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**WHITE PAPER**

# **Predictive Maintenance of Railway Bridges Through an Internet of Things Framework**

## An Implementation Proposal

By Hitachi Vantara

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April 2020

# Foreword

Often government is something we notice when it (quite literally) breaks down, when it falls apart, sometimes with tragic consequences.

Antonio Lugara' and Diego Bruciafreddo have drawn upon their backgrounds in civil and transportation engineering, data science, and the internet of things to develop a framework for identifying imminent failures of railway bridges before they lead to tragedy. The method doesn't rely on the manual inspection so common in identifying these types of incipient failures; instead, it uses sensor and communications technologies affixed to railway vehicles coupled with modern machine learning techniques to predict railway bridge degradation in time to implement preventative measures.

The blueprint is novel in two ways. First, this unconventional data is used to model the behaviors, including deflection, vibration and other modes of operation, validating them against the traditional closed-form engineering problem. Second, these statistical properties are continuously captured by passing vehicles so that trends toward degradation of the mechanical properties of the bridge can be discovered before such limits are breached, even presenting the opportunity to model the bridge's response to different vehicle loads over time.

It is easy to see how this nontraditional technique can yield promising results beyond the inspection of railway bridges, with the extension of the principles to conventional roads, buildings and even processes. Hitachi has made a commitment to Social Innovation and Lugara' takes an approach that combines the optimisation of economic, social and environmental values through its contribution to cost savings, safety improvements and improved use of materials.

I encourage you to read on, and to think about how this model might be applicable elsewhere.

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17 April 2020

# Contents

<b>Executive Summary</b>	<b>4</b>
<b>An Introduction to Predictive Maintenance</b>	<b>4</b>
<b>Railway Bridges and the Maintenance Problem: a Physical-Mathematical Framework</b>	<b>5</b>
<b>Continuous Monitoring of the Infrastructure as a Basis for Predictive Maintenance</b>	<b>16</b>
<b>The Internet of Things and the Predictive Maintenance of Railway Bridges</b>	<b>17</b>
Field Data	18
Engineering Data	22
Data From Remote Traffic Control Systems	22
Enterprise IT Data	23
Exogenous Data	23
<b>Hitachi's Lumada: A Framework for the Predictive Maintenance of Railway Bridges</b>	<b>25</b>
<b>Conclusions</b>	<b>35</b>
<b>Appendix A: References</b>	<b>37</b>

# Predictive Maintenance of Railway Bridges Through an Internet of Things Framework: an Implementation Proposal

## Executive Summary

In the field of civil infrastructures, the vast majority of those built since the middle of the last century are subject to a global deterioration of mechanical properties. This decline is due to varied loads and operating conditions compared to the design, to the aggression of atmospheric agents (for example, freeze-thaw cycles), and sometimes, to under-sized maintenance actions. The availability of new technologies of sampling, extraction and data analysis are some of the key factors that can automate and streamline maintenance strategies.

Within the era of the industrial internet of things (IIoT) there is a cross fertilization between railway engineering and information technology. This enrichment requires the use of vertically integrated knowledge to overtake the paradigms of the classical engineering.

This work is intended to provide several theoretical pointers regarding not only structural and railway engineering, but also the industrial internet of things. It explains how integrating the two creates a unified vision that allows administrators to recognize their complementarity in the specific cases analyzed. Understanding this, administrators can exploit new IoT technologies to automate and simplify maintenance activities and related complex and time-consuming structural verifications.

## An Introduction to Predictive Maintenance

Nowadays, more frequently than ever, organizations are looking at their operations and how to reduce costs. They are experiencing global supply chains, aging assets, raw material price volatility, increased compliance, aging workforce and additional bureaucratic constraints.

In the field of civil infrastructures, the vast majority of those, built since the middle of the last century, are subject to a global deterioration of mechanical properties. This decline is due to varied loads and operating conditions compared to the design, to the aggression of atmospheric agents (for example, freeze-thaw cycles), and sometimes, to under-sized maintenance actions.

A big opportunity to achieve these results is constituted by the development and application of a predictive maintenance (PM) framework<sup>1</sup>. The reduction of IT costs related to computing capacity, networks and data storage is pushing a new maintenance paradigm facilitated by the large amount of data generated by the proliferation of intelligent and interconnected sensors. The need to operate with ever smaller budgets and the continuous search for the extension of the useful life of the assets push organizations to build innovative solutions: Information technology (IT) enables the solution of problems through the collection, storage and analysis of heterogeneous databases built starting from endogenous and exogenous sources with respect to the systems being analyzed.

The PM, intersecting IT and operational technology (OT), help to provide organizations with key insights regarding the responses of civil infrastructures: in this specific case, railway bridges. Insights are provided with respect to static and dynamic stresses, as well as quality of materials, and enable organizations to optimize maintenance activities, processes and workforce schedules. PM could represent the killer application to compete within a globalized and under-pressure marketplace. It could contribute not just to guarantee the safe utilization of bridges, but also to reach benefits related to operative results and methodologies. Among the operative improvements are:

- Optimization of maintenance intervals.
- Substantial reduction of unplanned traffic ban periods and related alternative mobility.
- Optimization of the timing and methods of execution of maintenance activities, avoiding urgent intervention derogating from procurement regulations.

While with respect to methodologies and tools, it is possible to achieve the following results:

- Identification of the causes of deterioration through *ad hoc* analyses.
- Improvement of tools and processes for diagnosis.
- Determination of optimal maintenance procedures.

## **Railway Bridges and the Maintenance Problem: a Physical-Mathematical Framework**

Whether it is a viaduct or an overpass, a bridge is a civil engineering work that quantitatively meets the need of terrestrial communication to overcome obstacles; that need is indissolubly connected with the economic and social development of a civilization. Studies and realization of bridges for millennia have defined different structural declensions; however, each of them can be classified into the following paradigm:

- Position of the roadway (deck bridge or through bridge).
- Construction scheme (arch bridge, girder bridge, cable-stayed bridge and suspended bridge).
- Static scheme (isostatic bridge and hyperstatic bridge).
- Material of construction (masonry, steel, reinforced concrete and pre-stressed concrete).

Clearly, the structure of a bridge must meet all well-defined performance requirements to satisfactorily comply with the specifications of the vehicles. Furthermore, it is understood that, as a civil engineering work, a bridge exhibits a response that is a generic function of time: It is intimately connected with both the rheology of the constituent materials and the variables linked to the project load that have been raised from the socioeconomic system. It is also connected as the predictive models of transport demand adopted in the design phase. For instance, it is possible to think about the viscous phenomena that characterize the concrete, the relaxation phenomena of the steel or the number of vehicles that has dramatically increased from the post-war period to nowadays. The last statement expresses that an acceptable repeatability of the response over time cannot be achieved without a precise plan of interventions. Such a plan allows the restoration or strengthening of a specific characteristic once the need for that is proved. Neglecting, at least partially, the activities connected to the system development, the preservation of the features necessary for the bridge to serve the purpose it was designed for passes through the maintenance operations. When planning maintenance operations on a railway network it has to be taken into account that the communication route is interspersed with multitude of bridges. Moreover, as mentioned above, there are several structural declensions for the construction of a bridge, depending on local boundary conditions, and those can be found in an equiprobable manner. To clarify aforementioned information and to depict the importance of the bridge maintenance problem with respect to the guaranty of the functionality of the railway network, it is possible to check, for example, the data that can be found on the Italian Railway Network (RFI) website<sup>2</sup>, where it is stated that among over 16,000 km of railway lines there are almost 26,000 bridges and viaducts, for a total extent of about 800 km<sup>3</sup>.

The simplest method for routine maintenance is based on the concept of cyclical maintenance. That is, the interval between two successive maintenance operations is determined *a-priori* by physical-mathematical models. These models determine how long it is necessary to carry out interventions to maintain the effectiveness of the infrastructure. The method has a low initial cost but shows low effectiveness due to the intrinsic limitation of the models used. Such models are not able to grasp and predict the large number of real variables that influence the safety of the structure. For instance, activities based on cyclical maintenance are not able to detect phenomena, such as changing the response following a failure of the infrastructure foundations or due to violent natural phenomena.

A method that provides greater effectiveness but with a higher cost is known as condition-based maintenance. In summary, the maintenance on condition is based on the passage on the network of special trains. These trains are properly equipped to perform measurements of a set of characteristic parameters related to the proper functioning of the network. (See Figure 1.) The frequency of the passage of the train, as well as its characteristics, are related to the

importance of the line. This technique allows the execution of an intervention only when this is really necessary, but those measurements are discontinuous during the time and exerted with specific time windows.

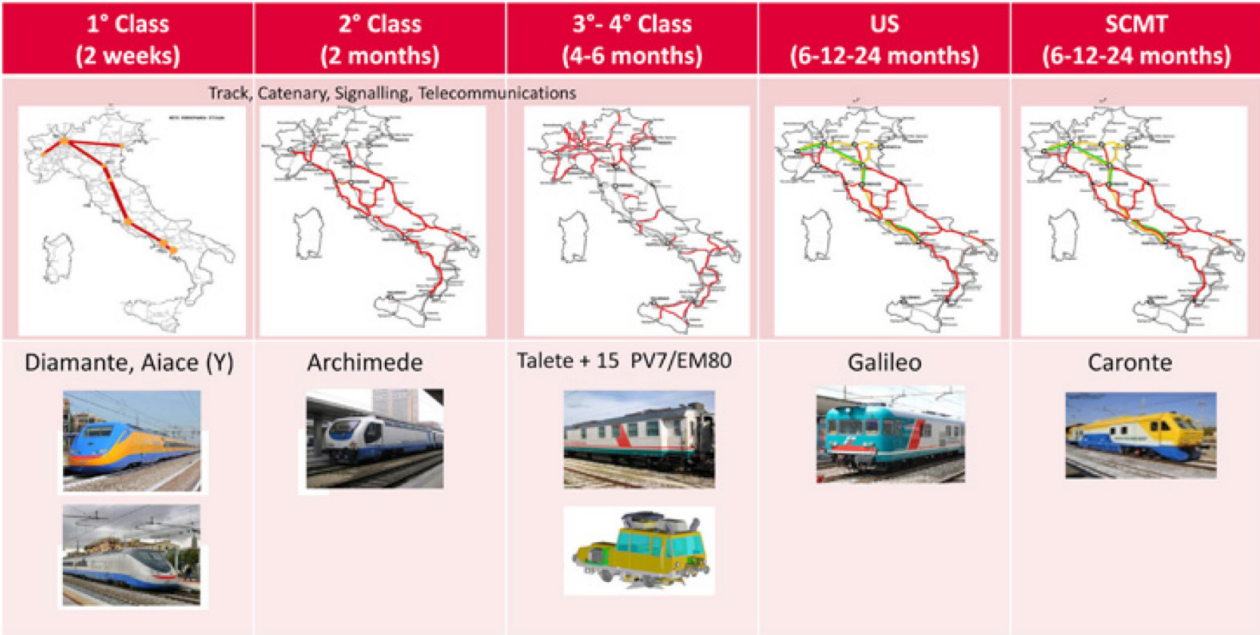


Figure 1. Fleet of RFI Diagnostic Trains and Measurement Intervals<sup>4</sup>

Although different methods of application are feasible (for example, see endnote 4, regarding RFI), the employment of condition-based maintenance is limited by high cost. This is due to the necessity of having a dedicated fleet of trains that are moving on the network without transporting freights or passengers. Furthermore, it is not easy to plan maintenance properly as the actions will be executed only when the registered parameters show some critical values. Additionally, like the cyclic maintenance, the method of the maintenance on condition is not able to perform a continuous monitoring of the network. As a result, it is not possible to recognize some problems on the network due to occasional events.

From the point of view of maintaining the proper network functioning, the methods explained so far are characterized as:

- Cyclical, with low costs and low effectiveness.
- Conditional, with high costs and medium-high effectiveness.

Due to the crucial importance of the transport system and the related risks that could be potentially serious, the necessity to use a highly effective system might be considered. The optimal functioning is reached when with equal effectiveness the costs become financially sustainable.

Considering its essence, one aspect of maintenance on condition that intrinsically costs, is the “single use” application of the recorded data. Such data may not even be stored and indexed once its diagnostic function has been completed.

Predictive maintenance is an evolution of condition-based maintenance, which aims simultaneously to increase effectiveness and cost containment (see, for example, Hashemian *et al.*<sup>5</sup>). This type of maintenance, through the constant collection of data, enables the generation of a statistically representative database. It facilitates the construction of mathematical models, which, analyzing the different correlations between measured signals and events, allow you to determine, or better predict, the incipient anomalies, even before those occur. It is clear that the application of this method cannot be considered apart from an extended campaign of measurements. The ideal conditions would be reached when the measurements would be taken at each passage on the line, a situation that would allow

continuous monitoring of the conditions of the system. This approach also enables the generation of a robust database consolidating the validity of statistical and physical mathematical deductions.

To better illustrate the general concepts, consider the simple example in Figure 2. It highlights the fact that the generation of a database fed by longitudinal data in close sequence can allow a continuous monitoring of the structure (or the monitoring of some of its features) of the railway bridges present on the network. A similar approach has been already applied in many researches (for example, Natoni<sup>6</sup>).

Consider the simplest conceptual model of a train crossing a bridge consisting of a beam with distributed mass and stiffness on which a traveling force  $P$  with constant speed  $c$  is moving. This representation is equivalent to the fact that the inertial effects related to the train mass can be neglected, and the spatial extension of the bridge is predominant compared with that of the train (Fryba<sup>7, 8</sup>).

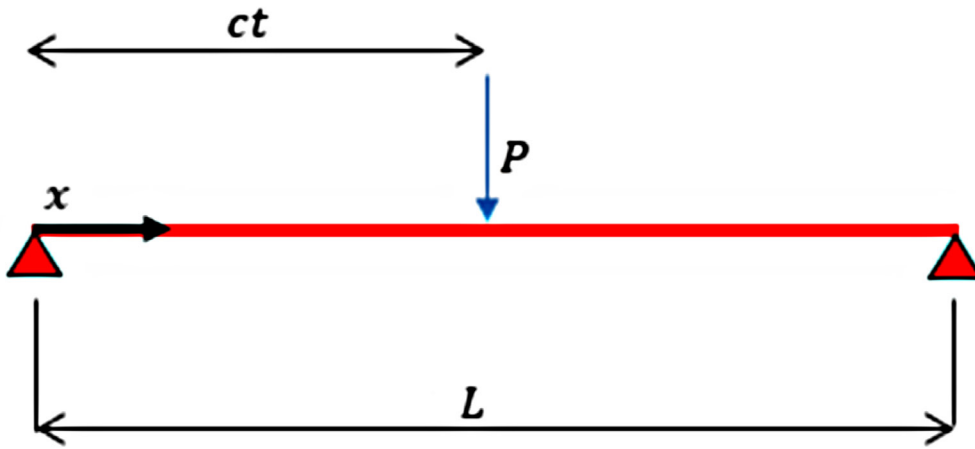


Figure 2. Reference Scheme To Model the Bridge Crossed by a Traveling Force

The following hypotheses are also considered:

- The behavior of the beam is described by the differential equation of Euler-Bernoulli inferred on the assumption of small deformations. Hook's law, the Navier hypotheses and the De Saint Venant principle are also all valid for this model. The beam has a cross-section area and a constant mass per unit of length.
- The mass in motion is relatively small in comparison to that of the beam, so it is possible to neglect the inertial effects.
- The speed of the moving load is constant and the direction is from left to right.
- Damping can be neglected.
- The beam is considered at rest and undeformed before the load application.

The equation of motion for the described case holds:

$$\mu \ddot{v}(x, t) + EI v^{IV}(x, t) = \delta(x - ct)P \quad \{1\}$$

Where:

- $\mu$  is the mass per unit of length of the beam.
- $E$  is the elastic flexural stiffness of the beam.
- $v(x, t)$  is the function that describes the vertical displacement of the beam.
- $\delta(x-ct)$  is the Dirac delta function characterized by the point of horizontal axis  $x_0 = ct$ , which allows the treatment of a concentrate load in the guise of a distributed one (Hoskins<sup>9</sup>).

The equation holds true for  $0 \leq t \leq t_D$  where  $t_D = L/c$  is the time of stay of the load P applied on the beam.

The solution of the above equation is possible in a closed form using a modal expansion for the displacement variable of the type:

$$v(x, t) = \sum_{n=1}^{\infty} v_n(x, t) = \sum_{n=1}^{\infty} \phi_n(x) q_n(t) \quad \{2\}$$

Where the single modal contribution of the displacement variable is written as the product of two single-parameter functions  $\phi_n(x)$ , representing the space of possible configuration and  $q_n(t)$ , which is the Langrangian parameter. The  $\phi_n(x)$  is dependent only on the geometric variable and the boundary conditions while the  $q_n(t)$  is the unknown quantity that defines, once determined for each instant, the amplitude of the  $n^{th}$  modal form.

In the case of a simply supported beam, the following hypotheses can be considered (Chopra<sup>10</sup>):

$$\phi_n(x) = \sin\left(n\pi\frac{x}{L}\right) \quad \text{and} \quad \omega_n = \frac{n^2 L^2}{\pi^2} \sqrt{\frac{EI}{m}} \quad \begin{matrix} \{3a\}, \\ \{3b\} \end{matrix}$$

It is also possible to identify the following variables:

- Total mass of the  $n^{th}$  mode:

$$M_n = \int_0^L \mu \phi_n(x)^2 dx = \mu \frac{L}{2} \quad \{4\}$$

- Equivalent stiffness of the  $n^{th}$  mode:

$$K_n = M_n \omega_n^2 = \mu \frac{L}{2} \frac{n^4 \pi^4 EI}{L^4} \frac{1}{\mu} = \frac{n^4 \pi^4 EI}{2L^3} \quad \{5\}$$

- Equivalent force of the  $n^{th}$  mode:

$$P_n(t) = P \int_0^L \delta(x-ct) \phi_n(x) dx = P \phi_n(ct) = P \sin\left(\frac{n\pi ct}{L}\right) = P \sin\left(n\pi \frac{t}{t_d}\right) \quad \{6\}$$



For the calculation of the equivalent force the properties of the Dirac function were used (see, for instance what is reported in endnote 5). It can therefore be seen that the equivalent force is a harmonic with angular frequency  $\omega_{D_n} = n \pi / t_d$ .

At this point in time, the problem, for each single mode, leads to the calculation of the response of a simple oscillator stressed by a harmonic forcing with frequency reported in the statement {6}. The result is the following:

$$M_n \ddot{q}_n(t) + K_n q_n(t) = P \sin(\omega_{D_n} t) \quad \{7\}$$

The solution of the equation {7} can be obtained as following (see Chopra, endnote 9):

$$q_n(t) = \frac{P}{K_n} \frac{1}{1 - \left(\frac{\omega_{Dn}}{\omega_n}\right)^2} \left( \sin(\omega_{Dn} t) - \frac{\omega_{Dn}}{\omega_n} \sin(\omega_n t) \right) \quad \{8\}$$

That making explicit the variables becomes:

$$q_n(t) = \frac{2P}{\mu L \omega_n^2} \frac{1}{1 - \left(\frac{n\pi c}{L \omega_n}\right)^2} \left( \sin\left(n \pi \frac{c}{L} t\right) - \frac{n\pi c}{L \omega_n} \sin(\omega_n t) \right) \quad \{9\}$$

The above equations, which have been applied for each mode and for infinite numbers according to the equation {2}, link the variables related to the moving system (magnitude of force and speed) with those relevant to the beam (mass, flexural stiffness, length) and determine its response by the following modal recomposition:

$$v(x, t) = \sum_{n=1}^{\infty} \sin\left(n \pi \frac{x}{L}\right) q_n(t) \quad \{10\}$$

If the modal equation is applied for  $x = L/2$ , it is possible to obtain ( $r$  is a non-negative integer):

$$\phi_n\left(\frac{L}{2}\right) = \sin\left(n \frac{\pi}{2}\right) = \begin{cases} 0 & \text{per } n = 2r \\ +1 & \text{per } n = 1 + 4r \\ -1 & \text{per } n = 3 + 4r \end{cases} \quad \{11\}$$

It is worth noting that all the contributions of even modes are irrelevant to the response at the centerline. Since the contributions of the higher modes can be neglected, an excellent approximation is obtained by using the first vibration mode only. In fact, as schematically shown in Figure 3 (see also Chopra, endnote 9), the increase related to the number of modes does not lead to significant variations in the response compared to that calculated for just the first mode.

It is possible for the first mode to put an immediate physical interpretation on the Lagrangian parameter  $q$  by assuming the meaning of the displacement in the centerline:

$$v\left(\frac{L}{2}, t\right) = \sin\left(\frac{\pi \frac{L}{2} 1}{L}\right) q(t) = q(t) \quad \{12\}$$

$$v\left(\frac{L}{2}, t\right) = \frac{2P}{\mu L \omega_n^2} \frac{1}{1 - \left(\frac{\pi c}{L \omega_n}\right)^2} \left( \sin\left(\frac{\pi c}{L} t\right) - \frac{\pi c}{L \omega_n} \sin(\omega_n t) \right) \quad \{13\}$$

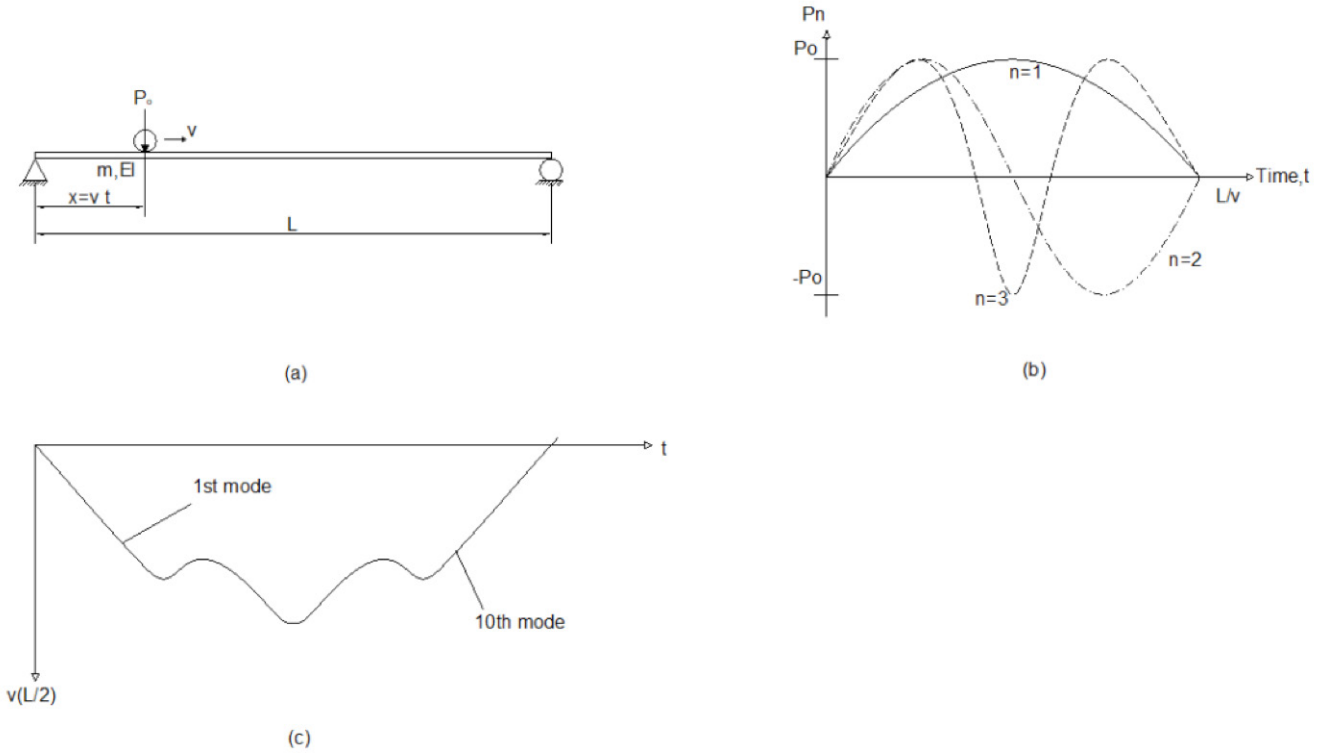


Figure 3. (a) Scheme of traveling force on the elastic beam. (b) The modal decomposition of the traveling force is shown; for the  $n^{th}$  mode it consists of  $n$  half cycles of sinusoidal forcing. (c) It is shown how the final results obtained considering the fundamental mode only and the one utilizing the first 10 modes, respectively, are almost coinciding.

According to what has been already explained, the traveling force and the beam represent a moving train and the bridge, respectively. With an accelerometer in a reference system integral to the train, it would be possible to record, moment by moment, the vertical accelerations defined as  $a_v(t)$ . The acceleration at time  $t$  corresponds to the acceleration experienced by the bridge on point  $x = ct$  and, therefore:

$$\ddot{v}(ct, t) = a_v(t) = \sin\left(\pi \frac{ct}{L}\right) \ddot{v}\left(\frac{L}{2}, t\right) \quad \{14\}$$

or rather by applying acceleration at the midpoint of the bridge it is possible to obtain:

$$\ddot{v}\left(\frac{L}{2}, t\right) = \frac{a_v(t)}{\sin\left(\frac{\pi c t}{L}\right)} \quad \{15\}$$

Utilizing the expression obtained for the displacements, it is possible to achieve:

$$\frac{a_v(t)}{\sin\left(\frac{\pi c t}{L}\right)} = -\frac{\pi c}{L} \frac{2P}{\mu L \omega_n^2} \frac{1}{1 - \left(\frac{\pi c}{L \omega_n}\right)^2} \left( \frac{\pi c}{L} \sin\left(\frac{\pi c}{L} t\right) - \omega_n \sin(\omega_n t) \right) \quad \{16\}$$

With simple calculation it is possible to get:

$$a_v(t) = -\frac{\pi c}{L} \frac{2P}{\mu L \omega_n^2} \frac{1}{1 - \left(\frac{\pi c}{L \omega_n}\right)^2} \left( \frac{\pi c}{L} \sin^2\left(\frac{\pi c}{L} t\right) - \omega_n \sin(\omega_n t) \sin\left(\frac{\pi c t}{L}\right) \right) \quad \{17\}$$

The equation {17} is valid, moment by moment, while the train is passing on the bridge. Now, supposing that the speed and mass of the train are known and the length of the bridge is also given or can be obtained by analyzing the vibrations of the system (identifying in this way the validity interval of the equation {17}); the only two unknown variables would therefore be the frequency and the mass of the bridge. Assume that we obtain these quantities using the  $a_v(t)$  measurements recorded at each passage of the train. This would mean that with each passage of a train on a bridge the relative fundamental parameters of the response could be determined, monitored and stored.

In theory, the aforementioned procedure allows the possibility to have a continuous monitoring of the response of a bridge. This determines its salient stiffness parameters and the temporal history of its response. As widely described in the literature (see, for example, Buda et al.<sup>11</sup>) the presence of a damage in a straight beam can be interpreted as a decrease of the physical and geometric characteristics of the cross section in a portion of finite length of the beam. As a more pertinent example, referring to the railway engineering, many methods are already known where a correlation between the status of the tracks and the measured parameters of the motion is quantified. For example, Bruner et al. propose a mathematical model of the railway infrastructure on which they defined a damage index based both on energetic consideration and measured parameters of the tracks.

The continuous monitoring of the stiffness features of the bridge and its mass could allow the observation of its temporal evolution and predict when it will start showing dangerous drift signals or simply to detect when the functionality of the system decreases and, if necessary, to perform a rigorous revision.

The equation {17} is valid when a train with known parameters passes over the bridge and the vertical accelerations in the centerline of the bridge are recorded. However, in this case an argument of convenience must be offered. Since thousands of bridges have to be monitored, theoretically thousands of measuring instruments would be required on the various bridges, and tremendous efforts would be needed from an organizational perspective. In the case of a train moving in line, with just one system of instruments installed onboard, it would be possible to monitor a multitude of structures that are crossed by the train during its route.

The above example depicts how it is possible, based on theories of physics, to correlate the recordings performed on board with precise structural parameters related to the infrastructure crossed. In fact, it legitimizes the rather intuitive consideration that, from the sole analysis of the behavior of the vehicle, a hypothetical driver can give an immediate judgment on the state of health of the bridge crossed.

However, to apply the methodology not just to a theoretical exercise, but to real trains circulating on the infrastructures, the mathematical model necessarily has to be more complex. The measured variables must be chosen in a targeted manner to capture the aspects that effectively provide information about the health status of the infrastructure.

To better illustrate the difficulties and the limits concerning the analysis applied to a real interactive system train-bridge-railway structure, it is necessary to identify in a more rigorous way the variables involved in the physical-mathematical problem of the calculation of the response of a train moving on a bridge. To consider the problem in its entirety, refer to Figure 4 (see endnote 5):

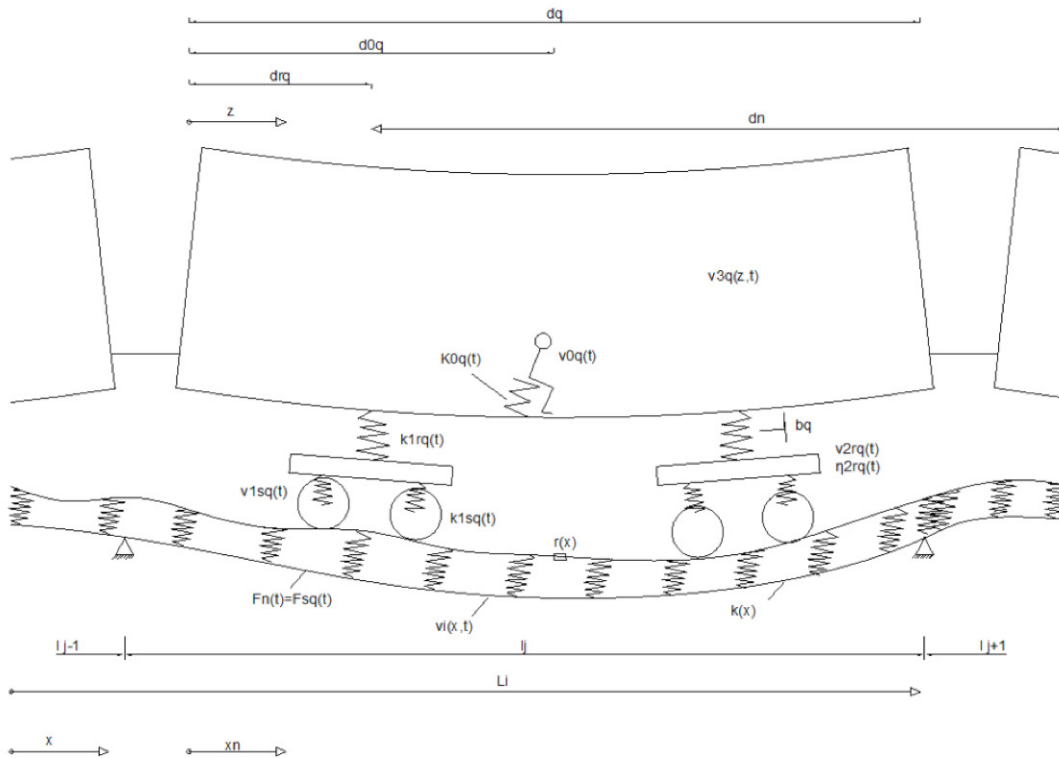
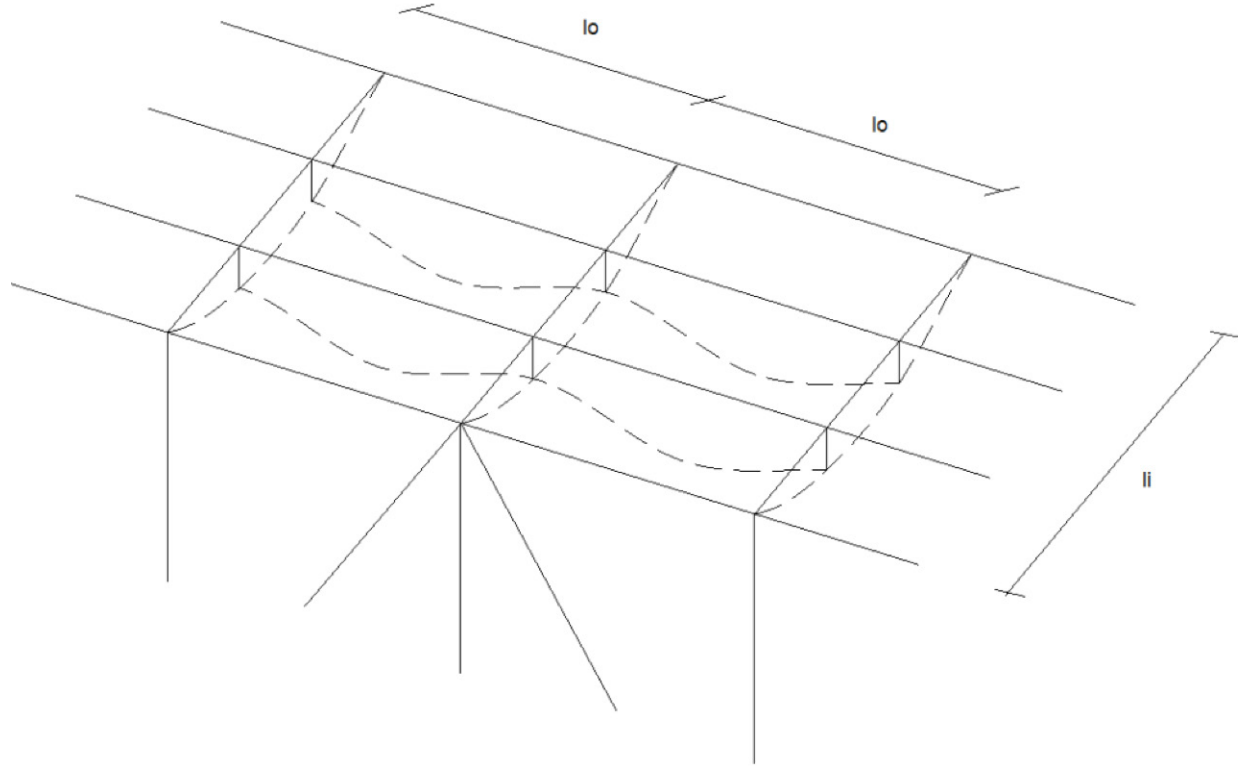


Figure 4. Representation of the Mathematical Model of a Moving Train on a Railway Bridge

Having fixed  $x$  so that the origin coincides with the starting point of the bridge, the mathematical model able to reproduce the railway bridge is a system of elastic beams with distributed mass  $\mu_i(x)$ . It has a stiffness of  $EI_i(x)$ , and damping proportional to the speed of vibration  $(\omega_{bi})$ , in which the subscript  $i$  represents the span whose total number is  $I$ . The vertical deflection functions  $v_i(x, t)$  is unknown.

The bridge supporting the railway structure is modeled with a variable distribution of elastic springs that simulate the variability of rigidity offered to the train depending on the distance from the crosspiece (see Figure 5) and the transversal position in which it moves. A typical equation (see Fryba, endnote 6) for the distribution of springs can be obtained as following:

$$k(\xi) = k_1 + k_2 \cos\left(2\pi \frac{\xi}{l_0}\right) \text{ con } 0 \leq \xi \leq l_0 \quad \{18\}$$



**Figure 5. Local Deformability of the Bridge Determined by the Distance From the Beams**

Referring to the model above, let  $k_i(x)$  be the distribution of springs that represents the bridge for the single span, while  $r_i(x)$  is the function that describes the irregularities of the layout. In the modeling of the bridge the effect of the ballast should also be taken into account. Even if it does not lead to an exact solution, the ballast could be modeled as an additional elastic layer of constant stiffness ( $k_2 = 0$ ) in the equation {18} that appropriately adds to the stiffness offered by the bridge. For alternative modeling see, for example, Desai *et al.*<sup>12</sup>, or Bruner *et al.*<sup>13</sup>.

The railway vehicle is modeled by a single wagon by introducing three dynamic systems interacting together: the frame of the wagon, the bogies and the axles of the wheelsets. An additional vibrating element can also be added inside the frame (for example, a passenger). (See Figure 4).

The frame of railway  $q^{mo}$  wagon, of length  $d_q$ , is modeled as a simply supported beam with distributed mass and elasticity. The densities of mass and elasticity are constant and respectively  $\mu_{3q}$  and  $E_{3q} I_{3q}$ . The beam rests on the two supports by means of elasto-plastic springs of constant  $K_{2rq}$  in a local reference system  $z$  with the origin of the coordinates located on the starting point of the wagon from the left. The function  $v_{3q}(z, t)$  is unknown. The bogies, each placed at the abscissa  $d_{rq}$  are modeled as rigid masses  $m_{2rq}$  with moment of inertia  $I_{2rq}$  (the subscript  $r$  can be 1 or 2), two unknown degrees of freedom, the average vertical displacement  $v_{2rq}(t)$  and the rotation  $\eta_{2rq}(t)$ . They are connected to the upper wagon through the aforementioned springs system and below to the axles that are represented as masses  $m_{1sq}$  (with  $s$  referring to the axis). These, in turn, are connected to the bridge with a system of springs characterized by rigidity  $K_{1sq}$ .

The passenger located at the  $d_{0q}$  described as a mass  $m_{0q}$  with vertical degree of freedom  $v_{0q}(t)$  is supported by an elastoplastic system  $K_{0q}$ .

To fix the train position globally we use the coordinate of the first axis from the left of the train  $u(t)$  [being  $u(t) = c t$  for constant speed equal to  $c$ ] and the distance  $d_n$  that identifies the gap of the  $n^{th}$  axis from the first to the left for which the relative position can be expressed as  $x_n = u(t) - d_n$ .

The unknown functions are therefore (considered positive downwards):  $v_i(x, t)$ ,  $v_{3q}(z, t)$ ,  $v_{2rq}(t)$ ,  $\eta_{2rq}(t)$ ,  $v_{1sq}(t)$ ,  $v_{0q}(t)$ .

For each unknown function it is possible to write the relative differential equation by adopting the D'Alembert principle of dynamic equilibrium:

$$-m_{0q} \ddot{v}_{0q}(t) - K_{0q}(t) = 0 \quad \{19\}$$

The term  $K_{0q}(t) = k_{0q} [v_{0q}(t) - v_{3q}(d_{0q}, t)] + B_{0q}$  is a compact notation for the elastoplastic force originating from the interaction of the motion of the passenger and the motion of the railway carriage.

The railway wagon identified by an Euler-Bernoulli beam has the following equation:

$$\begin{aligned} E_{3q} I_{3q} v_{3q}^{IV}(z, t) + \mu_{3q} \ddot{v}_{3q}(z, t) + 2 \mu_{3q} \omega_{b3q} \dot{v}_{3q}(z, t) = \\ = \delta(z - d_{0q}) K_{0q}(t) - \sum_{r=1}^2 \delta(z - d_{rq}) K_{2rq}(t), \quad q = 1, 2, \dots, Q \end{aligned} \quad \{20\}$$

Considering  $\delta(x)$  as a Dirac function, and  $K_{2rq}(t)$ , which is the visco-elastic force between railway wagon and bogies expressed in analogy to what previously mentioned:

$$K_{2rq}(t) = k_{2q} [v_{3q}(d_{rq}, t) - v_{2rq}(t)] + B_q \quad \{21\}$$

For the bogies, two equations for vertical and rotation displacement are obtained as following:

$$-m_{2rq} \ddot{v}_{2rq}(t) + K_{2rq}(t) - \sum_{s=1}^S K_{1sq}(t) = 0 \quad \{22\}$$

$$-I_{rq} \ddot{\eta}_{rq}(t) + b_q \sum_{s=1}^S (-1)^s K_{1sq}(t) = 0 \quad \{23\}$$

where  $r = \begin{cases} 1 \\ 2 \end{cases}$  per  $s = \begin{cases} 1, 2 \\ 3, 4 \end{cases}$  e  $q = 1, 2, \dots, Q$

The viscoelastic force between the axles and the bogies is described as following:

$$K_{1sq}(t) = k_{1q} [v_{2rq}(t) - (-1)^s b_q \eta_{rq}(t) - v_{1sq}(t)] \quad \{24\}$$

The motion of the single axle is equal to:

$$-m_{1sq} \ddot{v}_{1sq}(t) + K_{1sq}(t) - F_{sq}(t) = 0, s = 1, 2, 3, 4; q = 1, 2, \dots, Q \quad \{25\}$$

Where the force applied by the axle through the bridge is:

$$F_{sq}(t) = F_n(t) = k(x_n)[v_{1sq}(t) - v_i(x_n, t) - r(x_n)] + B \quad \{26\}$$

The last equation demonstrates the interaction between the vehicle and the railway bridge connected by means of an elastic layer and irregularity incorporating a viscous component B.

Finally, the railway bridge is characterized by the differential equation of the Euler-Bernoulli beam:

$$\begin{aligned} E_i \frac{\partial^2}{\partial x^2} [I_i(x) v_i''(x, t)] + \mu_i(x) \ddot{v}_i(x, t) + 2 \mu_i(x) \omega_{bi} \dot{v}_i(x, t) = \\ = \sum_{n=1}^N \varepsilon_{in} \delta(x - x_n) [F_q + F_n(t)], \quad i = 1, 2, \dots, I \end{aligned} \quad \{27\}$$

where  $F_q$  is the static force applied by the vehicle.

Each function  $v_i(x, t)$  holds true for  $L_{i-1} \leq x \leq L_i$  where  $\varepsilon_{in}$  has a unit value if  $L_{i-1} \leq x \leq L_i$ . The above equation holds true only if  $F_q + F_n(t) \geq 0$  (that is, if the vehicle maintains contact with the ground or vice versa it must be replaced with 0).

The known boundary conditions are:

- Bridge:

$$v_i(x, 0) = v_{i0}(x); \dot{v}_i(x, 0) = \dot{v}_{i0}(x) \quad \{28\}$$

- Wagon:

$$\begin{aligned} v_{3q}''(0, t) = v_{3q}''(d_q, t) = v_{3q}'''(0, t) = v_{3q}'''(d_q, t) = 0 \\ v_{3q}(z, 0) = v_{3q0}(z) \text{ e } \dot{v}_{3q0}(z, 0) = \dot{v}_{3q0}(z) \end{aligned} \quad \{29\}$$

- Bogies, axles and passenger (it is assumed that the vibrational motion of the different components of the train before entering the bridge is known):

$$\begin{aligned} v_{0q}(0) = v_{0q0} \text{ and } \dot{v}_{0q}(0) = \dot{v}_{0q0} \\ v_{1sq}(0) = v_{1sq0} \text{ and } \dot{v}_{1sq}(0) = \dot{v}_{1sq0} \\ v_{2rq}(0) = v_{2rq0} \text{ and } \dot{v}_{2rq}(0) = \dot{v}_{2rq0} \\ \eta_{0q}(0) = \eta_{0q0} \text{ and } \dot{\eta}_{0q}(0) = \dot{\eta}_{0q0} \end{aligned} \quad \{30\}$$

The described system of differential equations can be solved by any method of numerical analysis. However, the associated practical and computational burden assumes a relevance that makes it applicable only for some cases. In fact, the total number of equations is  $I + 6Q + N$ , so considering a train of 15 wagons ( $Q = 15$ ) with 4 axles ( $N = 60$ ) crossing a 4-span bridge ( $I = 4$ ), it will be obtained by a system of 154 coupled differential equations that well represent the implicit computational burden. Furthermore, the resolution is invalidated by the complexity related to the identification of the mechanical parameters related to the boundary conditions, such as:

- The stiffness that should be assigned to the bridge.
- The knowledge and availability of data relating to each bridge built.
- The health status of bogies and relative construction quality, and so forth.

Regarding additional difficulties, the model exposed so far, even if conceptually valid, doesn't account important phenomena like the circulation in curves, the dynamics concerning the bridge abutment, bridge pier discontinuity and so forth. Furthermore, the proposed set of equations is able to predict the dynamic of the system. However, as the paper is looking to a method to predict the damage from measurements, it is necessary to mention that there are many cases of collapse, properly named brittle fracture. These cases could happen without any appreciable variation of the dynamic response.

Yet, the set of equations introduced highlights the intrinsic complexity of obtaining solutions in a closed form, although the structure of the input data and the structure of the output data is known. The set suggests that the monitoring of the infrastructure for the purpose of predictive maintenance requires data analysis strategies that can be framed in the search for solutions to the proposed set of equations.

## Continuous Monitoring of the Infrastructure as a Basis for Predictive Maintenance

Considering what has been exposed so far, how would it be possible to proceed at a practical level to obtain an effective decision support system that can be built with a reasonable use of resources and an affordable complexity? To simply illustrate a strategy of real application, assume that the monitoring of the bridge starts at the time  $t_0$ , neglecting any previous information. This assumption will lead to the construction of a statistically representative dataset consisting of thousands of samples taken daily. A possible approach is to analyze the dataset using a method called "supervised." In this method, the structure of the input and output data is known (see the model described above), and correlation and dependencies are highlighted between the various variables objects of measurement. In this way, it is possible to constantly monitor the evolution of the variables being analyzed as time passes and along the utilization of the infrastructure.

An axiom states that a well-preserved and intact system must show a stable and perfectly framed response in the set of differential equations that govern the problem. This axiom can be used to understand which bridge requires attention thanks to the identification of potential drifts of the monitored parameters. The variables to be monitored for the interpretation of the behavior of the railway bridge are all those expressed in the equations shown above or part of them. Clearly, it could be thinkable, for particular cases, to simultaneously analyze measurements both onboard the train and on the bridge to handle use cases related to more complex scenarios. This approach bypasses the difficulty of modeling phenomena involved in the calculation, such as the effect of the ballast.

In addition to what was described so far, there is a further approach based on the mere analysis of the data: It consists of analyzing, without the direct application of physical-engineering theories, the amount of recorded data, and proceeding to the identification of recurring patterns using data discovery techniques based on "unsupervised methods." For instance, these methods identify recurrent relationships and patterns on multidimensional databases in conditions where the structure of the input data and the expected output are not known in advance.

Both the outlined conceptual approaches lead to the maximization of the results obtainable from the resources used for data measurement. They allow the construction of methods and models that facilitate a continuous network monitoring that is able to anticipate potential triggers that represent the symptoms of system failures.



Complex calculations are required, as well as the extraction and orchestration of the relative boundary conditions coming from several heterogeneous domains. This makes it unlikely that near-real-time analysis of the expected response can be performed compared to the measured one by entrusting the whole procedure to the “manual actions” of the technical personnel in charge. The amount of data to be managed, the complexity of data extraction and calculation processes, and the limited time interval in which to act, require the implementation of an automated solution. Such a solution must manage processes in parallel by balancing the enormous workload on a specially designed IoT framework. And this framework must operate a workflow in the face of the detection of certain threshold values or the identification of specific recurring patterns in the state variables being analyzed.

However, even if the mentioned *modus operandi* represents a significant evolution, it is important to underline that, at least referring to current knowledge, it is still necessary to add to the monitoring systems of dynamic response also other tests (such as visual inspections and specific investigations). This approach allows detection of defects that can be dramatically catastrophic, even without producing any significant alteration of the dynamic response until just before the collapse.

## The Internet of Things and the Predictive Maintenance of Railway Bridges

This section considers IoT and predictive maintenance of railway bridges, from the integration of heterogeneous data sources to the extraction of information, and logical-functional representation.

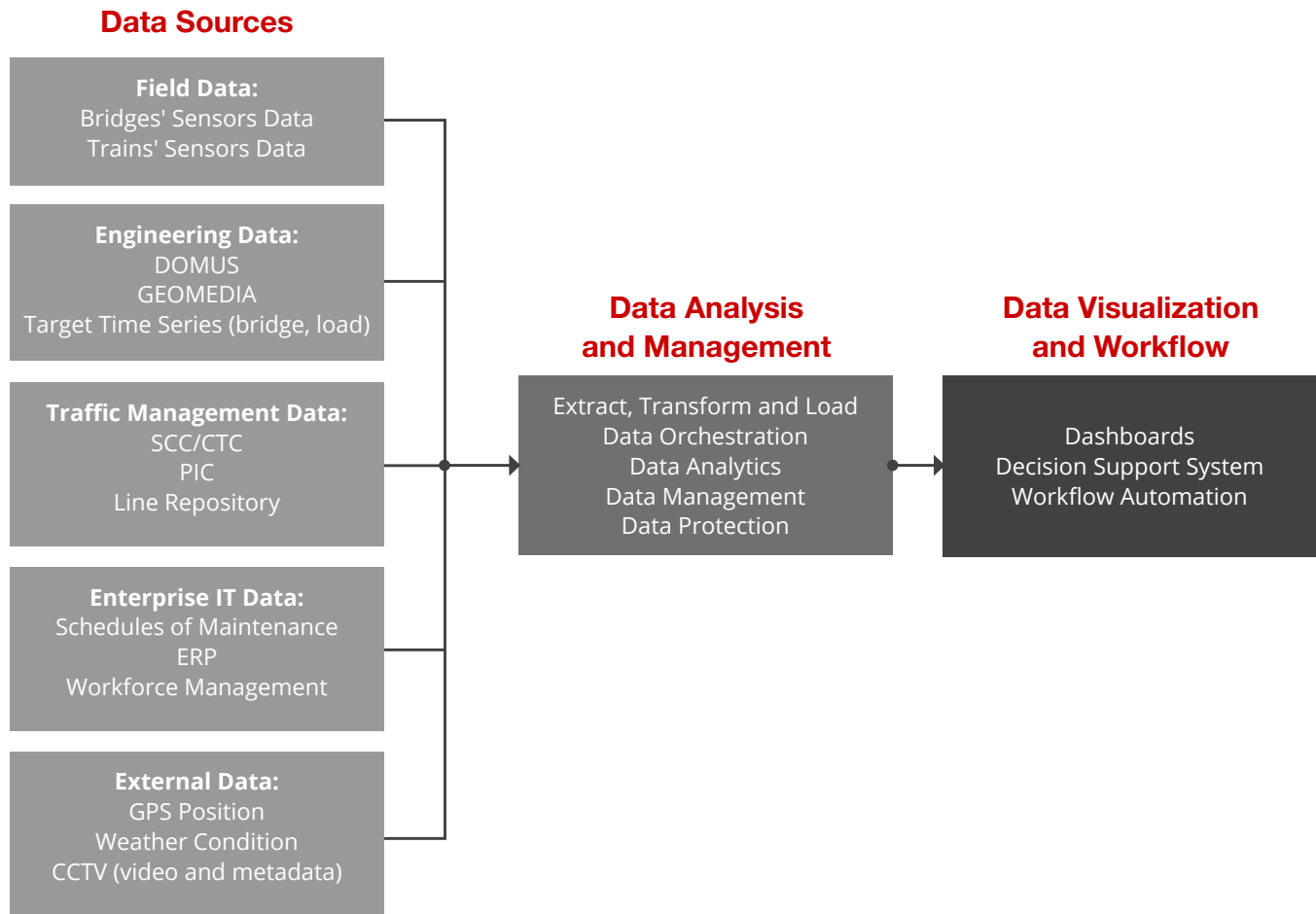
The theoretical approach discussed in the previous paragraph is of fundamental importance. It is used to design the IoT architecture necessary to build and use a data model able to broaden knowledge of the stability of trains and bridges and of their mutual interactions in different conditions of exertion. In fact, once the differential equations systems able to model the bridge’s response have been identified, it will be necessary to collect further data (for example, irregularities in the rail profile, incidence of hysteresis cycles of different materials during previous seismic events, and so forth). Such data is needed to calculate the expected response of the bridge and determine what could be particularly destabilizing for the train running: For example, impulsive variations of the vertical forces are particularly damaging to the pure rolling motion and could reduce the stability of the train.

It is known that the train passage excites the bridge and generates vibrations that will continuously affect the vehicle. Hence, we need to integrate information both from onboard the train and the bridge, using a substructural approach that models this highly complex interaction. In essence, as seen in the previous paragraph, it is possible to derive the equations of motion separately for the bridge and vehicle subsystems. Then, the same will be the object of association and resolution through integral calculation<sup>14</sup>.

Such data are often coming from different domains and in heterogeneous formats, thus requiring important extract, transform and load (ETL) operations of the same data. In this case, there will be at least five distinct data domains to be integrated:

- Data collected in the field from the bridge and train sensors.
- “Engineering” data related to the bridge design and the calculation of the mechanical parameters of the response.
- Data extracts from remote control or remote management circulation systems.
- Data coming from traditional IT platforms (workforce schedule management, previous maintenance data, and so forth).
- Any further exogenous data, such as weather reports and GPS coordinates.

The functional logic diagram of the hypothesized IoT solution is shown in Figure 6.



**Figure 6. Logical-Functional Schema of the IoT Solution**

The effectiveness of the proposed paradigm is a function of the integration capacity of the various data sources, often belonging to different operational domains. The paradigm seeks to construct a holistic data model able to harmonize databases, which, by integrating each other, provide information that cannot be obtained by analyzing individually the different data silos. The following are some considerations about the phases of data acquisition from the different sources.

## Field Data

This domain includes the data collectible from the two main elements constituting the “train-permanent way equipment-bridge” material system: specifically, from the train control and management system (TCMS) for rolling stock, and from the gateway that serves as the sensors collector installed on the bridge. In the first case, assuming the insertion of special accelerometers on the wagon and the bogies, the spectra of the vibrations that affect the train could be identified during the response of the bridge to the dynamic stress generated by the train passage. To achieve this, an architecture consisting of sensors onboard the train and an edge server connected through MVB and Ethernet buses must be used.

All the new-generation trains are equipped with an ad hoc server, which on one side interfaces with the TCMS to collect data on a local database and analyze them. On the other side, it takes care of the transfer of signals, counters and events towards the on-ground subsystem. A fundamental role is played by the vehicle logic that represents the modeling of the rolling stock in terms of subsystems, LRUs, failure modes, events, signals, counters and so forth, as well as interrelations. The onboard subsystem, according to the diagnostic rules implemented and the configuration of the vehicle logic, will send diagnostic data to the ground through two different communication channels:

- **Communication in near real time:** Variables related to the operation of specific equipment are constantly sent to the ground through ad hoc protocols [for example, Extensible Messaging and Presence Protocol (XMPP) or more modern Message Queue Telemetry Transport (MQTT) brokers], allowing monitoring of the fleets in operation.
- **“Batch” communication:** All the signals collected according to the various events are stored and sent at regular time intervals using special protocols for the transfer of large files (for example, file transfer protocol or FTP, as well as more modern MQTT brokers).

Both channels exploit a virtual private network (VPN) using protocols that encrypt the traffic passing through the virtual network while preserving the integrity of the transmitted data. Those data will be transmitted to the on-ground subsystem that consists of a converged IT solution (that is, integrating a computational layer, a relational database for data storage, disk space and connectivity), which is redundant and usable, even in the cloud. This solution, communicating with the onboard subsystem, receives and stores the data coming from the rolling stock within the line. It allows access to the various stakeholders through secure web interfaces, sends maintenance warnings and enables all phases of analysis and processing of the signals to identify incipient failures. It also allows the calibration and validation of diagnostic algorithms (see endnote 1).

The IoT monitoring system of the bridge, on the other hand, consists of three distinct elements (sensors, gateways and data analytics platforms) and extends over just as many domains (see Figure 7): the machine-to-machine (M2M) domain, the network domain and the application domain.

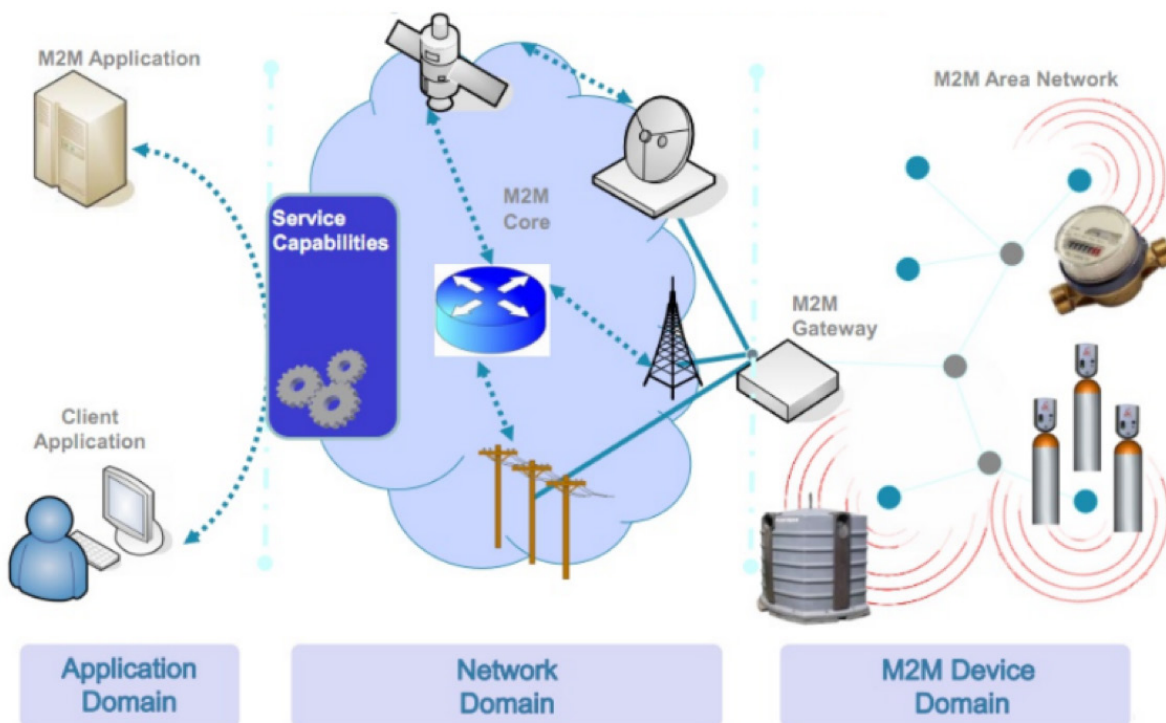


Figure 7. The Domains Characterizing an IoT Monitoring System<sup>15</sup>

Key elements of the system include:

- **IoT sensors.** These are instruments able to perform measurements with a sampling frequency either defined in advance or triggered, which will be sent to the gateway via the M2M area network. For the sake of an illustrative and not comprehensive example, two distinct types of sensors can be hypothetically applied to the bridge: a sensor for vibration analysis based on IEEE802.15.4 standard, and a sensor for temperature measurement based on IEEE802.11b / g / n standards (commonly known as Wi-Fi).

- In the first case, there will be a micro-electro-mechanical systems (MEMS) accelerometer able to calculate the force per unit of mass that will be connected to a microcontroller having the task also to manage the communication transceiver 802.15.4. From an application point of view, however, the microcontroller acquires the values from the accelerometer, and can perform trivial operations on-site (peak-to-peak or an overall on one or more axes).
- In the second case, a thermal sensor connected to a microcontroller will manage, in turn, a Wi-Fi communication transceiver. At the application level, on the other hand, the microcontroller acquires from the sensor and can perform on-board processing (for example, arithmetic, weighted average) and event detection (for example, temperature above a certain threshold).

In addition to the standalone sensors discussed above, there are several other solutions for the continuous monitoring of civil infrastructures. Among the emerging technologies in structural health monitoring (SHM), remote sensing systems represent a state-of-the-art approach<sup>16</sup>. Among the most effective remote sensing techniques for SHM is terrestrial radar interferometry. This technique can be quickly implemented on-site, guaranteeing a high spatial and temporal sampling resolution. It measures the vibration frequencies, the oscillation amplitudes, the modal forms, the damping factors and so forth. Therefore, this technique is suitable for measuring the state variables of bridges and viaducts. It provides results that are completely comparable to those that would be obtained with other “contact” techniques such as those using the accelerometers described above. In this case, the measurement takes place by exploiting the natural microwave reflectivity of the elements present in the irradiated scenario. In particular, the sensor used consists of a “coherent” real-opening interferometric radar (able to emit radar pulses with a known wavelength), equipped with one or more emitting and receiving antennas. The measurements take place along the instrument-scenario line of sight through the differential analyzes of the phase information of the electromagnetic waves emitted and reflected in the different time intervals. The potential displacements are then identified simultaneously on several points of the structure, as shown in Figure 8.

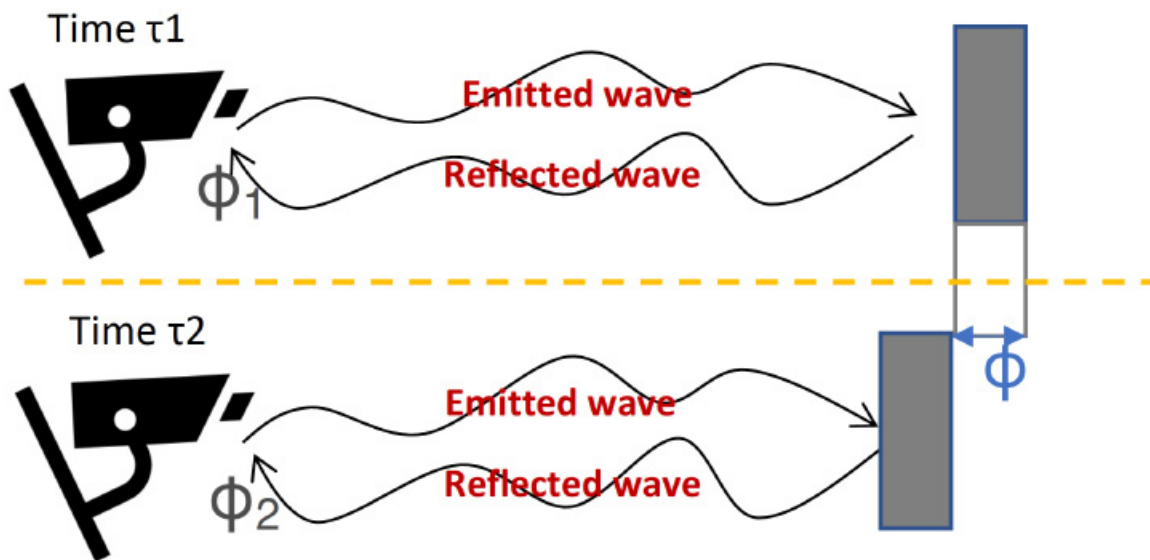


Figure 8. Interferometric Principle for the Calculation of Displacements

The interferometric principle for the displacements calculation is modeled by the following expression:

$$s = \frac{\lambda}{4\pi} (\varphi_2 - \varphi_1) \quad \{31\}$$

Considering:

- $s$  is the measured displacement.
- $\lambda$  is the emitted wavelength.
- $\varphi$  represents the measurement of the raw phase relative to each sampling.

Up to this point, methods have been described that apply to infrastructure already completed and operative. But we can equip new infrastructures in the construction phase with endogenous sensors that can perform effective and low-cost measurements. And fiber-optic sensors are a valid solution not only for monitoring displacements and deformations of load-bearing frameworks, but also for checking the state of deterioration of materials having knowledge of their physical-chemical developments. These solutions are suitable for applications in railway bridges, not only for the wide range of measurable parameters, but also for the insensitivity to electromagnetic fields (trains, storms, high voltage lines) and corrosion. In new reinforced concrete constructions, it is possible to fix the sensors to the reinforcement bars so that, once in operation, these will be able to identify the trigger of static crises, the appearance of the corrosive phenomenon, possible deformations in the geometry of the frame, and so forth.

- **Gateways.** These are multi-interface radio devices that can acquire data from heterogeneous sensors, guaranteeing scalability and modularity (see Gioia *et al.*<sup>17</sup>). For short-range connections (for example, M2M area network) they use Constrained Application Protocol on IEEE802.15.4 transmission standard, integrating perfectly with http, TCP/IP and RESTful protocol. The 802.15.4 standard can be considered a short range communication tool with low power consumption and a transfer rate up to 250 kb/s. Another technology to connect smart meters to the internet is the Bluetooth Low Energy, which reaches data transfer speeds of up to 1Mb/s. To connect from a gateway to a remote server it is possible to use technologies and transmission standards such as Wi-Fi/WiMAX or 4G/5G.
- **IoT or Data Analytics Platforms.** These platforms represent the ecosystem of applications where data from the field are collected, standardized and processed to construct statistically representative databases. These databases calibrate predictive models that will guarantee the identification of future problems already from their incipient phase. More details on these platforms are provided below.

Table 1 shows the OSI stack model, the TCP/IP model and the related IoT protocols used in each of the data transfer phases. It is therefore possible to reconstruct, from a logical point of view, the life cycle of the data from when it is sampled by the sensor, up to its use on the application side. In fact, reading the table from the bottom up, the last step, the application layer, represents the access point of the data in the analytics ecosystem; by consuming the measurement through a MQTT queue manager, for example, the data will be inserted into a database or data lake becoming the object of the required analyses.

TABLE 1. OSI AND TCP MODEL LAYER WITH RELATED IOT PROTOCOLS

OSI Model Layers	Internet (TCP/IP) Model Layers	IoT Protocols
<i>Application Layer:</i> message format, human-machine interface	Application Layer	HTTPS, XMPP, CoAP, MQTT, AMQP
<i>Presentation Layer:</i> coding, encryption, compression		
<i>Session Layer:</i> authentication, permissions, session control		
<i>Transport Layer:</i> addressing, routing, switching	Transport Layer	UDP, TCP
<i>Network Layer:</i> addressing, routing, switching	Network Layer	IPv6, 6LoWPAN, RPL
<i>Data Link Layer:</i> error detection, flow control, physical link, access	Link Layer	IEEE 802.15.4, Wi-Fi (802.11 a/b/g/n/ac), Ethernet (802.3), GSM, 3G, 4G, 5G
<i>Physical Layer:</i> bit stream, communication format, topology		

## Engineering Data

This domain contains data relating to the design, construction and hydrogeological details of the bridges being analyzed, and the history of defects recorded through general inspections over the years. In Italy, for example, according to Instruction 44C<sup>18</sup>, it is required “to systematically check the static conditions of the various structures for the repercussions they have on the safety and regularity of the service. The control will have to provide probative elements of judgment on the conditions of stability and conservation of the infrastructure ... integrating, if necessary, with appropriate checks and instrumental measures ...” The definition and registration of any defects found during technical visits on-site are done through a code that identifies the type, some additional coefficients that express the importance of the defect, and the relative level of intensity. These data flow into an ad hoc database considered as a support for the expression of the final judgment as required by the regulations in force. In Italy, the DOMUS system of the Italian Railway Network (RFI) is used for the collection and cataloging of the results of the inspections. Thus, it generates a source of structured data (the DOMUS, through its algorithm, will provide the fault index of the infrastructure) usable for technical insights and in-depth analysis (see Figure 9).

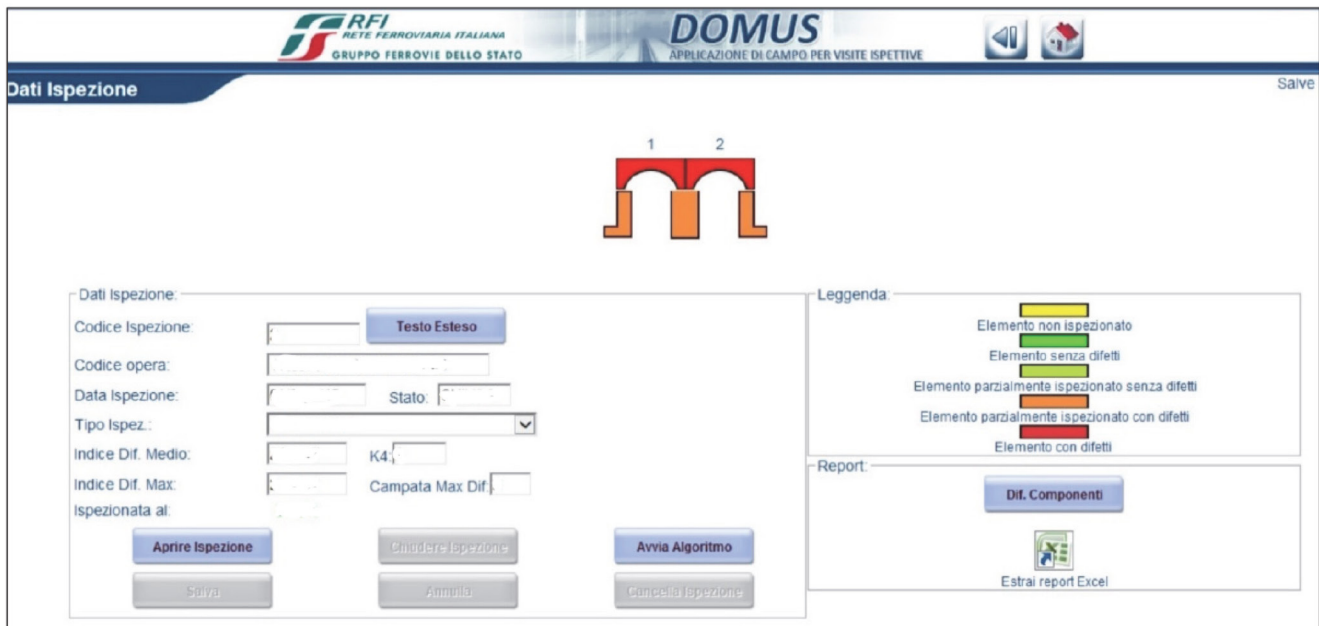


Figure 9. User Interface of DOMUS, RFI Tool

Further engineering data need to be integrated and correlated to identify collateral risks: for example, linked to hydrogeological instability or to the consequences related to seismic actions. In the first case, in Italy, the GEOMEDIA portal of RFI is used, from which it is possible to verify the presence of hydrogeological instability points; in addition, if necessary, other sources of exogenous data could also be considered, such as, for example, maps of the basin authority. In the second case, it could be useful to integrate from the databases present in the Italian Accelerometric Archive (ITACA)<sup>19</sup>.

## Data From Remote Traffic Control Systems

The read-only connection to the databases of traffic control and regulation systems, after their “opening” operated by the producers, is of fundamental importance. It collects the information that represents some among the boundary conditions to be applied to the systems of differential equations obtained from the analyses described in the previous paragraph. In fact, once the behavior of the structures has been modeled, the expected displacement ranges of the bridge will obviously also be a function of the dynamic load that will stress the bridge. Therefore, information such as mass, brake mass, acceleration and speed are of fundamental importance to near-real-time calculations of the expected response (in terms of displacements, speeds and/or accelerations). It is compared to the real harmonics reconstructed using the bridge sensors and/or those on board the train. A further fundamental data is the number of vehicles (and therefore of axles), with relative dynamic quantities, which form the convoy in transit.



In fact, relevant amplifications can occur for repeated loads arranged with spatial periodicity: Each of those, at its entrance and its exit from the bridge, *generates a train of waves that is added to the one induced by the already transited loads; each railway carriage produces vibrations having all the same phase, a circumstance that occurs for oscillation frequencies equal to a multiple of the transit frequency; the vibration is reinforced over time even if the loads that generated it are already transited, obtaining, in this way, long-lasting free oscillation due to the modest structural damping*<sup>20</sup>. The required information can be retrieved by interfacing, in function of the line, alternatively, either the command and control system (SCC), or the centralized traffic control (CTC), or the centralized lines control (CCL). SCC and CTC allow the control and management, even remotely, of circulation within the lines and into the stations. The SCC has the ability to manage not only traffic, but also diagnostics, maintenance, public information, and video surveillance. SCC (of which there is a variant dedicated to high-speed lines called SCC-AV) is able to interface both with unmanned peripheral items (stations, movement points, communication points and so forth) and with electromechanical devices along the line (switches, signaling and so forth). CCL, on the other hand, while not allowing remote control of the circulation, guarantees supervision and management functions. In the specific case discussed in the paper, from the SCC various values can be integrated, as reported into the extract shown in Table 2.

TABLE 2. EXTRACT OF SOME DATA THAT CAN BE INTEGRATED BY THE COMMAND AND CONTROL SYSTEM

Theoretic Timetable	Composition	Ongoing Information	Itinerary Selection
Location	Departure station	Railway station	Itinerary 1
Departure and arrival times	Number of vehicles	Scheduled times	Itinerary 2
Train category	Length	Minutes of delay	Itinerary n
Periodicity	Mass	Real time	...
...	Percent braked mass	Incoming track	...
...	Full speed	...	...
...	Locomotive	...	...

A further source of data relating to the circulation is represented by the line repository. Once digitalized in a relational database, it can be queried automatically to provide useful data, such as mileage, maximum speed in a defined section of the line (function of the vehicle type in transit and characteristics of the line), exact position of the bridge, presence of virtual or real signals, and so forth. To provide accurate and detailed information for the data model to be designed, in some situations, there exists an opportunity to install new informative or technological points close to the bridges that will be subject to direct monitoring (therefore with sensors on the bridge), not just indirect, using the measurements sampled by the train.

### Enterprise IT Data

To activate workflows and corrective actions, and also ensure cost chargeback, it is necessary to integrate information related to the workforce schedule, and past and future maintenance interventions. In general, it is vital to interface with enterprise resource planning (ERP) systems that contain information about work orders, inventory, production costs and so forth. Integrating economic variables will allow the construction of decision support systems (DSS) that are able to direct choices according to both efficiency and effectiveness indicators.

### Exogenous Data

In the context of a holistic multisource approach, to make predictive models as reliable and comprehensive as possible, it may be necessary to add external variables. These may include weather data (temperature, wind intensity and direction, humidity and so forth) and GPS positions where singular in-line events occur (for example, irregularities in the rails profile). These also involve the correlation of structured data (for example, measurement of vibrations collected by an accelerometer while the train is running over) with unstructured data (for example, video recorded by IP cameras along the line) through the construction of intelligent metadata and time stamps. In fact, through modern video analytics solutions it is possible to correlate a specific numeric measurement with a video recorded in the time frame in which the measurement was performed. Thus, these solutions allow you to settle false positive situations or

provide visual details related to the measurement carried out: everything achievable through the automated creation and archiving of the videos and their associated metadata that, automatically, correlate these with the respective sampled measurements.

Data sources necessary to set up the analytical problem must be defined, and the actions necessary for their use from the data analysis layer must be completed (for example, through the construction of specific connectors and the use of application programming interfaces or APIs). Once these tasks are completed it is of fundamental importance to configure a data analytics platform that is able to receive data in different formats and from heterogeneous sources. Such a platform must facilitate the work of data scientists and analysts in “cleaning” them. In fact, once a data ingestion channel has been established, be it batch and/or in real time, it is necessary to orchestrate the various data streams that must be subject to various transformations (for example, outlier removal, applications of mathematical functions and so forth) before forming a statistically representative dataset. Once the sample preparation phase has been completed, the platform must guarantee the integration with different libraries of machine learning (ML) and artificial intelligence (AI) algorithms: Therefore, it acts as an incubator for the calibration of predictive models, also allowing the validation and potential fine-tuning activities. The platform described also must allow the orchestration of calibrated predictive models, to perform real-time analysis, ascertaining early warnings useful to identify incipient problems. The definition of predictive rules and models can be deployed following two approaches (see endnote 1):

- **Knowledge-based.** It considers competencies and know-how acquired by designers and maintainers, and it also utilizes failure mode, effects and criticality analysis (FMECA), and analysis of reliability, availability, maintainability (RAM). Thanks to those analyses and to the previous experiences acquired, it is possible to identify a priori the bridge’s abnormal behaviors described by known thresholds of its relevant variables. Those data are sampled per specific frequencies and compared with the thresholds; once the detected values overcome the expected ones, alarms and triggers are sent to the appropriate stakeholders. This approach deals with supervised models.
- **Data-driven.** Thanks to the diffusion of assets’ digitalization, the maintenance engineering has an increasing volume of multisource and heterogeneous data. Often, however, those data are collected in different databases (DBs), creating silos that do not allow easy comparative analyses. To solve this problem, it is possible to utilize distributed file systems and big data platforms that allow the creation of heterogeneous and statistically representative data lakes. Such data lakes contain structured, semistructured and unstructured data, analyzable in its entirety through a holistic approach, applying AI techniques, ML and predictive analytics. Suitable conditions have been created to identify the relationships between apparently independent data, extracting insights, devices’ behavioral patterns and dependencies previously unknown and now usable to predict abnormal behaviors. This approach utilizes unsupervised models.

The data analysis platform must be able to interface for data destaging with relational databases (RDBMS or SQL) and nonrelational databases (NoSQL). In fact, the choice of databases is of fundamental importance for the success of the IoT project, and must be performed taking into account the differences between the two macro-categories and the different peculiarities of the NoSQL DBs. SQL DBs use tables that store values on rows and columns, while nonrelational DBs can use archives made up of different formats (for example, documents, graphs, key-value archives and so on). The relational DBs require the construction of *ad hoc* schemes to accommodate the input data, unlike the NoSQL DBs. With the exception of Cassandra DB, No SQL DBs have a schemaless approach that eliminates the need for an initial data schema and allows data to change their structure over time. Another difference, perhaps the most important, is that the NoSQL DBs can split the workload on a distributed cluster. This approach maintains remarkable performance, ensuring the horizontal scalability (therefore on multiple servers) that SQL DBs cannot support. With the ability to overcome the traditional relational approach, supporting applications requiring the storage of large quantities of data in a short time, nonrelational DBs are spreading rapidly. The NoSQL databases are therefore more flexible and use less complex data models, guaranteeing better performance in the management and querying of data. According to Brewer’s theorem<sup>21</sup> (also known as CAP theorem, indicating consistency, availability, partition tolerance) a distributed system is able to satisfy only two of these three properties at the same time:

1. **Consistency:** All the nodes of the network can see the same data at the same time.
2. **Availability:** It ensures that for every request for writing or reading there is corresponding feedback on the successful completion of the action.
3. **Partition tolerance:** The system, in its entirety, must be able to function despite an arbitrary loss of messages.



Therefore, it is possible to derive the following combinations shown in Figure 10:

- **CP:** Consistency and partition tolerances are adopted in databases such as Redis, MongoDB, Hypertable, HBase and BigTable.
- **AP:** Availability and partition tolerances are guaranteed in Dynamo, Voldemort, CouchDB, Riak and Cassandra.
- **CA:** Consistency and availability are characteristics of the RDBMS in which the system is not distributed.

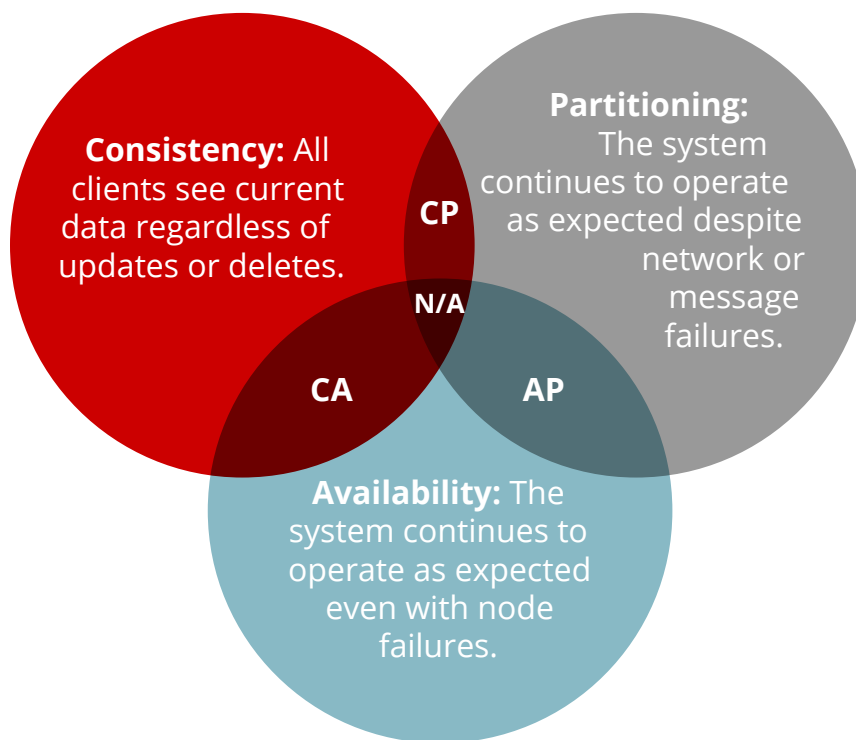


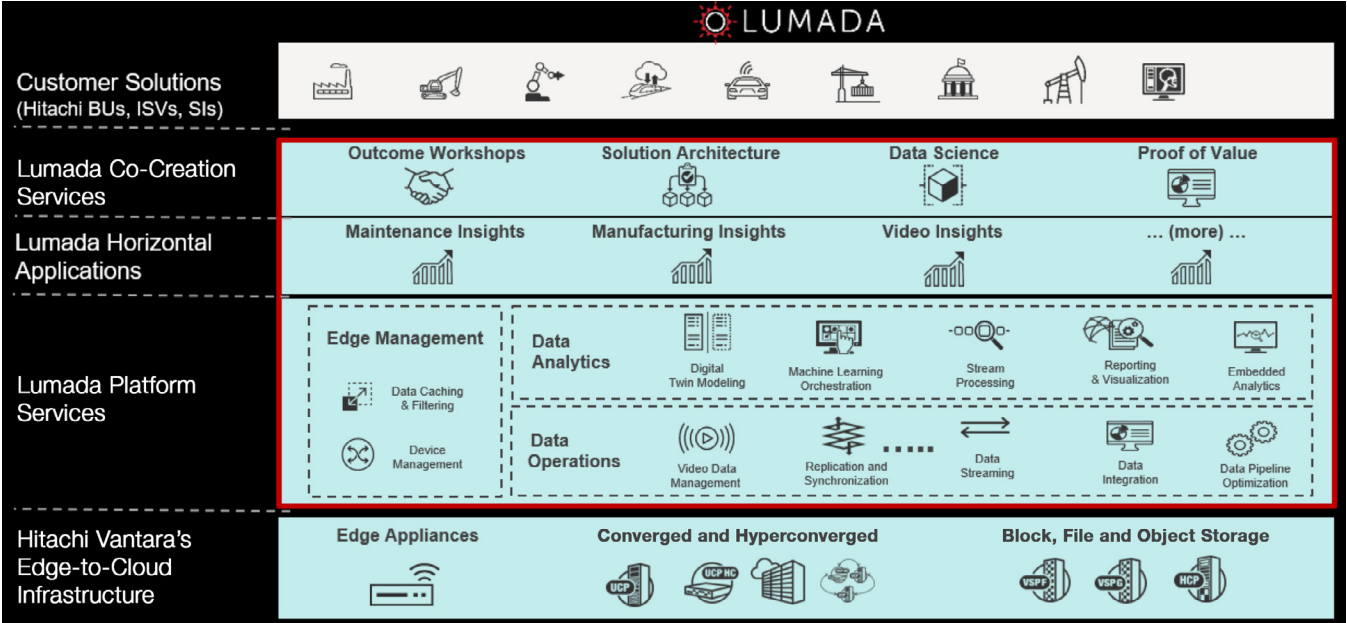
Figure 10. Graphic Representation of Brewer's Theorem or CAP Theorem

Once the DB on which the input data will be stored and the related data transformations have been defined, the data analytics platform will create appropriate dashboards, and activate and orchestrate specific workflows based on the outputs of the predictive models. This approach transforms the whole IoT framework in a large and distributed decision support system (DSS). In fact, upon the occurrence of certain alarms arising from the analyses described above, the DSS will independently implement all the planned actions. Such actions can range from sending emails or messages in real time to the Movement Manager (DCO) to evaluate whether to interrupt or slow down circulation, up to the automatic work order scheduling to allow maintenance teams on-site to verify the truthfulness of the alarm received. Using such an architecture, inspections of infrastructure could be scheduled with a data-driven approach and updated in near real time.

### Hitachi's Lumada: A Framework for the Predictive Maintenance of Railway Bridges

To satisfy both the hardware and software exigencies described above, Hitachi developed Lumada solutions for digital innovation, vertically integrating and consolidating all the required IoT components within a unique stack. The Lumada framework (see Figure 11), in fact, is designed to manage the entire life cycle of different types of assets and devices. It measures real-time performances, builds statistically representative datasets along the useful life of the asset, and performs technical and financial forecasts and optimizations. Its modular and flexible architecture

preserves previous investments: Thanks to public APIs, it supports third-party solutions (both proprietary and open source), even if already installed within the customer’s framework. Lumada can establish both real-time and batch connections with single devices, a fleet of assets and measuring devices, even if geographically spread or in movement. Thanks to its data ingestion tools, it is able to visualize data coming from assets, store data on big data platforms, and analyze the entire data lake through AI and ML tools. It acts on specific workflows in response to achieved results and integrates with corporate IT systems. The modular approach deals with not just functions that are able to be integrated within the ecosystem, but also the scalability in types and numbers of monitored devices. Assets can be added or removed without affecting the global availability of the solution.



*BUs = business units, ISVs = independent software vendors, SIs = systems integrators, UCP = Hitachi Unified Compute Platform, UCP HC = hyperconverged, Hitachi Unified Compute Platform HC, VSP F = Hitachi Virtual Storage Platform F series, VSP G = Hitachi Virtual Storage Platform G series, HCP = Hitachi Content Platform*

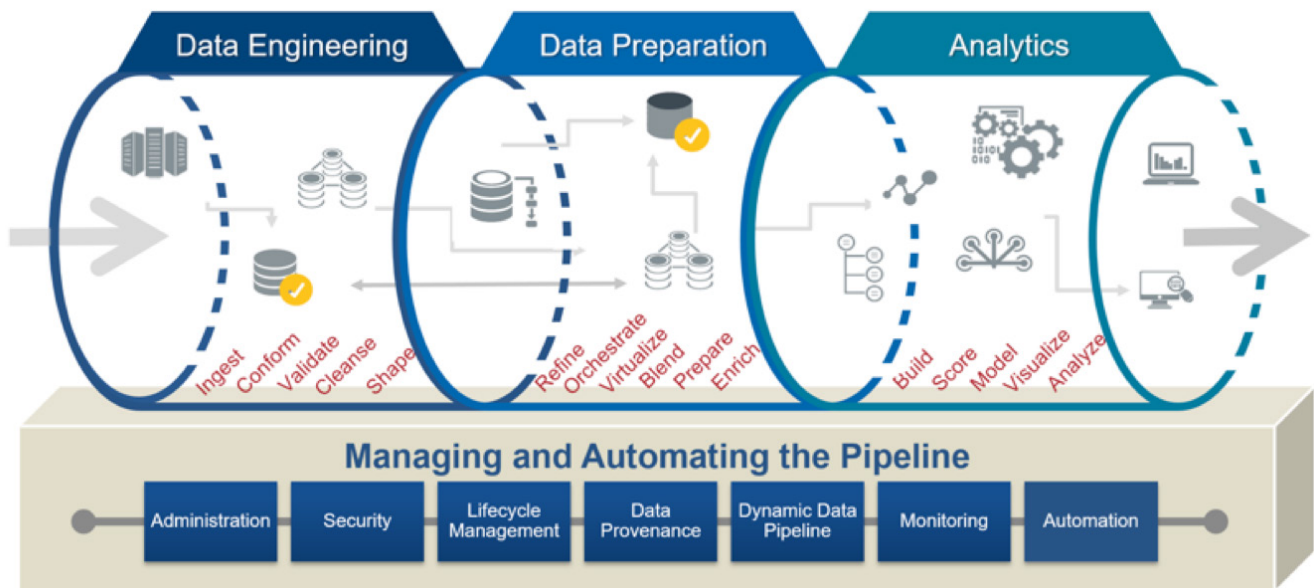
**Figure 11. The Conceptual Architecture of the Lumada Framework**

In this case, to meet the functional requirements addressed in the previous paragraph, the use of a data analytics software suite, Pentaho, from Hitachi Vantara, is proposed. Pentaho, an integral part of the Lumada framework, manages the end-to-end data cycle (see Figure 12). It collects, transforms, orchestrates and analyzes variables from heterogeneous and multiformat sources. Then, it visualizes the results obtained through the construction of dashboards, reports and infographics, which are accessible through the cloud and on the move. Pentaho offers two complementary modules: Pentaho Data Integration (PDI) and Pentaho Business Analytics (PBA). Use PDI to manage, through a graphical drag-and-drop interface, all the processes and flows related to the construction of statistically representative datasets. Calibrate and validate predictive models, using inferential statistics, AI, ML and deep learning (DL).

In fact, thanks to the integration with the most widespread data analysis engines (for example, *Spark* and *MapReduce*), PDI simplifies and accelerates the integration process of existing databases with additional exogenous sources. It uses a rich library of predefined components to interface with SQL and NoSQL sources, distributed file systems, business applications and much more. Thanks to powerful orchestration tools for the data to be analyzed, PDI allows the results to be viewed in real time, during the extraction and cleaning of the sample. It increases the effectiveness of calibration and model validation, displaying intermediate results during the operations, building workflows that automate data collection and analysis, and ensuring the automated execution of the entire data pipeline

(see Figure 12). Beyond building the ideal environment to transform, analyze and orchestrate heterogeneous data sources, PDI drastically reduces complexity and duration of such time-consuming activities as:

- Manual programming of transformations and data analysis.
- Construction of normalized databases.
- Construction of reusable templates for subsequent analysis.
- Reuse of algorithms already written in *R* or in *Python* or from libraries, such as *Spark MLlib* and *Weka*.



**Figure 12. End-to-End Processes and Flows That Can Be Managed Using Pentaho**

Thanks to the adaptive big data layer functionality, Pentaho is able to interface with the most common big data repositories on the market, both in reading and writing. It extracts the required data, processing them in memory on the random access memory (RAM). Also, it can consume them on the internal analysis engine of PDI or on third-party engines, such as Spark and MR, without the need to modify any code line; the change of engine (and related instructions) will be transparent for the data scientist since Pentaho will automatically convert it. Hence, Pentaho delivers on the concept of the adaptive layer, which builds a workflow of transformations and analysis of data that will be agnostic with respect to the engines that will then be utilized for implementation. In fact, using the graphical interface (see Figure 13) it is possible to construct the flow of transformations and analysis considered most suitable, to then test different analysis engines. Then, evaluate which is the best in terms of the effectiveness of predictions and computational and temporal resources required. All this makes it possible to abstract the databases, the predictive algorithms, and the analyses necessary for their calibration and validation, both from the hardware layer and from the analysis engine. It is possible, over time, to use new and more performing technologies, both on premises and in the cloud, without the need to write even a new line of code to adapt the various data models created.

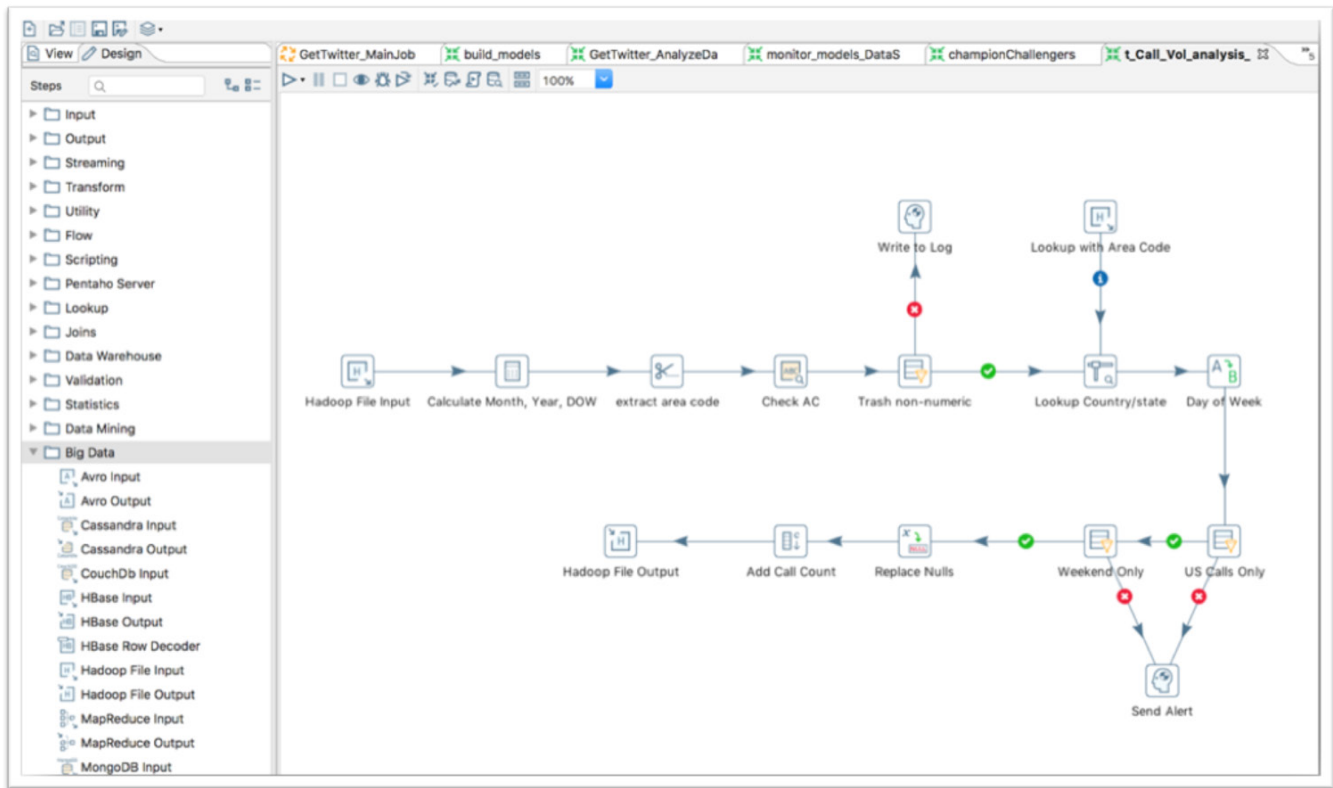


Figure 13. Transformation of Data Through the Use of the Graphic and Intuitive Interface of PDI

PDI can access, both in reading and in writing, a wide range of data repositories, as shown in this nonexhaustive list:

- **Relational database management system (RDBMS):** Oracle, IBM® DB2®, MySQL, Microsoft SQL Server.
- **Spark and Hadoop:** Cludera, Hortonworks, Amazon EMR, MapR, Microsoft Azure HDInsight.
- **NoSQL databases and object storage:** MongoDB, Cassandra, HBase, Hitachi Content Platform.
- **Analytic databases:** Vertica, Greenplum, Teradata, SAP HANA, Amazon Redshift, Google Big Query, Microsoft Azure SQL Data Warehouse (DW).
- **Business applications:** Salesforce, Google Analytics.
- **Files:** XML, JSON, Microsoft Excel, CSV, txt, Avro, Parquet, ORC, unstructured files with related metadata, including audio, video and visual files.
- **Real-time data integration:** allows data streaming from Apache Kafka using Spark streaming and the most common IoT protocols, without the need for any additional code writing.

The results obtained from the analysis and from the orchestration performed utilizing PDI must then be memorized on specific databases (Data Warehouse) and displayed through dashboards, scorecards, smart maps and so forth. The Pentaho suite contains the Business Analytics component suitable for the construction of the tools necessary to utilize the data being analyzed. In fact, PBA creates dashboards that are updated in real time and also accessible on the move via the cloud and/or integrated within existing web pages or applications. PBA has a library of graphs, maps and prefilled infographics. The user, autonomously and without having to write any line of code, will be able to build the most suitable dashboard to visualize the results of the predictive analysis (see Figure 14).

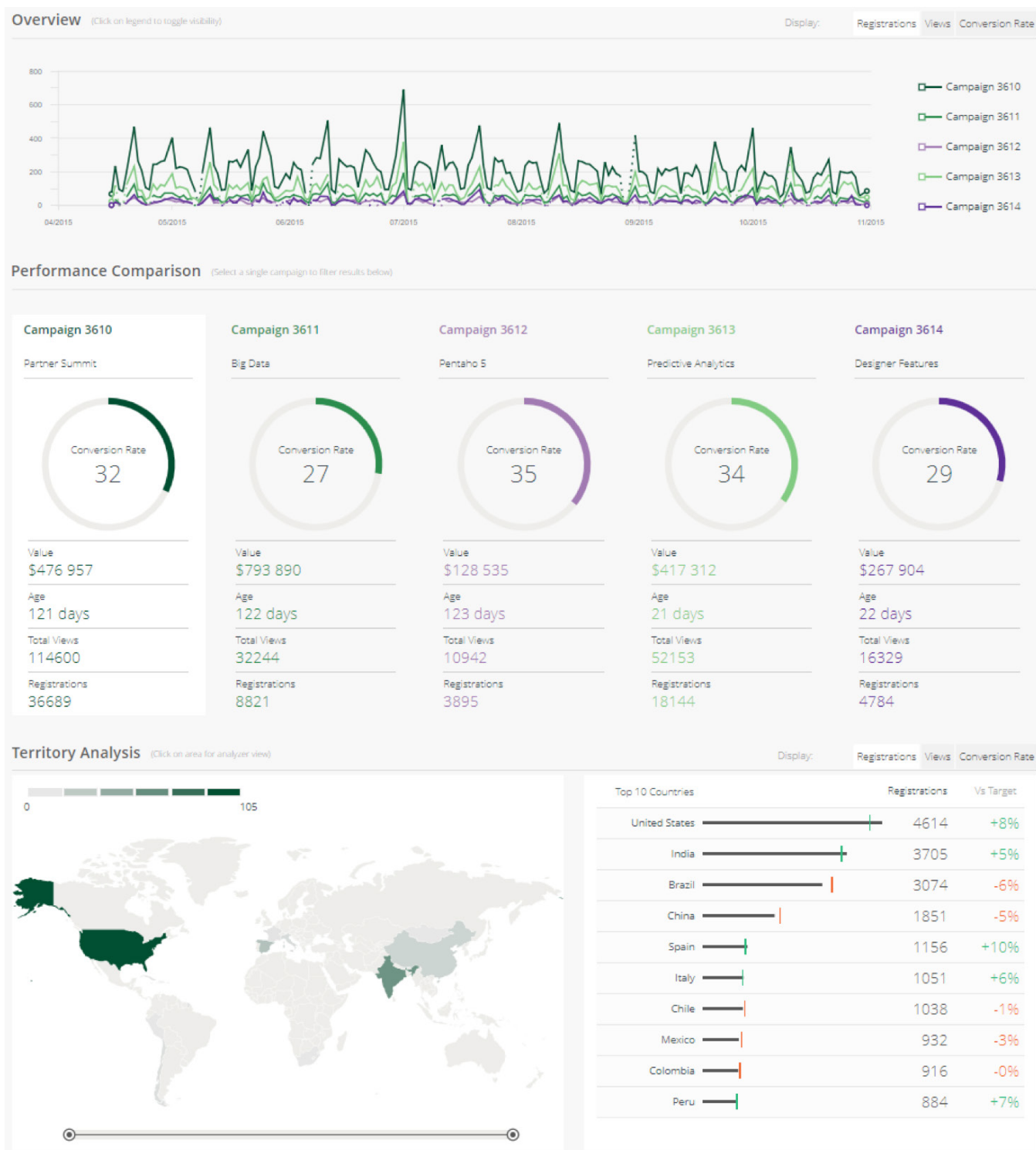
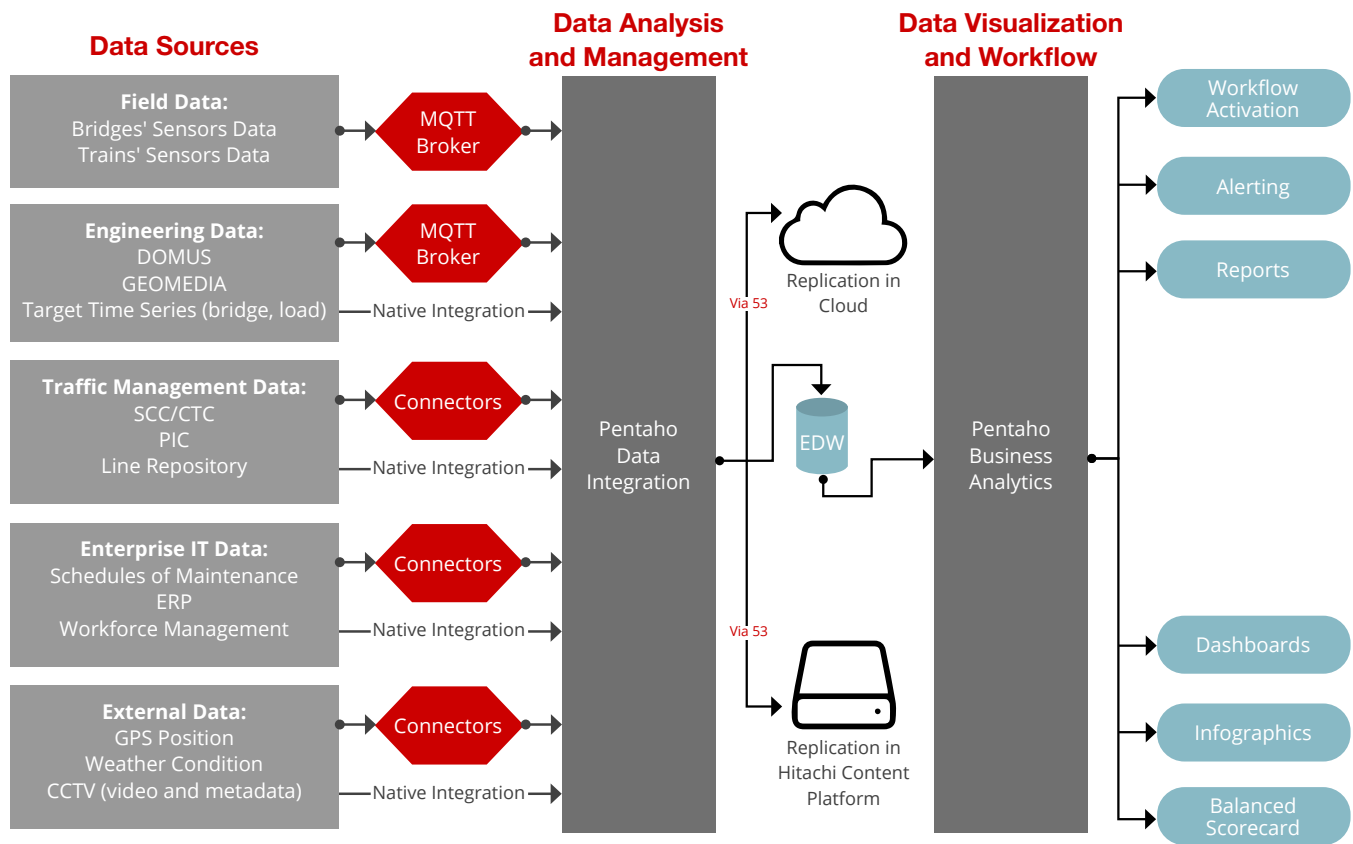


Figure 14. Example of a Pentaho Information Dashboard With Heterogeneous Indicators That Are Updated in Real Time

The functional logic diagram shown in Figure 6 identified a series of operational and engineering requirements, and the related data analytics functionalities necessary to satisfy them. To contextualize operational needs and IoT functionalities within a Pentaho-based architecture, consider the scheme shown in Figure 15.



**Figure 15. Logic-Functional IoT Architecture for Predictive Maintenance of Railway Bridges Based on the Pentaho Platform**

Exchange the five macro-categories of data (data sources) with PDI by exploiting the wide range of interfaces that Pentaho natively disposes of. Or, build appropriate connectors via the public APIs, making the incoming data flow totally automated. Field data, for example, could be managed and streamed by MQTT brokers. These brokers connect with edge servers and TCMS for the train, and with the gateway for the bridge, to ensure that the sampled data flow reaches the data analytics platform. There, both near-real-time analysis and more in-depth analysis related to models' calibration will be performed. The engineering data can be collected through the native integration that PDI offers to the most common RDBMS, or, depending on the case, through an MQTT broker. DOMUS and GEOMEDIA could be interfaced, for example, through direct queries to their respective databases, thanks to JDBC drivers. The information concerning the circulation, having to preserve the immutability of the sources, should be accessed in read-only mode on an extracted DB, after appropriate opening of the database by the equipment suppliers; in this way, it would be possible to read all the information necessary for the calculation of the structural reaction, without having to modify and certify the equipment again (for example, SCC, CTC and so forth).

The line repository, a mostly static database, could be digitized on a relational DB accessed on demand by Pentaho in a completely automatic form, without additional connectors. The production data, contained on supervision systems such as ERP or asset management, require specific connectors to be accessed when it is not possible to directly query the databases on which they are stored. Finally, the computation will also include exogenous data such as weather forecasts or unstructured data: The first ones can be natively integrated using streaming (for example, Kafka), and for the second ones there are ad hoc features in PDI that guarantee interfacing for the purposes of



analysis. With all this placed just before the passage of a vehicle on the bridge, the IoT solution would be able, autonomously, to perform the following actions:

- a. Acquisition of static and dynamic data related to the rolling stock that is about to cross the bridge (traffic management data).
- b. Collection of engineering data relating to:
  - i. Bridge:
    - Number of spans and relative length.
    - Construction type and related technical data.
  - ii. Train:
    - Number of wagons and related geometry, and wheel arrangement.
    - Number of axles per wagon.
    - Static load per axle.
    - Brake mass.
    - Speed.
- c. Integration of any exogenous data (external data).
- d. Acquisition of the expected response for that specific bridge stressed by that determined dynamic load (function of the data acquired in the three previous steps).

Once the convoy is approaching the bridge, however, further actions will be carried out:

- e. Collection of the harmonic functions sampled both from the sensors on board the train and from those possibly installed on the bridge (field data).
- f. Comparative analysis between the values identified at point (d) and the values obtained at point (e). These analyses can take place applying dynamic time warping (DTW) methods that measure the distance  $\Delta(t)$  between the aligned sequences received as input by the system (train + bridge) with respect to the target time series [calculated at point (d) when utilizing a knowledge-based approach, or derived from measurements in which the sample size tends to wide values].

Let  $\Psi e(t)$  be the expected value extracted by the target series. It can be higher or lower with respect to the value really measured on field in real time  $\Psi r(t)$ ; let  $\varphi(t)$  be the threshold, known a priori, that once overtaken certifies that the behavior of the bridge can be considered as anomalous. Per each sampling time stamp, for the monitored subsystem to run with optimal operating conditions, the following inequation needs to be satisfied (see endnote 1):

$$\Delta(t) = |\Psi e(t) - \Psi r(t)| < \varphi(t) \quad \{32\}$$

The DTW methods are used for the final phase of the comparison, but it is necessary to deepen how to reach the value of the structural reaction, in the two cases of species analyzed in the previous paragraph, the knowledge-based and the data-driven.

- a. **Knowledge-based:** These methods deal with circumstances in which FMECA and RAM analyses are available, and therefore in specific cases in which there is a broad knowledge of the boundary conditions and their evolutions during the time and the operations (thus, it is referred mainly to bridges recently installed). This will be the case that will deal with supervised problems, in which both the structures of the input variables (mostly time series data) and those of output are known. At this point it becomes necessary to identify the subset of the parameters of {27} able to generate a drift of the motion parameters measured with respect to the expected

target value. To predict an early warning, it becomes essential to identify which are, among the  $n$  boundary conditions of the equation {27}, those most prone to generate a drift. This being the case, it is intended to focus on three different models: Long Short-Term Memory (LSTM), Auto-Regressive Integrated Moving Average (ARIMA), and Random Forest Regressor.

1. **LSTM:** For a correct contextualization of such models, it is necessary to refer to recurrent neural networks (RNN): that is, a particular type of artificial neural networks able to keep track of dependencies between nodes. It is, therefore, possible to preserve the sequential information in an inner layer of the network, making it possible to use the knowledge previously acquired in the subsequent temporal passages. LSTM are therefore, a special type of RNN introduced to address the long-term memory shortage of vanilla RNNs. In principle, the LSTM consists of a cell, an input gate, an output gate, and a forget gate (see Figure 16). The role of the forget gate is particularly interesting because allows the model to eliminate past inputs that are no longer of interest to predict the future. The major advantage of this method compared to a classic time series model (for example, ARMA, ARIMA) is the adaptability of the forget gate: An ARIMA model a priori calculates the number of lags that the model will take as input, and such number will be prefixed in the model specification. The forget gate within the LSTM, on the other hand, allows the model to vary the dependence on the temporally earlier lags.

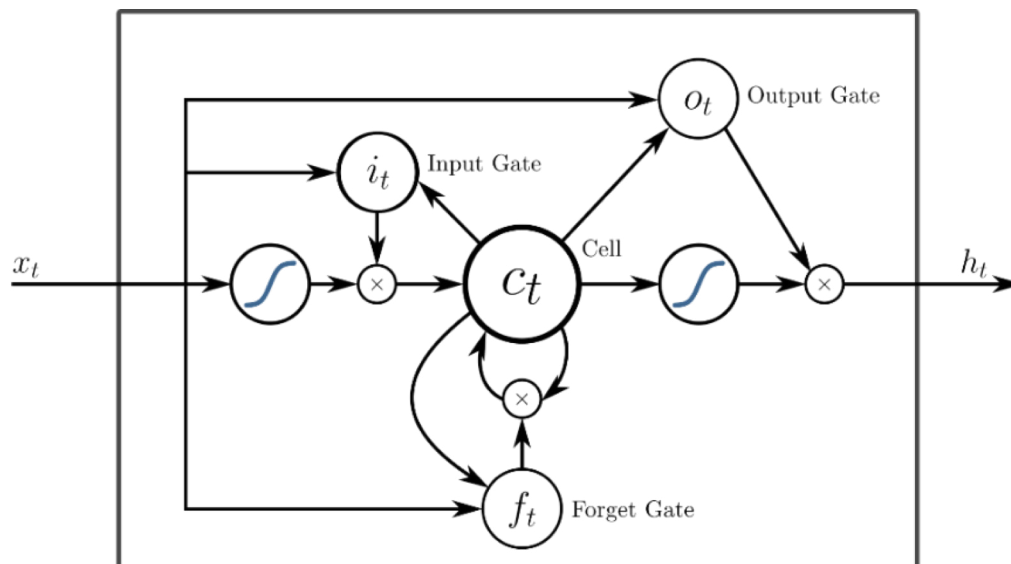


Figure 16. Graphic Representation of an LSTM

The cell stores the values inherent at arbitrary time intervals, while the three gates act as “regulators” of the information flows that enter and leave the cell when the iterations progress. The LSTM networks are therefore suitable for classifying, processing and making predictions based on time series data where, often, time lags of unknown duration can occur between significant events of a historical series. LSTM are not subjected to distortions in computations generated by the presence of time lags occurring between time series events, making these networks clearly more effective than traditional RNNs, *hidden Markov* models, and so forth.



Following are the compact forms of the equations for the forward pass of a LSTM unit with forget gate:

$$f_t = \sigma_g (W_f x_t + U_f h_{t-1} + b_f) \quad \{33\}$$

$$i_t = \sigma_g (W_i x_t + U_i h_{t-1} + b_i) \quad \{34\}$$

$$o_t = \sigma_g (W_o x_t + U_o h_{t-1} + b_o) \quad \{35\}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c (W_c x_t + U_c h_{t-1} + b_c) \quad \{36\}$$

$$h_t = o_t \circ \sigma_h(c_t) \quad \{37\}$$

where:

$x_t \in \mathbb{R}^d$  represents the input vector to the LSTM.

$f_t \in \mathbb{R}^h$  is the activation vector of the forget gate.

$i_t \in \mathbb{R}^h$  is the activation vector of the input gate.

$o_t \in \mathbb{R}^h$  represents the vector of the forget gate.

$h_t \in \mathbb{R}^h$  represents the output vector of the LSTM.

$c_t \in \mathbb{R}^h$  represents the state vector of the cell.

$W \in \mathbb{R}^{h \times d}, U \in \mathbb{R}^{h \times h}, b \in \mathbb{R}^h$  represent the matrices of the weights, and the parameters that will be computed during the calibration phase of the model.

Note that at time  $t_0$ ,  $c_0 = 0$  and  $h_0 = 0$ , while the operator  $\circ$  represents the product of Hadamard. The subscript  $t$ , indexes the calculation iterations, while the indexes  $d$  and  $h$  represent, respectively, the number of boundary conditions provided in input, and the number of latent units (hidden units).

2. **ARIMA:** These models, which are part of the family of nonstationary linear processes, are used to analyze time series, also keeping track of the seasonality of the data. In the latter case it will be referred about the ARIMA model  $(p, d, q)$ , capable of storing different series of order  $d$ , where the parameter  $p$  represents the order of the autoregressive model and therefore the number of time lags, while  $q$  is the order of the moving average model. The operation of ARIMA is based on the definition of  $x_t$  as a linear combination of the previous values  $x_{t-1}, x_{t-2}, \dots, x_{t-p}$  and a "background noise"  $\epsilon_t, \epsilon_{t-1}, \dots, \epsilon_{t-q}$ . The ARIMA model  $(p, d, q)$  can be expressed using the following formulation, and can be estimated using the Box-Jenkins approach<sup>22</sup>:

$$(1 - \sum_{i=1}^p \alpha_i L^i) (1 - L)^d X_t = (1 + \sum_{j=1}^q \beta_j L^j) \cdot \epsilon_t \quad \{38\}$$

Furthermore, the Autoregressive-Moving Average models also have the peculiarity of being able to incorporate previous shocks into the forecast of future output: This derives from the moving-average component in the model, which is nothing more than the effect of the random part  $\epsilon_t$ : that is, the effect of unobserved error terms. A deviation from the normality of the error terms, such as a shock (for example, a particularly violent and unexpected weather event), will lead to a reverberation effect on the future values of the forecast.

3. **Random-Decision Forest (RDF):** This model, which is part of the so-called ensemble methods (using multiple learning models to maximize effectiveness), is a classifier composed of several decision trees and capable of providing as output the class corresponding to the exit of tree classes individually considered<sup>23</sup>. In essence, RDF

uses a “*dividi et impera*” approach, in which  $n$  disjointed models (weak learners) are coupled to act in unison, becoming, according to a holistic approach, a single “strong learner.” The theory behind RDF consists of the creation of a whole “forest” of random and unrelated decision trees, to elaborate the most effective prediction possible. A decision tree consists of a root node capable of creating a binary division until a given initial criterion is satisfied. This binary division (see Figure 17) provides a predictive value based on the “inner” nodes and which leads, when the iterations progress, to the terminating nodes (final class).

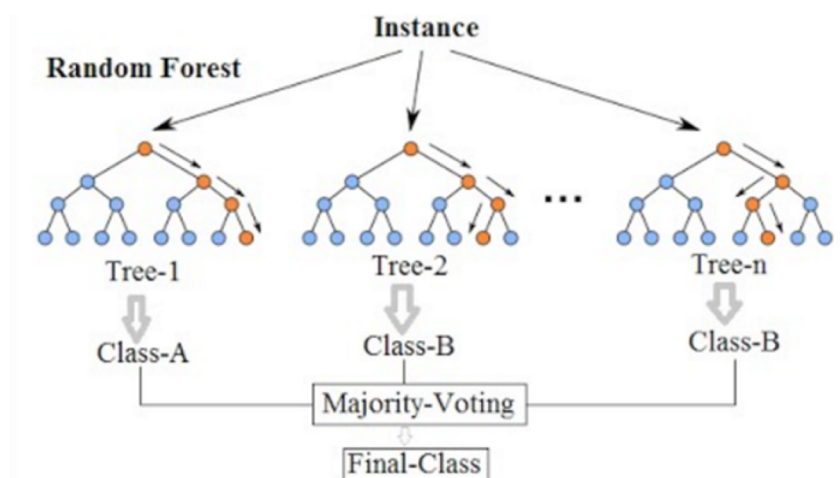


Figure 17. Simplified Representation of a Random Forest Model

In the specific case treated by this paper, considering the complexity of the variables involved, to make the application of RDF effectively implementable, it is essential to make a selection of the most significant variables, reducing their number and complexity. For this reason, before using the RDF model, appropriate reduction tools should be used, including, by way of example but not limited to, the following: *Least Absolute Shrinkage and Selection Operator (LASSO)* and *Principal Component Analysis (PCA)*.

LASSO is a regression analysis method that selects and normalizes variables to increase the accuracy and interpretability of statistical models. PCA, on the other hand, is a technique for simplifying data deriving from the domain of multivariate statistics. PCA can be applied both through linear and matrix resolutions. The application of a reduction method is, therefore, a necessary but insufficient condition for the prediction of the instability conditions of the railway bridges being analyzed by RDF.

- b. **Data-driven:** When there is not enough information on the boundary conditions of the bridge, on their history over time and events (for example previous earthquakes, displacements at support, frost and thaw cycles, and so on) it is much more complex to calculate analytically the expected response provided from the bridge. This is precisely because it is not possible to correctly compute all the variables involved. In these cases, therefore, the set of displacements, speeds or accelerations targets that will be analyzed with the DTW method at the passage of each train, will have to be derived indirectly. The greater the number of samplings, the more accurate this estimate will be. The models that can be used in such cases are the same as those described for the knowledge-based approach. The difference is that, since it is not possible in this case to analytically compute the target structural response, it will be required to proceed with its indirect measurement. Recall the central limit theorem stating that *the sum (or average) of a large number of independent random variables and having the same distribution is approximately normal and independent of the underlying distribution*. It is possible to hypothesize that as the width of the analyzed sample increases, the sampling distribution will tend to the distribution of the population. Therefore, by carrying out several thousand measurements at the passage of the various trains on the  $i$ -th bridge, it will be possible to tend to the approximation of the structural reaction function according to the known boundary conditions (vehicle mass, travel speed, number of axles, length of the bridge, constructive geometry and so on). In this way we can derive, with an inverse engineering approach, the possible effects, as a whole, of boundary conditions not known a priori (displacements at support, degradation of the mechanical properties of materials, and so on) and obviously not individually identifiable.

All this given, if the inequation {32} is satisfied, the IoT solution acts, just saving and indexing the sampled quantities and all the boundary variables, and recording the satisfaction of the safety conditions. Otherwise, it could send an alert to the Central Operations Manager (DCO), allowing inspection of all the necessary information on a dashboard updated in near real time. In addition, the system could send all the documental attachments in an email (engineering data, sampled variables, deformations, vibrations speed, line data and videos or images if available from cameras nearby, and so on) to facilitate rapid and effective countermeasures aimed at minimizing the risk for subsequent convoys, also resolving potential false positives. In both cases, the outputs of the analyses carried out by PDI over time would be saved on a specific data warehouse (EDW). This EDW will provide the necessary inputs to PBA to feed dashboards, infographics and deploying actions, which, through PDI, automatically and in near real time would be implemented when certain threshold values are exceeded.

In addition to the actions required for the construction of a predictive maintenance framework for railway bridges, the architecture proposed in Figure 15 also contemplates an advanced component of protection of the data collected and analyzed. In fact, PDI, through native integration with external file systems, allows the archiving of data stored on the main database, moving them, against preset thresholds, on an external object storage (for example, Hitachi Content Platform or HCP). This move guarantees the compliance and immutability of data, also preserving the legal value for the purposes of any legal disputes. But, PDI can also move the data directly to the cloud (public or private) to make the main database lean and functional, while retaining all the data collected from commissioning forward. This data offloading procedure not only guarantees an improvement in the performance of the entire architecture, but also allows cost optimization: In fact, the cost per gigabyte on a performance DB (including hardware and software) is much higher than that of an object storage where the data must only be stored and accessed solely in the face of rare events. Finally, it should be noted that HCP could represent a first archiving layer that, upon reaching specific thresholds, would automatically and autonomously proceed to offload parts of the DB in the cloud. This would be accomplished even without the intervention of Pentaho, exploiting the intelligence on board.

Using a cyber-security module designed ad hoc, all communications among the different frameworks' layers, among those and the distributed assets to be monitored, as well as all the connections with the end users are protected by advanced encryption tools. The Lumada framework provides everything needed to build a tailor-made IoT platform to address all customer needs. It uses both proprietary Hitachi and third-party technologies, to build a vertically integrated solution that aligns with project needs. Hitachi provides not only the technology, but also the domain knowledge to advise the involved stakeholders in defining technical specs, in industrial processes optimization, and within the end-to-end cycle of value creation.

Lumada customization enables the creation of a predictive maintenance framework for railway bridges that integrates domain competencies with technologies that enable both predictive analytics and computerized decision support systems. This framework makes it possible to interface in almost real time with the various bridges open to the traffic and with the trains in transit, memorizing events, diagnostic signals and counters. In this way it will be possible to construct a multisource dataset that is statistically representative and enables the extraction of predictive models, to carry out maintenance operations in just-in-time/in-case logic, significantly increasing the safety of trains in line and eliminating any potential maintenance inefficiency.

## Conclusions

The vast majority of civil infrastructures built since the middle of the last century are subject to a global deterioration of mechanical properties due to varied loads and operating conditions that challenge the design, the aggression of atmospheric agents (for example, freeze-thaw cycles), and, sometimes, undersized maintenance actions.

Due to increasingly tight budgets and the number of infrastructure elements to be maintained, it is of fundamental importance to be able to reconcile economic sustainability with maintenance effectiveness. Thanks to a deep engineering knowledge, using new IoT technologies for sampling, collecting, transmitting and analyzing data, it is possible to create data-driven maintenance frameworks. Such frameworks monitor the state variables of bridges in near real time by sensors. They are installed both on the bridge and on commercial trains that, suitably equipped, can act as

moving sensors during their transits. The possibility of identifying critical structural responses and/or identifying their drifts along the time and the operations represents the driver of choice for directing field inspections with a just-in-case approach. This approach extends the useful life of the infrastructure, carrying out custom-made maintenance operations only when strictly necessary.

To achieve this goal, a fundamental collaboration must occur among the various stakeholders, such as the railway infrastructure management company, the companies managing the train services, the suppliers of signaling and traffic management equipment, the rolling stock manufacturers, and the suppliers of big data and analytics technologies. Working closely to the stakeholders, a system integrator will bring consulting skills to help to blend all the contributions. This collaboration could lead to a modest initial economic investment divided between the various components mentioned above. This step would equip a limited number of commercial vehicles with accelerometers on bogies, to choose some of the bridges most suitable for such analyses, equipping them with *ad hoc* sensors, thus building a test scenario.

In this way, the IoT platform would be able to receive data coming from both train sensors and those present on the bridges, calculating the parameters of the bridge motion and function of the relative boundary conditions. This automated test environment would read the boundary conditions of the dynamic load, integrate them with those of the bridge to be crossed, and calculate the expected modal functions. It would identify any anomalies between the expected values and those measured in real time from the instrumentation, both onboard the train and on the bridge. The know-how deriving from a test environment of this caliber would be of fundamental importance for the calibration and validation of mathematical models. It would also support the certification of the end-to-end IoT architecture necessary to scale from the test environment to a more extensive production scenario.

The construction of an automated and data-driven decision support system could represent, in the maintenance domain, an objective function. This function would be able to guarantee the improvement of both efficiency and effectiveness indicators, minimizing, at the same time, the risks for train circulation.

Within the era of the industrial internet of things there is a cross fertilization between railway engineering and information technology. This vertically integrated knowledge is needed to complement, extend and overtake the paradigms of the classical railway engineering.

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WP-597-B BTD April 2020