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Optimisation of Maintenance Policy based on operational Reliability Analysis (Application to Railway Switches & Crossings)

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Abstract

The present communication reports on a collaboration between ALSTOM Transport and Luleå Technology University, under the sponsorship of Trafikverket, the Swedish Infrastructure Manager.

For 2020, the European Rail Research Advisory Council (ERRAC) has set among other the following objectives [2] : doubling passenger traffic and tripling freight traffic and reducing the life-cycle cost of infrastructure by 30%. This need applies to rail infrastructure in general. Clearly, the highest leverage will be obtained by concentrating the efforts on key cost and availability drivers. For instance, it is reported that switches and crossings (S&C) are one of the subsystems that cause the most delays on Swedish Railways while accounting for at least 13% of maintenance costs. (It is the main reason why we chose to base our study on this subsystem).

Intelligent data processing allows to understand the real reliability characteristics of the assets to be maintained. Furthermore simulation and optimisation techniques are applied in order to adapt the maintenance strategy so as to achieve minimum cost while guaranteeing target availability.

The first step has been to determine the S&C reliability characteristics based on field data collection. Because field failure data are typically strongly censored, we have developed our own statistics software package to process field failure data, as commercial packages have not been found satisfactory in that respect. The resulting software, named RDAT® (Reliability Data Analysis Tool) has been relied upon for this study: it is especially adapted to statistical failure data analysis.

The next step will be to customize the maintenance interval by adapting it to individual switches and crossings behaviour characteristics. In order to predict and optimize life-cycle cost (LCC) and availability, Monte Carlo simulations will be performed with stochastic Petri nets. The failure rates estimated with RDAT® will be used as inputs to the Petri net. Such a model lends itself to maintenance optimization. Indeed, designs of experiments can be used in conjunction with simulations in order to express both LCC and availability as functions of various maintenance-related decision variables (such as preventive maintenance frequency, maintenance efficiency, etc, see [7]).

Further improvement could result from applying condition-based maintenance, where preventive maintenance times would no longer be predetermined but rather based on the observed S&C condition, as measured by : number of displacement cycles, current absorbed, vibration intensity during train passage, traffic intensity etc. It is planned to resort to the Watchdog Agent ® software, of Intelligent Maintenance System, to that end [4].

Keywords – Reliability ; Availability ; Life Cycle Cost (LCC) ; Switches and Crossings ; Optimization ; Condition Based Maintenance (CBM) ; Crow Model ; As Good As New (AGAN) ; As Bad As Old (ABAO) ; Maintainability.

Introduction

Switches & Crossings are one of the largest contributors to maintenance costs in the Swedish Rail Network. Maintenance cost reduction is, as on many other networks, an important objective, which must be combined with that of achieving a sufficient availability or, more generally, quality of service.

The approach followed here has been in a first phase, to analyse failure data collected by Trafikverket in order to characterise switch & crossing reliability, with a view to adapting the maintenance policy to the reliability characteristics.

In the first part of this paper, the data analysis is addressed .First the statistical software package developed is described, then the data collection and filtering method : due to the large number of assets, it was necessary to filter out some data in order to extract meaningful features.

In the second part, the results obtained so far and their interpretation are discussed.

The second Phase of the project, LCC and availability optimisation, has just begun : the definitions are given and the methodology which we plan to use is described.

Finally, indications are provided on the third phase of the study, which will consist of assessing the feasibility and cost-effectiveness of condition-based maintenance.

Phase 1 : Reliability characteristics of Switches and Crossings

A. RDAT® software :

ALSTOM Transport Information Solutions' RAM Center of Excellence has developed in collaboration with StatExpert Inc. a statistical data processing tool, RDAT® ("Reliability Data Analysis Tool"), in order to estimate reliability functions and failure rates from field data, to test statistical trends and to quantify the influence of environmental and mission profile factors on reliability. That software tool is particularly well suited to highly-censored data, which are typically encountered in failure records (Censored data are data that correspond to incomplete observations, i.e. in this context, not all members of the observed population have had a failure over the period of observation).

The RDAT® based analysis consists in two steps. At first we proceed with a non-parametric analysis.
The non-parametric analysis allows to analyze data without assuming an underlying life distribution and avoids the potentially large errors brought about by making incorrect assumptions about the distribution. To this end the Kaplan-Meier model has been implemented in RDAT. However, the confidence bound on non-parametric analysis is generally wider than in a parametric analysis [8].
The second step consists in performing a parametric analysis. A parametric model is a set of related mathematical equations in which alternative scenarios are defined by changing the assumed values of a set of fixed coefficients (parameters). Four failure models have been implemented in RDAT : Exponential distribution; Weibull distribution; Normal distribution and Lognormal distribution. To select the best model, a goodness- of- fit test is applied.

The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question. Two different models have been implemented in the Reliability data analysis tool, the AIC (Akaike's Information Criterion) and the R^2 [1].

This process can be applied for three types of analysis :

The first one is the "First failure analysis". It consist of using the first failure after the installation date of an item of equipment to determine the reliability characteristics of this equipment. The first failure analysis is really adapted when the equipment has few failures during its operational life and when the period of observation contains the installation date of each equipment studied.

We also determine the quality of the maintenance based on the Kijima model [9]. The maintenance quality is measured by a parameter denoted Rho, which can vary between 0 and 1.
$\rho = 1$ means that the maintenance quality is AGAN (As Good As New), i.e. the maintenance operation brings the item back to a reliability level corresponding to age 0 (the maintenance operation is perfect).
$\rho = 0$ means that the maintenance quality is ABAO (As Bad As Old), i.e. that the maintenance operation just allows the mission to continue but leaves the item with a reliability corresponding to the age accumulated so far.

The second type of analysis is the “AGAN analysis”. If the Kijima factor is equal to 1 we re-estimate the reliability characteristics by taking into account all failure that occurred during the observation period with the hypothesis of perfect maintenance.

The third type of analysis is the “ABAO analysis”. If the Kijima factor is equal to 0 we re-estimate the reliability characteristics by taking into account all failures that occurred during the observation period with the hypothesis of minimum maintenance. To this end we use the Crow-AMSAA [11] model to estimate the most suitable reliability law to represent the equipment studied.

B. Field data collection :

Trafikverket has provided us with field data collected over 5 years (between 2005 and 2009). The assets under study are the turnouts which equip the Swedish Railway network. This Return of Experience collected during this period of observation shows around 43 500 failures. The Swedish Railway network is divided in 8 regions : Stockholm (CST) ; Boden (BDN) ; Göteborg (G) ; Ånge (AG) ;Hallsberg (H) ; Malmö (M) ; Norrköping (NR) ; Gälve (GA).
The maintenance is currently subcontracted to a different maintenance company for each region.

Our first step was to clean this data base in order to screen out dubious data and to focus only on the types of turnouts that we wanted to study. In fact, since the 1990’s some old types of turnouts have been replaced systematically with modern turnouts as part of Trafikverket’s asset renewal strategy.
The second step was to reduce again the data studied in order better to highlight the wear behaviour. Therefore with Trafikverket’s collaboration we jointly decided to focus on selected data with the following filter :

- Taking into account the 60 most critical tracks
- Taking into account the 13 most interesting types of turnouts
- Distinguishing 2 types of turnouts : turnouts which are on the main tracks (Swedish acronym is nhsp) and turnouts which are on side tracks (Swedish acronym is ahsp). The frequency of movements is different on those two types of turnouts.

After applying these filters, the number of failures has been reduced to 16.500. Under advice of Trafikverket's maintenance expert a last filter has been applied in order to distinguish failures that happened during the hot season and during the cold season. Indeed, in Sweden the temperature is an important factor which has to be considered in the analysis. The cold season is from November to March (included) and the hot season from April to October.

As shown in Figure 1, for both seasons, the main failure contributors are, in decreasing order, (1) switch blade position detector, (2) switch devices (motor, gearbox, coupling,…), (3) heating system (especially during cold season) and (4) switch blades. These four subsystems represent 92% of failures when the failed item is known. Unfortunately, 30% of failures have not been completed or have no failure identification. This is the reason why it was impossible to analyse reliability characteristics in function of the subsystem failed or in function of the failure mode because too many data are incomplete.

	Season					
Subsystem failed	**Cold**	**Cold %**	**Hot**	**Hot %**	**Total**	**Total %**
Subsystem unknown	***2770***	***30,70%***	***2057***	***27,50%***	***4827***	***29,2%***
Switch device (motor, gearbox, coupling, bars, …)	***1470***	***16,30%***	***1616***	***21,60%***	***3086***	***18,7%***
Switch blade position detector	***2521***	***27,90%***	***2520***	***33,70%***	***5041***	***30,5%***
Heating system	***1194***	***13,20%***	***120***	***1,60%***	***1314***	***8,0%***
Switch blade	***623***	***6,90%***	***710***	***9,50%***	***1333***	***8,1%***
Snow protection	105	1,20%	47	0,60%	152	0,9%
Sleeper (bearer)	7	0,10%	13	0,20%	20	0,1%
Rail joint (mostly insulated rail joint)	80	0,90%	109	1,50%	189	1,1%
Rail	36	0,40%	31	0,40%	67	0,4%
Locking device	57	0,60%	62	0,80%	119	0,7%
Fasteners	66	0,70%	98	1,30%	164	1,0%
Crossing	79	0,90%	79	1,10%	158	1,0%
Cross over panel	4	0,00%	3	0,00%	7	0,0%
Check rail	10	0,10%	7	0,10%	17	0,1%
Ballast	8	0,10%	10	0,10%	18	0,1%
Total	9030	100%	7482	100%	16512	100,0%

Figure 1: Distribution of failures among subsystems

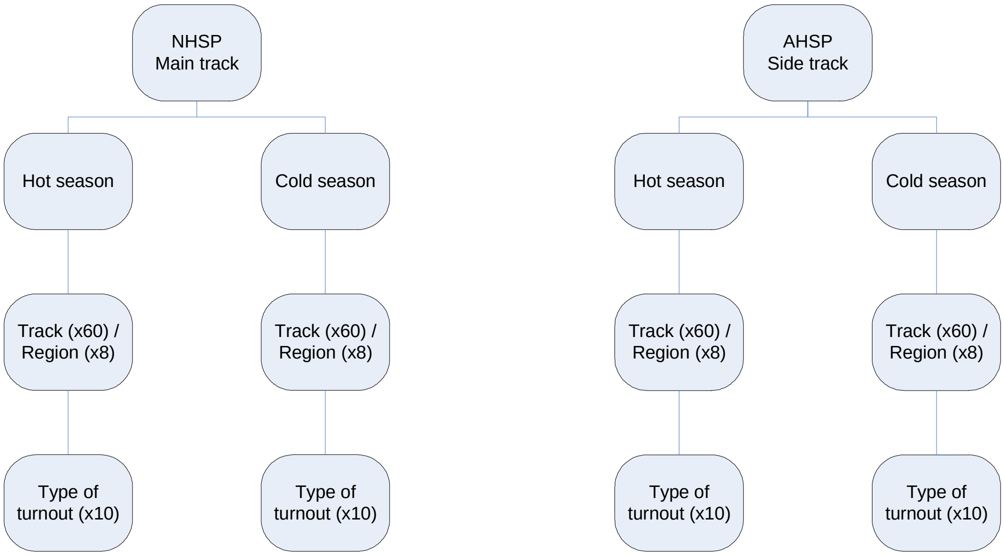

Figure 2 : Filter architecture

Figure 2 shows the final filter architecture which represent 616 analyses for Nhsp turnouts and 256 analyses for Ahsp turnouts. The 13 most interesting turnouts are the following :

1. DKV
2. EV-SJ50-11-1 9
3. EV-SJ50-12-1 12
4. EV-SJ50-12-1 13
5. EV-SJ50-12-1 15
6. EV-UIC60-1 14
7. EV-UIC60-1 15
8. EV-UIC60-1200
9. EV-UIC60-1200-BL33
10. EV-UIC60-300-1 9
11. EV-UIC60-760-1 9
12. EV-UIC60-760-1 14
13. EV-UIC60-760-1 15

C. Results and interpretation

First failure analysis :

In the first step, to estimate reliability, the first failure analysis has been used. The best fit was always obtained with the Weibull law. This first level of analysis gives a good overview of the turnout's behaviour. However, to use the first failure analysis effectively, it is necessary to have the first failure after the installation; unfortunately in the majority of turnouts studied (more than 90 %), the first failure of the turnout did not happen between 2005 and 2009 but earlier. Moreover, the first failure analysis does not take into account the subsequent failures; therefore, in order to improve this first estimation, the estimation of maintenance quality has been performed.

Kijima analysis :

As explained in Part 1, the Kijima factor (Rho) analysis allows to characterise maintenance efficiency. In 70% of the cases Rho was found equal to 1, and in 30% of the cases, to 0.5 or 0. This implies that in the majority of cases the maintenance can be considered as AGAN. However, Trafikverket's maintenance experts know that this is not the case, and their knowledge thus led us to favour an ABAO model instead.
The difference between expert view and Kijima results can perhaps be explained by the fact that in the Kijima analysis the preventive maintenance actions are not taken into account whereas the main objective of the preventive maintenance is to avoid or to postpone the occurrence of a failure. In order to estimate the real corrective maintenance quality, one would have to analyse the intrinsic reliability without preventive maintenance operations.

ABAO Analysis :

After maintenance expert consultations, it has been assumed that the maintenance quality can be considered as ABAO. Thus, the Crow-AMSAA model is the best model to characterize the reliability function of turnouts studied [11].
The instantaneous failure intensity is obtained as follow : $\lambda_i(t) = \lambda \cdot \beta \cdot T^{\beta-1}$ (1)
The cumulative failure rate is accordingly given by : $\lambda_C = \lambda \cdot T^{\beta-1}$ (2)
For each parameter a confidence bound has been estimated, using the chi-square test (with a confidence level of 80%) (Fig.3 and 4).

	Hot season		**Cold season**	
Type of turnout	**% of Beta estimated > 1**	**% of Beta upper bound > 1**	**% of Beta estimated > 1**	**% of Beta upper bound > 1**
nhsp_DKV	69%	100%	42%	50%
nhsp_EV-SJ50-11-1 9	81%	100%	48%	88%
nhsp_EV-SJ50-12-1 12	89%	100%	39%	94%
nhsp_EV-SJ50-12-1 13	82%	100%	69%	94%
nhsp_EV-SJ50-12-1 15	56%	94%	36%	67%
nhsp_EV-UIC60-1 14	N/A	N/A	N/A	N/A
nhsp_EV-UIC60-1 15	100%	100%	N/A	N/A
nhsp_EV-UIC60-1200	75%	90%	56%	88%
nhsp_EV-UIC60-1200-BL33	89%	95%	N/A	N/A
nhsp_EV-UIC60-300-1 9	74%	97%	35%	78%
nhsp_EV-UIC60-760-1 9	100%	100%	N/A	N/A
nhsp_EV-UIC60-760-1 14	68%	95%	50%	92%
nhsp_EV-UIC60-760-1 15	76%	100%	45%	77%

Figure 3 : Growth factor Beta as function of types of turnout and season for turnouts installed on main tracks

For the turnouts installed on main tracks, Figures 3 and 4 show that in hot season, most of Betas estimated are greater than 1. This implies an increasing failure rate. This conclusion is confirmed by the estimation of the upper bound of the Beta parameter's confidence interval, which is greater than 1 in at least 90% of the results analysed.
In contrast with the cold season results, Figures 3 and 4 show that the Beta estimated is more spread out than in the hot season.

	Hot season		Cold season	
Type of turnout	**% of Beta estimated > 1**	**% of Beta upper bound > 1**	**% of Beta estimated > 1**	**% of Beta upper bound > 1**
ahsp_DKV	73%	100%	35%	70%
ahsp_EV-SJ50-11-1 9	67%	95%	40%	81%
ahsp_EV-SJ50-12-1 12	100%	100%	33%	100%
ahsp_EV-SJ50-12-1 13	100%	100%	100%	100%
ahsp_EV-SJ50-12-1 15	75%	100%	63%	100%
ahsp_EV-UIC60-1200	N/A	N/A	N/A	N/A
ahsp_EV-UIC60-1200-BL33	100%	100%	N/A	N/A
ahsp_EV-UIC60-300-1 9	83%	100%	78%	100%
ahsp_EV-UIC60-760-1 14	100%	100%	100%	100%
ahsp_EV-UIC60-760-1 15	82%	100%	80%	90%

Figure 4 : Growth factor Beta as a function of types of turnout and season for turnouts installed on side tracks

Typically the wear-out behaviour of an asset can be explained by multiple accelerating stresses. A general multivariable relationship is needed. We plan to use the general log-linear relationship, the Cox model [10] which describes a life characteristic or reliability as a function of stresses (or covariates):

$$R(\underline{X}) = \exp\left(\alpha_0 + \sum_{j=1}^{n} \alpha_j \cdot X_j\right) \qquad (3)$$

where: α_J = the model parameters to be estimated
X = the vector of stresses or covariates

The Cox model has been implemented in RDAT®, it allows to estimate the influence on reliability of factors such as :

- Quality of maintenance
- Frequency of visual inspections
- Load on tracks (in thousands of ton-kilometres)
- Number of moves
- Location
- Temperature or season

Phase 2 : LCC and Availability optimization methodology

ALSTOM Transport Information Solutions' RAM Center of Excellence has investigated methodologies to optimise LCC subject to availability or service level constraints ([6],[7]).
The following definition of LCC and Availability estimation has been adopted, in agreement with Trafikverket :

Life Cycle Cost :

$$LCC = AC + PMC + CMC + EC + CC \qquad (4)$$

With :

AC: acquisition cost
PMC: preventive maintenance cost
CMC: corrective maintenance cost
CC: consequential cost (e.g. cost of lost minutes)
EC: energy cost

To this end, we will need inputs such as Traffic load (in MGT/year), the elasticity of cost (the cost does not vary linearly with the load), the type of turnouts studied, the number of movement per turnouts (moves per day), the use of diverging track (% of traffic category), the age of turnouts (years), and the next date for the important replacements. It will be based on a fixed date of replacement for 3 main components (Engine, blade, crossing).

Availability :

The following definition, reported in [12], has been adopted.

$$A = \frac{UT - (DTIF + DTOM)}{UT} \qquad (5)$$

With :

UT: Allocated uptime
DTIF: Downtime due to infrastructure failures
DTOM: Downtime due to overdue maintenance (e.g. maintenance that could not be performed in time).

A first approach has been developed in cooperation with JVTC ([5], [6]) and has been built upon, in cooperation with the universities of Angers and La Rochelle (France).
It must be kept in mind that the problem is one of multivariate optimisation, i.e. all the decision variables must be selected simultaneously in order to reach the optimum. If only one decision variable at a time is optimised, a global optimum is not reached. In order to handle this situation, we rely on the method of design of experiments ([7]).
Each "experiment" is in fact a simulation, which, as explained above, leads to values of LCC and availability. Then, a relationship is required, where both

LCC and availability are expressed as functions of the various decision variables, by the technique of design of experiments (response curves).
Finally, classical optimisation algorithms are applied in order to minimise LCC subject to the constraint that availability must exceed a certain threshold.
Figure 5 and 6 show response surfaces of availability and LCC schematically as functions of two decision variables: the maintenance factor and the detection rate (for the case studied the number of moves and the preventive inspection frequency could be selected).

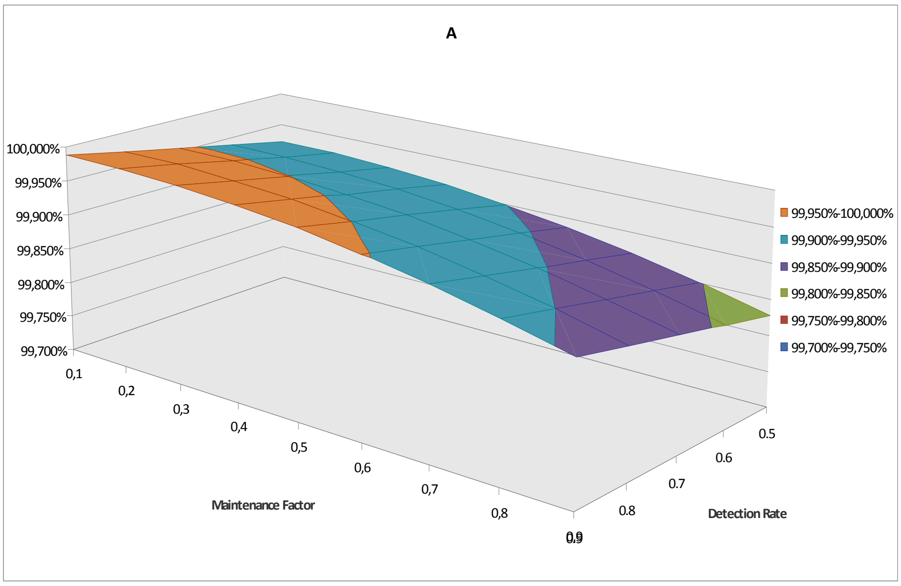

Figure 5 : Availability as a function of maintenance factor and detection rate

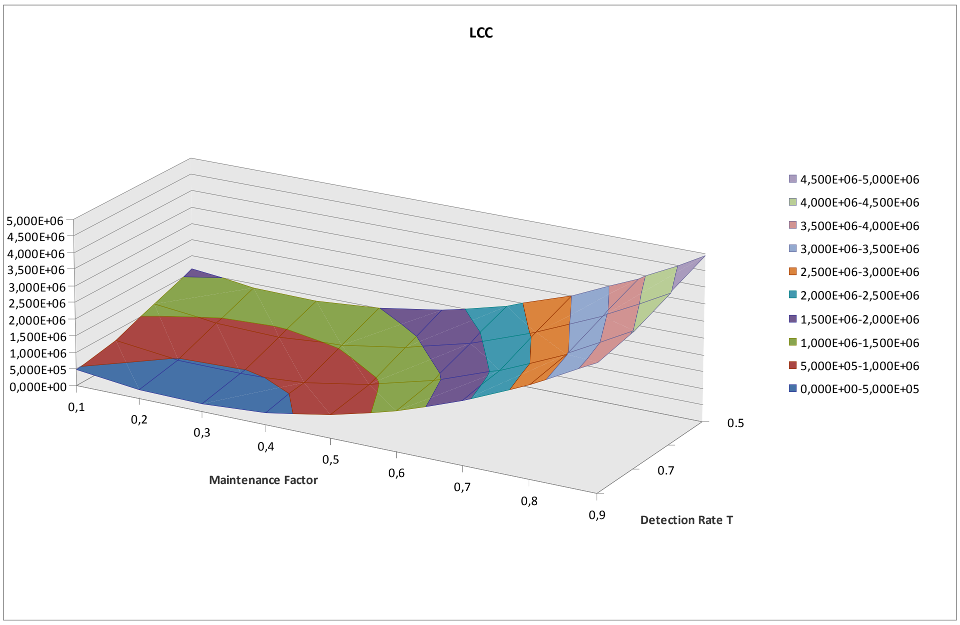

Figure 6 : LCC as function of two influence factors

Phase 3 : Feasibility of Condition-Based Maintenance

Next, an investigation will be performed by JVTC and ALSTOM, into the feasibility of equipping switches & crossings with sensors to monitor critical parameters (such as absorbed current or energy or time to move blades) and, based on the sensed data, proposing condition-based maintenance strategies. A cost-effectiveness assessment of those strategies will then be performed.

In this third phase, some of the techniques developed by the IMS consortium (such as the Watchdog Agent ® software) [4] will be used, in particular, health status will be continuously estimated and the mean residual life-time will be constantly updated in order to recommend preventive maintenance based on that status.

To this end, it is envisioned to use the Principal Component Analysis (PCA)technique in order to model the correlation between features and/or variables. The following variables has been listed : Number of moves, force expended during moves, current absorbed during moves, temperature evolution (we know that the temperature gradient has a real impact on the position detection function of the turnout), time to move.
IMS has developed a health prediction method which requires to know the level of each variable or feature listed above in “normal condition” and in “faulty condition” for each failure mode in order to predict abnormal conditions of operation.

Summary & Conclusion

The first phase of the project confirms an increasing failure rate and some preliminary indications have been obtained on the most important failure contributors, which are the switch blade position detectors, switch devices, heating system in the cold season, and switch blades.
The wear rate (as measured by the Weibull shape factor) is rather low. This is not surprising in view of the fact that the data collected are data that reflect the maintenance policy, the goal of which is to postpone wear.
It is planned to focus on switches that are less maintained (due to their lower criticality) in order to attempt to capture the intrinsic reliability, i.e. in the absence of maintenance.
In order to characterise more clearly the dependency with respect to various factors (such as switch type, location, maintenance efficiency,) a Cox model with appropriate covariates is now being set up.

The next steps will be, first, to investigate an optimisation model (based on design of experiments) in order to seek the most cost-effective classical maintenance policy ; and, second, to assess the feasibility of a condition-based maintenance strategy relying on continuous monitoring.

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