Dynamic Bayesian Networks Modelling Maintenance Strategies: Prevention of Broken Rails

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Abstract

In this paper, an assistant tool for the maintenance of rails in a metro context for normal steel wheeled trains is proposed. The theory of Dynamic Bayesian Networks offers an interesting frame to solve this specific problem. We present a modular modelling of the current rails' diagnostic process. It simulates the rail degradation, the behavior of the various actors involved in the defect detection, but also the maintenance action decisions. This model provides indicators, such as the non detection rate or the number of false alarms, helpful for the determination of optimal maintenance parameters.

1. Introduction

The infrastructure maintenance is an important field of interest for railway operators. Particularly, the rail integrity is a critical subject for train control as well as for maintenance strategies. Over all the possible rail flaws, broken rail is obviously the most sensitive point.

Two facts have a strong influence on the availability and safety of the railway system: the occurrence of critical defects of infrastructure subsystems and false alarms for instance triggered by monitoring devices designed for the defect detection. For these two points, the railway operators need a degradation model of the rail and, as accurate as possible, an estimated rate of good detection of defects by their measuring devices. Then, various maintenance strategies can be simulated and their impact on the broken rail monitoring process can be completely estimated.

In this paper, Dynamic Bayesian Networks theory will be introduced for the rail degradation and for the broken rail monitoring process model. Section 2 will deal with the practical context of our study and some theoretical elements will be very briefly given in section 3. Then, the structure and the parameters of our model will be presented in section 4. Finally, it will be validated and its results will be discussed in section 5.

2. Context of the study

Implementing a new command-control- system (CBTC like) on some lines of the Paris metro network, the RATP Company needs to identify precisely the impact of rail flaws on safety and availability of the railway system: the assessment of the current broken rail monitoring process regarding the new CBTC system has to be made. Depending on the nature of defects, the disturbance will be more or less penalizing for the passenger service. A statistical model of the rail defects evolution should help the identification of the most critical flaws.

To simplify the analysis, the rail states along the main deterioration process are clustered into four classes: OK (the rail has no defect), IC (Internal Crack), SC (Surface Crack) and BR (Broken rail). Currently, the diagnosis of rail defects results from the combination of diagnoses from by the four actors (detecting devices or specific staff) involved in the broken rail monitoring process: these actors are characterized by different inspection periodicities and different detection efficiency according to the type of defect and its location in the rail.

- First, a special vehicle equipped with ultrasonic sensors diagnoses the rail on average twice a year. It can detect the 4 classes of defects. This diagnosis is always confirmed by in-situ complementary measurements performed by a specific team using for instance portable ultrasonic devices [2]. The special vehicle and the specific team are considered as a single actor in the Model.
- Secondly, some walking survey teams are passing along the lines on average one or twice a month. They can not detect IC.

- During the passenger service, metro drivers can feel some shocks from the rails, and so, can contribute through their reporting to the detection of some BR.
- Finally, the track circuit, commonly used for signaling tasks [1], analyses the rail impedance and so can detect some BR when no train are present on the area.

For our study, we dispose of a great amount of information, distributed among databases (from signaling and track departments) and expert advices. But, this information is sometimes uncertain, imprecise, or even missing. For all of these reasons, the formalism of the Bayesian network theory offers an adequate framework to represent our system and its maintenance.

3. Bayesian Networks

Proposed in the early 80's as probabilistic expert systems, Bayesian Network (BN) is a reasoning formalism that is more and more used in data-mining and knowledge modelling [5, 7, 10].

BN formalism jointly uses the graph theory, in order to graphically define dependency relationship between variables, and the probability theory to represent how strong is the relationship between each variable and its parents in the graph. Figure 1 introduces an example of BN, modelling a simple system, characterized by two variables, *X* and *Y*.

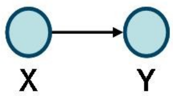

Figure 1: A basic BN modelling the dependency between two variables *X* and *Y*.

In this paper, only discrete variables with *d* possible states are considered. Nodes represent the variables of the system (defined over all its possible states) and the connecting arrows indicate relationships between these variables. Root nodes (nodes having only descendants) are described by a Probability Table (PT) composed of the class belonging probabilities $P(X)$ over the *d* possible values of *X*. Children nodes (node having one parent at least) are described by Conditional Probability Tables (CPT), composed of $P(Y|X)$ over each value of *Y* knowing the value of *X*.

The strength of BN lies particularly into their efficient inference algorithms [10, 7]. They allow determining the probability distribution of one variable, knowing the states of some eventually observed nodes.

Another advantage of BN is the fact that the structure (graph) and the associated parameters (CPT/PT) can be determined by using data (even in incomplete form), or by using expert opinions, or combining both. For instance, in [3], the author provides some guidelines for building BN with expertise and [6] gives a good introduction about probability elicitation (estimation from expertise).

Finally, BN are a compact representation of the joint probability distribution over all the variables. So, BN are also able to sample data according to this distribution, i.e. simulate the system in various modes.

An extended version of BN, including temporal information, provides the Dynamic Bayesian Networks (DBN). In that case, the probability distributions change over the time in a recurrent way [8, 9]. It is therefore possible to calculate the distribution of *X* at the present time knowing the distribution of *X* in the past time.

4. Modelling the rail diagnosis process: a modular approach

4.1 Modelling the detection systems.

The two first monitoring systems, ultrasonic vehicle (UST) and walking inspectors (WT), work identically: their presence on a rail length is time dependant (couple of months for UST and couple of weeks for WT). Each system has its own decision frame: {OK, IC, SC, BR} for UST and {OK, SC, BR} for WT. According to their own classification result, a maintenance decision is issued or not.

The following figure introduces the sub-model thus obtained for the ultrasonic vehicle. A similar bayesian network was built for walking survey team.

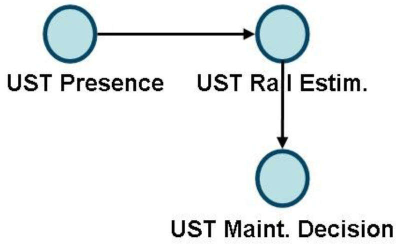

Figure 2: Bayesian Network modelling the diagnosis procedure of the ultrasonic vehicle.

The modelling of the contribution of metro drivers (Dvr) to maintenance decision must take into account a contextual variable. Indeed, trains occupy a given portion of track only during a certain time a day (depending on trains' length, their speed, the headway, etc.) and only if the line is operating. So, the driver's presence node will be conditioned by the state of an operating node, as introduced in figure 3.

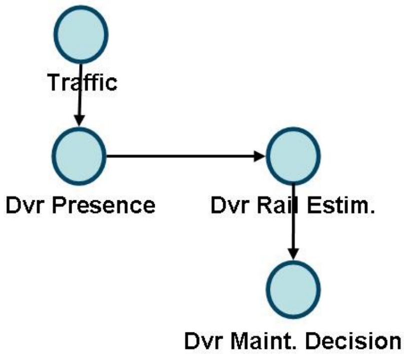

Figure 3: Bayesian Network modelling the diagnosis procedure of Metro drivers.

Concerning the track circuits (TC), their contribution to maintenance action decision deals with more parameters to consider. Indeed, the track circuit accuracy for detection depends on several points.

At first, the season: summer high temperatures expand rail and, thus, sometimes the electrical conductivity is enough, even if the rail is broken. Moreover, if the TC becomes defective, the signaling works similar as in broken rail situation and it delivers false alarms. Finally, as previously explained, if a metro train runs on the considered length of rail, the TC is shunted. It will be therefore unable to detect broken rails. The shunting duration depends on the length of the train, its speed, and other parameters depending on the chosen TC technology. This dependence will induce a link between the TC rail estimation and the train presence. Figure 4 introduces the sub-network modelling the maintenance action decisions triggered by the TC detections. For all these networks, maintenance decisions strategies are currently taken according to expert advices about the rates of good detection for each detector, each one independently from the others.

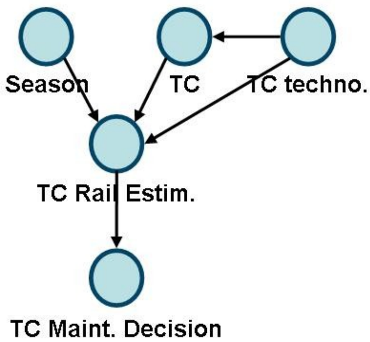

Figure 4: Bayesian Network modelling the diagnosis procedure of Track circuits.

The modelling of the dynamic evolution (for the rail degradation and the maintenance decisions) is presented in the following section.

4.2 Modelling the dynamics.

At a precise time *t*, the maintenance decision is simply the merging of all the maintenance decisions taken by each detector. A hypothesis of the Model is: if a maintenance action is operated at time *t*, the rail is supposed to be reconditioned at time *t*+1.

On the contrary, if no maintenance action is provided, the rail will follow a degradation process from the OK state to "Broken Rail" state, through the minor faults states "Internal Crack" or "Surface Crack". Figure 5 introduces the complete bayesian network, joining previously introduced diagnosis sub-models, rail process degradation and maintenance action policies.

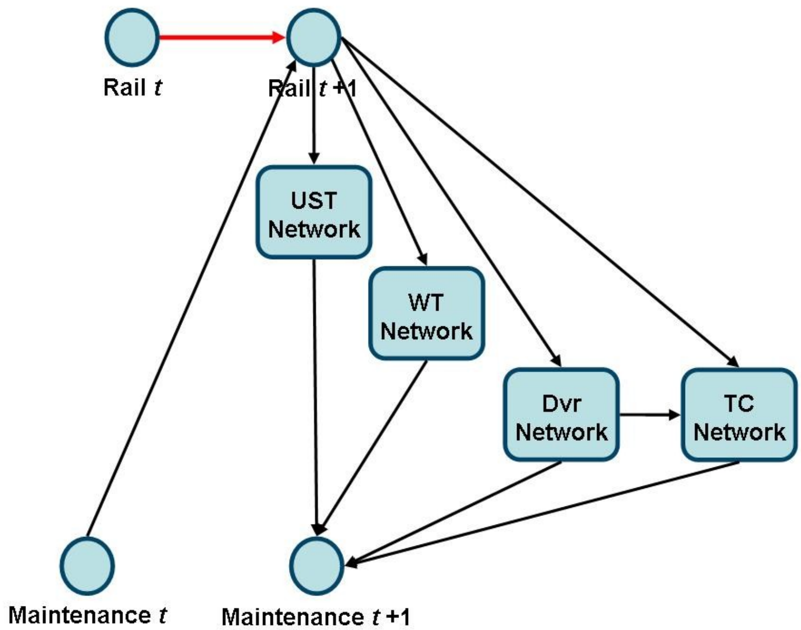

Figure 5: Dynamic bayesian network modelling the rail degradation, its diagnosis and the maintenance strategy.

4.3 Parameters estimation.

The BN structure being defined, the final step of such a modelling consists in the estimation of the probability tables (conditional or a priori) associated to each node. In our case, these parameters were both estimated by database analysis and expert advices. In some critical cases (weak data or uncertain experts) one approach could enforce the other one.

Estimation of the degradation modelling parameters:
The determination of these probabilities is the key point of our study. A too slow degradation process leads to an unrealistic "static" system. On the contrary, a too fast process is beyond any periodical inspections. Some information on the rail degradation can be found in the databases. But, data are strongly left and right censured [4]. The defect appearance time that is recorded is the one when detection equipment is in-situ position, and actually not when it exactly occurs. So, most of the defect appearance times (expected for some broken rails) were left censured. Moreover, the curative or systematic preventive maintenance actions, planed by the current maintenance strategy, modify strongly our opinion on the rail life duration. Indeed, the railway portions renewal policy induces a right censure of the mean time before getting a broken rail. To solve this problem, parameters are first obtained from the database. Then, these probabilities are consolidated by some expert advices, considering the mean annual number of broken rails and the mean time before broken rail appearance.

Estimation of the detection module parameters:
These probabilities are mostly learnt according to both the expert advices and the diagnosis parameters determined by the current experience schedule.
The next section introduces a validation of the global model, introduced in figure 5. Then, results of various simulations, based on a predetermined experience schedule, are presented and discussed.

5. VALIDATION

In this section, we will take advantage of the bayesian networks as generative models for the data sampling of our maintenance process modelling. This property will provide simulation sets for various experimentation parameters, helpful in a maintenance strategy determination.

5.1 The sampling outputs of the model.

Let suppose that, at time *t*=0, the rail is new and no maintenance decision was planed. Then, we can note that the initialing state of nodes “Rail *t*” and “Maintenance *t*” is respectively, “OK” and “No”. The bayesian network introduced in figure 5 supplies the behavior of the node “Rail *t*+1” as a function of nodes “Rail *t*” and “Maintenance *t*” via the elements of the conditional probability table:

$$P\left(Rail\ t+1 \,\middle|\, Rail\ t, Maintenance\ t\right) \qquad (1)$$

A standard sampling algorithm was used to produce a value of “Rail *t*+1” in respect of the rule:

$$P\left(Rail\ t+1 \,\middle|\, Rail\ t = OK, Maintenance\ t = No\right) \qquad (2)$$

Moreover, the node “UST Presence” being deterministic (the ultrasonic auscultation is periodic), if at the current time an auscultation is done (“UST Presence”=Yes), we can use a similar sampling algorithm to describe the behavior of node “UST Rail Estim”. For example, if the obtained value in eq.2 is “Rail t+1”=IC, then, the value of the node “UST Rail Estim” will be given by the conditional probability:

$$P\left(UST\ Rail\ Estim. \,\middle|\, Rail\ t+1 = IC, UST\ Presence = Yes\right) \qquad (3)$$

And so on, all values of our variables, descending of previously calculated nodes, will be progressively generated. This algorithm will finally provide the state of the variable “Maintenance *t*+1”: Yes or No.

The following figure introduces various portions of simulations. The upper curve represents the evolution of the actual rail state. The second one is the maintenance decision (with possible false alarms: FA) resulting from the estimated rail state. The three last curves deal with the presence and the maintenance decision of the detection equipments (except the drivers).

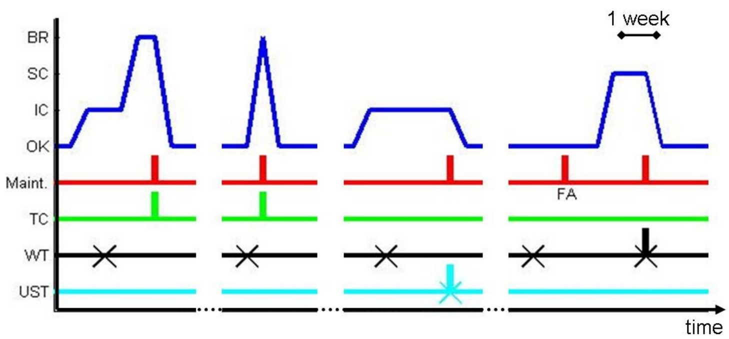

Figure 6: Simulations of maintenance and detection equipments.

In brief, the initial values of nodes “Rail *t*” and “Maintenance *t*” provide the values of nodes “Rail *t*+1” and “Maintenance *t*+1” through our model of rail defect detection. These final values just have to be injected as inputs of the system to generate the next set of values.

5.2 Experimental results.

The data generation provides simulations of the system behavior during a fixed period. The evaluation of these results can be done in respect of four criteria:

- The good maintenance decision rate (were all the detected ruptures and correctly maintained?)
- The decisions rate, based on false alarms (were some maintenance decisions taken as the rail was not broken?)
- The mean time between ruptures
- The mean time to repair (or to detect) a broken rail

These indicators are computed for one year simulations and, thus, can possibly be not representative of the variability of the system. It was therefore necessary to average them on a high number of realizations. In the following results, the sampling step is fixed to one day and indicators are averaged over five realizations of 10000 years sampling. For this study, we considered the following variables:

- Δt: Mean delay between trains (s)
- V: Mean speed of trains (m.s^{-1})
- L: Mean length of trains (m)
- L_{TC}: Mean length of Track Circuits (m)
- P_{UST}: Ultrasonic vehicle auscultation period (day)
- P_{WT}: Walking team auscultation period (day)

After modelling the diagnostic, maintenance and operation parameters (considering a reference scenario S_0) for the currently implemented broken rail monitoring process, a set of fourteen scenarios was defined, for various changes of the reference values of the considered variables. In this paper, we will introduce results obtained modifying the ultrasonic vehicle auscultation period (P_{UST}) or the mean length track circuit (L_{TC}).

Influence of the ultrasonic auscultation period.
For this simulation, only the ultrasonic auscultation period was changed (initially P_{UST}=T_0), with three considered options: $T_0/2$, $T_0/3$ and $T_0/6$. The other parameters were fixed to the reference values.
Figure 7 introduces the influence of P_{UST} on the annual number of broken rails and the number of preventive actions, triggered by an ultrasonic auscultation.
We can note that, as expected, the more frequently ultrasonic equipment sound the infrastructure, the more preventive actions will be planed. Early defects are therefore more easily diagnosed, and then, corrected before they turn to the critical state of broken rail.
Moreover, the gain in terms of broken rails is especially significant for the two first simulations ($T_0/2$ and $T_0/3$) and, beyond, seems to decrease.
Nevertheless, these results eminently depend on the considered rail degradation process modelling. It could be interesting to complete and refine the current model to determine more precisely which value of P_{UST} is optimum in terms of annual broken rails.

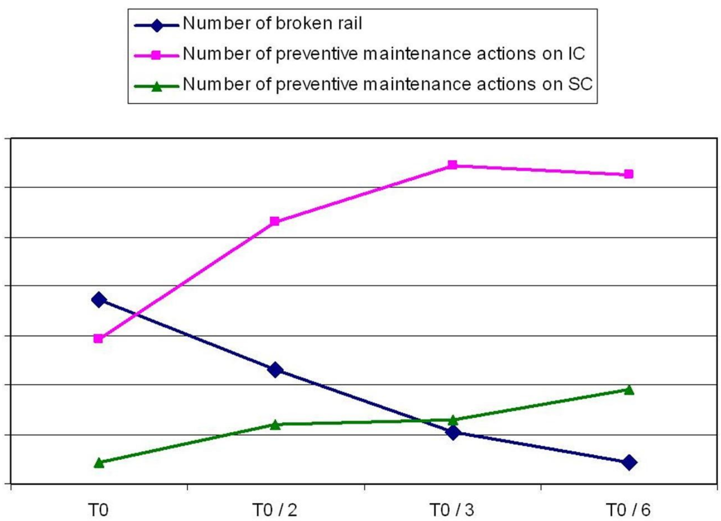

Figure 7: Influence of P_{UST} on the annual broken rails and preventive maintenance actions.

Influence of the mean track circuits length.
For these tests, two parameters were changed:

- The mean track circuit length L_{TC} could take value in the set {L_0x2, L_0x3, L_0x4}, where L_0 is the reference value of L_{TC}.
- The mean speed of train could be doubled, for each value of L_{TC}.

The first significant fact is that all indicators (number of broken rails, preventive maintenance actions…) are quite not sensitive to the length of track circuits. Nevertheless, it appears that, if the number of false alarms due to drivers keep constant (for a given speed), the number of false alarms due to track circuits decreases significantly with higher L_{TC} values. Such a result is perfectly comprehensible. Indeed, the higher L_{TC} is, the less numerous track circuits are and then, the less they failed (triggering false alarms). The following picture introduces this fact.

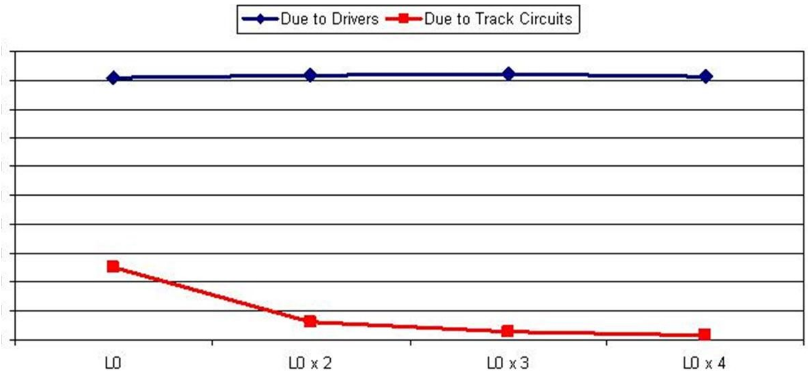

Figure 8: Influence of L_{TC} on false alarms.

If the decreasing of the number of false alarms is a significant benefit in terms of availability of the infrastructure and of maintenance costs, the outstanding of this improvement is that, as illustrated by figure 9, track circuits become less relevant in terms of broken rails detection. This fact is enforced with higher train speed. So, if an enlargement of track circuit offers a better availability of the system and a better reliability of our diagnosis process, it also decreases the influence of track circuit in terms of broken rails detection. It means that another diagnosis system shall be able to take decision in place of track circuits to ensure a good detection rate of critical events such as broken rails.

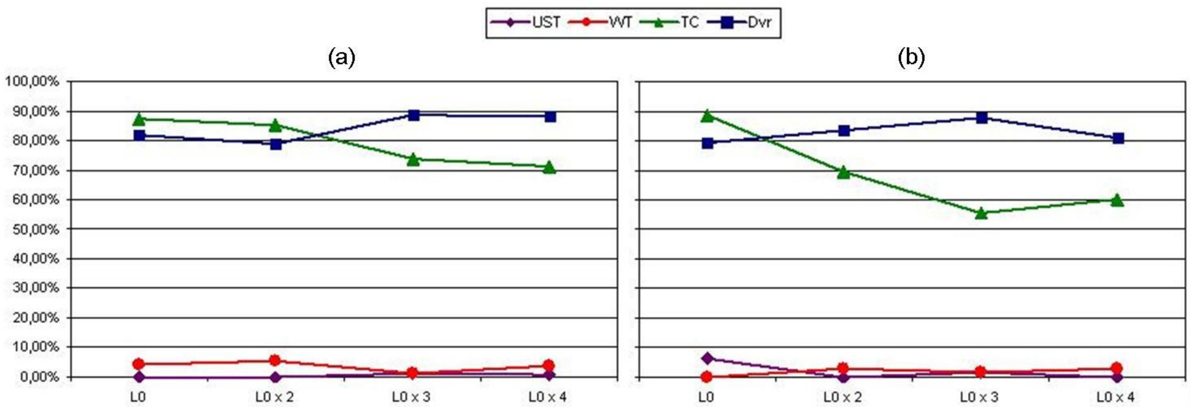

Figure 9: Proportions of broken rails detected by each detection system in respect of L_{TC}:
(a) Reference value V=V_0, (b) V=V_0 x 2

6. Conclusion

In this paper, we introduce a maintenance strategy model for the prevention of broken rails. This modelling is based on the dynamic bayesian network theory, with a modular approach. Thus, our model can be divided in sub networks, eventually interconnected, describing the rail degradation process, the different inspection equipments and finally, the maintenance actions decision. The originality of this work is that the considered approach is generic and can easily be extended to all kind of maintenance processes modelling for determining Maintenance and/or Diagnosis optimal parameters.

Due to specificities of our database (incompleteness, left and right censures), the learning of probability tables needed to be consolidated by expert opinions. Then, our model has been validated by various simulations, implying modifications of some parameters of our system.

In this paper, we only introduce some of the obtained results to illustrate the ability of the approach to simulate all kinds of scenarios, modifying maintenance decisions, diagnosis parameters or running variables. One advantage of the introduced method leads in the fact that all new information (from database or expert advice) or modification of the diagnosis process can easily be taken into account to amend the Model.

Further studies might improve the modelling of the rail degradation process. Finally, the integration of optimization algorithms will furnish useful tool to determine, in respect of some predetermined criteria, the optimal diagnosis and/ or maintenance parameters.

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