# Towards a real-time Structural Health Monitoring of railway bridges

Matteo Vagnoli, Rasa Remenyte-Prescott, John Andrews
Resilience Engineering Research Group, the University of Nottingham
Science Road, University Park,
NG7 2RD, Nottingham, United Kingdom

**Abstract**

*More than 350,000 railway bridges are present on the European railway network, making them a key infrastructure of the whole railway network. Railway bridges are continuously exposed to changing environmental threats, such as wind, floods and traffic load, which can affect safety and reliability of the bridge. Furthermore, a problem on a bridge can affect the whole railway network by increasing the vulnerability of the geographic area, served by the railway network. In this paper a Bayesian Belief Network (BBN) method is presented in order to move from visual inspection towards a real time Structural Health Monitoring (SHM) of the bridge. It is proposed that the health state of a steel truss bridge is continuously monitored by taking account of the health state of each bridge element. In this way, levels of bridge deterioration can be identified before they become critical, the risk of direct and indirect economic losses can be reduced by defining optimal bridge maintenance works, and the reliability of the bridge can be improved by identifying possible hidden vulnerabilities among different bridge elements.*

*Keywords: Real-time monitoring; Structural Health Monitoring; Bayesian Belief Networks; Steel truss bridge.*

## 1. Introduction

A continuous improvement of the reliability and robustness of the railway system is desirable in order to support the continuous expansion of the railway infrastructure within the transportation network. Indeed, the daily life of millions of people, and the economy of many industrialized countries, strongly depends on the quality of the services provided by the railway system, due to the fact that the railway has high load capacity and speed, and consequently, new passengers and freight companies are using the railways. Railway bridges are a vital element of the railway network as, on average, there is one bridge for every 700 meters of the track in the European railway network (European Commission, 2012). For these reasons, the railway system and, particularly, railway bridges are generally considered as the key system of the transportation Critical Infrastructures (CI) (Murray et al., 2007, Johansson et al., 2013).

Railway bridges are designed to operate for a long period of time, for example more than 35% of the bridges of the European railway network are over 100 years old, and as a consequence, they are exposed to continuously changing environmental threats, such as wind and floods, that can affect safety and reliability of the whole railway network (Le et al., 2013). Moreover, in order to improve railway capacity, railway bridges, especially, old bridges, are being pushed to their physical limit, due to the increased transfer speed, train frequency and length (Reyer et al., 2011; Pipinato et al., 2016).

Generally, the health state of the railway bridge is evaluated by visual inspections, which are carried out at intervals of one to six years. However, during a visual inspection the structure can be examined superficially based on expert knowledge, which can be subjective, and thus the outcomes can be significantly variable in terms of structural condition assessment (Chase, 2004). Hence, real-time Structural Health Monitoring (SHM) methods for railway bridges can significantly improve the reliability of the railway network by providing rapid and reliable information to decision makers regarding the health state of the bridge, and its elements, by considering environmental threats, such as wind, ice, flood, and deterioration mechanisms, as part of the analysis (Brownjohn et al., 2013).

Several SHM studies on railway bridges have been developed in the last years (Doebling et al., 1998) (Kim et al., 2015) (Sanayei et al., 2015) by adopting either: *i)* a model-based approach, which relies on the development of a mathematical model of the bridge (such as a Finite Element (FE) model), in order to assess the health state of the bridge by evaluating the difference between measured and simulated structural parameters; *ii)* a non-model-based method, which relies on the analysis of experimental measurements of the bridge in order to assess its health condition. Furthermore, ensemble methods, which merge together a FE model updating strategy and non-model-based method, have been recently proposed (Zhong et al., 2014; Shabbir et al., 2016). Although, computational time and influence of noisy data can be of concern in these SHM methods, followed by the main limitation that the bridge is not usually studied as a whole system, but the analysis focus is placed on the health state of a bridge element (such as abutments, slabs, joints, girder, bearings, etc.). However, railway bridges can impact the reliability of the whole transportation network, for example a bridge failure can result in the interruption of economic activities, by increasing the vulnerability of the geographic area served by the railway network (FHWA, 2011). Therefore, it is beneficial to analyse it as a system. Hence, in order to ensure safety and reliability of the bridge, and consequently of the whole transportation CI, the analysis of the bridge health state should consider the bridge as a whole system, by evaluating each bridge element and its interactions with other elements, in order to identify possible hidden vulnerabilities and to provide reliable, robust and rapid information to the decision maker (Zio, 2016).

In this paper, an SHM methodology based on a Bayesian Belief Network (BBN) (Rafiq et al., 2015) method for a truss steel railway bridge is proposed, with the aim of assessing the health state of the whole bridge continuously, by taking account of the health state of each bridge element. Indeed, an assessment of how a degradation mechanism affects the health state of the bridge over time is needed in order to prevent bridge failure. In this way, the risk of direct economic losses, such as bridge repair works, and indirect economic losses, such as network unavailability and service delays, that can affect the transportation CI after a bridge failure, can be significantly reduced by defining an optimal maintenance schedule (Lokuge et al., 2013) (Venkittaraman et al., 2014). Furthermore, variations of the bridge behaviour can be pointed out by the proposed BBN monitoring method, as soon as they occur. In this way, bridge managers can take robust and rapid decisions on whether the bridge needs to be take repaired and brought to a new safe condition, or, even if the bridge is exposed to some continuous degradation mechanism and environmental threats, the safety and reliability are still guaranteed. In the proposed method, a Finite Element (FE) model of a truss railway bridge is developed using the SAP2000 software, with the aim of calculating the displacements of the bridge elements due to a static load. The displacements are used as the evidence of the bridge behaviour and, thus, as the input of the BBN. In order to account for the environment effects on the bridge, a deterioration mechanism is introduced by modelling the formation and growth of micro-cracks at the joints, which are difficult to spot during visual inspections (Mehrjoo et al., 2008).

The paper is organized as follows: Section 2 presents the proposed methodology and describes the FE model, the degradation mechanism and the BBN method; Section 3 shows the results of a case study; the conclusions and future work are discussed in Section 4.

## 2. The proposed BBN methodology

A first step towards a real-time monitoring SHM is proposed by developing a BBN, in order to provide information to bridge managers about the health state of the bridge. In this way, bridge managers are able to take rapid condition-based decisions by evaluating whether the bridge needs to be maintained, or its safety and reliability are still guaranteed. The proposed method is illustrated by developing an FE model of a steel truss railway bridge. The FE model simulates the behaviour of the bridge due to external loads, such as the train load, and furthermore, the effect of the micro-cracks at the joints is analysed as degradation mechanism. A BBN of the bridge is then developed by defining one node in the BBN framework for each major element of the bridge. The behaviour of the bridge, which is obtained by using the FE model, and the information retrieved from interviews with bridge managers and structural engineers is used to define the Conditional Probabilities Tables (CPTs) of the BBN. The proposed method aims to update the health state of the bridge and of its elements automatically, as soon as sensors provide a new measurement of the bridge behaviour. As a result, using the BBN the undesired health state of the bridge can be pointed out by identifying its most degraded element(s).

### 2.1 The steel truss bridge model

A truss steel bridge has been chosen in this study due to the fact that the degradation mechanisms of the steel, such as corrosion and cracks, can develop rapidly after they have started, and, consequently, an early detection and management of such condition can be of great importance to bridge owners, for reducing the risk of failure and the whole-life cycle cost of the bridge (Katipamula et al., 2005).

The bridge model, which is developed by using the SAP2000 software, is 30m long, 7m wide and 8m high, as shown in Figure 1. The components of the bridge have been realized considering the S355 steel, as this is the steel commonly used in Europe to build steel railway bridges (Pipinato et al., 2016). The bridge is modelled to allow the transit of trains in two directions, and consequently two railway tracks have been modelled by following the most commonly used dimensions (Country Regional Network, 2012). The reference system, used in this paper, is as follows: the side of the bridge at y = 0m, is defined the right side of the bridge, whereas at y = 7m is defined the left side of the bridge.

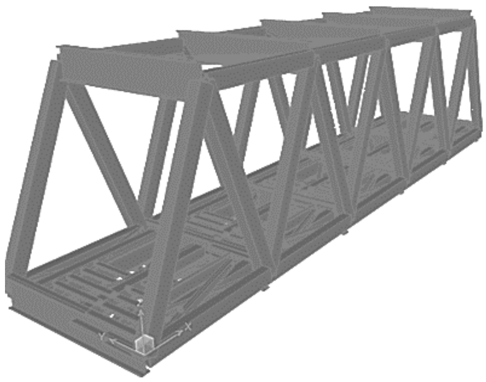

**Figure 1.** FE model of the steel truss railway bridge

### 2.2 The micro-cracks degradation mechanism

(Mehrjoo et al., 2008) claims that more than 40% of the steel truss bridges are affected by the formation of micro-cracks at the joint location, which typically can develop around the holes of the bolts or rivets during the assembling phase of the bridge. Furthermore, these micro-cracks are difficult to identify during visual inspections due to their size, and the limitations of visual inspections, which can examine the bridge structure superficially (Chase, 2004). The environmental conditions, which continuously affect the bridge elements through the cycle of loading and unloading, e.g. trains are continuously passing over the bridge, can lead to a continuously increasing size of the micro-cracks. Therefore, the bridge can suffer with fatigue unexpectedly.

The formation and growth of micro-cracks leads to a reduction of the cross sectional area at the joints, and consequently, in order to simulate this degradation mechanism, in this study, the cross sectional area of the degraded bridge elements has been reduced by as much as 30% of its initial value.

Displacements of the bridge joints are considered as the monitored parameter of the bridge behaviour due to the fact that the natural frequency and mode shape analysis have shown to be prone to measurement contamination, and besides displacements could be an interesting variable to be monitored in the near future, due to the technology improvements of sensors (Doebling et al., 1998) (Zhao et al., 2015). A static uniform load of 40 kN/m has been applied to the bridge in order to simulate a train, which has been stopped on the track, and the displacements at the joints are consequently retrieved using the FE model.

The displacements of the top chord on the right hand side of the bridge that have been retrieved using the FE model are depicted in Figure 2. The bridge healthy state is shown by the solid line in Figure 2, whereas, the degraded states, due to the reduction of the cross sectional area of the truss components by the 10% and the 30% of its initial value, are represented by the dotted and dashed lines in Figure 2, respectively. The displacements of the degraded top chord are larger than those of the healthy case, and, moreover, as the bridge degradation grows, the displacements of the top chord on the right hand side of the bridge increase consequently.

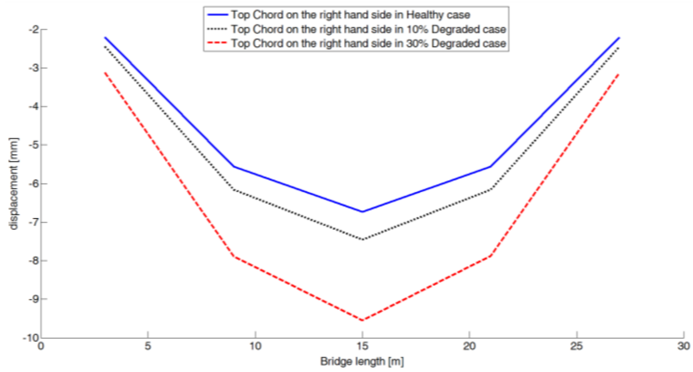


**Figure 2.** Displacements of the top chord on the right hand side of the bridge model

### 2.3 Real-time SHM method based on Bayesian Belief Network

In order to develop a SHM method for monitoring the health state of the railway bridge, a BBN is developed. The BBN can monitor the evolution of the bridge health state by considering the health state of its elements, and updating the health state of the whole system, as soon as the virtual sensor system of the FE model provides a new measurement. Hence, the health state of the bridge and its components is updated automatically every time when a new evidence of the bridge behaviour, i.e. a new displacement of each joint location (6 joints on the bottom chords and 5 joints on the top chords, in this case study), is provided by the FE model. The steel truss bridge is analysed within the BBN framework by defining a node for each major element of the bridge, and finally, with the aim of assessing the influence of each bridge element on the health state of the whole bridge, a node representing the health state of the whole bridge is introduced in the BBN.

Figure 3 shows the above mentioned idea, which can be explained following a top-down reasoning process: the FE model is perturbed by introducing the effect of environmental threats, which lead to the deterioration of the bridge materials, such as the growth of the micro-cracks at the joints. A monitoring measurement system of the displacements of the four chords is simulated by using the FE model, which mimics the sensor system on each chord. Therefore, every time that a new measurement of displacements is available, it is used in the BBN framework, where it is processed by a *virtual sensors* node, in order to assess the health state of the correspondent bridge element. The health state of each bridge element is then evaluated at the following level of the BBN, due to the fact the health state of each bridge element is influenced also by the health state of other bridge elements. Indeed, if a bridge element degrades, other elements are subject to an increasing load. For example, the node called *Top chord left,* which represents the health state of the top chord on the left hand side of the bridge, is influenced by the health state of the other chords, and consequently each *virtual sensors* node is connected to the *Top chord left* node, as shown in Figure 3. Finally, the health state of the whole bridge, which is depicted by the *Bridge health state* node, is affected by the health state of each bridge element.

These dependencies among different elements of the bridge are expressed by using CPTs. The CPTs are completed by merging the information from the simulation of the bridge behaviour by using the FE model and the expert elicitation process (Rafiq et al., 2015) (Andrews et al., 2017). The *virtual sensors* nodes have 6 possible states, depending on the difference between the displacement of the healthy bridge element and those of the degraded element: the healthy state is defined if the difference is less than 1%; then, the 5 degraded states are defined by arbitrarily considering a constant 5% step of the above mentioned difference (e.g. the first degraded state requires a difference between the displacement of the healthy bridge element and those of the degraded element higher than 1% and lower than 5%; the second degraded state requires a difference between 5% and 10%, etc.). Particularly, as soon as the displacements of the bridge element increase, the virtual sensors nodes assess the amount of the increment, and define the adequate health state. On the other hand, three mutually exclusive health states are defined for each bridge element and the whole bridge (i.e., for the nodes on the bottom two levels of the BBN) (Rafiq et al., 2015): *i)* a healthy state, if no corrective or repair action are required; *ii)* a partially degraded state, if some repair or prevention activities are needed, such as methods for restoring the corroded steel to shiny metal; *iii)* a severely degraded state, if strengthening or replacement of bridge elements is required, such as welding of a chord or beam, replacement of elements etc. (Ryall et al., 2000).

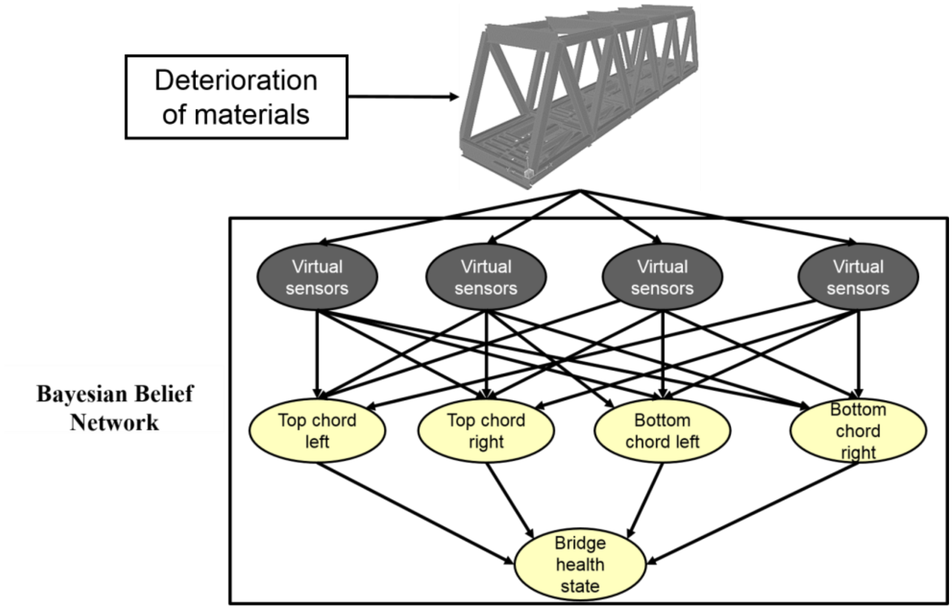


**Figure 3.** Bayesian Belief Network of the steel truss bridge with influence of the degradation of materials

# 3. Modelling results

The proposed SHM method for railway bridges assesses the health state of the bridge element, and the health state of the whole bridge, by updating the health state of each bridge element, using the displacements provided by the FE model. In this way, the reliability of the railway network can be improved by providing rapid and reliable information to bridge managers, regarding the health state of the bridge, by considering environmental threats, such as the deterioration mechanisms. Furthermore, possible hidden vulnerabilities can be pointed out by analysing the bridge as a whole system, i.e. considering the possible influence among different bridge elements.

In this section, an example of the steel truss bridge, which is subject to the degradation of the bottom chord on the left hand side, is presented. In Section 2.2, the degradation mechanism has been presented, by explaining how the micro-cracks at the joints grow due to the effects of external factors, such as passing trains and wind, which constantly apply a load to the bridge structure. Figure 4 shows the evolution of the displacement of the bottom chord on the left hand side of the bridge: the solid dark line shows the displacement of the healthy chord, however, as soon as the material of the bridge degrades due to the environmental effect, and consequently the micro-cracks grow, the displacements become larger, as shown by the dark dotted line in Figure 4. Therefore, as the bridge structure is continuously influenced by the load-unload cycle, the micro-cracks become larger, and consequently, the cross sectional area of the bottom chord on the left hand side decreases. As a consequence, the displacement of the bottom chord on the left hand side increases as the micro-cracks growth, as shown in Figure 4.

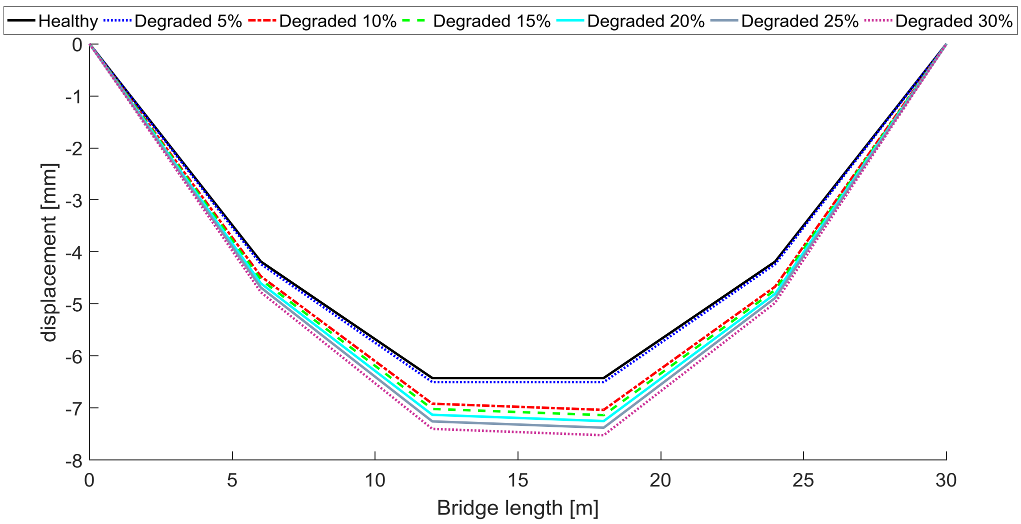


**Figure 4.** Displacements of the healthy and degraded bottom chord on the left hand side of the bridge model

The seven displacement patterns depicted in Figure 4, which represent the time evolution of the degradation process of the steel truss bridge, are used as the input to the BBN in order to update the health state of the whole bridge, and of its elements. Indeed, it is worth mentioning that the simulated degradation mechanism of the materials of the bridge, which is shown in Figure 4, is a gradual process that continues over time after its initiation. Therefore, seven types of evidence of the bridge behaviour would be available over time, and as soon as a new measurement is available from the sensor system, the BBN could compute the probability of the health states of each bridge element and, thus, of the whole bridge. Figure 5 shows the real-time evolution of the posterior probability distributions of the health state of the steel truss bridge (node 5) and its components (node from 1 to 4, for the top and bottom chords on the right and left hand side, respectively): the real-time monitoring starts with the steel bridge in the healthy state, as shown by the displacement pattern depicted by the solid dark line in Figure 4 that is the first evidence (Evidence 1 in Figure 5) of the bridge behaviour provided by the measurement system of the FE model. Therefore, the probability of each health state for each bridge element, and for the whole bridge, is consequently computed, and as no degradation is present in all the components of the bridge, the probability of the healthy state is the largest (green bar in Figure 5). Then, the degradation mechanism is initiated, and therefore, the displacements of the bottom chord on the left hand side increase, as shown by the dark dotted line in Figure 4. The new measurement is immediately taken by the BBN (Evidence 2 in Figure 5), which updates the probability of each health state of each bridge element. Figure 5 shows that when Evidence 2 is used by the BBN, the probability of the partially degraded state of the bottom chord on the left hand side (yellow bar of node 4 in Figure 5) increases accordingly. It should be noted that also the probability of the degraded health states of other elements of the bridge (node from 1 to 3), and of the whole bridge health state (node 5), increases due to the influence among different bridge elements. In this way, possible hidden vulnerabilities of other bridge elements can be pointed out consequently.

The process of monitoring continues in the same way, by providing the new available measurement of the displacement of the bridge elements to the BBN, which assesses the health state of the element of the bridge, and then of the whole bridge. Generally, Figure 5 shows that the probability of the partially degraded state of each bridge element (node from 1 to 4) increases and, consequently, the probability of the healthy state of the whole bridge (node 5) decreases. Particularly, the probabilities of the degraded states of the bottom chord on the left hand side (node 4) show the highest increment, as the degradation mechanism directly affects this bridge element. In this way, the health state of the bridge, and of its elements, can be monitored, by identifying the most degraded elements of the bridge. Hence, optimal maintenance programme can be adequately scheduled, based on the degradation level of the bridge elements.

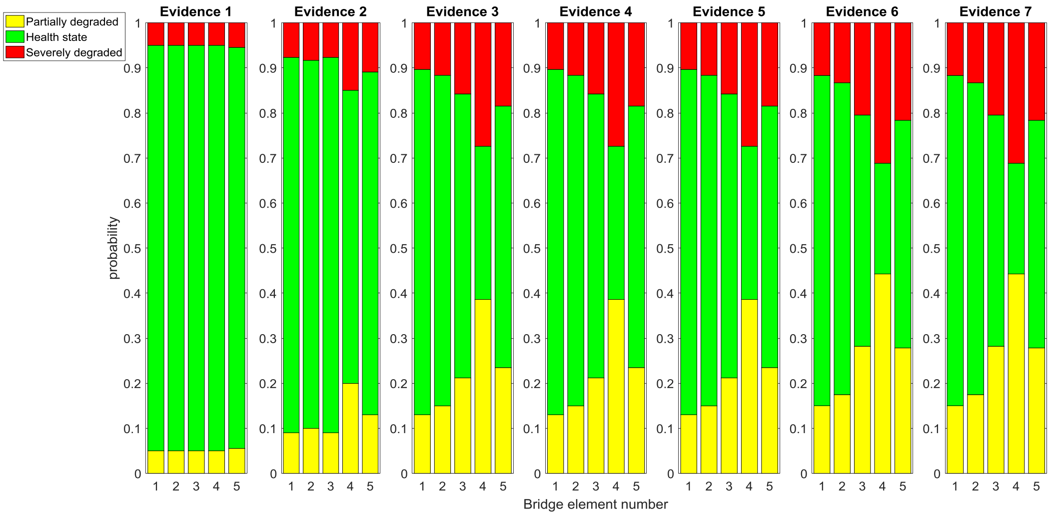


**Figure 5.** Evolution of the health state of the bridge using displacements as evidence of bridge behaviour

## 4. Conclusion

Railway bridges are pushed to their physical limits due to continuously changing environmental conditions, such as increasing traffic and climate change that produces extreme events in terms of strong winds and storms. Even though, recently the technology of sensors and data analysis has enhanced significantly, the railway bridges are mainly evaluated by visual inspections. However, in order to improve the reliability of the railway network by providing rapid and reliable information regarding to bridge managers the health state of the bridge, real-time SHM methods are needed. In this way, bridge manager can achieve an optimal management of the bridge, by reducing the risk of economic losses and disruption of the service.

In this paper, a truss steel bridge has been modelled by using the Finite Element software SAP2000. The effects of environmental factors on the health state of the bridge have been assessed by simulating the initiation and growth of micro-cracks of the joints, by gradually reducing the cross sectional area of the truss elements of the bridge. A BBN has been developed in order to monitor the health state of the steel truss bridge, by considering the health state of its elements. The monitoring method has demonstrated to efficiently monitor and assess the evolution of the health state of the bridge elements over time, by updating the health state of the each bridge element as soon as a new evidence of the bridge behaviour is provided by the sensor system. Therefore, bridge managers can be informed with the health condition of the bridge, and optimal maintenance schedule of the bridge can be achieved by identifying the most degraded bridge element. In this way, the reliability of the whole railway network can be consequently improved.

Real-time condition monitoring SHM methods for bridges are needed, in order to reduce the risk of possible losses, the whole life cost of the bridge and the vulnerability of the whole railway network. The proposed method is a first attempt to achieve this aim. Although, a good illustration of monitoring the evolution of the health state of the bridge has been given by the developed method, some further development are needed. For example, the relationship between joints and beams within the same chord need to be considered in the structure of the BBN, and a more robust definition of the CPTs is needed. In addition, the method needs to be tested using sensor measurements on a real bridge.

## Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 642453.

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