- FORESEE -

Future proofing strategies FOr RESilient transport networks against Extreme Events

– Deliverable *4.3*–

Theorical framework on hybrid data assessment

"An Object-Oriented Hybrid Data Assessment Framework for Real-Time Diagnostics of infrastructure"

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	Participant Legal Name	Country
15	EIDGENOESSISCHE TECHNISCHE HOCHSCHULE ZUERICH (ETH Zürich)	Switzerland
9	LOUIS BERGER SPAIN SA (LB)	Spain

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Authors list		
Abdallah, Imad Dertimanis, Vasilis Chatzi, Eleni	EIDGENOESSISCHE TECHNISCHE HOCHSCHULE ZUERICH (ETH Zürich)	abdallah@ibk.baug.ethz.ch v.derti@ibk.baug.ethz.ch chatzi@ibk.baug.ethz.ch
Robles Urquijo, Ignacio	LOUIS BERGER SPAIN SA (LB)	irobles@louisberger.com

Reviewers' list		
Reviewer: Surname, name	**Organisation**	**Email**
Delgado Zaldivar, David	FERROVIAL AGROMAN SA (FERR)	david.delgado@ferrovial.com
Richter, Marvin Bogen, Manfred	FRAUNHOFER GESELLSCHAFT ZUR FOERDERUNG DER ANGEWANDTEN FORSCHUNG E.V. (FRAUNHOFER)	marvin.richter@iais.fraunhofer.de manfred.bogen@iais.fraunhofer.de
Garcia Sanchez, David Beltran Hernando, Iñaki	FUNDACION TECNALIA RESEARCH & INNOVATION (TEC)	david.garciasanchez@tecnalia.com inaki.beltran@tecnalia.com
Osmani, Saimir Cademartori, Marcello Fuggini, Clemente	RINA CONSULTING SPA (RINA-C)	saimir.osmani@rina.org marcello.cademartori@rina.org clemente.fuggini@rina.org

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EXECUTIVE SUMMARY

This report describes a conceptual framework for the online monitoring and diagnostics of infrastructure relying on fusion of heterogeneous data that is made available regarding the condition "state" of the system. We utilize an object–oriented (OO) formulation of graphical models, such as Bayesian Networks and Random Forest classifiers.

To this end, an infrastructure network is viewed as a "system of systems", or otherwise an assembly of systems (e.g. bridges, roadways and tunnels making up a highway network) that are defined on the basis of abstract superclasses, attributed with specific properties and methods. Properties define the current state of the respective object, while methods communicate state information and determine the interaction among objects and events. The term state refers to a set of mutually exclusive "positions", which a specific object may reach. This position describes the object's performance or overall condition (e.g. safe, critical, complete failure, etc.). An unknown state is also defined to take into account possible combi- nations of events that have not been registered during the design phase and would eventually be identified in the graphical models through the telemetry data flow. Triggering events, within the FORESEE context, refer to occurrence of hazards (floods, landslides, earthquakes, etc.).

The envisioned assessment framework is purely probabilistic, e.g. a set of probabilities is initially assigned to all events and updated accordingly, based on actual information extracted from the system. This information may either be acquired using sensors (through corresponding sensor objects), or may be estimated using simulations from models of different granularity (traffic models, nonlinear structural analyses). **The term "hybrid" is used herein to not only refer to the fusion of heterogeneous data, but to further denote the additional incorporation of simulations into the assessment framework.** We illustrate the proposed framework in connection to the FORESEE case studies.

1 INTRODUCTION

The term transport infrastructure in this document refers to the components and networks that support the mobility of people and goods, including elements like roads, tunnels, bridges and railways. The functionality of the society and the global economy depends on the undisrupted operation and high performance of these critical assets. Despite the criticality of these networks, the maintenance and inspection protocols for transport infrastructure heavily rely on the use of traditional schemes, such as visual inspections (scheduled and emergency) complemented with non-destructive evaluations, when a higher resolution assessment is deemed necessary (e.g. use of Ground Penetrating Radar or ultrasonic methods). On the other hand, recent years have witnessed the advent of data; traffic and meteorological information is continuously monitored; interferometric Synthetic Aperture Radar (InSAR) data can be used to track ground movement, allowing for tracking of the influence of extreme weather and hazard events on bridges and tunnels, as demonstrated in WP2 of FORESEE (D2.1). Structural Health Monitoring (SHM) systems are further increasingly made available on critical infrastructure components, as is also the case for most of the case studies included within FORESEE. Recordings of critical static (displacements) and dynamic (accelerations, strains) quantities is now feasible via use of easily deployable and low cost sensing technologies. However, mere availability of this diversified and heterogeneous information in raw format does not suffice. In order to extract indicators of performance it is of the essence to develop intelligent data assessment schemes able to translate raw data into actual information on condition. To what concerns the best practices that are currently specified by standards, a lack of systematic, quantitative and automated tools for monitoring, detection and diagnostics of transport infrastructure is noted. FORESEE aims to develop such a toolkit (WP5) to support decision making for critical transport infrastructure systems in the face of extreme events.

The reason why such automated hybrid data assessment schemes are not yet standardized may be attributed to the fact that state–of–the–art Condition Monitoring (CM) and SHM methods are not yet deemed as robust and reliable. This is linked to the fact that these algorithmic tools are still not straightforward to adopt, calibrate and robustly use by the non-data-analytics- expert. Operation & Maintenance (O&M) engineers, owners and operators demand robust and reliable results that aggregate the information in user–friendly output formats, and covey it in a way that is intuitive for the engineers to interpret. Another hurdle stems from the fact that such tools, when in place, they are typically "local", in the sense that they are configured for monitoring only a single or specific elements. For example it is common to install monitoring systems for monitoring typical bridge components such as bearings, but the link between this monitored information (i.e., the displacement of the bearing) and the condition of the bridge system as a whole, and by extension of the network within which this bridge is included is not obvious. Such cross communication and interaction capabilities are generally lacking.

A remedy to this problem may be provided via use of probabilistic graph structure algorithms, such as decision trees and their ensemble variants (namely, Random Forests). Event trees are traditionally used in quantitative risk analysis of diverse engineering systems, laying a path from an initiating event to an end state of a system. An initiating event in this context may correspond to high rainfall or an earthquake tremor, and the corresponding end states may pertain to flooding of a tunnel or dislocation of a bridge deck (with respect to its supports), respectively. For a given initiating event, multiple end states are possible. Intermediate chronological events make up the branches leading from the initiating event to the end state, and each event is associated with a probability of occurrence.

As part of Task 4.4 of the FORESEE toolkit, we establish an object–oriented (OO) module based on use of graphic models, namely Random Forests (ensemble of Decision Trees) and Bayesian networks, for hybrid condition assessment and prognosis of critical infrastructure. Decision trees in particular form the main pillar of this module, since they offer numerous advantages to achieve these objectives. The advantages are summarized in that i) they are easily updated from data [1], ii) they are visually more appealing and simpler to interpret, while it is easier to track an event path in a way that follows the sequence and chronology of how events are interlinked [2]. The infrastructure network is considered to comprise a "system of systems", or otherwise an assembly of objects. For instance, element components (like: piers, decks, illumination, ventilation), system elements (like links, bridges, tunnels), transport network systems (roadways, highways, railways), as depicted in Figure 1. Figure 2 offers a zoomed view into one of the objects of the network, namely a bridge. The diversified data sources that can be made available, via contact and non-contact (optical or satellite) sensors is depicted, along with the various hazards that may be acting on a bridge element.

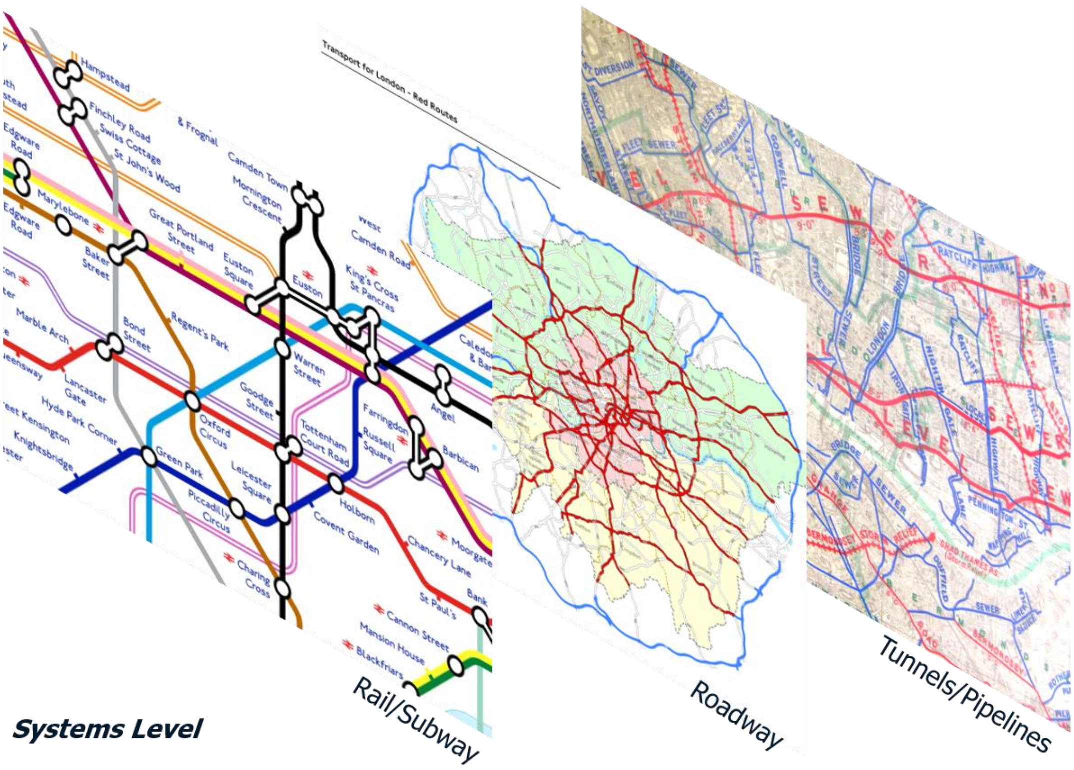

Figure 1. Transport Infrastructure: A system of systems

In the tree structure, the end states correspond to a prediction of a fault/damage (not directly observable). Such an end state could be flooding (or the level/severity of flood) for a tunnel, or a deck dislocation for a bridge. In the latter case, the end state could read simply as True/False, or could correspond to the level of dislocation depending on the granularity of the available data. Triggering, or initiating, events could be "heavy rain" or "earthquake" which in principle are directly measurable as they occur. The consequences (the faults emanating from them) of these triggers are not known, or directly observable but can be inferred via use of the OO framework we propose to predict and quantify them probabilistically. On the basis of our proposed supervisory module, (i) events are classified and event probabilities are updated either via offline feed (inspection logs) or real- time feed (telemetry of monitoring data); and (ii) new initiating events and end states are

identified. In the first step, a set of condition and/or structural data samples can be trained using decision trees, which are initially provided by engineers. Then, by running new data through the trees, classification and prediction may be carried out. Data that does not fit the existing decision tree structure is used to identify new initiating events and end states.
The object–oriented (OO) architecture allows to interpret a multi–layered diagram of transport infrastructure objects and the interactions among them. Decision trees are embedded locally in a specific object (i.e., a bridge, a tunnel, etc). Under this layout, inspection information and monitoring/SHM data are also locally registered and they are used to determine the current state of an object and/or notify neighbouring objects for the occurrence of an event or a change in their state. We stipulate that such a framework can be used for real-time monitoring and diagnostics of structures, root cause analysis of future failures and quantitative risk analysis in the context of operation and maintenance scheduling of components.

2 PROBLEM FORMULTION

In order to introduce a concise vocabulary, we will be referring to

- a roadway/railway network, as a "*network*" (system of systems)
- an element of these networks, e.g. a bridge or a tunnel, as a "*system*"
- an element of such a system, e.g. a bridge pier or a tunnel lining, as a "*component*"

To contextualize the problem, we start with a single *system* of an infrastructure *network*, namely a bridge, which itself is an assembly of *components* (piers, deck, etc…). This example can then be expanded to any kind of system or system of systems given that the proposed framework is object-oriented and abstracted in nature, so it is agnostic to the actual system under study.

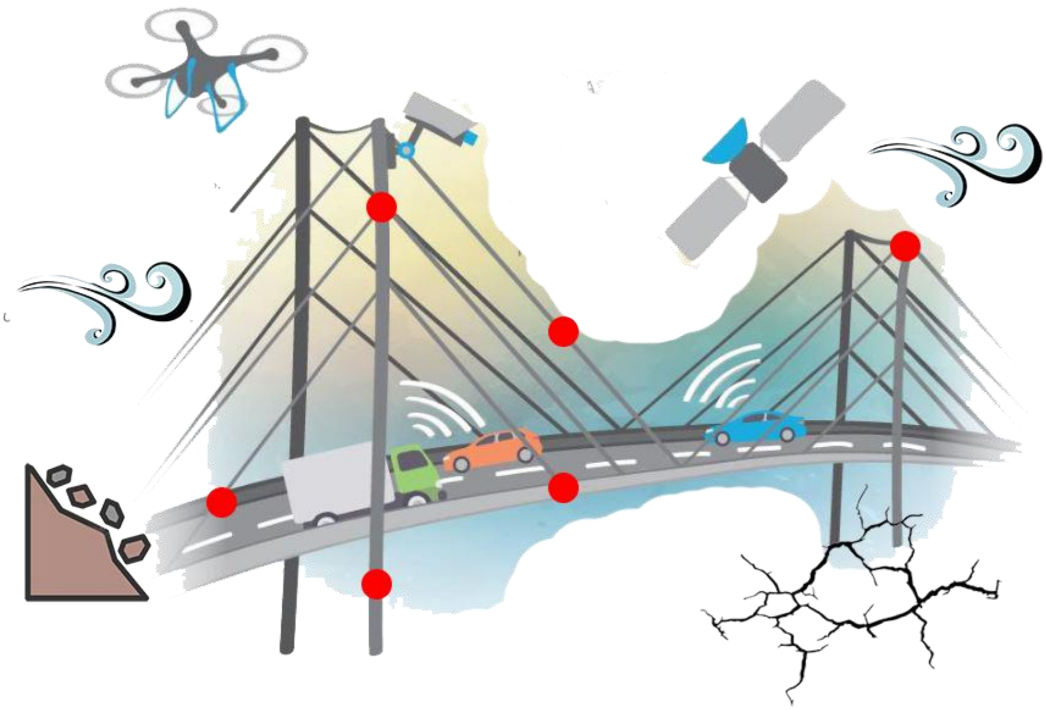

Figure 2. Object-level: Schematic of a bridge with diversified monitoring systems in place and its interaction with the environment. Potential hazards depicted include: extreme winds, earthquakes leading to soil softening or damage to the piers, and landslides from the hill side. Image adapted from ©EC 2019

2.1 ILLUSTRATIVE ASSET CASE: THE BRIDGE

Figure 2 sketches a generic bridge asset and its interaction with the surrounding context. The bridge is exposed to wind and traffic loads, earthquakes leading to soil softening or damage to the piers and landslides from the neighbouring hill. In this example, the bridge is composed of several interrelated components that fulfil specific tasks. The most important of these tasks are listed in Table 1, along with their main functionality. It must be noted that each component consists of a number of sub- components on itself, rendering the bridge a complex multi–level engineering system. Indicatively, the bridge deck consists of girders, stiffeners, deckplates and bearings supported by the piers. It is thus apparent that the structural and operational integrity of the asset are strongly dependent on the constitutive components of system.

Table 1. The main components of a generic bridge structure and their functionality.

Component	Function
Pile/Foundation	Ensures load bearing capabilities and support of the bridge
Pile cap	Distributes the load into the piles
Tower/Column/Pier	Ensure that the loads are transferred from the deck down to the foundation/supports
Cables/Suspenders	These insure that the loads are transferred from the deck down to the foundation/supports
Girder	Primary support for the deck
cross-braces	Stabilize the main girders against lateral buckling
Bearing	Allow the superstructure to move with respect to the substructure and enable load transmission from the superstructure to the substructure
Stiffener Panels	Stiffen the Deckplate against out of plane deformations
Deckplate / Deckslab	Part of the main load bearing structure, enabling
transverse by vehicles Retaining Wall	Ensures that the soil and fill supporting
the roadway and approach	embankment are retained
Embankment/Abutment	Ensures the bridge-end contacts the ground, transfers the bridge structure to the roadway, and transfer loads from the superstructure to its foundation elements
Sensors	Measure quantities critical for operation and monitoring (e.g. traffic, wind, temperature/humidity, bearing's displacement, deck vibration, pier settlements etc.)
Safety systems	Ensure the safety and structural integrity of the bridge and the safety of the users of the bridge under extreme events

2.2 THE MONITORING PROBLEM

Under this setting, the problem considered herein pertains to the establishment of a robust, data–driven supervision platform for the monitoring of civil infrastructure (tunnels, bridges, highways, etc.) in the face of extreme events (hazards), which combines three main drivers:

A module attributed with the ability of tracking, identifying and classifying individual objects based on data inflow. The data comes from both i) real–time telemetry from monitoring systems, and ii) offline feedback from historical inspection logs regarding the condition of components. The implications of these events onto the global state of the system/network is also made possible.

The development of a probabilistic prognosis framework, aiming at projecting the current state of all individual components to the future, and providing both short and long–term predictions of the local and global safety margins.

Flexibility of the tool to integrate new components (e.g. modified piers, new retaining walls) and systems (more bridges, new tunnels in a road network, etc.) in the context of evolving structures.

Due to the inherent complexity of the monitored system, the envisioned supervision platform should be further attributed with adaptive tools that may create sequences of events that were not predicted during the design stage of a structure. The conceptual framework of such a platform is outlined in the following sections.

3 OUTLINE OF THE OO FRAMEWORK

3.1 DATA INGESTED BY THE FRAMEWORK

- Simulation Models (e.g. structural models for bridges, flood simulations for tunnels, traffic)
- Drawings/Material properties of a typical structure
- Inventory data/Historical inspection logs
- Monitoring Data based on sensorial information
- Typical damages (Expected Faults)[2]
- Possible interventions/restorations
- Hazard Information: weather and environmental data, earthquakes, landslides, and floods

The challenge with data ingestion is the fact that the faults on transport infrastructures occur in non-benign and low probability combinations of operational and environmental conditions (rare or extreme events). The FORESEE toolkit focuses on extreme events, namely hazards, which might be limited in relevant fault instance data. This is a challenge for any learning algorithm, and therefore, in addition to direct measurements, input from numerical models (simulators) is essential for the assessment framework we propose. Hence, the term "hybrid" is used herein to not only refer to heterogeneous data fusion, but to further denote the additional incorporation of simulations into the assessment framework.

3.2 DESCRIPTION

The proposed monitoring framework is based on the OBEST paradigm [3, 4] and its predecessor [5], in which engineering systems and their constitutive components are represented as objects (e.g. instances of predefined classes) that are interlinked and exchange information with respect to their current state. The exchanged information refers to information on the asset itself (e.g. condition), on the experienced loads (e.g. traffic), on the relevant hazards (e.g. earthquake), on available measurements (e.g. vibration (SHM), or satellite), and the type of actions (e.g. repairs/ maintenance) that are available. An initial analysis of this framework was presented by the authoring team in [6] in the context of O&M for wind turbine structures. The OBEST framework comprises four different views that describe the functionality of a system in various levels. These

[2]It is suggested, where feasible to adopt the format developed in the Intervention Mitigation Action (IMA) tool developed by TECNALIA within the context of the affiliated EU project RAGTIME. This tool includes hazards, damages and thresholds for the different components of typical assets (bridge, tunnel, pavement, slope, and rail opentrack)

are the system structure diagram, the interaction diagram, the state transition diagram and the data flow diagram.

The system structure and interaction diagrams describe the constitutive objects of the system and their interaction, respectively. For a bridge system, a merged view of both is displayed in Fig. 3, where the boxes correspond to the individual components and subsystems and the arrows to their interactions. In general, a piece of information received by an object results in altering its internal state or a subset of its fundamental characteristics (attributes). For example, an inventory information reporting deterioration of the condition of a bearing for a bridge, will impact the corresponding performance indicator (PI) of the bridge object. On the other hand, the change in the assignment of a seismic zone, will redefine the calculation of the seismic design spectrum according to the code, with a direct consequence on the calculation of the probability of failure. This accordingly implies the transmission of another piece of information that communicates its new condition to further objects. Thus, the behaviour or state of each component in the system is entirely encapsulated within the confines of an object. The performance of the entire bridge is represented by combining and connecting object models for individual components or subsystems.

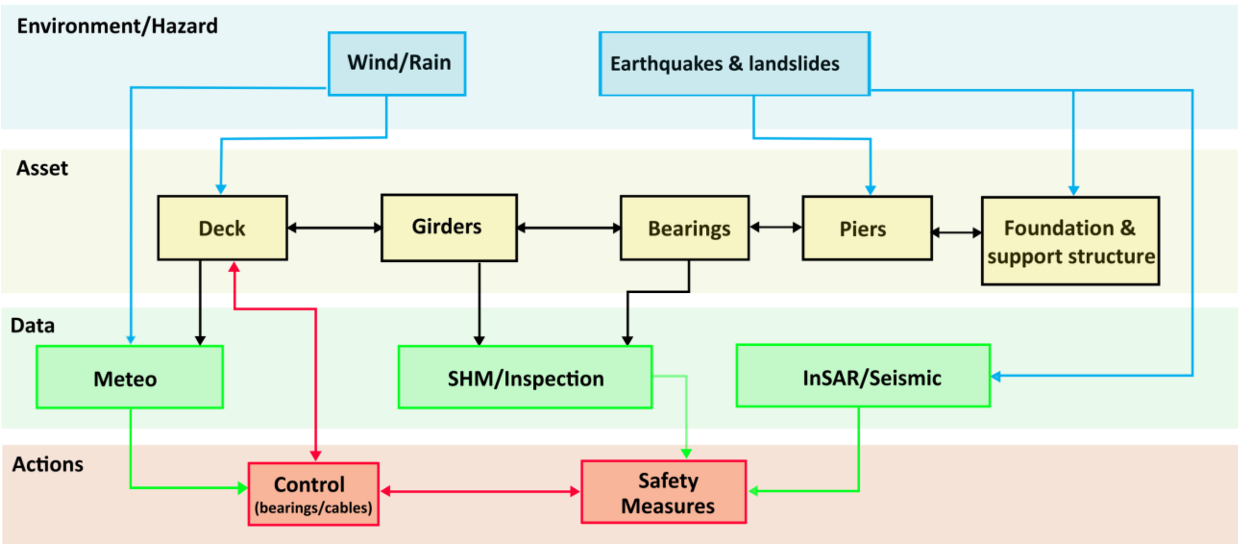

Figure 3. A simplified bridge structure and interaction diagram (combined).

3.3 DATA–DRIVEN DIAGNOSTIC FRAMEWORK

The diagnostic aspect of the framework consists in using incoming data to identify new branches in the event tree and classify initially unknown end states. Such end states could be labelled to reflect performance as for example normal, critical, abnormal, at fault, total failure, and unclassified. This depends on the convention utilized for the registration/generation of data. It is suggested that the format follows the convention followed in the IMA tool developed for the RAGTIME project. As the continuously updated stream of data (inspections, SHM) is propagated through the event trees of each component, state classifications and predictions are continually accomplished. Decision trees offer the benefit of straightforward interpretation by non-expert operators, since they offer a visualization of the chain of events following a triggering hazard event. Another advantage of decision trees is related to the diagnosis process, which is the task of locating the source of a system fault, once this is detected, by tracing the sequence of events in the tree that lead to fault or failure [7].

Such an object oriented framework which is capable of learning and can be continuously updated, is well-suited in the context of a system that is evolving/ageing in time. For instance, ageing and degradation of the concrete of a bridge deck or wear of the bearings introduce new and previously unaccounted states, which could be captured via the decision tree learning process. Finally, a common scenario involves the renewal and replacement of certain components (e.g. replacement of worn gusset plates), which may be deemed necessary during the life span of a bridge system. In the context of the proposed object oriented framework, this can be readily achieved and seamlessly integrated with the already existing components (objects).

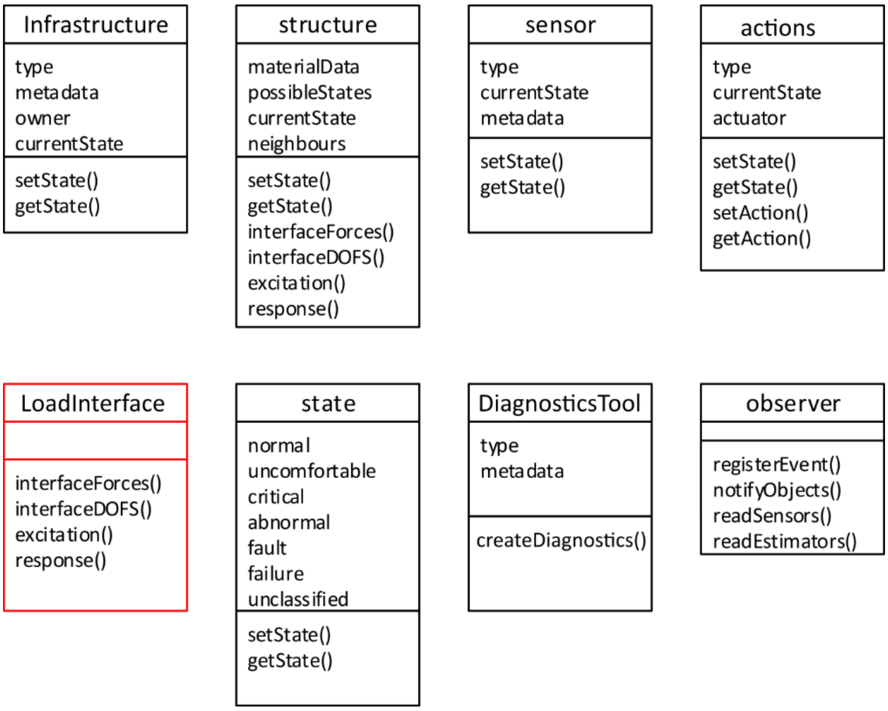

Figure 4. Indicative classes and interfaces (in red) of the supervisory platform. The classes listed in the figure are intentionally left abstract so that these may be adjusted to different assets (roads, tunnels, bridges, roadways.

The framework we propose is probabilistic in nature. The first possibility here is to use the decision tree, where the conditional probability of an end state $EndState_i$ depends on the conditional probabilities of the preceding events e_i on a path such that:

$$P(EndState_i) = P(e_1) \cdot P(e_2 | \ e_1) \cdot P(e_3 | \ e_2, e_1) \ldots \tag{1.1}$$

It is worth noting that limitations appear in the event of correlations or when the component displays a behaviour with feedback (i.e., after a repair or update in the system) or for evolving systems (e.g. aging of the system), which implies a need to establish several decision trees based on the possible ordering of the events or based and conditioned on new initiating events. One way around this problem is to convert decision tree learners to undirected Markov networks 8 or make use of hidden Markov decision trees [9,10]. An alternative is to map the decision trees learners into Bayesian Networks for further assessment of the conditional probabilities [11]. The conditional probabilities of the end states are a means for predicting the likelihood of potential fault or failure occurring.

3.4 OBJECTS

An extensive outlining of the individual classes that define the objects of any possible infrastructure system/subsystem falls outside the aim of the current study. However, our framework relies on a number of abstract class and interface definitions, which may be easily inherited to other pending subclasses. These are illustrated in Fig. 4 and follow the conventional object oriented design pattern. In the current stage of our conceptual interpretation, these are separated into two broad categories: the first corresponds to classes directly related to the system under study and its constituent subsystems (e.g. *Infrastructure* class, *structure* class, *sensor* class, etc.), while the second category defines the aspects of the supervisory platform that correspond to loads (hazards), interactions, events and information flow (e.g. associated interfaces and *eventTree*, *state* and *observer* classes).

The specified properties and methods of the definitions of Fig. 4 are indicative and may include any individual method that is integrated into the monitoring platform. For example, an adopted SHM method that may be used for tracking the remaining fatigue life of a structural element can be placed within the *setState()* method of the *structure* class. Similarly, a structural model (e.g. one established on the Structural Software for Analysis and Design - SAP2000) can be used for estimating unmeasured quantities (like strains) required for the *action* class. Such a model can be registered within the *readEstimators()* method of the *observer* class. In Figure 5 we make our example specific to a subsystem of a bridge, namely the pier-girder-deckplate assembly.

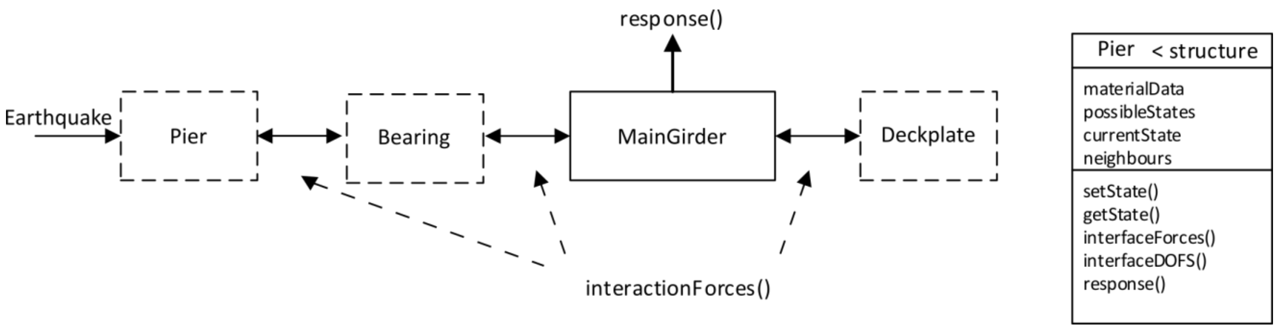

Figure 5. Interaction diagram for the pier-girder-deckplate of a bridge. Pier extends class structure.

4 DIAGNOSTICS & PROGNOSTIC TOOLS FOR THE FRAMEWORK

4.1 RANDOM FOREST ENSEMBLE CLASSIFIERS

Decision trees:

A Decision Tree (also called Classification or Prediction Tree) is designed to classify or predict a discrete category from given (typically labelled) data [12]. Decision Trees (DTs) are a non-parametric supervised learning method used for classification (and regression). In the machine learning sense, the goal is to create a classification model (classification tree) that predicts the value of a target variable (also known as label or class) by learning simple decision rules inferred from the data features (also known as attributes or predictors). In Figure 6 an internal node N denotes a test on an attribute, an edge E represents an outcome of the test, and the Leaf nodes C represents the final class labels or class distribution, which correspond to the faults that we wish to identify.

Four reasons motivated us to work with decision tree classifiers. First, they can be learned and updated from data relatively fast compared to other methods. Second, they are visually more intuitive, simpler and easier to assimilate and interpret by humans/engineers. Third, unlike other classification methods, with decision tree classifiers it is possible to perform data-driven root cause analysis of faults; one can trace a path from the end state (e.g. deck dislocation) to the initiating event (e.g. earthquake intensity and/or spectral content), in a way that follows the sequence and chronology of how events are interlinked. Last, it has been shown that the accuracy of decision tree classifiers is comparable or superior (especially ensemble decision tree classifiers) to other models and in fact display the best combination of error rate and speed [13,14,15,16].

A decision tree is a tree-structured classifier built by starting with a single node that encompasses the entire data and recursively splitting the data within a node, generally into two branches (some algorithms can perform multiway splits) by selecting the variable (dimension) that best classifies the samples according to a split criterion, i.e. the one that maximizes the information gain (Equation 2) among the random subsample of dimensions obtained at every point. Formally, the splitting is done by choosing the attribute that maximizes the Information Gain (IG), which is defined in terms of the impurity degree index I_d:

$$I_G(T,M) = I_d(T) - \sum_{m \in M} \frac{|T_m|}{|T|} I_d(T_m) \tag{1.2}$$

where T is the training data in a given node, M is one of the possible dimensions along which the node may be split, m are the possible values of M, $|T|$ is the size of the training data, $|T_m|$ is the number of objects for a given subset \$m\$ within the current node, and I_d is the function that represents the degree of impurity of the information (Figure 6). The splitting continues until a terminal leaf is created that meets a stopping criterion such as a minimum leaf size or a variance threshold. Each terminal leaf contains data that belongs to one or more classes. Within this leaf, a model is applied that provides a fairly comprehensible prediction, especially in situations where many variables may exist that interact in a nonlinear manner as is often the case in civil and mechanical infrastructure [17].

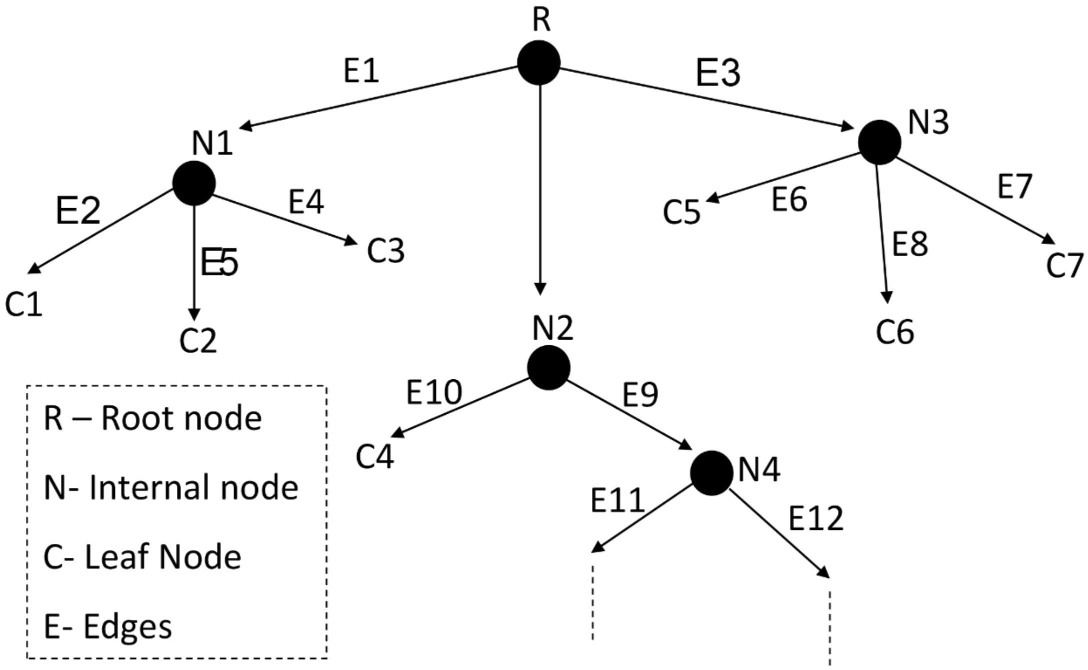

Figure 6. Graphical representation of a decision tree (DT) classifier. DT terminologies are also shown.

<u>Ensemble Decision trees - Random Forests:</u>
Random Forests (RFs) form a popular and useful tool for non-linear multi-variate classification and regression, which yields a good trade-off between robustness (low variance) and adaptiveness (low bias). A Random forest is an ensemble ML model that trains several decision trees using a combination of bootstrap aggregating (a.k.a. bagging) and random feature selection. The final model output is determined by a majority vote of the outputs of the individual trees. One of the attractive features of RF is the ability to estimate the importance of each features in the trained model. Decision trees (the basic ML models comprising the ensemble) use a heuristic method to determine which feature to split on while recursively constructing the model; in our case this heuristic method is the Gini criterion, described more in the work of Breiman & Cutler.

As the Random Forest algorithm repeatedly samples from the data set and the feature set, any negative effects due to correlated features/input variables/events is somehow reduced. In other words, there is no explicit requirement for inputs/features to be uncorrelated.

Massive feature extraction for classification:
We resort to a direct and massive feature extraction from monitoring and inspection data, and/or simulated time series, to be used as features in the Random Forest classifier.

Parameters optimization for classification:
The random forest classifier hyperparameter optimization is performed using a randomized grid search according to the work of Bergstra et al. [18]. The main grid search hyperparameters are: number of Decision Trees; Min Samples to Split; Min Samples at Leaf; Max Features; Nodes per Layer; Max Tree Depth; Bootstrap Training.

Performance evaluation:

The following broadly exploited metrics will be employed to judge the performance of the framework, through verification on reference data.

- Confusion matrix
- Receiver operating characteristic curve (ROC curve)

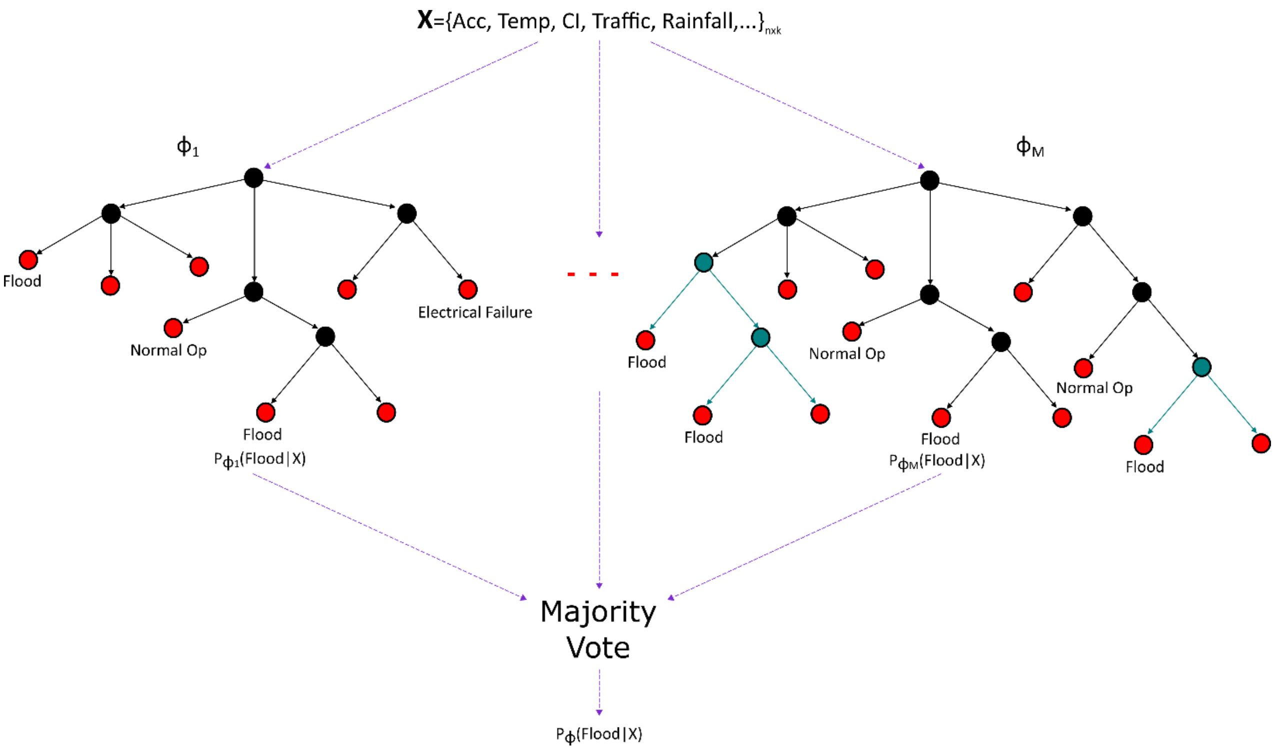

Figure 7. Random Forests: an ensemble of decision tree learners for a <u>single system</u> in a system of systems (e.g. tunnel in a network). X denotes the vector of inputs, while the leafs represent outcomes/faults. Bootstrap the training data and feature space before aggregating the learned decision trees. The "leaf" (outcome) from each contributing tree is combined into a final classification through a "majority vote" mechanism. The majority vote selects the class that receives the largest number of classifications, or "votes", from the trees of the forest.

The reference data will either be obtained from actual information, such as the information on flooded components of a roadway network for extreme rain events (Case Study 5), or from simulations using structural models of bridges under earthquake excitation (Case Study 1).

Figure 7 offers a schematic of such a Random Forest, which occurs as an ensemble of trees, on the example system of a tunnel, which is evaluated for faults (flooding) under heavy rain events (triggering hazard event). On the other hand, Figure 8 extends this concept to the "system of systems" level, i.e., the roadway network, which may be viewed as a forest of forests. In this case, the RF of the "tunnel" represents one of several systems in the network, with related faults pertaining to "flooding". This influences, and therefore serves as input to, a "bridge" system situated in the same roadway. The bridge RF is further assessed under the possible influence of a seismic event (hazard input). Then, both of these systems feed into the "highway system", which is evaluated for a "blockage" type of fault.

Tracing of root cause of faults for Diagnostics:

An attractive feature of random forest classifiers is that they are readily disposed to interpretability, since they indicate the possible sequences of features which lead to a particular fault. When diagnosing faults, we are interested in identifying the root causes (or sequence of events) that lead to a large portion of the overall abnormal behavior. The decision tree edges leading to faults become root cause candidates. The idea here is to create diagnostics and off-line root cause analysis for individual target fault classes by selecting important features that correlate with the largest number of faults.

A limited number of proposed pragmatic algorithms exist in the literature on the basis of which decision tree classifiers can be scanned/probed for root cause analysis [19]. One implementation is described in [20]. In Task 4.4. of FORESEE, we extend this idea of root cause tracing in a single Decision Tree to the ensemble Random Forest classifier according to [21,22,23]. Once a RF is built it can be used in two modes:

- Diagnostic Mode: where the RF is used for root cause analysis, in order to identify the sequence of events leading to a fault (e.g. flooding, pier damage)
- Prognostic Mode: where the trained RF is used for tracing the onset of events that are likely to lead to a fault. It is important to note that, as any learning method, the RF will only be able to predict events which have been "learnt". In other words, we may only predict events in the range of inputs for which the RF has been trained, whether that is via actual or simulated data. For example, it is not possible to predict events outside the range of training data, e.g. for an earthquake of a higher magnitude and a significantly different spectral content to what has been used for training.

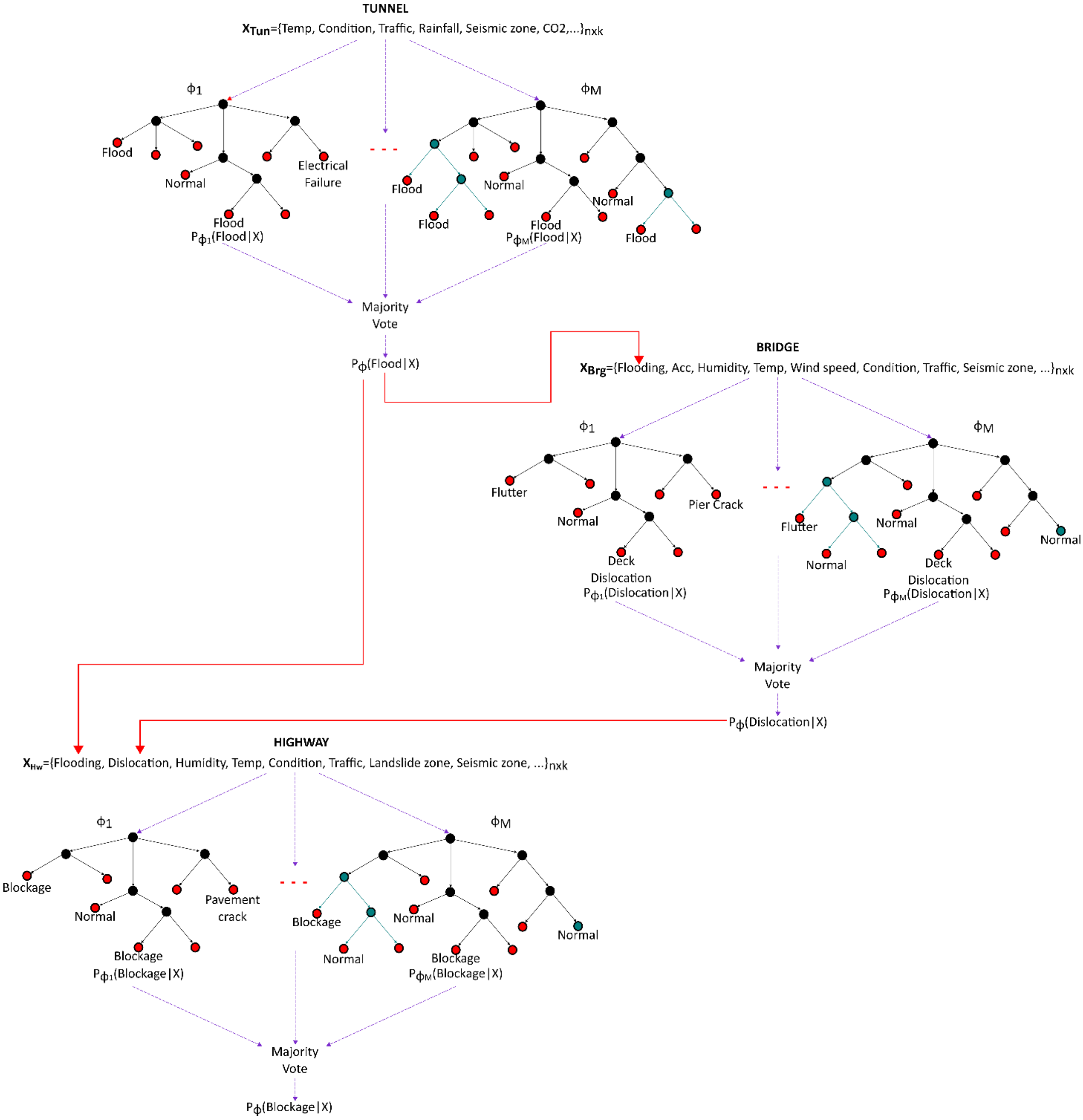

Figure 8. Indicative schematic of a connected graph of random forests for a <u>system of systems,</u> in this case: the roadway network.

4.2 BAYESIAN NETWORKS

Here we discuss a further useful probabilistic graphical model, the Bayesian Network (BN), which represents a set of variables and their conditional dependencies via a Directed Acyclic Graph (DAG) [24] to represent a joint probability distribution [25]. It can be used to compute the probabilities of occurrence of various events or as a means for classification. It explains a phenomenon or serves as a probabilistic predictor of events. A Bayesian Network consists of:

1. a set of variables and a set of directed edges between variables;

2. each variable has a finite set of mutually exclusive states;
3. the variables together with the directed edges form a DAG.

The nodes or vertices of the DAG represent the random variables and the arcs or edges represent the conditional dependencies (to reduce the complexity). The BN uses a tree augmented naïve (TAN) Bayes learning model to create a simple BN model. The use of TAN structure increases the classification accuracy because this structure reveals the relationship between a predictor and another predictor in addition to the target variable. A BN is typically used for analysing an event that occurred and predicting the probability that any one of the numerous possible known causes was the contributing factor. Figure 9 shows a simple BN structure. In Figure 9 (a), random variable $X2$ influences whether the random variable $X1$ is activated, and both $X2$ and the $X1$ influence the output random variable Y. Figure 9 (b) indicates the simple formula of the conditional probability of the target variable.

Hence a crucial assumption is made whereby a node only depends on its immediate parents, not on all predecessors in the ordering. Therefore, the joint probability distribution can be written as follow:

$$P\left(X_1,\ldots,X_n\right)=\prod_{X_i\in\mathbf{X}}P\left(X_i\mid Parents(X_i)\right) \tag{1.3}$$

The Bayesian network is one of most efficient prediction methods for probabilistic inference of unobserved, or latent, variables provided the joint distribution is given. The posterior distribution for an unobserved variable X_u can be calculated as follows:

$$P\left(X_u\mid X_o,\boldsymbol{\theta}\right)=\frac{P\left(X_u,X_o\mid \boldsymbol{\theta}\right)}{P\left(X_o\mid \boldsymbol{\theta}\right)} \tag{1.4}$$

where, X_u is the unobserved variable, X_o is the observed variable and $\boldsymbol{\theta}$ is the vector of parameters in the Bayesian Network. We do not elaborate on the methods to solve the posterior distribution as it is a whole separate field onto itself.

A BN is completely determined once the graph and the entailed dependence structure are specified for the qualitative part. The quantitative component consists of feeding the BN with the (un)conditional probability distribution for every variable to completely determine the joint distribution of Eq. 3. The ability to insert evidence can then be performed throughout the graph in both a bottom-up and top-down manner. Inference is an attractive feature BNs possess and is undoubtedly enticing to update forecasts on the basis of observations. Mathematically, it consists of the use of the simple Bayes' formula for conditional probability. However, according to the complexity of the graph, this operation may quickly become intractable so recent developments on more adapted algorithms were proposed [26]. One shall understand complexity through both the degree of nodes, which is the number of edges incident to it, together with their number of states [27].

It has been shown that Bayesian networks could outperform decision tree-like classifiers and that they are better suited to capture the complexity of the underlying decision-making with regard to a system. However, one of the disadvantages is that Bayesian networks are somewhat limited in terms of interpretation and efficiency when rules are derived from the direct knowledge of the system (which could be limited - epistemic uncertainties), while rules derived from decision tree-like classifiers in general have a simple and direct interpretation. In the FORESE Task 4.4 tool we utilize both graphical structures in order to harness the merits of both schemes.

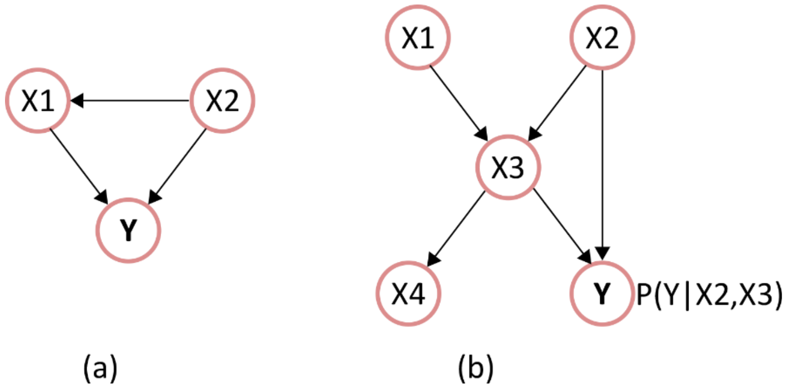

Figure 9. A simple Bayesian Network.

Diagnostic Bayesian Networks:

A diagnostic network is a specialized form of a Bayesian network which is used as a classifier for performing fault diagnosis. For example, in Figure 9 instead of performing a causal inference in the form of $P\left(Y|\ X_2, X_3\right)$ we perform a so-called diagnostic inference in the form of $P\left(X_2|\ Y\right)$ versus $P\left(X_3|\ Y\right)$. In a sense, here, we know that a fault Y has occurred and we are interested in diagnosing the probability of X_2 versus X_3 being the direct cause of it. This reasoning could be generalized/extended to a chain-like of variables (causes) leading to the final effect (fault).

This Diagnostics Bayesian Network consists of two types of nodes: class (i.e., diagnosis) and attribute (i.e., test) nodes. When performing diagnosis, each test performed is an indicator for a possible set of faults. As an example, consider a simple test of the state of a lighting inside a tunnel with the results *ON* or *OFF*. With no other information, this is an indicator for a number of potential problems such as a broken bulbs or damaged wiring. By this principle, every test node in the network has a set of diagnosis nodes as parents. As in the standard Bayesian network, every node has an associated conditional probability distribution. For a specific diagnosis node, this distribution represents the probability of failure. For test nodes, this distribution represents the probability of a test outcome given the parent (i.e. causing) failures [27].

One way Bayesian Diagnostic models can be represented is with the specialized adjacency matrix referred to as the D-Matrix. A D-Matrix relate the faults and the tests monitor. We can formally define it as the following: Let $\mathbf{F}$ represent a set of faults and $\mathbf{T}$ represent a set of tests. Assume each $F_i \in \mathbf{F}$ is a Boolean variable such that $eval(F_i) \in \{0,1\}$ and each $T_j \in \mathbf{T}$ is also a Boolean variable such that $eval(F_i, T_j) \in \{0,1\}$. We define $eval(F_j, T_j)$ to then be the following:

$$eval(F_j, T_j) = \begin{cases} 1 & if\ T_j\ detects\ fault\ F_i \\ 0 & \text{otherwise} \end{cases} \tag{1.5}$$

In the context of a Bayesian Network, this leads to the following definition: A D-Matrix is an $n \times m$ matrix $\mathbf{M}$ such that for every entry $m_{i,j}$, a value of 1 indicates that F_i is a parent of T_j while a value of 0 indicates that F_i is not a parent of [28].

Figure 10 shows an indicative example of a Bayesian Diagnostics Network for a Tunnel-Bridge-Highway system. What becomes clear here is that direct input/knowledge is required by experts in order to build such Bayesian Networks. It is reminded that in this case, the Bayesian Network works in diagnostic, as opposed to causal, model. This means that it is described by an orientation of arrows that is different to the RF (Figure 8). Namely, in this case, the arrows point to the parent, i.e., the triggering events. The BN offers a visualization of the probability for a fault to occur conditional on multiple events $X_1, X_2, ..., X_n$. **In Task 4.4 and 5.2.1, we will be using the BN structure to take expert feedback from engineers operators into account for the assessment.** There is, however, ongoing research on unsupervised algorithms to learn the structure of Bayesian Networks directly from data. An unsupervised, or semi-supervised, approach of this type can be linked to the work conducted as part of Task 4.5 of the FORESEE project, where exploitation of SHM data is sought for the tasks of damage detection and characterization.

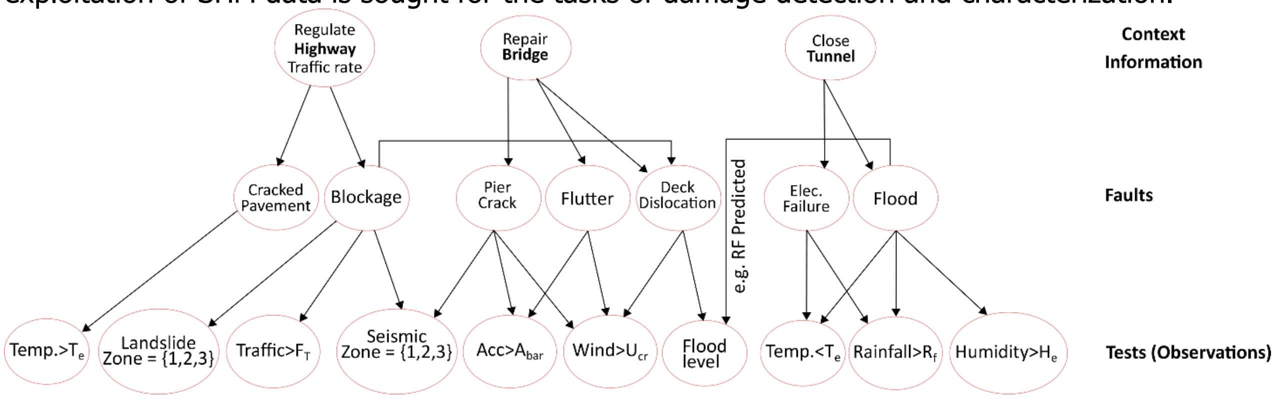

Figure 10. Indicative schematic of a Bayesian Diagnostics Network for a system of systems

4.3 HYBRID DATA FUSION

There are three levels of data fusion considered in this framework.

Fusion at the input of the individual diagnostic tool level:

An ensemble Random Forest classifier inherently considers input (features, otherwise known as predictors) from multiple and heterogeneous data sources, e.g. InSAR settlement information, traffic load, SHM accelerations/strains, hazard level, etc, all ingested into the learning algorithm without any a-priori assumption about their individual marginal probability distribution or joint distribution. Furthermore, the input could be numerical or categorical in nature.

Fusion of Data with Models:

The aim of FORESEE is to detect and prognose faults for infrastructure systems in the face of extreme events, representing hazards (e.g. earthquakes, high rainfall, landslides). The fusion tool we propose relies on informa- tion from the system (e.g. bridge, tunnel) response under such extreme loads. Since extreme hazards are typically low probability events, it is not expected that ample data will be available for training. For this, data alone is not enough. Instead, fusion with models (e.g. structural models, traffic simulators, or flood models) will be necessary in order to create simulations of extreme load outcomes.

Fusion at the Outputs of the diagnostic tool level:

Both the Random Forest and the Bayesian Network diagnostic models predict, synergistically, the same quantity of interest; namely, an end state/fault emanating from a triggering event. To this end, we propose an ensemble learning method to fuse the prediction of both models. The scheme is based on local Clustering and bootstrap aggregation (Bagging) methods, which rather than treating the stochastic output of the models as competing individual information sources, treats those as part of an ensemble, thus diversifying the hypothesis space. We call the proposed fusion method: unsupervised local cluster-weighted bootstrap aggregation, as described in an upcoming FORESEE journal publication [29].

5 UTILIZATION WITHIN THE FORESEE CASE STUDIES

It is noted that what is outlined below if the possible set of information/data that can be fed into the RF and BN algorithms described previously. However, further input may be exploited from the traffic flow models produced as part of WP3, as well as algorithmic tools such a the risk mapping (WP2), earthquake assessment (WP4), and optimal intervention algorithm (WP4), whereby information on different risks and thresholds for defining leaves (faults) may be derived. Finally, as aforementioned, the classification system of the IMA tool developed in the context of the RAGTIME project can be utilized for defining damage classes and Key Performance Indicators (KPIs).

CASE STUDY #1 - Carsoli-Torano (Italy): A24 Highway & CASE STUDY #2 Naples to Bari (Italy) - A16 Highway

- <u>Relevant Systems</u>
  The case study focuses on the road linear network and critical assets, focusing on tunnels and bridges.

- <u>Relevant Hazards</u>
  The main hazards that affect this case study are earthquakes, extreme weather (mainly in the form of snow), and the cascade effects on transport in cases of heavy traffic.

- <u>Relevant Data</u>
  Meteo data,quarterly and annual inspection data, consolidated maintenance programmes on pavements, green works, hydraulic regulation, etc.

  For CS2, it is expected to integrate the current monitoring systems with SHM, geotechnical monitoring and satellite (SAS) data stemming from work in WP2.

- <u>Relevant Models</u>
  Structural models of typical bridges, established in the SAP 2000 engineering software.

- <u>Relevant Faults</u>

Bridge damage, with the gravity preferably defined in accordance to the IMA toll of project RAGTIME, e.g. dislocation of the deck after seismic events. Highway blockage.

CASE STUDY #3 - Montabliz Viaduct (SPAIN)

- Relevant Systems
  The bridge system itself.

- Relevant Hazards
  Natural risks (flood, wind, fog, snow) and man-made hazards (accident - fires).

- Relevant Data
- Monitoring data including a) movements (foundations, top of the pile, etc.); b) strains (critical sections of foundations, piles and deck); c) temperature (longitudinal and transverse thermal gradients in piles and vertical and horizontal in deck); d) wind (speed and direction) and e) accelerations.

- Relevant Models
  Structural model of the bridge. Traffic flow models relating to work conducted in WP3.

- Relevant Faults
  Accidents due to extreme weather events

CASE STUDY #4 – RAILWAY TRACK 6185 (Oebisfelde-Berlin Spandau)

- Relevant Systems
  The railway track. This includes all parts of the track, including embankment, super-structure, electrical devices nearby the track and surroundings, like pavements etc.

- Relevant Hazards
  The extreme events in this case study will be flooding caused by rain and rising water levels in the river lying nearby a railway track.

- Relevant Data
  All necessary data and relevant information will be collected regarding the exact location and surroundings for the Case Study.

- Relevant Models
  The Case Study will be done virtually with simultaneously water level rising and analyses step by step.

- Relevant Faults
  Structural damage. Electrical system faults.

CASE STUDY #5 - M-30 RING ROAD (MADRID-SPAIN)

- Relevant Systems

The highway, which incorporates a number of tunnels.

- Relevant Hazards
  Flooding and other extreme events due to rainfall in the valley (east side of the ring). Man-made events including cyberattack and accidents (average number of 14 interventions/day due to accidents) or fire (generally caused by accidents).

- Relevant Data
  Historic and real-time monitoring data on rainfall, accidents, cyber-attacks, and flooding in critical sections and tunnels of the road system. Data on pumped volume of water. Traffic volume data.

- Relevant Models
  Flooding & traffic models.

- Relevant Faults
  Delays, traffic jams.

CASE STUDY #6 - 25th April Suspended Bridge - Lisbon (Portugal)

- Relevant Systems
  This singular structure is a multimodal element and includes both rail and road.

- Relevant Hazards
  Earthquakes and man-made (train accident).

- Relevant Data
  The bridge features a structural integrity monitoring system, consisting of 200 sensors with the ability of data acquisition and processing in real time, which provides more than 8.5 billion measurements per day, including acceleration, displacement, rotation and tensions.

- Relevant Models
  Structural model of the bridge. Traffic flow models.

- Relevant Faults
  Structural damage, blockage due to train accident

6 LINKS TO THE WORK CONDUCTED WITHIN FORESEE

The hybrid fusion framework we describe is flexible in that it admits different types of data as inputs.

- In this sense, the metrics developed as part of the "Level of Service and Resilience in infrastructures" module of Task 1.1 (**WP1**) could form an indicator that serves as input to our system-specific RFs. This is not straightforward since such an incorporation would require the standardization of such metrics across assets.

- The remote monitoring data generated as part of **WP2** (InSAR data) are already exemplified as a type of data-input, which can be informative on ground motion and settlement.
  The risk mapping module developed as part of **WP2** can guide the specification of "faults" and relevant triggering events.

- The adaptation measures, developed as part of **WP3**, and the intervention and mitigation actions, defined in WP4, could contribute to the "actions" class of our OO framework, based on which an evolving system model can be developed.

- The development of shakemaps (Task 4.2) and the SHM algorithms (Task 4.5) developed within **WP4** can be used to define the inputs of hazard intensity and condition indicators of the monitored system, respectively.

- The damage classification system and the corresponding KPIs documented in the extended database of the **IMA RAGTIME** tool, can be exploited for defining condition levels, which herein are assumed as the leaves of the constructed RFs.

- The proposed framework can be used to associate a particular type of damage with occurrence of a triggering event. For instance, when examined in the context of a bridge exposed to an earthquake hazard, this approach can be compared against the results produced as part of Decision support module developed by RINA-C in Task 3.4.2 (**WP3**). On the other hand, when treating the bridge as a system lying within a more extended system (highway), it possible to replace the RF describing the bridge with the outputs of the tools in Task 3.4.2, such as fragility functions, loss functions, vulnerability functions.

- The established Object Oriented Hybrid Data Assessment framework will form an important tool of the Data integration process (**WP5**). As part of preliminary work for Task 5.2.1 the graph probabilistic structures (RFs & BNs), which naturally form a means for integrating diverse data sources are prepared for incorporation within the FORESEE toolkit.

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