Optimal Metro-Rail Maintenance Strategy using Multi-Nets Modeling

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Abstract: Reliability analysis has become an integral part of system design and operating. This is especially true for systems performing critical tasks such as mass transportation systems. This explains the numerous advances in the field of reliability modeling. More recently, some studies involving the use of Bayesian Networks (BN) have been proved relevant to represent complex systems and perform reliability studies. In previous works, the generic decision support tool VirMaLab, developed to evaluate complex systems maintenance strategies, was introduced. This approach is based on a specific Dynamic BN, designed to model stochastic degradation processes and allowing any kind of state sojourn distributions along with an accurate context description: the Graphical Duration Models. This paper deals with a multi-nets extension of VirMaLab, dedicated to maintenance of metro rails. Indeed, due to fulfillment of high-performance levels of safety and availability (the latter being especially critical at peak hours), the operator needs to estimate, hour by hour its ability to detect broken rails.

Keywords: Maintenance, railway infrastructure, reliability, availability, optimization, decision support, Probabilistic Graphical Models

1. Introduction

Reliability analysis is an integral part of system design and operating. Moreover it can be an input to optimize maintenance policies. Recently, Dynamic Bayesian Networks (DBN) have been proved relevant to represent complex systems and perform reliability studies. The major drawback of this approach comes from the constraint on the sojourn times which are necessarily exponentially distributed, as in usual Markovian approaches. To avoid this constraint, a new formalism named Graphical Duration Models (GDM) was introduced [1]. This approach, based on semi-Markovian models, allows representing all kind of sojourn time distributions. Then the degradation process of complex systems (multi-components, multi-states, eventually influenced by contextual variables) can be accurately modeled and thus, the related reliability indicators correctly estimated. With this generic approach (named VirMaLab, for Virtual Maintenance Laboratory) various industrial applications were developed, especially as decision support tools for the optimization of railway infrastructure maintenance strategies.

In this paper, an extension of the commonly used VirMaLab formalism will be introduced. This new application deals with the broken rails prevention and detection in a
context of renewal of the command-control systems for railway Paris steel-wheel metro lines. The final objective of this application of VirMaLab is to evaluate and compare various diagnostic, maintenance and operating scenarios, in terms of availability, broken rails frequency, etc. Due to the fulfillment of high-performance levels of safety and availability (the latter being especially critical at peak hours), the operator (RATP) needs to estimate, hour by hour its ability to detect broken rail. But, for many reasons (time computation, accuracy of parameters, learning data…), the modeling of a rail degradation process with a one hour step is impossible.

To address this problem, a multi-nets model was developed, allowing a variable granularity in respect of the state of the rail. Usually, in VirMaLab applications, the whole model infers with a constant step. Here, four models were introduced, with their own inference step fixed in accordance with the defect severity (from one month for early inner rail cracks to one hour when broken rails occur) and their own set of diagnosis devices (all defects levels are not detected by the same means of appliances). Finally, the three first models emphasize the use of the preventive maintenance strategies on the availability of the network whereas the last model focuses on the corrective maintenance and evaluates, hour by hour, the response of the diagnosis system in terms of broken rail detection ability.

Parameters of these models are learnt by use of REX databases and/or expert advices. Then, the global model is validated by various experiments with the standard running, diagnosis and maintenance parameters. Receiving the validation of these first results by RATP experts, new sets of scenarios can be computed, evaluating the influence of any parameters. To evaluate a given maintenance strategy, various indicators are analyzed, from annual numbers of broken rails (for the safety questions) and preventive maintenance actions to delays before broken rails detection, including corresponding impacts on availability: the latter is expressed in the model through the related number of lost round-trips, a round-trip being the basic unit to express production of service for RATP, and corresponds to the journey of a given train from one extremity of the metro line (a broken rail induces a stop of operations on the related part of the line), or for minor cases, a degraded situation with trains proceeding at reduced speed till the defect is consolidated). Then, the acceptable speed is strongly decreased up to the rail refurbishment.

This paper is divided in four sections. The section 2 introduces the VirMaLab generic approach and will briefly focus on the Graphical Duration Models formalism. Then, the original multi-net extension of this decision support tool, dedicated to the broken rail prevention in a context of renewal of the signaling and train control systems of RATP steel-wheel lines, will be introduced in section 3. Finally, some conclusions and perspectives are discussed in section 4.

2. The VirMaLab Approach

2.1 Introduction of the Generic Approach

During a previous study, a model named VirMaLab (for virtual maintenance laboratory) was proposed, this model being able to settle the optimal diagnosis parameters and the most adapted maintenance policy for a predetermined context and according to running constraints, was proposed.
Figure 1 introduces this generic approach used for building such a decision support tool in order to determine optimal maintenance strategies. This approach is divided into three steps:

- The first one consists in the mathematical modelling of the physical state of the system and the associated time evolution of its various components. This means being able to determine whether the system is still fault free after a given running time, knowing its initial state and the running parameters.

On the contrary, if a defect appears, it is therefore necessary to determine, among a predefined list of possible defects, in which damaged state the system is. Due to the variability of contexts and the system size, a probabilistic approach is adopted. Doing this way, the probability of facing a given system’s state is estimated rather than calculating its deterministic existence. One of the most commonly used approaches is based on the Markov Chains formalism, frequently modelled by Bayesian Networks. Nevertheless, this approach needs a Markovian hypothesis. This means that sojourn times in each state must necessarily be exponential. If some systems confirm this assumption, most of industrial applications underline non Markovian behaviours. In this case, a Markovian degradation process modelling can introduce non negligible biases. Then, the estimated maintenance parameters can be far from optimal results [2]. To overcome this drawback, the VirMaLab approach introduces an original semi-Markovian modelling of degradation processes, able to fit all kinds of sojourn time distributions: the Graphical Duration Models (GDM), introduced in section 2.3, [1].

Figure 1: Generic Approach for the VirMaLab Maintenance Decision Support Tool

- The second step consists in the modelling of diagnostic devices (detection rate, false alarms rate…) and their setting parameters (periodical auscultations, etc). According to results of the diagnosis’ measurement campaign, each reference frame recommends the use of a maintenance action adapted to the current estimated state of the system. When a maintenance action is realized, the state of the system and its degradation process has to be updated to take into account the corrective action impact.

- Finally, the third step consists of diagnosis and maintenance of the system being characterized by a set of parameters and each action having a defined cost (financial, human, etc.), the last phase consists in quantifying the maintenance policy in term of safety, cost, availability, service quality etc.
Then, with such decision support tool, one can evaluate various maintenance strategies and determine, for a given cost function \( s \), the best set of maintenance and diagnostic parameters. It can be applied to simple systems but also to multi-states and multi-component systems (with possibly interacting components). The learning of such modelling can be done with both expert advices and REX databases.

### 2.2 Bayesian Networks Formalism

BN are mathematical tools relying on both the probability theory and the graph theory [3]. They allow to qualitatively and quantitatively representing uncertainty. Basically, BN are used to compactly describe the joint distribution of a collection of random variables \( X=(X_1, \ldots, X_N) \) taking their values in \( \mathcal{X} = \{X_1, \ldots, X_M\} \).

Formally, a BN denoted by \( M \) is defined as a pair \( (\mathcal{G}, \{p_n\}_{1 \leq n \leq N}) \) where \( \mathcal{G}=(\xi, \varepsilon) \) is a Directed Acyclic Graph (DAG) and \( \{p_n\}_{1 \leq n \leq N} \) a set of Conditional Probability Distributions (CPD) associated with the random variables. These distributions aim to quantify the local stochastic behaviour of each variable. The graph nodes and the associated random variables being both represented by \( \xi = \{X_1, \ldots, X_N\} \). \( \varepsilon \) is the set of edges encoding the conditional independence relationships among these variables. Finally, \( \mathcal{G} \) is said to be the qualitative description of the BN.

Besides, both the qualitative (i.e., \( \mathcal{G} \)) and quantitative (i.e., \( \{p_n\} \)) parts can be automatically learnt, if some complete or incomplete data or experts opinions are available [4]. Using BN is also particularly interesting because of the easiness for knowledge propagation through the network. Indeed, various inference algorithms allow computing the marginal distribution of any sub-set of variables. The most classical one relies on the use of a junction tree [5].

Finally, note that such modelling is able to represent dynamic systems (e.g., which contain variables with time dependent distributions) via the DBN solution [6]. A DBN is a convenient extension of the BN formalism to represent discrete sequential systems. Indeed, DBNs are dedicated to model data which are sequentially generated by some complex mechanisms (time-series data, bio-sequences, number of mechanical solicitations before failure...). It is therefore frequently used to model Markov chains. Figure 2 illustrates this property, introducing a DBN modelling the Markov Chain of the sequence \( X=(X_t, \ldots, X_\infty) \) taking its values in the set \( \mathcal{X} \). This DBN is described by the probabilities that quantify the transitions from one state of \( \mathcal{X} \) to another. More precisely, a DBN defines the probability distribution of a collection of random variables \( (X_t)_{t \geq 1} = (X_1, \ldots, X^0)_{t \geq 1} \) where \( t \) is the discrete time index.

![Figure 2: Dynamic Bayesian Network Modelling a Markov Chain](image)

### 2.3 Graphical Duration Models

The Graphical Duration Model is a specific DBN, using semi-Markov models. The main idea is the introduction of remaining time variable into the graph that allows to model multi-state systems featuring complex sojourn times. Figure 3 shows a GDM in its
DBN form. The solid lines define the basic structure; dashed lines indicate optional items and red bold edges characterize dependencies between time slices.

**Figure 3:** Graphical Duration Model in the form of a Dynamic Bayesian Network

The model handles two kinds of variables:

- \((X_t)_{t \in \mathbb{N}}\) represents the system state over a sequence of length \(T\).
- \((X^D_t)_{t \in \mathbb{N}}\) represents the remaining time before a system state modification (remaining sojourn time). These variables are called duration variables.

Optionally, it is possible to introduce a context description of the studied system by means of a prior graphical model \(\mathcal{M}_c\). It aims to define the distribution of a possible collection of context variables (covariates) \(Z_t = (Z_{p,t})_{p \in \mathbb{P}}\) (one variable at least) that works on variable state \(X_t\) and/or duration variable \(X^D_t\). Besides, the DAG of a GDM shows that the current system state \(X_t\) depends on the previous system state \(X_{t-1}\), the previous remaining duration \(X^D_{t-1}\) and, optionally, on contextual variables \(Z_{n,t}\). On the other hand, the current duration variable \(X^D_t\) is dependent on the previous duration variable \(X^D_{t-1}\), the current state \(X_t\) and, optionally, on the previous state \(X_{t-1}\) and some contextual variables \(Z_{n,t}\).

Consequently, the process \((X_t)\) (respectively, \((X^D_t)\)) is not Markovian since

\[
\begin{align*}
X_{t-1} &\not\perp\!\!\!\perp X_t, \\
X^D_{t-1} &\not\perp\!\!\!\perp X^D_t \\
\end{align*}
\]

where the notation \(\perp\!\!\!\perp\) means that variables \(A\) and \(B\) are statistically dependent.

On the other hand, the GDM structure leads to

\[
\begin{align*}
\left( X_{t-1}, X^D_{t-1} \right) &\perp\!\!\!\perp \left( X_{t+1}, X^D_{t+1} \right) | \left( X_t, X^D_t \right) \\
\end{align*}
\]

So, the set \((X_t, X^D_t)\) engendered by a GDM is Markovian, despite \((X_t)\) is not. The GDM generalizes the recent studies on discrete semi-Markovian processes [7]. On the practical point of view, this approach allows specifying arbitrary state sojourn time distributions by contrast with a classic Markovian framework in which all durations have to be exponentially distributed. This modelling is therefore particularly interesting as soon as the question is to capture the behaviour of a given system subjected to a particular context and a complex degradation distribution. More details on this GDM (quantitative description, optional context description …) can be found in [8] [9].

3. Application of the VirMaLab Approach to Rail Maintenance Optimization

3.1 Introduction of the System

In an automation context, the implementation of a new signaling and train control system on some steel-wheel lines of the Paris underground network enforces the RATP
company 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 signaling and train control system has to be made as the headway will be significantly reduced (for instance on line 5 this interval between two trains will be reduced to 90s at peak hours, being 105s at the moment) and the existing signaling system will be modified. Moreover the performance criteria for availability associated to the new signaling and train control system are high.

Depending on the nature of defects, the disturbance is 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), $X_1$ (Internal Cracks < 2.4mm), $X_2$ (Internal Cracks < 30mm) and BR (Broken rail, introduced in Figure 4).

![Figure 4: Broken Rail due to the spreading of an Inner Crack](image)

Currently, the diagnosis of rail defects results from the combination of diagnoses from the four actors (detecting devices or specific staffs) involved in the broken rail monitoring process: these actors are characterized by different inspection periodicities and different detection efficiencies according to the type of defect and its location in the rail.

- A specific ultrasound vehicle (USV) dedicated to preventive maintenance actions is equipped with ultrasonic sensors. It diagnoses the rail on average twice a year. It is the only device able to detect the 4 classes of defects.
- Some walking survey teams (WT) are passing along the lines on average once or twice a month. They only can detect BR and have therefore a corrective function.
- During the passenger service, metro drivers (Drv) sometimes feel some shocks from the rails, and so, can contribute through their reporting to the detection of some BR.
- The track circuit’s (TC) normal function is the detection of trains on a given rail section. Depending on this block is free or not, the corresponding signaling indication will be permissive or restrictive (moreover the signaling permits a maximum of one train on a given TC). As the TC analyses the rail impedance, so it can detect some BR when no train are on the area. TCs finally detect almost 70% of broken rails and are actually the first contributor in BR detection.

In its metro automation programs, RATP has to renew the command control system, and with new implemented systems the role of TC has changed in terms of signaling: whereas in past systems TC ensure the basic detection of all trains, with new systems TC are useful only for the detection of non-equipped or failed trains. But with lines modernized with the new system, the occurrence of a BR is a more critical event as in the
past because of the reduced interval between trains and the fact that several trains could be present on the same TC. The prevention of BR and a minimum number of false alarms for BR are key points to fulfill safety and availability requirements. Our study aims to furnish a decision support tool allowing (across various indicators) to evaluate and compare some simulation runs and maintenance strategies.

A great amount of information, distributed among databases (from signaling and track departments) and expert advices are available. But, this information is sometimes uncertain, imprecise, or even missing. For all of these reasons, the formalism of the Bayesian network theory, introduced in section 2.2, offers an adequate framework to represent our system and its maintenance.

3.2 StatAvaries: A Multi-nets Extension of the VirMalab Approach

The adopted modeling is based on the VirMaLab generic approach, introduced in section 2.1. Nevertheless, the aims of this study do not include economic parameters (only indication about the impact on production in terms of round trip is highlighted). So, only the two first blocks (Degradation process and Maintenance modeling) will be considered.

A metro line is constituted of hundreds of elementary rail sections (between 5 and 18 meters long), with various ages, various states, etc. The development of a degradation model of a complete line has been therefore considered as too complex in terms of modeling and too demanding regarding computation capacities. To tackle this issue, a track is assumed to be the sequence of a set of independent elementary rail sections. The proposed model focuses on only one of these elementary sections and then, results are extrapolated to larger track sections to obtain reliability indicators on the considered portion of line.

Contrary to the preliminary study [10], the second specificity of this application consists in the necessity of being able to evaluate, hour by hour, the consequences of a BR especially during peak hours) when the rail degradation speed unit should be between the week and the month. The development of a rail degradation process model with a one hour step is therefore absolutely unsuitable (in terms of complexity, accuracy...). To overcome this problem, an original multi-nets approach (introduced in Figure 5) is proposed. Each state of the rail $S_i$ (taking its values in \{ok, $X_1$, $X_2$, BR\}) is characterized by a VirMaLab Bayesian Network with a sojourn time distribution $S_i D$, learnt from REX databases.

![Figure 5: Multi-nets Structure of the VirMaLab Decision Support Tool StatAvaries](image)

The two first layers of the multi-nets are characterized by one month iterations. The second one, dedicated to $X_2$ defects, has a one week step. Finally, the last network, evaluating the ability of the system to detect BR, has one hour iteration.
3.3 VirMaLab: Preventive Maintenance Network

This first model introduced in figure 6 deals with the rail’s preventive maintenance strategy. As a VirMaLab modeling, it is constituted of two blocks. The first one describes the degradation process of the rail, using the GDM formalism (introduced in section 2.3). The rail degradation can be influenced by several contextual variables such as the type of rolling stock (changing from one line to another), the curve radius (and we give the possibility to consider only the inner or upper rail) and the steel’s stiffness. The second block of this model describes the diagnosis actors (devices or staff) and the maintenance strategy. Three actors trigger periodic auscultations of the rails: the USV, WT and drivers (whose presence depends on the state of the traffic, with peak hours, operation closure at night, etc.).

Figure 6: Structure of the three VirMaLab Preventive Networks

The modeling of the last device, meaning the TC, is a little more complex. Indeed, several Track Circuits technologies are implemented on each line of the RATP network, each technology having different failure rates (if a TC is down, it is unable to detect any BR), different mean length. Moreover, the analysis of RATP databases under-lines that, during warm seasons, the rail dilatation helps keeping the electric contact of many BR. In this case, the TC ability to detect BR registers a 50% decrease. All this variables have, therefore, to be taken into account in the final modeling. All four diagnosis actors provide an estimation of the current state of the rail (integrating their own good detection and false alarm rates) that influences the maintenance decision. When a maintenance action is performed, it is assumed that the system turns to the ok state in a single iteration.

3.4 VirMaLab: Corrective Maintenance Network

This second model, introduced in Figure 7, focuses on BR’s detection and corrective actions. Indeed, it evaluates both the ability of the system to detect a BR and the impact of such an event on the global indicators (time before detection, availability by the corresponding number of impacted revenue service trains through the assessment of the loss of production, etc.).

This network is activated when a BR occurs. To evaluate the time before the detection, only the actors with a short reaction time are considered. USV and WT diagnosis, whose checking periods are on a relative long-term basis, are therefore not taken into account and drivers are compared to a real time device. The actors with a short
reaction time to BR are Drv and TC. Indeed, in service periods, Drv systematically diagnoses the rail (a train runs at least each 105s-115s and the model iteration is one hour long).

![Structure of the VirMaLab model for the 'one hour step' slice of the StatAvaries Multi-nets](image)

**Figure 7:** Structure of the VirMaLab model for the ‘one hour step’ slice of the StatAvaries Multi-nets

### 3.5 Experiments running of the Final Decision Support Tool

Each experiment begins in the good (ok) state. Then, a sojourn time $T_{ok}$ is generated in respect of $ok^D$. During this period, some indicators are computed (mainly false alarms). After $T_{ok}$ iterations (i.e., $T_{ok}$ months in terms of rail degradation) an inner crack appears and the second network is activated. A new duration $T_{X1}$ is generated on respect of $X_1^D$. To allow quick degradations modeling, this duration can be null. In such cases, the third network is immediately activated. On the other hand, during these $T_{X1}$ months, the preventive maintenance strategy is evaluated analyzing false alarms, good detections etc. If any maintenance action is performed, the system is reinitialized during the next iteration. If no preventive maintenance action is taken, and the $X_1$ sojourn time is over, the third network is activated with a new duration $T_{X2}$. The preventive maintenance policy is one more time evaluated. If the $X_2$ defect is not detected and/or if no preventive maintenance action is performed, the rail will break after $T_{X2}$ weeks.

Then the last network is activated. No sojourn time is generated since the BR is a blocking state. Indeed, the only way to end this state is the detection of the defect and the replacement of the rail.

To facilitate the use of this multi-nets model for both maintenance operators and managers of the automation lines project, a user-friendly interface was developed. It allows determining the following parameters:

- The considered line (among the 11 RATP steel-wheel underground lines)
- The rail context: The whole line or only the curved rails (possibly only the upper rail).
- The critical curve radius. It determines the set of curves on which a BR could have particularly critical consequences in terms of passengers’ safety.
- The rail quality. For different reasons, an operator can decide to change the steel stiffness. Consequently, the rail degradation process must reflect the stiffness of the corresponding steel.

- Operations and Rolling stock specifications: service periods (including the different peak and off-peak hours’ ones: during one day, 6 periods are defined to reflect the transportation offer that varies according to time) and their associated headways, commercial speed (used as mean speed for the trains running in scenarios), length and axle load. These parameters influence the rail degradation speed and are also necessary to evaluate some final indicators.

- Diagnosis parameters: Good detection and false alarms rates, USV and WT auscultation periods, parameters of the TC technologies encountered on the considered underground line.

When all parameters are defined, the inference can begin. Due to the modeling complexity, the computation of an experiment can be quite long (around 2 hours). Moreover, to ensure good results, a very high number of temporal steps are considered. For each simulation, the behavior of the elementary rail portion is analyzed over 50,000 years (indicators for the complete line are therefore obtained by meanings over nearly 20-40 years, depending of the length of the line). A solution based on an exact inference algorithm [5] was studied but the currently used structure of our network does not allow the implementation of such algorithms. Nevertheless, the accuracy of obtained results was proved during the study by computing many times the same experiment. Same results were systematically obtained.

After discussions and assessments with RATP experts, the final indicators must provide information about:

- broken rails: number of annual BR on the line, mean time (in hours) before their detection and the contribution of each diagnosis device in these detections. Number of annual ‘dangerous’ BR (occurring in a critical ‘in curve’ context)
- maintenance actions: number of annual preventive and corrective maintenance actions, ratio of actions triggered by false alarms and their distribution among all diagnosis devices
- loss of production: when a BR occurs, the operations’ rules induce speed reductions or stopping of service in the corresponding area. Then, the operations’ performance defined by the train headway cannot be maintained and the number of running trains strongly decreases. RATP names this loss of trains running ‘monthly lost round trips’

As an illustration, the next section will introduce results obtained in one of the scenarios investigated for RATP. The aim of this paper is not to list all results obtained during the study but to introduce the VirMaLab multi-nets extension, illustrated by one experimental example. For more information on some of the obtained results, readers can contact the authors.

3.6 Some Results

This section introduces some of the obtained results, detailed for the line 7 in Paris metro network. The aim is not to detail all results of the study but to give some illustrations of the proposed methodology. For confidentiality reasons, exact values of indicators are deleted. Nevertheless, the interest of these results lays in the evolution of indicators according to variations of main components of the model, and in the comparison between the reference scenario and the prospective ones.
3.7 Impact of Preventive Maintenance in various Running contexts

In this study, one of the considered scenarios deals with the influence of the USV auscultation period on maintenance actions and network’s availability, in respect of the traffic frequency. Figure 8 focuses on the impact of the systematic preventive maintenance actions (triggered by USV inspections) on the annual number of broken rails. For this experiment, the ultrasonic auscultation period was changed, with value in $[2T_0, T_0, T_0/2, T_0/6]$ (where $T_0$ is the reference period, currently used on line 7), and balanced by two various running settlements:
- the first one analyses the influence of the USV auscultation period with the current traffic frequency (peak hours around 114s)
- the second one prospects what could be the influence of the USV auscultation period if the traffic was increased by 25% (the peak hours headway being at 90s).

![Figure 8: Influence of the USV Period on Rail’s Degradation – Application to line 7 in both actual running parameters (light curves) and with an increased traffic (bold curves)](image)

We can note that, as expected and for both traffic conditions, the more frequently ultrasonic equipment sound the infrastructure, the more preventive actions will be planed (blue curves). Early defects are therefore more easily diagnosed, and then, corrected before they turn to the critical state of broken rail (red curves). Moreover, the increase of trains’ traffic accelerates the rail degradation process. Indeed, with the current auscultation period $T_0$, with an higher traffic, the annual number of broken rails increases by 50% inducing an unacceptable availability level of the infrastructure (comparison of bold and light red curves).

Then, if RATP wants that the traffic increase substantially on its renewed lines, as expected by its on-going programs for modernizing the command-control systems, the developed model shows that it is recommended to adapt accordingly the preventive maintenance strategy; for example by increasing the USV auscultation frequency.

3.8 Impact of the Inhibition of some Diagnosis Systems on BR Mean Time Detections

The modernization of signaling and train control systems in RATP raises some questions related to the currently involved actors in the process permitting the detection of BR: drivers and TC. At the moment, no corresponding project is foreseen but the implementation of a driverless command-control system on a steel-wheel line could occur in the future; another possible evolution for signaling in RATP could be the replacement
of TC by other detection means such as axle counters (less demanding in terms of maintenance than TC), as TC have a reduced role in new deployed command-control systems. To help exploring these prospective scenarios, the developed model permits some experiments that quantify the impact of removing drivers or track circuits from the process of detection of BR. In both cases, the BR detection mean times increase by 33.8% to 60.7%, according to the inhibited system and the considered traffic frequency...

Such results confirm that, if TC and drivers are no longer necessary to drive and control trains for some automation contexts, their ability to detect quickly broken rails makes them indispensable in terms of infrastructure’s safety and availability: it means that their possible removal from the process permitting the detection of BR would need to be compensate by other dedicated means.

3.9 Impact of preventive Maintenance on Critical Broken Rails

Another interesting indicator deals with critical occurrences of broken rails, taking place in curves with small curvature radius (in that the probability for a derailment is higher). As introduced previously, mechanical constraints on the rail are higher in curves. So, this context triggers a quicker degradation and a then higher number of internal cracks (with finally a higher number of BR). As all the rolling stock’s weight leans on the curves upper rails, most of in curves BR occurs on these upper rails and can therefore involve dangerous situations.

Figure 9 introduces the influence of Preventive Maintenance on the Localization of BR and on their number. The improvement of preventive maintenance shows a decrease of ‘in risky curves’ BR numbers with finally a nearly equivalent behaviour of both contexts (Alignment and risky curves).

4. Conclusions

In this paper an original maintenance strategy modeling was introduced, dedicated for the prevention and detection of broken rails, in a context of renewal of the signaling and train control systems for Paris steel-wheel metro lines. This modeling is based on a generic approach named VirMaLab (Virtual Maintenance Laboratory) using the Dynamic Bayesian Network theory, with a modular approach. Thus, the proposed modeling can be divided in sub networks, possibly interconnected, describing the rail degradation process, the different diagnosis actors (devices and staff) and finally, the maintenance actions decision.
The originality and innovation of this work is that, if the application introduced in this paper deals with the railway infrastructure, the considered approach is generic and can easily be extended to all kind of maintenance processes modeling for determining Maintenance and/or Diagnosis optimal parameters. Moreover, the use of Graphical Duration Models ensures an accurate degradation process modeling, whatever sojourns times distributions in the different system’s states are. Finally, the multi-nets extension allows introducing a multiple temporal sampling, satisfying both the degradation dynamic and the accuracy required to quantify correctly the impact of broken rails and their related false alarms, in order to support RATP in its decisions.

As an illustration of this generic approach, some results are introduced, focusing on the influence of some diagnosis parameters (ultrasonic diagnosis periodicity, inhibition of some broken rails detectors, traffic frequency etc.) on safety and availability indicators (annual numbers of broken rails and preventive maintenance actions, broken rails detection mean time etc.). These experiments were realized for the line 7 of the Paris metro network. These results illustrate the ability of the approach to simulate all kinds of scenarios, modifying maintenance decisions, diagnosis parameters or running variables.

Another advantage of the introduced method lies in the fact that all new future available information (from databases or expert advices) or modification of the diagnosis process can easily be taken into account to amend the modeling. Finally, the integration of meta-heuristics in the inference algorithm is actually in progress. It will furnish useful tool to determine, in respect of some predetermined criteria, the optimal diagnosis and/or maintenance parameters.

References

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