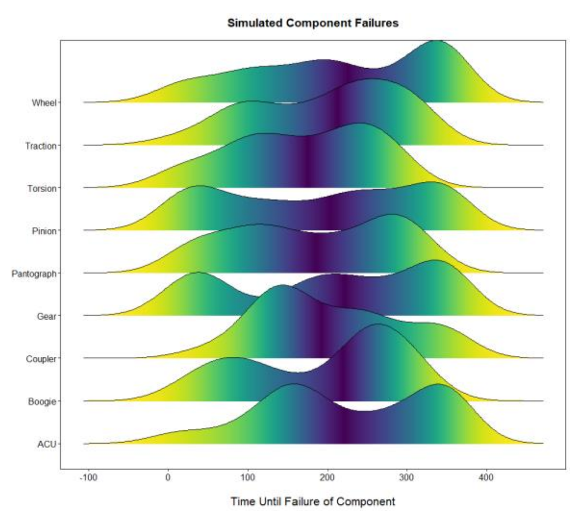

Fig. 2. Simulated Time to Failure of Components

The structure of the DBN based on the vector of coefficients $\tilde{A}$, results into the directed graph on Figure 3. describing state, $R(t-1)$, diverging into $R(t)$. Among these are obvious relationships between the reliabilities, but there are some instances where the resulting relationships should be taken with a grain of salt.

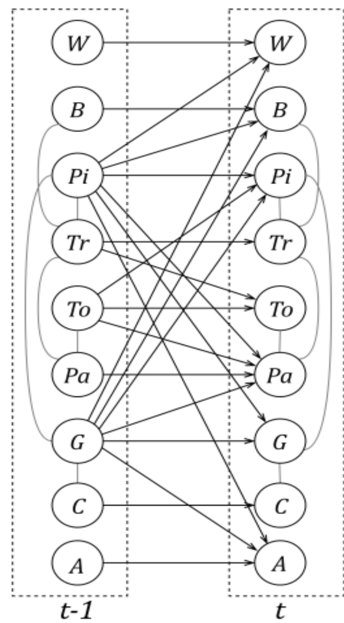

Fig. 3. DBN of the TATRA RH8D5M (MRT3 System)

Figure 4 gives a graphical representation of the resulting parameters. A similarity of the parameter and the reliabilities is discovered among the component reliabilities.

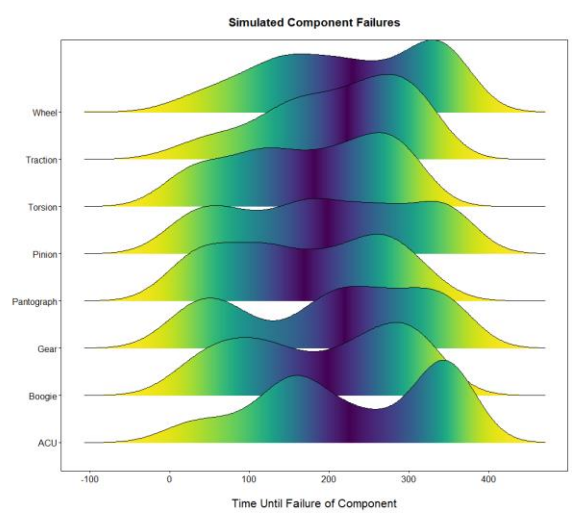

Fig. 4.ACU parameters of the MRT System

For the overall implication of the results, it is noted that the structure of the DBN implies that there are causal relations among the reliabilities regardless of the location or isolation of the component. The strength of these relations are expressed by the equations of the parameters which are graphically represented by Figure 4.

4. CONCLUSIONS

Modelling the reliability of the wheel, bogie, pinion, traction, torsion, pantograph, gear, coupler, and the air conditioning unit as a renewable exponentially distributed, it has been shown that VAR (1) process and constraint-based algorithm may be fitted at the reliabilities and discover relationships and correlation among the components allowing for the reliabilities to be depicted graphically as a DBN. With the represented VAR (1) process, parameter learning through maximum likelihood estimates was able to derive the conditional probability distributions of the reliability, where further predictive inference could occur.

The problem with the methodologies performed are that like event-based Bayesian network approach in modelling reliability, multi state reliabilities would be difficult to represent using a VAR process. A powerful approach in multi-state reliability modelling are with a dynamic Bayesian network representing a semi-Markov model with more than 2 time slices.

The structure for the system would be better if it was based on a combinatorial-based model such as the static or dynamic fault tree (DFT) analysis or a reliability block design. These models allow for dynamic Bayesian networks to model Boolean constructs such as AND or OR gates. Such studies would require expert knowledge on the manila rail transit system.

An event-based approach in representing the DFT of the system in Bayesian networks can also be considered when modelling reliability. This approach allows modelling both continuous states and time to failure distributions with the use of dynamic discretization (Marquez et al, 2009).

Using the model suggested in this paper, it would be possible to make predictive inferences with the same power as multivariate time series. Future researchers of the subject should also consider making a sensitivity analysis on the model. This model can also be applied in spare parts inventory optimization and cost to benefit analysis.

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