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Improving linear transport infrastructure efficiency by automated learning and optimised predictive maintenance techniques (INFRALERT)

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Abstract. The on-going H2020 project INFRALERT aims to increase rail and road infrastructure capacity in the current framework of increased transportation demand by developing and deploying solutions to optimise maintenance interventions planning. It includes two real pilots for road and railways infrastructure. INFRALERT develops an ICT platform (the expert-based Infrastructure Management System, eIMS) which follows a modular approach including several expert-based toolkits. This paper presents the methodologies and preliminary results of the toolkits for i) nowcasting and forecasting of asset condition, ii) alert generation, iii) RAMS & LCC analysis and iv) decision support. The results of these toolkits in a meshed road network in Portugal under the jurisdiction of Infraestruturas de Portugal (IP) are presented showing the capabilities of the approaches.

1. The INFRALERT concept to optimise transport infrastructure maintenance

The condition of transport systems has enormous societal and economic relevance since economic opportunities are likely to arise where transportation infrastructures are able to answer mobility needs and ensure access to markets and resources [1]. Our growing economic require an enlargement of transport capacity, most especially for land transport. However, the economic situation and the lack of land prevents from enhancement of the rail and road network. On the other hand, as our networks are more congested, there are fewer chances to perform maintenance while the extensive use of the infrastructure accelerates its deterioration. In this situation, the only open door to boost land transport capacity is by making a better use of the existing network reducing maintenance interventions and extending the life of existing assets. This is the motivation of the ongoing H2020 project INFRALERT [2] which proves its developments in the road and railways systems.

INFRALERT exploits the similarities of linear infrastructures and develops systems and tools for support Infrastructure Managers (IM) or Maintenance Contractors in maintenance interventions decision making. Figure 1 shows in a dashed box the INFRALERT platform and its interaction with

the IM/MC and the different data bases. INFRALERT aims at the development of models and ICT tools to optimise the performance of existing linear land transport infrastructure. It develops an expert-based information system to support and automate infrastructure management from measurement to maintenance. Figure 2 illustrates the concept and the scope of INFRALERT which has been conceived using a modular approach to facilitate its flexibility and applicability. It includes a data management system (i.e. the Data Farm) and a set of toolkits covering Data Analytics modules (asset condition, alert management and the RAMS & LCC) and a decision support tool which receives the results of the Data Analytics modules and optimise maintenance interventions. All these modules are conceived as plug-ins into a common shell, which is the expert-based Infrastructure Management System (eIMS), allowing communication among the different modules, with external data bases and the user. INFRALERT is conceived to be compatible with existing asset management systems.

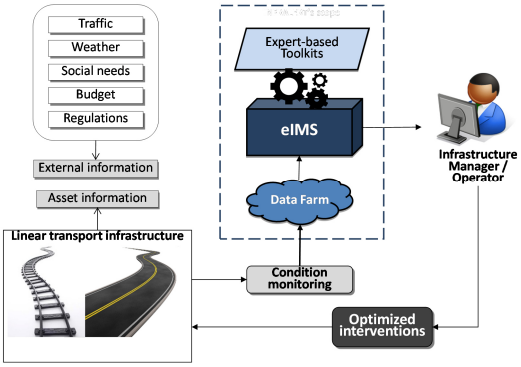

Figure 1. INFRALERT platform.

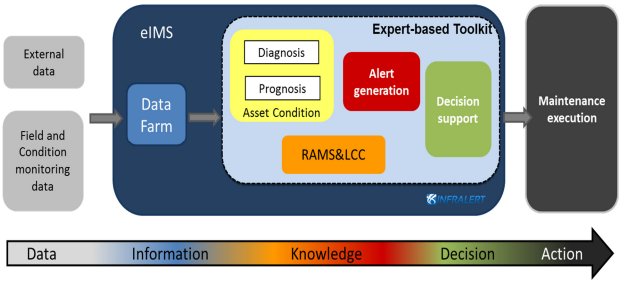

Figure 2. INFRALERT modular concept.

The development of the INFRALERT project will be validated in two real infrastructure systems: a meshed road network in Portugal owned and managed by Infrastruturas de Portugal (IP) and a rail corridor in Sweeden owned by Trafikverket. This paper present the methodologies developed by the different tools in the expert based toolkit (Figure 2) and their preliminary results obtained in part of the road network.

2. Use case: the road pilot

The road pilot in Portugal comprises 539 km of roads in the Coimbra region under IP jurisdiction. It includes a rich variety of road types (principal, national, regional…). The network is classified based on sections of an average length of 6.6km and 87 nodes.

IP Pavement Management System (SGPav) stores information of maintenance activities carried out since 2007 and road condition data such as longitudinal (IRI) and transverse unevenness (Rut Depth), cracked area and pavement macrotexture. IP Maintenance strategy categorises interventions in major or routine maintenance. Major maintenance includes relevant works in terms of cost, length and complexity while routine maintenance includes smaller scale and lower complexity works, such as pavement localised repairs or other activities such as drainage system cleaning, shoulder treatment, minor works performed in bridges and any urgent repairs.

The basis of the data stored in SGPav is related to the section element (start and end node). Inside this database, the section table has a number of selected fields that are relevant in order to summarize the most important information associated with the part of the road it represents. Besides this main table, other relevant tables contain further information based on the field measurements and the pavement historical information with all the road maintenance work performed up to date.

3. Expert-based tookits and test cases

Following the Data Analytics tools (asset condition, alert management and RAMS&LCC) and Decision Support tool are presented together with results from the road pilot in Portugal.

3.1 Nowcasting and Forecasting of Asset Conditions

The main aim of this toolkit is to develop methodologies for linear asset condition assessment and prediction by identifying and segregating hierarchy of conditional information for nowcasting and forecasting. Nowcasting focuses in what is known today while forecasting is the process of exploiting past and present data to make deductions about the future. For nowcasting and forecasting, the asset and condition data is accessed from the Data Farm as shown in Figure 3. Pre-processing methods such as data cleaning and dynamic segmentation is carried out on this data to obtain meaning information.

There are different types of nowcasting and forecasting approaches available based on principle of physical, data-driven, and knowledge-based [3, 4]. Data-driven approaches rely on monitored and historical data that are used to learn the systems behaviour [5]. Regression analysis is a commonly applied approach for modelling of pavement deterioration. Weighted regression approach has been used to better capture the nonlinear behaviour of the degradation [6]. An important consideration in maintenance modelling of linear assets is dynamic segmentation, which allows multiple sets of attributes to be accompanied with any segment of a linear feature. Each time an attribute value changes, it can "dynamically" locate the segment. To achieve good forecasts the input to the models needs to be homogeneous over their respective length. An example for dividing road infrastructure into statistically homogenies segments is the cumulative difference approach which is described in the AASHTO pavement guide [7].

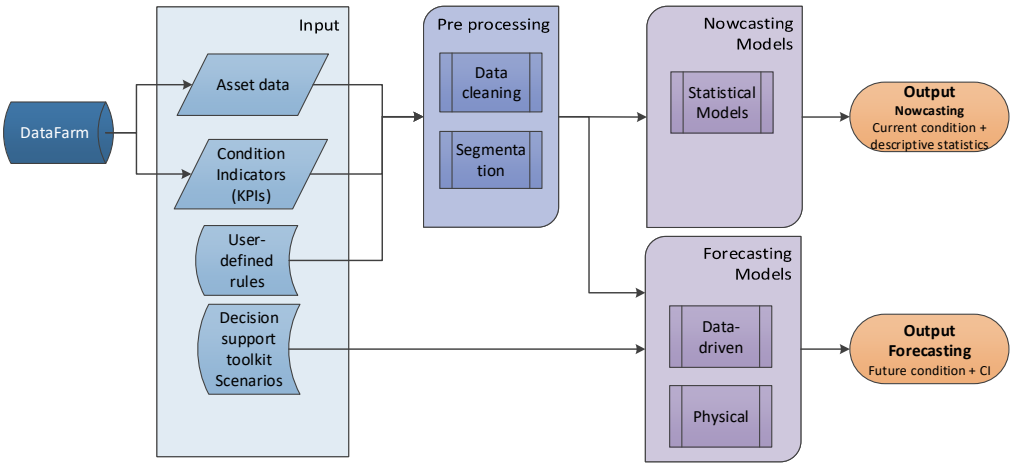

Figure 3. Asset condition toolkit flowchart.

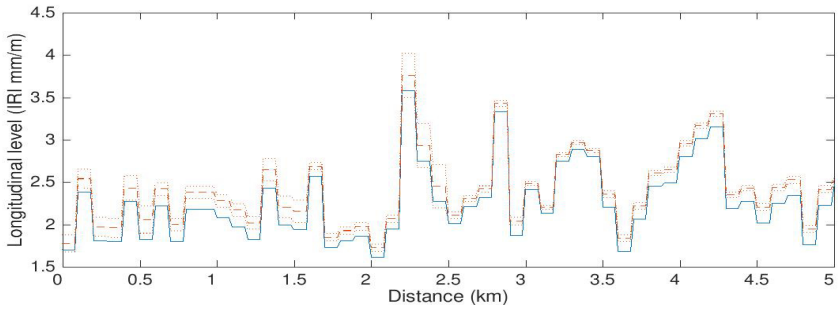

Figure 4. Forecasted output for road case. Current condition (blue solid); forecasted condition after 3 years (red dashed) and associated 95 % confidence levels (dotted)

For the road pilot, forecasting of the longitudinal unevenness (IRI) was performed based on the weighted regression model. The data originates from annual road surveys from 2012-2015 for road section EN101-3 D061. Input to the regression model was the IRI values that first were divided into

homogenous segments using the AASHTO approach based on the pavement quality index. The quality index is an aggregated indicator, which is calculated as a function of longitudinal unevenness, transversal unevenness, and cracking. The forecasted output after 3 years with 95% confidence intervals for 100 m sample segments over 5 km is shown in Figure 4. The prediction with uncertainty will be forward to the Alert Management system.

3.2 Alert generation

The aim of the Alert Management toolkit is to prioritise predicted maintenance alerts of linear infrastructure assets, 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 work-orders. Two kinds of alerts are predicted and involved in the proposed methodology shown in the block diagram of Figure 5.

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 values of the explanatory features of the asset. As result, the module provides the following outputs (Table 1): i) Alerts indicating that a specific feature exceeds its prescribed threshold and ii) Technical Severity Levels (TSL) of the estimated alerts. 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.

Module AM2 (Alerts based on Work Orders) predicts alerts from the point of view of whether maintenance is or is not required (Yes-No); 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 triggered by the estimator contained in the first block (Alert Estimator) which has been previously trained with the explanatory features (e.g. measurements) and the historical maintenance interventions through a machine learning processing. Submodule AM21 also provides an optional output using a second block (Asset Condition Classifier), which "learns" from the Maintenance Manager (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.

Table 1. Results from AM1 module.

ID	CT	IRI	RUT	W CTL1	TSL CT1	W CTL2	TSL CT2	W IRI	TSL IRI	W RUT	TSL RUT
225	**36**	**2.25**	**4.85**	YES	45.76	YES	4.12	No	0.00	No	0.00
243	**4**	**1.75**	**2.71**	No	0.00	No	0.00	No	0.00	No	0.00

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 result, the module provides: i) alert triggered: required maintenance; ii) Global Technical Severity Level (GTSL) for the asset; iii) K-Most probable interventions; and iv) probabilities of occurrence of the most probable interventions.

The data used to develop the toolkit are the IRI, Rut and CT corresponding to a set of previous measurement campaigns, from which the empirical statistics were inferred to generate a larger data set. In order to check the accuracy of the different machine learning predicting models used, the last campaign (2014) is chosen as a testing sample, keeping this year out of the training set. Selecting the Decision Tree model (DT) as an example, the results are shown in Figure 6. The upper panel of Figure 6 shows the performance evaluation of the DT model. This evaluation was made by using a confusion matrix, based on counting those test records correctly and incorrectly predicted. This matrix shows the

real and the predicted maintenance based on the list of maintenance activities of Table 2. Class T0 is associated to no-alert, and T1 to alert without maintenance required (warning). The lower panel of Figure 6 shows a comparison between the real maintenance carried out and the predicted ones. According to this, results are reliable and the errors are mainly between T4 and T3.1, as suggested by the confusion matrix. This figure represents the most probable maintenance intervention; however, the models offer several possibilities with a score for each one.

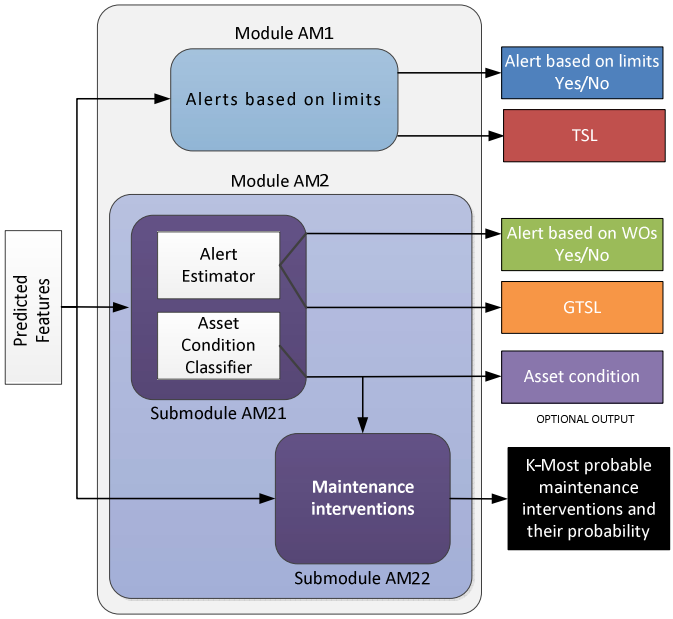

Figure 5. Work-flow diagram of the toolkit.

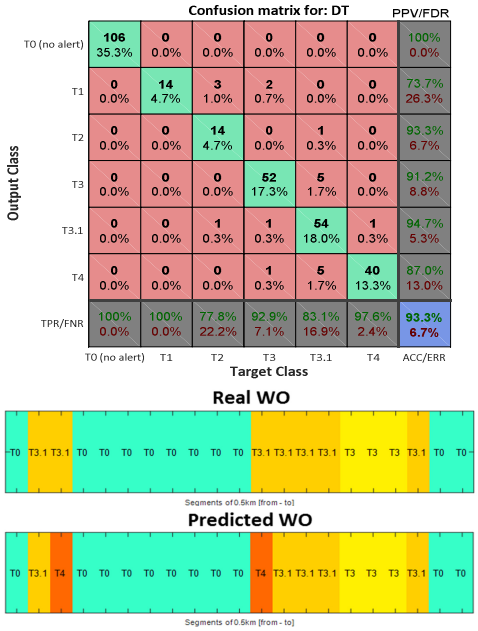

Figure 6. Result example (DT model).

Table 2. Types of maintenance used for alert generation and RAMS/LCC.

M	Alert	Description	M	Alert	Description
T0	No	No request	T3.1	Yes	Profile milling and fill
T1	Yes	Do nothing	T4	Yes	Regulating course
T2	Yes	Surface treatment	PC	Yes	Full-depth patching (corrective)
T3	Yes	Thin asphalt surfacing	PP	Yes	Crack fill (preventive)

3.3 RAMS and LCC analysis

The aim of this toolkit is to perform real-time RAMS&LCC analysis to assess the Reliability, Maintainability, Availability and Safety (RAMS), and the Life-Cycle Cost (LCC) of the infrastructure. RAMS & LCC provides probabilistic information to be considered for decision support.

The application of RAMS analysis [8] in civil engineering, although relatively recent, has a high potential to predict the number and distribution of failures in infrastructures, which in turns provides an estimation of the availability. RAMS enfolds a rich set of parameters [9] and distribution functions characterizing the reliability and maintenance need of the infrastructure. RAMS parameters are provide relevant probabilistic information for the maintenance planning.

LCC analysis takes into account all the costs associated with the lifetime of the system. For complex systems, such as railway and road infrastructures, the cost of maintenance plays a very important role because operation and maintenance comprise a major share of the system's life-cycle

and they are the most sensitive to cost uncertainties. These uncertainties are associated to internal risks, which can be quantified through RAMS parameters.

One of the innovations of the INFRALERT's RAMS&LCC toolkit is to make use of the previously calculated RAMS in the assessment of maintenance costs. The integration of stochastic RAMS in the LCC analysis allows obtaining reliable predictions of system maintenance costs and the dependencies of these costs with specific cost drivers through sensitivity analyses. Moreover, using the computed RAMS probability distributions, the associated uncertainties are integrated into the LCC determination. The output provided by these stochastic LCC are finally used for long-term planning in the decision support tool. Figure 7 depicts the general workflow of the RAMS&LCC process.

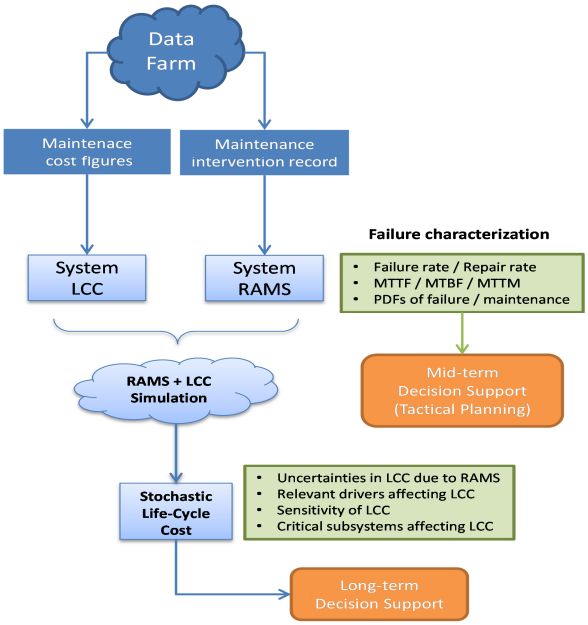

Figure 7. Overview of RAMS&LCC methodology.

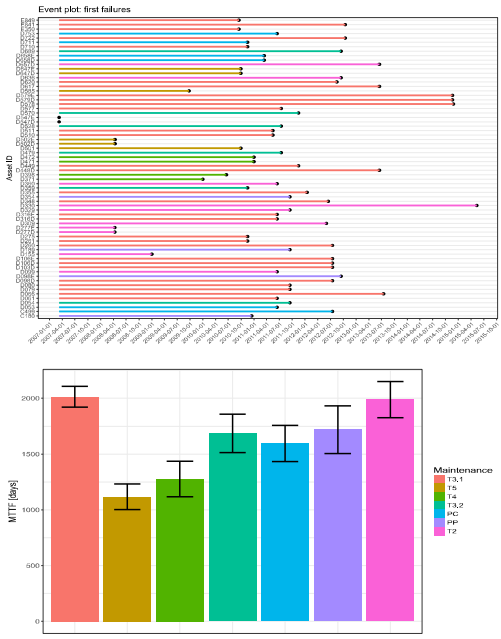

Figure 8. MTTFs by failure mode.

For the road pilot in INFRALERT, different models for RAMS have been applied depending on the characteristics of the road section under study. For sections with a large number of the same intervention, the reliability function is modelled using a Non-Homogeneous Poison Process (NHPP) [10]. Information about Mean Time Between Failures (MTBF) or the degradation trends through the rate of failures [11] can be calculated. However, when studying the road use case there are few sections that allow this kind of study, which forces to apply a time-to-event modelling to obtain Mean Time To First Failure (MTTF). This paper shows the results of the road sections with scarcity of accumulated data.

The upper panel of Figure 8 shows the event plot for the first maintenance interventions performed after January 2007 in the whole road network. Different road sections are displayed in the y-axis, while the x-axis represents the temporal scale from 2007 to 2015. In this figure only time-to-first-event has been plotted. The different colours correspond to the types of maintenance described in Table 2. Weibull distributions are used to model the reliability function for each type of maintenance. From the reliability, it is possible to estimate the probability of these interventions happening in a given time slot, which furthermore can be used for the optimization of tactical planning in the decision support tool. The calculated MTTF with confidence intervals for the different maintenance tasks is shown in the lower panel of Figure 8.

From individual maintenance costs and the calculated mean times, the overall costs per type of maintenance can be calculated using the LCC model. The probability distribution function of MTTFs

allows studying the level of uncertainty in the LCC model, which is fed to decision support tool for long-term planning. This simulation is currently under development in INFRALERT.

3.4 Decision support tool

The final objective of the INFRALERT system is to provide Infrastructure Managers/Owners and Maintenance Operators/Contractors with intelligent software tools to support the decision-making process when planning maintenance activities and interventions. This section presents the application of INFRALERT for tactical planning (or mid-term planning) in the road pilot in Portugal (IP owned).

On tactical planning level, IP maintenance department has to allocate major interventions over a 5-year time horizon. The interventions are aggregated as single events over the 500 m-segments of certain road sections in order to avoid multiple traffic interruptions on the same section. The allocation of such intervention events is done on a monthly basis. In detail, the decisions to create a tactical plan include: i) the allocation of a starting month for intervention events (within the next 5 years) and ii) the selection of a minimum level of intervention (corresponding to maintenance types T1, T2, T3, T3.1 and T4 in Table 2) on a section. This selected minimum level determines which segments of the respective section actually have to be maintained, which are the ones whose state (at some point during the considered time period) would cause an alert with an intervention level equal or higher than the selected minimum.

The decision-maker has to consider certain restrictions like: i) minimum quality level for road segments, ii) usage of a given yearly budget for interventions; iii) maximum overall 5-year budget, iv) capacity of supervisory staff (which means that interventions can be allocated to a restricted number of sections per region only), v) only one intervention event per year is allowed in each section.

The tactical planning has to optimise three items in the objective function (which are balanced by weighting factors): i) minimize maintenance interventions costs; ii) maximize quality index (which is a function of the predicted conditions of road segments and predicted failure events coming from RAMS analysis) and iii) maximize availability of the network (which depends on the capacity reduction of sections due to interventions). Maintenance interventions costs are derived from LCC analysis and provided by the toolkit on RAMS & LCC.

The allocation and selection of interventions in the tactical plan is based on the maintenance alerts generated by the Alert Management toolkit, which is based on predicted future conditions coming from the Asset Condition toolkit. Thus, input for tactical planning are no concrete work orders to be scheduled but predicted work orders provided with the corresponding probabilities of occurrence. Due to this uncertainty of the real amount of work to be done the ending time of intervention events at each section will only be known at execution time. Furthermore, the working time needed for interventions cannot be seen as a fixed, deterministic duration, but has to be modelled as a stochastic variable in the model. In particular, the probabilistic information provided by the RAMS analysis toolkit calculations will be used as input in relation to the interventions duration.

These characteristics make the tactical planning a stochastic optimization problem which calls for specific modelling and solution techniques to be applied. A mathematical optimisation model which reflects the uncertainty in the problem description has been developed as foundation for the decision support tool. The handling of such uncertain information in the decision support tool is done using a scenario approach. A set of future scenarios is simulated as follows:

- For each of the condition parameters characterising the road quality (features), a time series of possible values is predicted, using the Asset Condition toolkits for forecasting.
- Based on these predicted conditions the respective intervention alerts are generated by the Alert Management toolkit.
- Additionally, based on RAMS analysis possible failure events are generated, using e.g. results from MTTF, MTBF calculations.

The resulting scenarios represent possible "states of the world" and are used in the optimisation algorithms of the decision support tool to derive decisions, but also to calculate the objective function and restrictions for a selected tactical plan.

4. Conclusions

This paper presents the modular concept of the INFRALERT eIMS for optimizing maintenance interventions in railways and road infrastructures together with the methodologies and preliminary results validated in a meshed road network in Portugal of some of its modules (the items in the expert-based toolkit, Figure 2). In particular, the following methodologies have been explained including the corresponding test results on the road pilot: i) The methodology for nowcasting and forecasting of asset condition which is an input for the following item; ii) the methodology to support and automate the prediction of maintenance intervention alerts (which combines the current and predicted asset condition with operational and historical maintenance data to get information about the needed maintenance tasks) by means of data analytics and machine learning models, which provides forecasted alerts and maintenance alerts to be consider in the maintenance planning; and iii) the methodology to compute probabilistic RAMS parameters which provide relevant information for the maintenance planning. In addition, the following methodologies have been introduced although no test results have been shown: i) the approach to introduce the probabilistic RAMS information for computing of the probabilistic LCC which is a relevant piece of information for the decision support and ii) the formulation and the methodology to solve the tactical planning (mid-term which means up to 5 years in a monthly basis for the road pilot) optimization problem which receives the predictions and computations from the alert management and the RAMS & LCC systems.

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