

Historical maintenance relevant information road-map for a self-learning maintenance prediction procedural approach

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Abstract. A large percentage of transport infrastructures are composed of linear assets, such as roads and rail tracks. The large social and economic relevance of these constructions force the stakeholders to ensure a prolonged health/durability. Even though, inevitable malfunctioning, breaking down, and out-of-service periods arise randomly during the life cycle of the infrastructure. Predictive maintenance techniques tend to diminish the appearance of unpredicted failures and the execution of needed corrective interventions, envisaging the adequate interventions to be conducted before failures show up. This communication presents: i) A procedural approach, to be conducted, in order to collect the relevant information regarding the evolving state condition of the assets involved in all maintenance interventions; this reported and stored information constitutes a rich historical data base to train Machine Learning algorithms in order to generate reliable predictions of the interventions to be carried out in further time scenarios. ii) A schematic flow chart of the automatic learning procedure. iii) Self-learning rules from automatic learning from false positive/negatives. The description, testing, automatic learning approach and the outcomes of a pilot case are presented; finally some conclusions are outlined regarding the methodology proposed for improving the self-learning predictive capability.

1. Introduction

INFRAALERT is a European Horizon 2020 project focus on two different pilot cases, one for road and other for rail, whose aim is to develop an expert-based information system to support and automate linear asset infrastructure management from measurement to maintenance. This enfold the collection, storage and analysis of inspection data, the prediction of interventions to keep the performance of transport networks in optimal conditions, and the optimal planning of maintenance interventions. The results also facilitate the assessment of new construction strategic decisions.

For this purpose, one of the goals of the project focusses on the development of an intelligent alert management system [1], with the purpose to analyse asset conditions and operational information, to provide alerts whenever the infrastructure reaches, or is close to reaching, a critical level either in the present time or in a forthcoming scenario. It combines the current and predicted asset condition with operational and historical maintenance data, to get information about the needed maintenance tasks to avoid later severe degradation, safety mismatching and/or comfort conditions. By means of data



analytics and machine learning methodologies, the system generates a prioritised listing (ranked on severity level) corresponding to the alerts generated by all assets of a linear transport infrastructure.

The concept of maintenance alerts is linked to any asset (e.g. part, element, component, subsystem, system) when its functional condition is in danger or will be jeopardised in a future scenario. An alert is generated when the condition of an infrastructure asset crosses a threshold limit value defined by a standard in a specific forecasted scenario and/or recorded know-how information from previous maintenance interventions. The evolving condition, soundness/unsoundness, of an asset in forecasted scenarios depends on the technical characteristics of the asset itself, the set of other assets implied in the infrastructure, the evolution of the stresses and environmental loads the infrastructure is undergoing, and many other characteristics/attributes denoted under the generic term “feature”.

Service loadings and their frequency acting on an asset are the main reason for a decrease in the reliability and occurrence of failures, which obligate to carry out maintenance interventions. The historical evolution of the asset features and the historical recording of maintenance operations are valuable sources of information to predict further maintenance interventions.

The existing knowledge on historical maintenance works, and their corresponding asset condition encountering during the repair, can be used in a non-structured manner to gather a repository of knowledge on severity of failures and the according maintenance interventions carried out, besides the resources demanded, to bring the infrastructure back into service.

A structured database of historical maintenance interventions, founded on quantifying the information available on the said repository of knowledge, paves the way for using data analytic techniques in order to infer tools for decision making, be either fully or semi-automatic.

There follow the procedures and codes to ascertain the reliability of positive alert levels from false positives/negatives based on existing recorded knowledge of previous maintenance interventions and activities. The use of machine learning, data analytics, data inference and statistic techniques, allows addressing this goal compiling and processing the prior available pieces of information regarding maintenance interventions and operations.

2. Alert Management toolkit

The aim of this toolkit is to prioritise assets of the infrastructure, according to the required maintenance interventions based on the forecasted severity of degradation and failure of the assets themselves, and the know-how brought in by the information recorded in the historical maintenance interventions.

There are two types of alerts. The first ones are triggered by the deviation of the predicted condition of an asset from the Standards, the other ones are inferred by correlating the recorded information from previous maintenance interventions. Figure 1 depicts a block diagram reflecting the automated learning algorithms associated to the prediction of the two alert types.

Module AM1 (Alerts based on limits) is responsible for generating alerts from the point of view of those features that overcome their associated limits or reference thresholds, using as inputs the forecasted features of the asset. In particular, the goal of this module is to compare the value of each forecasted feature with the corresponding limit to determine/quantify the asset state condition. As results, the module provides the following pieces of information/outcome:

- Alerts indicating that a specific feature exceeds the prescribed threshold limit.
- The technical severity levels (TSL) of those alerts based on limits. The TSL is an objective value used to prioritise the alerts according, for instance, to a distance criterion between the value of the feature and the threshold.

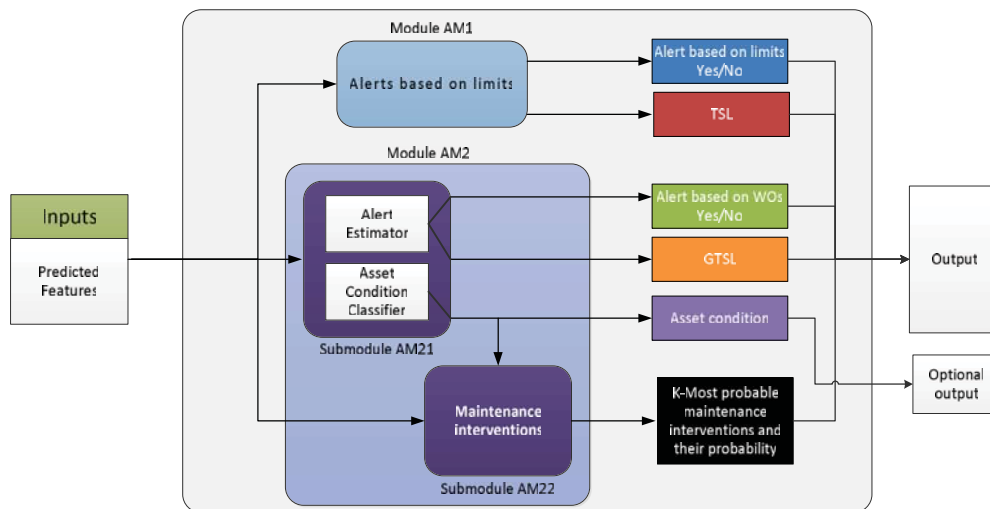


Figure 1. Block diagram of the general work-flow of the alert predictor.

Module AM2 (Alerts based on Work Orders) predicts alerts based on whether maintenance is or is not required (YES-NO), according to the forecasted features of the asset; it also estimates the most probable maintenance interventions to be conducted. To achieve this, the module embodies two different functional submodules. The first one (AM21) is specifically devoted to triggering alerts regarding the need of maintenance and their corresponding level of global technical severity (GTSL) in terms of all forecasted features considered as a whole; here, the alerts are not based on overcoming specific limits but they are triggered by the estimator contained in the first block (Alert Estimator) which has been previously trained through a machine learning processing with the measured features and the historical maintenance interventions. These outputs (alerts and GTSL) are used by the Maintenance Manager (MM) for designing maintenance plans. Submodule AM21 also provides an optional output, to be used by the MM, of the asset condition associated to the forecasted features both at individual feature level and at the overall performance level of the asset (regarding the simultaneous contribution of all feature effects as a whole). This last task is performed by the second block (Asset Condition Classifier), which has been also trained with historical intervention data to “learn” from the MM know-how, with the final purpose of predicting a subjective evaluation of the asset condition (from the set of forecasted features) without the intervention of the MM.

The second submodule (AM22) aims at determining the set of k-most probable maintenance interventions that have to be conducted, as well as their corresponding probabilities of occurrence, via a learning procedure based on historical intervention database. As results, the module provides the following outputs:

- Alert triggered: required maintenance (ALERT).
- Global Technical Severity Level (GTSL) for the asset.
- K-Most probable interventions: a listing of maintenance intervention types ordered according to the estimated probability of occurrence, regarding to the triggered alert.
- Probability of occurrence of the most probable interventions.

As this last module is based on machine learning techniques, it is necessary to define the self-learning procedure. Next section focusses on this point and the methodology used discerning from “false positives” and “false negatives” predictions, according to the following rules:

- A false positive arises when an estimate (from models) indicates a given condition has been reached, when it has not; it is commonly regarded as a "false alarm". Therefore, an erroneous positive case has been assumed.
- A false negative appears when an estimate (from models) indicates that no alert has been detected (i.e. the predicted asset state condition is right), while it was later detected by a corrective maintenance intervention; therefore, erroneously no failure/fault was forecasted.

Before getting into the various cases which may arise, a description of the way-of-proceeding to follow by the maintenance team is suggested when an alert is triggered, whether it be corrective or predictive; the case of preventive intervention is not taken into account herein as it follows a predefined plan laid on specific rules.

3. Triggered-alert procedure

When a triggered alert is communicated to the maintenance team, this may have either a "corrective" or "predictive" cause. In both cases a summary of the steps to be conducted by the MM follows and it is shown in Figure 2:

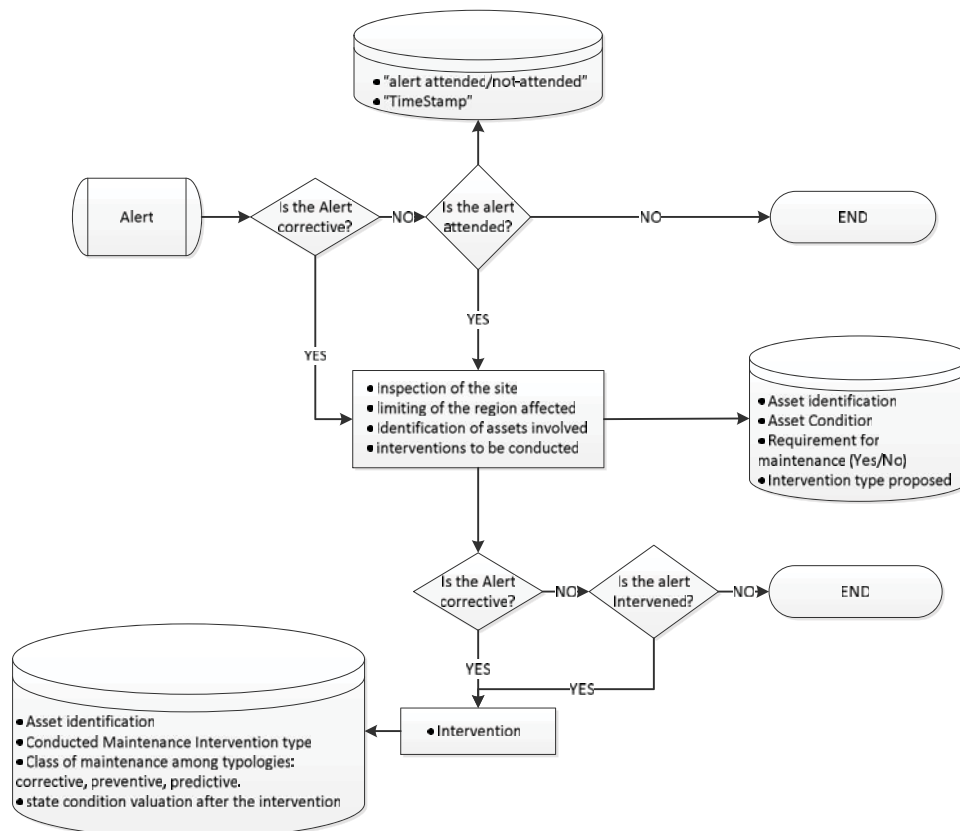


Figure 2. Triggered-alert procedure diagram flow.

- I. A decision has to be made regarding whether the triggered alert is attended or not, according to the information available with respect to the severity of the alert and the internalities and externalities affected; therefore, two cases are presented:
 - If the alert is not attended, the procedure stops (it does not continue) after recording this decision. In case of a corrective alert this decision may imply safety action to guarantee the integrity of the infrastructure, service and other affected personal/material values.

- If the alert is attended, the procedure continues to step II after recording this decision, and the following information:
 - ❖ Information recorded in the Data Base: “alert attended/not-attended”, the “Timestamp” to reflect the time the decision regarding the alert is made at. Other time logs relative to the alert (e.g. the time scenario the predicted alert is estimated at).

II. In case the alert is attended/inspected, a second level of ordered actions should take place:

- Inspection of the site where the alert takes place.
- Identification of the region affected by the alert.
- Identification of all assets involved.
 - ❖ From those actions, the following information is captured:
 - General qualitative assessment of the full set of assets involved:
 - Qualitative (lexicographic) or quantitative (numeric, if possible) state condition valuation.
 - Assessment of each asset involved:
 - Qualitative (lexicographic) or quantitative (numeric, if possible) state condition valuation.
 - ❖ Other pieces of information recorded and stored in the Data Base are:
 - Asset identification (Asset-ID).
 - Asset Condition:
 - Subjective evaluations associated to any individual feature (A_i).
 - Subjective evaluations associated to a combination of features (C_i).
 - A global subjective evaluation associated to the asset condition as a whole (G).
 - Requirement for maintenance (RfM): Yes/No.
- (Optional) Identification of the overall cause/origin of the alert.
 - ❖ Information recorded and to be stored in the Data Base:
 - General qualitative (lexicographic) or quantitative (numeric, if possible) assessment of the general cause and origin.
- (Optional) Identification and assessment of each unit cause/origin of the alert:
 - ❖ Information recorded to be stored in the Data Base:
 - Unit cause/origin.
 - Qualitative (lexicographic) or quantitative (numeric, if possible) cause valuation.
- Identification of the interventions to be conducted for eliminating/diminishing the alert:
 - ❖ Information recorded in the Data Base:
 - Asset implied.
 - Intervention type proposed (Mproposed).

III. In case the alert is intervened (a maintenance intervention is carried out to re-establish the performance of the transport network), a third level of ordered actions should take place:

- Identification of the real interventions carried out which eliminated/diminished the alert. The information captured and recorded in the Data Base for each involved asset is:
 - Asset identification (Asset-ID).
 - Conducted Maintenance Intervention type (Mconducted).

- Class of maintenance (CM) regarding the typology: corrective, preventive, predictive.
- Qualitative (lexicographic) or quantitative (numeric, if possible) state condition valuation just after the intervention: asset's state condition nowcast (MaintDescrip).

Besides, all recorded data have associated a timestamp field to identify the date and time when the action is carried out (when the alert is regarded as either “not-attended”, “attended” or “intervened”).

4. Predicted false cases considered

The false cases may arise when wrong estimates are due to: i) wrong forecasting of a feature, ii) wrong prediction for requesting maintenance (Yes/No), iii) wrong prediction for maintenance type. A description of the cases follows.

4.1. Wrong forecasting of a feature

Two possible cases, false positive and false negative, are analysed in separated manner:

a) False positive. This case takes place when the alert is triggered by the expected value of a single feature, a prior combined single feature, or a multiplicity of features, due to a wrong forecasting of the features' values. The Triggered-Alert Procedure, activated by the MM, ends by assessing all assets implied in the alert, and by recording information of the state condition of those assets. The new information will enrich the data base corresponding to the state condition of the assets involved. The machine learning (ML) procedure will learn from the enriched data base information, improving the success rate according to the quality of the captured information in further prediction runs.

b) False negative. This case arises when the expected value of the feature (single, combined or a multiplicity of features) is below the value-to-be and also falls below the TSL (Technical Severity Level) threshold [1]. In this case the Triggered-Alert Procedure is not activated and no alert is triggered. Eventually a corrective warning may brought up and the Triggered-Alert Procedure activated, which will record the pieces of information identified in section 3.

4.2. Wrong prediction for requesting maintenance

Similar to the previous paragraph, two possible cases, false positive and false negative, may arise:

a) False positive. This takes place when Submodule AM21 [2] predicts the need of maintenance, and an alert is triggered. This case follows a similar pattern than case a) of section 4.1. The ML procedure will be improved according to the data base enrichment.

b) False negative. This takes place when Submodule AM21 does not detect the need of maintenance and no alert is triggered. This case follows a similar pattern than case b) of section 4.2.

4.3. Wrong prediction for maintenance type

In this case, the requesting for maintenance is supposed to be correctly estimated as positive, otherwise the procedure goes back to section 4.2. Only the general “false type” case prediction is possible:

a) False type. The alert has been triggered due to a requesting for maintenance (Module AM21), and an estimated maintenance intervention type is provided. The Triggered-Alert Procedure is activated by the MM, and the assets implied are assessed by the maintenance intervention team. The team detects that the maintenance type estimated does not corresponds to the predicted type; it means a wrong maintenance type prediction by module AM22 [2] has taken place. The Triggered-Alert Procedure is continued, acting according the unit actions specified in the procedure. The information captured by this procedure (reflecting all pieces presented in section 3) is recorded and stored in the Data Base, which enriches the data base information. Later estimations by the ML algorithms will be benefited by the new enriched Data Base.

5. Pilot case

The pilot case is a road network in Coimbra, region in the centre of Portugal, managed by Infraestruturas de Portugal (Figure 3). The available information consists in two different data bases. The first one corresponds to the results of different measurement campaigns in which representative features of the state condition of the road are obtained, and the second one compiles the historical maintenance interventions carried out in the net from years 1933 to 2014. By correlating both data bases the inputs and targets for the machine learning models are inferred. However, the data recorded has previously filtered to extract the relevant information to be used by the system before triggering the whole maintenance predictive methodology.

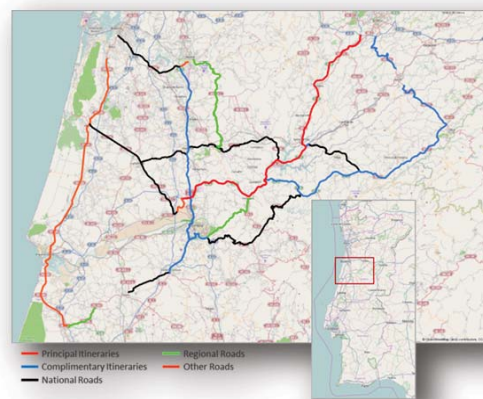


Figure 3. Road pilot case demonstration in Portugal.

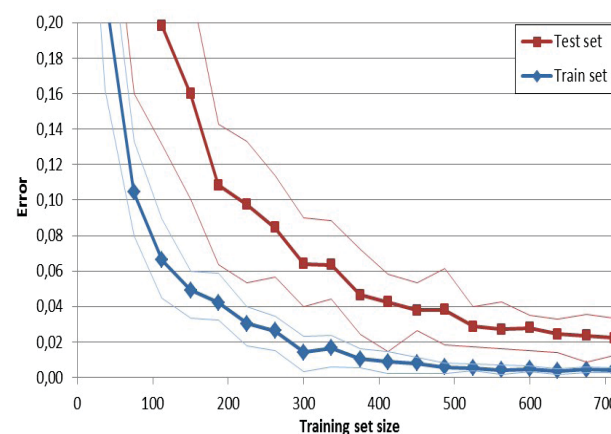
With the information available for the pilot case, the models have been implemented by means of Matlab code. In particular, these are based on Decision Trees (DT), k-Nearest Neighbours (KNN), Support Vector Machines (SVM) and Artificial Neural Networks (ANN). In order to check the accuracy of those models, the last year data-set (2014 campaign) is used as a testing sample, keeping this year out of the training set. The performance evaluation of the models was made by using a confusion matrix, based on counting those test records correctly and incorrectly predicted. In those matrixes appear the real (M) and the predicted maintenance type based on Table 1. Class T0 is associated to no-alert, and the rest of classes belong to different maintenance alerts. Figure 4 shows the confusion matrix for the DT model where the columns correspond to the known class (target class specified by the work-order) and the rows correspond to the predictions made by the model (output class). Thus, the diagonal elements show the number of correct classifications made for each class, and the off-diagonal elements show the errors made by the model predictions. Each cell also contains the same information as a percentage of the total test set size. In the last row and column, these plots also contain the performance measures derived from the confusion matrix; those are the accuracy (ACC), recall or true positive rate (TPR) and precision or positive predictive value (PPV), showed in green; as well as the respective complements: error rate (ERR), false negative rate (FNR) and false discovery rate (FDR), showed in red.

Table 1. Description of maintenance types.

	Alert	Description
T0	No	No maintenance requested
T1	Yes	Do nothing
T2	Yes	Microsurfacing, Surface dressing
T3	Yes	Thin Hot-Mix Asphalt overlay (thickness ≤ 5 cm)
T3.1	Yes	Surface milling with Thin Hot-Mix Asphalt overlay (thickness ≥ 5 cm)
T4	Yes	Thick Hot-Mix Asphalt overlay (thickness > 5 cm) combined or not with milling

Once the models provided a good level of prediction; the self-learning process described in this paper was checked. A simulator, based on the available real data, was carried out in order to increase gradually the input data for the models. The learning curves of the example model (DT) are shown in Figure 5. The two bold lines represent the average value of the train and test sets; the rest of lines are generated with the 20th and 80th percentiles of train and test sets and provide an insight of the variance of the predictions (thin lines). As the training set sizes get larger, these curves converge toward a threshold representing the amount of irreducible error in the data.

Confusion matrix for: DT							PPV/FDR	
Output Class	T0 (no alert)	T1	T2	T3	T3.1	T4	ACC/ERR	
	106 35.3%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100%	0.0%
	0 0.0%	14 4.7%	3 1.0%	2 0.7%	0 0.0%	0 0.0%	73.7%	26.3%
	0 0.0%	0 0.0%	14 4.7%	0 0.0%	1 0.3%	0 0.0%	93.3%	6.7%
	0 0.0%	0 0.0%	0 0.0%	52 17.3%	5 1.7%	0 0.0%	91.2%	8.8%
	0 0.0%	0 0.0%	1 0.3%	1 0.3%	54 18.0%	1 0.3%	94.7%	5.3%
	0 0.0%	0 0.0%	0 0.0%	1 0.3%	5 1.7%	40 13.3%	87.0%	13.0%
TPR/FNR	100% 0.0%	100% 0.0%	77.8% 22.2%	92.9% 7.1%	83.1% 16.9%	97.6% 2.4%	93.3% 6.7%	
Target Class								

**Figure 4.** Confusion Matrix (DT model).**Figure 5.** Learning curve (DT model).

6. Conclusions

This communication presents a procedure to record the adequate information in order to be used by automatic learning systems to predict maintenance interventions in future scenarios. The methodology presents evidences, through a pilot case, that with new relevant information it is possible to reduce the error in the prediction of the maintenance intervention to be carried out in the linear assets of a road network. A diagram flow is presented in order to have a general view of the procedure to follow in order to learn from false positive/negative predicted cases and the way they are considered are analysed.

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06428). The content reflects only the authors' view and it is stated that the Union is not liable for any use that may be made of the information contained therein.

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