Proceedings of 7th Transport Research Arena TRA 2018, April 16-19, 2018, Vienna, Austria

INFRALERT: improving linear transport infrastructure efficiency by automated learning and optimised predictive maintenance techniques

Noemi Jiménez-Redondo[a*], Álvaro Calle Cordón[a], Ute Kandler[b], Axel Simroth[b], A. Reyes[c], F.J. Morales[c], Johan Odelius[d], Stephen M. Famurewa[d], João Morgado[e], Emanuel Duarte[e], Daniele Iorio[f], Marco Fruttero[f], András Juszt[g]

[a]*CEMOSA S.A., Benaque 9, Málaga 29004, Spain*
[b]*Fraunhofer IVI, Zeunerstr. 38, 01069 Dresden, Germany*
[c]*Universidad de Sevilla, ETSI, Camino Descubrimientos, 41092-Sevilla, Spain*
[d]*Luleå University of Technology,Operation and Maintenance, 97187-Luleå, Sweden*
[e]*Infraestruturas de Portugal, SA, Direção de Asset Management, Rua de Santa Apolónia, 65, 1100-468, Lisboa, Portugal*
[f]*DMA S.r.l., Via Andorno 22, 10153 Turin, Italy*
[g]*Régens Plc., 19/D. Prielle Kornélia Street, H-1117 Budapest, Hungary*

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. 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 architecture of the eIMS as well as the functionalities, methodologies and exemplary results of the toolkits for i) nowcasting and forecasting of asset condition, ii) alert generation, iii) RAMS & LCC analysis and iv) decision support. The applicability and effectiveness of the eIMS and its toolkits will be demonstrated in two real-world pilot scenarios, which are described in the paper: a meshed road network in Portugal under the jurisdiction of Infraestruturas de Portugal (IP) and a freight railway line in Northern Europe managed by Trafikverket.

Keywords: intelligent maintenance, linear transport infrastructure, condition nowcasting & forecasting, alert management, RAMS & LCC, decision support, maintenance & interventions planning

Nomenclature

eIMS	expert-based Infrastructure Management System
IM	Infrastructure Manager
KPI	Key Performance Indicator
LCC	Life Cycle Cost
RAMS	Reliability, availability, maintainability and safety

1. Introduction

An efficient transport system is more than ever critical for the economy and for the social empowerment of the citizens. Almost regardless to the economy growth rate the demand for transport capacity grows almost everywhere, but in congested areas there is no room available for new infrastructures. The only viable solution is making a better use of the existing network by more effective maintenance interventions and extending the life of the existing assets. The good news is that new technologies allow a frequent and accurate monitoring of the infrastructure: frequency and accuracy of the measurements enable the implementation of new maintenance strategies, where the accuracy and speed of the feedback is a key issue. Furthermore, tactical and operational maintenance planning and scheduling of interventions can be done based on more reliable and accurate information about the actual and predicted condition of the infrastructure and its assets, so that the real maintenance needs now and in the future are well covered.

This is the motivation of the ongoing H2020 project INFRALERT (Infralert 2016) whose developments are demonstrated on existing road and railways systems. There are some previous FP6-7 projects aligned with the goals of INFRALERT for railway infrastructures. Among them, ACEM-Rail (grant agreement no. 265954) developed some preliminary tools for maintenance planning, such as tamping planning. The AUTOMAIN project (grant agreement no. 265722) focussed on possession time reduction (capacity enhancement) by improving inspection and monitoring capabilities, automating and optimising maintenance planning, and speeding-up maintenance activities through lean analysis. The OPTIRAIL project (grant agreement no. 314031) developed tool and framework for more effective planning of infrastructure maintenance activities based on expert knowledge and condition monitoring/maintenance management data. The main objective for the INNOTRACK project (grant agreement no. 31415) was to reduce the LCC, while improving the reliability, availability, maintainability and safety (RAMS) characteristics. INNOTRACK's innovations and outcomes related to INFRALERT include: track subgrade monitoring and assessment evaluation and predictive models for S&C. In addition, the on-going H2020 project In2Smart (grant agreement no. 730569) develops an intelligent asset management framework based on a similar concept and including also advanced monitoring technologies. On the other hand, regarding road infrastructures, the AM4INFRA is an H2020 project that started in 2017 (grant agreement no. 713793) that is in line with multi-asset perspective underlying INFRALERT. AM4INFRA aims to deliver the first ever common European asset management framework approach that enables consistent and coherent cross-asset, cross-modal and cross-border decision-making. Finally, TRIMM project under the FP7 (grant agreement no. 285119), gave a good contribution in highlighting the cost-benefit analysis of road monitoring techniques and utilisation in asset management. In this context, INFRALERT aims to develop an expert-based Infrastructure Management System (eIMS) to support and automate asset management from measurement to maintenance. This includes the collection, storage and analysis of inspection data, the determination of maintenance tasks necessary to keep the performance of the infrastructure system in optimal condition, and the optimal planning of interventions.

The eIMS will provide the system architecture and functional design for the integrated system. It will include and support:

- The Data Farm as a tool for the collection and organisation of condition monitoring data: Merging data from multiple sources delivering frequent measurements requires a high level of automation. The data organisation starts with an accurate localisation and mapping of asset condition information of the infrastructure.
- An automated Health Assessment and Prediction tool to perform accurate asset condition nowcasting and forecasting, applying novel hybrid modelling techniques.
- A comprehensive automatic pattern recognition system able to correlate historical condition measurements of the infrastructure with maintenance actions.
- An Alert management system which analyses asset condition and operational information to provide alerts whenever the infrastructure reaches or is close to reaching a critical level in the present time or in the near future.
- Methods and tools to evaluate system, subsystems and component RAMS parameters dynamically and stochastically.
- LCC models that assess maintenance costs of the different activities taking into account the uncertainty inherent in the RAMS.
- Decision support tools for interventions planning on the tactical and operational level, capable to handle uncertain information in the decision-making process coming from stochastic input like uncertain alerts, RAMS and LCC parameter.

The eIMS will be the shell that allocates different modules and decision support tools so that all the developments within INFRALERT will be integrated into a single system. This system will be developed in a modular architecture, which will ensure the flexibility required for implementation on any linear asset, as well as the interoperability required for the seamless integration with other information systems owned by the Infrastructure Managers or maintenance contractors.

The developments of the INFRALERT project will be validated in two real infrastructure systems as pilot demonstrators: (1) A meshed road network in Portugal owned and managed by Infraestruturas de Portugal, where tactical planning of major interventions will be demonstrated. (2) A rail corridor in Northern Sweden owned by Trafikverket, where decisions on repair and maintenance activities have to be made in a short-term horizon.

The paper is structured as follows: Section 2 provides an overview on the underlying concept of the eIMS from an architectural perspective, i.e. it describes how the different modules are organised, and gives insights into the implementation of the system. Section 3 briefly explains the functionalities and methodologies used in the expert-based toolkits that constitute the eIMS, together with exemplary results from the pilot demonstrators, which are also presented in Section 4. Section 5 concludes the findings from the project made so far.

2. The concept of eIMS

2.1. Overall architecture

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 developed eIMS platform and its interaction with the IM or maintenance contractor and the different data bases. The eIMS collects and organises all external (e.g. traffic, budget, regulations) and internal information necessary for decision-making in a single Data Farm. With internal information we refer to data that describe the infrastructure itself, i.e. asset register and condition information from monitoring and measurement. The operator interacts with the platform by using the different toolkits to support decision-making on interventions planning, and triggers the execution of maintenance interventions.

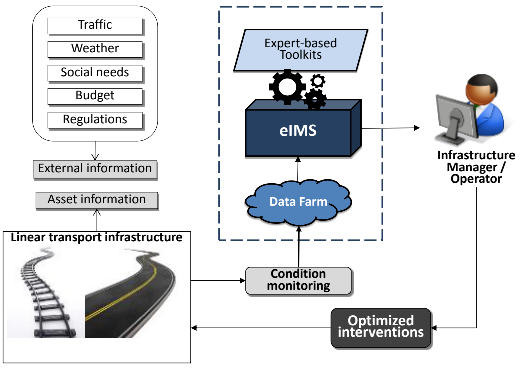


Fig. 1 Concept and scope of INFRALERT

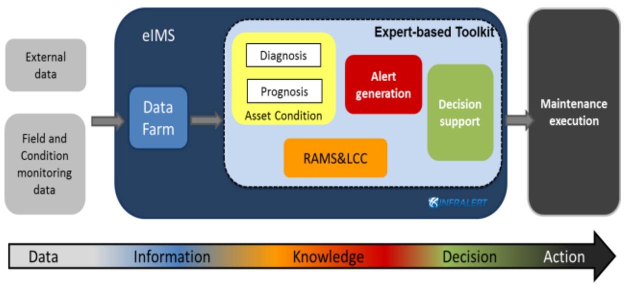


Fig. 2 eIMS platform

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 the Data Farm as a data management system and a set of toolkits covering Data Analytics modules (asset condition prognosis and diagnosis, alert management and RAMS & LCC analysis) and a decision support tool which receives the results of the Data Analytics modules and optimises maintenance interventions. All these modules are conceived as plug-ins into a common shell, which is the expert-based Infrastructure Management System (eIMS), allowing seamless communication among the different modules and with external data bases and the user. Therefore, INFRALERT is conceived to be compatible with existing asset management systems.

2.2. Implementation details

2.2.1. Software architecture and component diagram

The implemented eIMS framework is open and cloud based, thus the software architecture fully support distributed deployment. The development Java-based environment supports the state of the art of DevOps standards. The development of the eIMS framework follows a module-based approach, what enables adding features one by one. The main purpose of the Middleware is to achieve a standard way of adding and handling new modules and integrating current toolkits. As it can be seen in Figure 3 a Java-based 3-tier software architecture is recommended as basic system architecture for the eIMS. The layers of the system are: the presentation layer, the "business logic" layer (which is also responsible for the computations) and the data storage layer. Toolkits are implemented vertically across the layers. This means that every toolkit has components in every layer (blue dotted rectangles). Obviously, the core of the eIMS has been implemented in the business logic layer, where the implemented classes are able to interoperate with each other. The storage layer called "Data Farm" provides an integrated and cloud-based data ontology for all stakeholders to access the innovative INFRALERT services that is well scalable, portable, extendable as acceptable cost.

The eIMS requires the execution of various toolkits which may easily need high computation power. Besides, the eIMS must be cloud-based. In order to fulfil these tasks as much as possible, a system composed of easily scalable micro-services has been developed instead of having one big monolith application. The Figure 4 shows the hosting environment, which contains the frontend webserver and the inner application server container and also the common database ontology called Data Farm. The services built by using Spring Cloud based on Java works properly in any distributed environment, including the developer's own machine, bare metal data centres and even on Docker container platform.

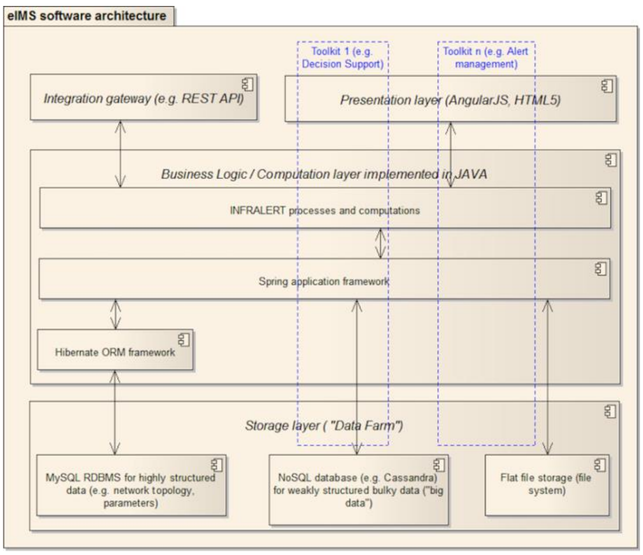


Fig. 3 eIMS software architecture

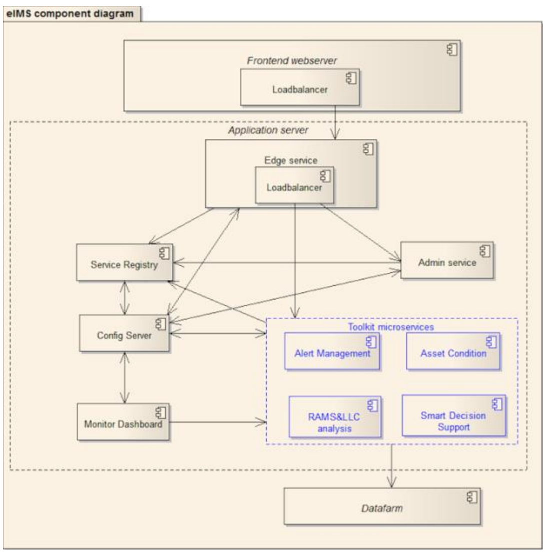


Fig. 4 eIMS component diagram

2.2.2. User processes and graphical user interface (GUI)

User processes are the processes where eIMS provides a user interface, so they can be managed by the user. In the architecture, this user interface is represented by the presentation layer. The implemented GUI is web-based. It is an SPA (Single Page Application) which uses a RIA (Rich Internet Application) technology that enables responsive and modern HTML5 web applications. In Figure 5, some examples of the eIMS GUI wireframes can be seen.

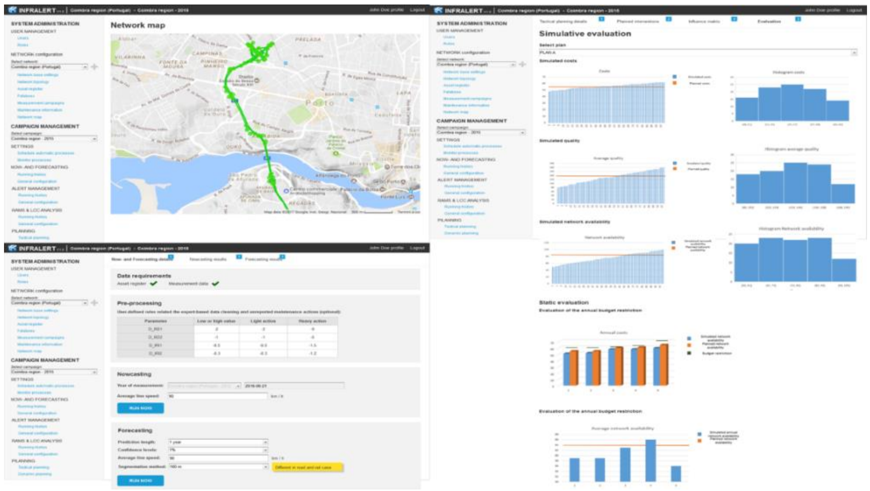


Fig. 5 GUI wireframes

3. Expert-based toolkits

In the following subsections the Data Analytics toolkits (asset condition, alert management and RAMS&LCC) and the Decision Support tool are presented together with exemplary results from the pilot tests.

3.1. Nowcasting and forecasting of asset conditions

The asset condition toolkit takes inspection and condition monitoring data as input, processes them and produces an assessment of the current condition (nowcasting) as well as a prediction of the future evolvement of the condition (forecasting). The output of the nowcasting is used on a strategic level to assess the development of the quality of the infrastructure network.

The main purpose of the forecasting is to improve maintenance planning on a tactical level allowing optimization of maintenance tasks and resources by knowing beforehand which part of the network requires maintenance. The time period for such a maintenance planning is typically between 12 and18 months for railway infrastructure and up to 60 months for road.

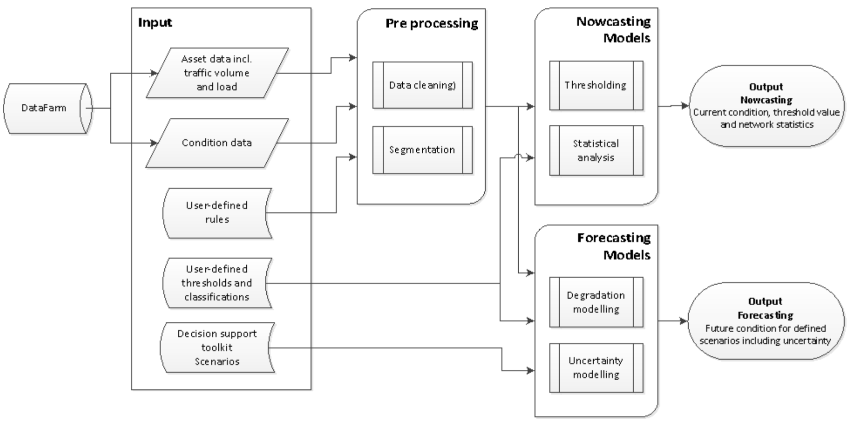


Fig. 6 Flowchart of the asset condition toolkit

A flowchart describing the processing blocks of the asset condition toolkit for road and rail use cases is shown in Figure 6. The main building blocks are: input, pre-processing, nowcasting, forecasting and output modules. The tasks and data requirement for each module is clearly presented in the figure. Inputs to the asset condition modules are mainly historical condition data over time and with a specified location. The data is pre-processed before applying nowcasting and forecasting models by: dividing it into homogenous segments and cleaned using some defined rules. The cleaning takes care of data quality issues, inconsistencies in the measurement data and empty records. The outputs of the module are the current condition (nowcasting) and future condition (forecasting). Typically, nowcasting is performed by means of thresholding. That is, the condition of a segment is categorised as being within a certain range related to design level, maintenance level and other alert levels with different severities. This output provides valuable information about infrastructure network and it enables the assessment of the overall quality of the network to support strategic decision on maintenance and reinvestment. Nowcasting output includes: condition level of each segment, table of descriptive statistics and cumulative distribution of the networks/section condition.

An example of the output for nowcasting implementation in the toolkit is presented in Figure 7. The figure presents quality description of a geometry parameter using cumulative percentage over a given railway section for two measurements conducted the same year. For quality classification of railway geometry, six thresholds are commonly used: Design Level, Maintenance Level, Alert level, Intervention Level Low, Intervention Level High, and Immediate action level (EN 13848-5). In Figure 7 the Maintenance Level is highlighted to compare how much of the line section is below this threshold for the two measurements.

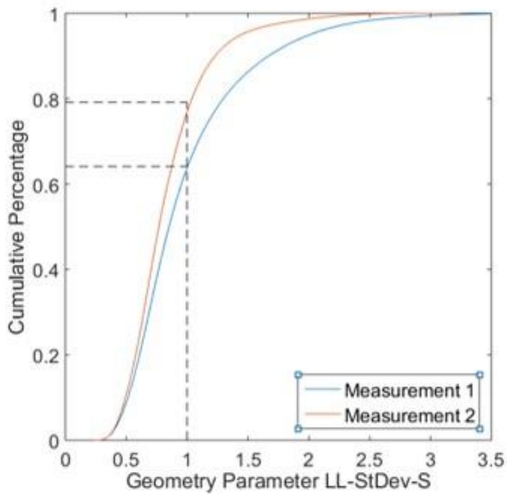


Fig. 7 Nowcasting of railway geometry (StDev Longitudinal Level). The dotted lines show the cumulative percentages of the track segments that are below the Maintenance Level.

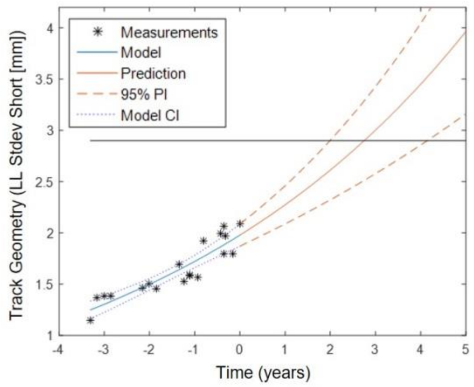
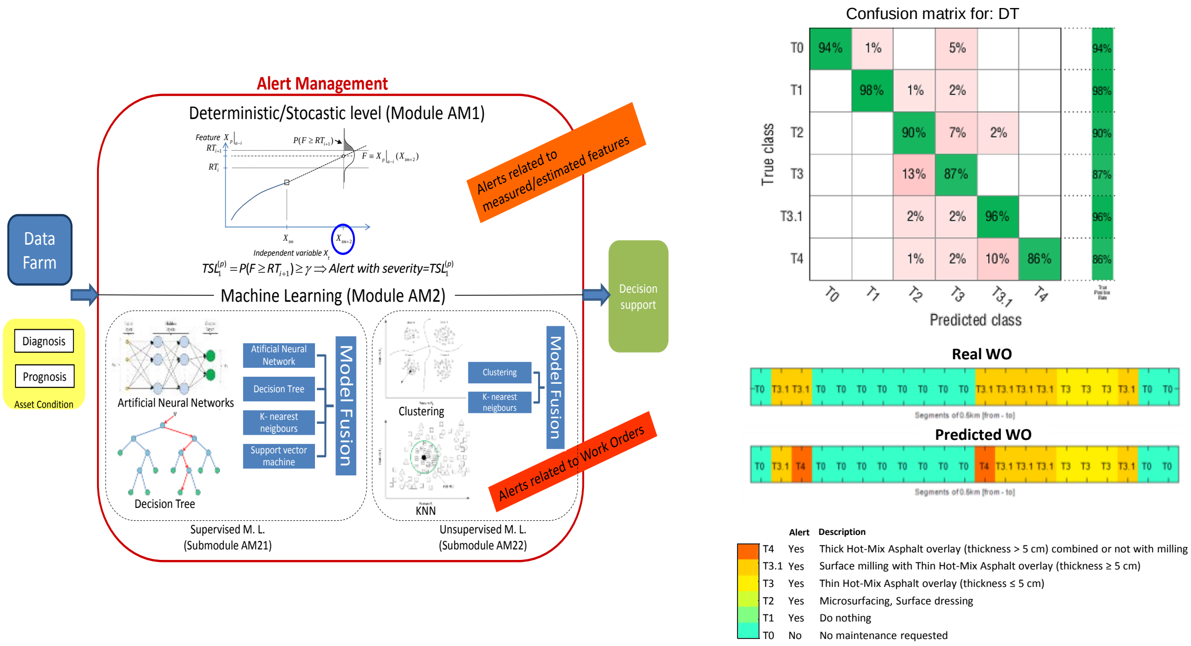


Fig. 8 Forecasting of railway geometry.

In forecasting, the goal is to establish a degradation pattern and to estimate the remaining useful life (RUL) of the asset (Vaidya & Rausand, 2011). Forecast is a critical aspect of extracting information from data and must carefully be carried out to avoid wrong decisions. Randomness of nature, events, materials, people, instruments and processes are some reasons why uncertainty modelling is important to obtain reliable condition assessment and forecast for linear asset. Modelling of uncertainty represents the difference between the predicted response and the true response (that can neither be known nor measured accurately), and comprises of several parts: model parameters, model form, and process noise (Sankararaman, 2015). There are several methods in the literature for uncertainty representation, for instance, probability theory (Kolmogorov, 1956), fuzzy set theory (Zimmermann, 2010; Sikorska et al., 2011), evidence theory (Shafer, 1976), imprecise probabilities (Weichselberger, 2000), etc. The uncertainty presented in INFRALERT is mainly based on the model form approaches. A common approach for forecasting is data-driven, however physic-based and symbolic models can be added to improve condition prediction performance in an approach called hybrid modelling. The hybrid approach with uncertainty modelling does not only improve prediction accuracy but also enables the prediction of different evolution paths of the asset condition in the future due to measurement uncertainty, inherent variability of the degradation process and model idealization. A result of the forecasting of rail condition is presented in Figure 8. The hybrid modelling approach addresses two critical issues for linear infrastructure degradation modelling. One is the need for pre-processing and data-cleaning. The other is the need for a noise model that can take into consideration non-constant error which is often the case for infrastructure geometry features. The implemented hybrid model uses an expert-based model for data pre-processing and a parametric data-driven model for forecasting. The parametric model can be expressed as $y = f(X, \beta) + \epsilon$; where y is the response variable that is a function of the predictors X and unknown variables β, and ε is the noise. In the example depicted in Figure 8, the response variable was the standard deviation of the longitudinal level and the model function was exponential as in $\beta(1)e^{\beta(2)t}$. A combined error model was used $y = f + (a + b|f|)$, which include both a constant random error term (a) and a proportional error term (b).

3.2. Alert generation

The aim of the Alert Management toolkit is to predict and prioritise maintenance alerts and the required maintenance interventions based on the forecasted severity of degradation/failure of the assets themselves, and the know-how brought in by the information recorded in the historical maintenance work-orders repository. Two alert grades are predicted and involved in the proposed methodology outlined in the block diagram of Figure 9a. A first module, AM1, estimates pre-alerts based on detecting those features overcoming their associated limits or reference thresholds. Those features exceeding their prescribed thresholds are used to assign a level of technical severity (TSL) to the associated pre-alert. The TSL is quantified using a pre-defined distance criterion between the value of the feature and the threshold. The second module, AM2, estimates alerts and the most probable interventions to be conducted based on the historical information stored in the maintenance work-orders repository. This module embodies two different functional submodules. Submodule AM21 triggers 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; the methodology is based on Supervised Machine Learning modelling previously trained with the explanatory features (e.g. measurements) and the historical interventions repository. 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 types database.



a) b)

Fig. 9 Alert generation toolkit. a) Workflow diagram, b) Example of results

The same structure is kept in rail and road pilot demonstrators as they both are linear asset. The outcome of this toolkit is used as an input for the Decision Support System in order to obtain the most efficient maintenance plan. The toolkit's predictions are compared with a set of real conducted maintenance interventions using an available measurement campaign as input (not used as a training set for the models) in order to obtain the accuracy of the techniques and models. An example extracted from the road case, shown in Figure 9b, presents an accuracy of 93.4% (1159 positive predictions out of 1241 sections). Disaggregating the results by maintenance types (T0 to T4), 843 sections out of 859 are correctly predicted as T0, 39 out of 41 as T1, 148 out of 187 as T2, 28 out of 30 as T3, 80 out of 93 as T3.1 and 21 out of 31 as T4. This implies that the largest errors are obtained when the model predicts T2 (accuracy of 90%), T3 (acc. 87%) and T4 (acc. 86%) types as suggested by the confusion matrix derived during the calibration step of the models (Figure 9b).

3.3. RAMS and LCC analysis

One of the main objectives of INFRALERT is to find cost-efficient maintenance strategies. Therefore, the assessment of costs is an important element for the project. Life-Cycle Cost (LCC) analysis is a well-known engineering technique that estimates the sum of all costs incurred during the whole life cycle of a system, including acquisition, ownership and termination costs.

In railway and road infrastructures, operation and maintenance comprise a major share of the system's life-cycle and they are the most sensitive to cost uncertainties. Acounting for such uncertainties is crucial at operational level and for long-term decisions. The integration of stochastic Reliability, Availability, Maintainability and Safety (RAMS) parameters in the LCC analysis allows obtaining reliable predictions of system maintenance costs and dependencies of these costs with specific cost drivers through sensitivity analyses.

The RAMS & LCC toolkit embedded in the eIMS is devoted to a combined RAMS and LCC calculation and can be divided in three main blocks: i) Data collectors and pre-processing tools, ii) RAMS&LCC simulators and iii) Trackers of system's RAMS&LCC related Key Performance Indicators (KPI). The workflow is illustrated in Figure 10: The data collection process extracts relevant data from the Data Farm (cost figures and work orders) and prepares that data (e.g. cleaning and filtering) for the application of suitable RAMS statistical models. The second main block corresponds to the combined RAMS&LCC analysis where cost models are built according to the system and richness data. The outputs of the module characterise system failures and maintenance cost and are used for tactical and strategic planning. These outputs are also used to track previously identified KPIs. The upper panel of Figure 11 shows costs estimations of replacement activities carried out on the switches and crossings component of the INFRALERT's rail demo case. These costs have been estimated by considering corrective maintenance interventions and extracting component's mean-times-to-failure and -restore from work orders. The lower panel shows a sensitivity analysis, where the percentage change in the total LCC-value (for replacements) is calculated by varying the different factors entering in the LCC formula a 10%.

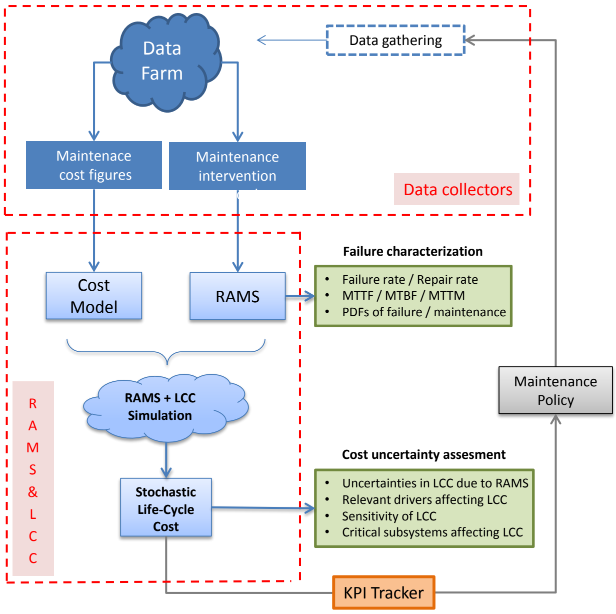


Fig. 10 Overview of RAMS&LCC toolkit

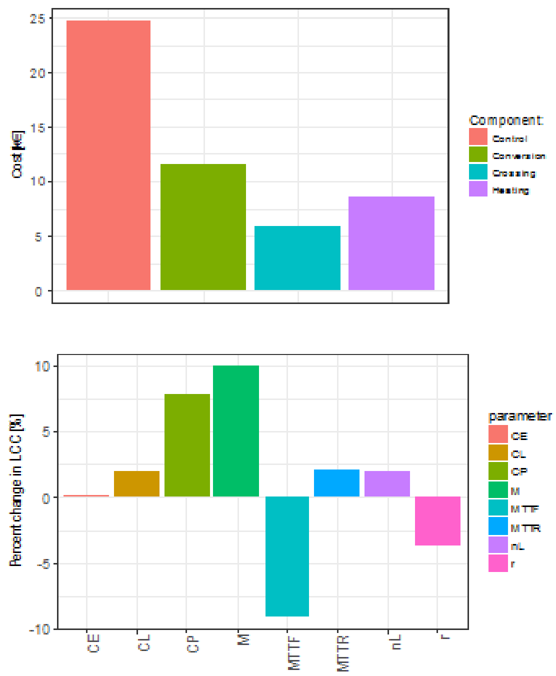


Fig. 11 Estimated costs for S&C replacements

3.4. Smart decision support

The smart decision support toolkit is the final step of the semi-automated data processing chain of the INFRALERT eIMS. Since maintenance and intervention planning is the end point of this chain there is high demand for interactivity with the user of the system. To assure a high acceptance and usability of the planning tools, a generic framework has been designed to integrate smart decision support with existing procedures and toolkits for asset condition assessment, alert generation and RAMS & LCC analysis. This framework is general enough to be easily adapted and applied to a wide range of maintenance and intervention planning scenarios. It provides the basis for the development of specific optimisation models following a condition- and risk-based planning concept.

In compliance with existing practices and standards, maintenance planning is separated in three levels: strategic, tactical and operational planning. In strategic planning, the assets are grouped; for example with respect to asset type, geometric characterisations, or traffic volume. For each asset group, the best maintenance policy or the best mix of policies is determined. Inputs of strategic planning are failure rates, deterioration and maintenance models. The selected policies have to meet RAMS targets or given KPIs and have to minimise LCC. Therefore, strategic planning is connected to the RAMS & LCC toolkit.

For tactical and dynamic planning, the current and future track condition has to be determined by nowcasting and forecasting tools. The output of the alert management toolkit is a prioritised list of maintenance activities which are necessary in the medium-term and in the short-term, based on predicted conditions. They are scheduled on two levels, in a medium-term time horizon in tactical planning and in short-term in dynamic planning. In tactical planning, the alerts or interventions will be selected, combined and allocated to time intervals. Based on the resulting coarse tactical plan, the operator can order material, book machines and plan track possessions or road closures. The tactical plan will also be the input for operational planning. There, the selected and allocated maintenance interventions together with newly added and urgent activities will be scheduled in detail. Thereby, operational constraints like manpower, machines available, material available, etc. will be considered in the planning model. Eventually, maintenance is executed according to the schedule, assets are inspected and new measurement data is generated. This results in new information in the asset data farm and a feedback to the whole planning process. Figure 12 provides an overview on the described decision support framework.

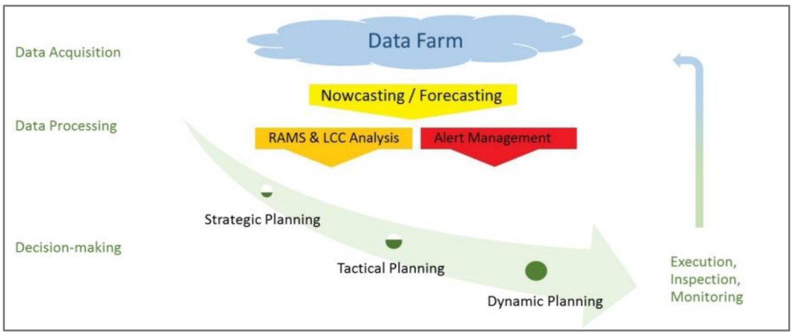


Fig. 12 Decision support framework

An important novelty of INFRALERT's smart decision support is the introduction of a concept to deal with uncertainties in maintenance planning: Uncertainties arise because the condition of assets is changing permanently over time due to degradation, thereby developing in an unpredictable or at least non-calculable manner. The consequence is that future condition development, but also risk assessment and costs associated to interventions to be executed, are uncertain in planning, and that maintenance schedules have to be adapted continuously with current information. The essential difference to traditional planning approaches relies on how the concept makes use of information about the "uncertain" condition of infrastructure assets and about the "uncertain" risks associated to degradation: In the eIMS framework, nowcasting and forecasting provides asset condition and relevant diagnosis and prognosis information about lifetime, failures, defects, quality indexes and their future development. This information will be integrated directly into the models underlying the decision support process as probabilistic inputs, describing infrastructure variables and maintenance restrictions. Thus, the determination of interventions is done in a condition-based manner. Besides, the concept is risk-based since it considers the underlying risk and failure modes and probabilities coming from RAMS analysis. In the new planning concept, decisions are always made by balancing the trade-off between the risks and consequences of failures on the one hand and the associated costs and traffic disruptions on the other one.

4. Pilot demonstrators

4.1. Meshed road network

The road pilot in Portugal (in progress) comprises 539 km of roads in the Coimbra region under IP jurisdiction (Portuguese road and rail networks infrastructure manager). It includes a rich variety of road types (principal, national, regional, etc.). All the available data is based on the IP Pavement Management System (SGPav) which stores information of maintenance activities carried out since the initial construction and road condition data since 2007, such as longitudinal (IRI) and transverse unevenness (Rut Depth), cracked area and pavement macrotexture. SGPav is then used to support the company's maintenance strategy, categorising 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 data stored in SGPav is related to the section element (start and end node). The network selected for the road pilot includes sections of an average length of 6.6 km, connecting 87 nodes. For each section, besides general information associated with the part of the road it represents, extensive information was made available for the project's development, including all the field measurements, the pavement historical information with all the road maintenance work performed up to date.

4.2. Railway line

The rail pilot (in progress) consists of two track sections on the heavy haul route of the rail Swedish Transport administration's network. The northern section is about 135 km long while the southern section is about 165 km long. They are both single tracks with mixed traffic of iron ore freight, passenger trains and other freight trains. The train speed on the line is between 80 and 120 km/h. The maximum allowable axle load on the line section is 30 tonnes and the annual accumulated tonnage is about 30 MGT. The track sections have continuous welded rail, head hardened 60E1 rail type, with concrete sleepers and Pandrol fasteners and fast clips. These line sections operate in extreme climatic conditions which can influence the reliability, availability, maintainability and safety characteristics of the infrastructure. The winter season sees snowfall and extreme temperatures. The annual temperatures vary between -40°C and 25°C. These track sections are considered relevant for the project due to the socio-economic significance to industrial and mining activities in Sweden that calls for high maintenance requirements. The predicted increase in the traffic on this line between 2006 and 2050 is about 136%, this is reported to be the highest in the entire Swedish network. Intelligent management system such as eIMS is required to support decision making to enhance capacity, availability and better use of resources on existing infrastructure. For the demonstration and validation of the condition and decision models, and other developments in this project, the following data has been provided: track geometry data, relevant information from asset register, work order records for corrective maintenance actions, reported preventive maintenance actions between 2008 and 2012, regular predetermined maintenance tasks and other information describing the maintenance practices on the track section.

5. Conclusions

This paper presents the implementation of the INFRALERT eIMS for predicting and optimising maintenance interventions in linear infrastructures. The development has been framed as a modular and general concept, and can address the maintenance of any type of linear assets. In particular, this system has been successfully tested in two different pilot cases: a road network and two rail lines. The description presented focuses on four main modules of the system: i) a module for nowcasting and forecasting of asset condition which is a basic input for the following process units; ii) a module 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, it provides forecasted maintenance alerts to be considered in the maintenance planning; iii) a module to compute probabilistic RAMS parameters which provides relevant information for the planning; and iv) a module to solve the tactical planning optimization problem which receives the predictions and computations from the alert management and the RAMS & LCC systems. The results of each toolkit have been summarised in Section 3.

Acknowledgements

This research was carried out within the INFRALERT project. This project has received funding from the EU Horizon 2020 research and innovation programme under grant agreement No. 636496.

References

Infralert 2016. INFRALERT: Linear Infrastructure Efficiency Improvement by Automated Learning and Optimised Predictive Maintenance Techniques (H2020 Programme, European Commission, Research Directorate, Grant agreement No 636496)

EN 13848-5, 2008. European standard EN 13848–5: Railway applications – Track – Track geometry quality – Part 5: Geometric quality levels, European Committee for Standardization (CEN).

Vaidya, P., & Rausand, M., 2011. Remaining useful life, technical health, and life extension. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 225(2), pp 219-231.

Sankararaman, S., 2015. Remaining useful life prediction through failure probability computation for conditioned-based prognostics. In Annual Conference of the Prognostics and Health Management Society, October 2015, Coronado, California USA.

Kolmogorov, A. N., 1956. On Skorokhod convergence. Theory of Probability & Its Applications, 1(2), pp. 215-222.

Zimmermann, H. J., 2010. Fuzzy set theory. Wiley Interdisciplinary Reviews: Computational Statistics, 2(3), pp 317-332.

Sikorska, J. Z., Hodkiewicz, M., & Ma, L., 2011. Prognostic modelling options for remaining useful life estimation by industry. Mechanical Systems and Signal Processing, 25(5), pp. 1803-1836.

Shafer, G., 1976. A mathematical theory of evidence. Vol. 1. Princeton: Princeton university press.

Weichselberger, K., 2000. The theory of interval-probability as a unifying concept for uncertainty. International Journal of Approximate Reasoning, 24(2-3), pp. 149-170.