Condition and criticality-based predictive maintenance prioritisation for networks of bridges

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Numerous bridges are exposed to increasingly frequent and intense extreme events due to climate change, while serving more traffic than originally designed due to population growth. Thus, predictive maintenance of bridges is of paramount importance for securing structural safety and bridge network reliability. However, the application of predictive maintenance for networks of bridges, considering condition and criticality of bridges within the network, has not seen much attention in practice and literature. Presented herein is a maintenance prioritisation method for networks of bridges, based on: a deterioration model for individual components considering uncertainty; life-cycle cost analysis; grouping of components maintenance to reduce traffic interruption and setup cost; and criticality evaluation of bridges using a specifically tailored version of closeness vitality and traffic simulation. This method has been applied to a network of 21 bridges in Portugal, composed of several heterogeneous elements. It showed a substantial decrease in maintenance cost, compared to the Structures Investment Toolkit, and significant differences between criticality of bridges within a network. The proposed methodology can be applied to any networks of bridges or serve as the basis for updated maintenance decision support systems for infrastructure asset networks.

Keywords: transport infrastructure management; road networks; optimization; network analysis; closeness vitality; network traffic simulator
1. Introduction

Transport networks are an essential prerequisite of the economic growth of a country, which is linked with the accessible resources to society and the effectiveness of their usage (Ivanová & Masárová, 2013). Transport networks contribute to public prosperity by serving human mobility and productivity (Chan et al., 2010). Inland networks have the highest number of passengers and trips, compared to water and air networks, with roadways dominating over railways. In the European Union, for instance, roads counted for 92.3% of inland passengers in 2016 (Eurostat, 2017). Bridges are vulnerable and critical elements of road networks, which are mainly positioned at intersections of highways. A bridge disruption, can lead to catastrophic consequences not only on existing users, whose safety is threatened, but also on the society at large (Li et al., 2020). Possible effects include productivity decrease, loss of reachability to isolated areas, traffic rerouting and subsequently increase in travel time, distance, carbon monoxide emissions and environmental pollution.

Only in the U.S., there are more than 600,000 bridges, from which around 40% are over 50 years old and 9.1% are structurally deficient, with 188 million trips/day happening across structurally deficient bridges (ASCE, 2017). Bridges progressively deteriorate over their lifetime. Their deterioration can be accelerated by heavy traffic, inadequate maintenance or extreme events, consisting of natural hazards (e.g. heat and cold waves, river and coastal floods, landslides droughts, wildfires, windstorms) and man-made events (e.g. terrorism, vandalism, accidents, negligence). Most bridges are exposed to more intense events and carry significantly more traffic than originally designed due to climate change and population growth (EU Science Hub, 2019; Yang & Frangopol, 2019). Possible impacts of climate change on bridges, as identified by Nasr et al. (2020), include accelerated material degradation, higher flood levels and more
frequent flooding, damage to pavements and railways, as well as higher scour rates. As a result, bridge monitoring, condition prediction, and maintenance are crucial for avoiding structural failures. This urgent need is highlighted by recent disastrous events, such as the Morandi bridge collapse in 2018, causing the death of 43 people (Milillo et al., 2019).

In practice, maintenance of transport infrastructure assets, including bridges, is conducted in numerous ways, following different asset owners’ guidelines (Hadjidemetriou et al., 2020). The decision for the need for maintenance is mainly based on condition assessment. Bridge assessment is traditionally conducted manually by inspectors. However, this procedure is time-consuming and subjective since it relies on inspectors’ knowledge and experience. Researchers and asset managers aim to overcome this limitation by exploiting latest condition monitoring technologies to automate the procedure. Vision-based methods can automatically detect and evaluate defects. For instance, Zhu et al. (2020) proposed a methodology based on convolutional neural networks and transfer learning that automatically analyses and identifies a large number of collected frames. Those technologies can contribute to acquiring data to the maximum extent, achieving a dynamic monitoring of bridges along their life-cycle. A consistent component level evaluation can lead to the identification of the most vulnerable bridges and an improved maintenance decision-making at the network level (Bittencourt et al., 2018).

Several traditional bridge maintenance programs as well as researchers have focused on achieving optimized life-cycle cost of individual bridges, ignoring the interactions between bridges within a transportation network. Eamon et al. (2012), for instance, implemented deterministic life-cycle cost analysis to define expected cost outcomes for a variety of bridge spans, considering different traffic volumes. Another
example is the work of Wei et al. (2020) that described an automated deep reinforcement learning method for acquiring an optimized structural maintenance policy. Their method was applied on individual bridges comprising of 7 to 263 elements. However, bridges are part of networks of bridges, connected by roads, and thus, failure, degradation and even the maintenance time of a bridge have an impact on the wider network. A network perspective adoption adds new dimensions in decision support systems for bridge management, such as systems criticality (Frangopol & Bocchini, 2012). Subsequently, decision makers face a complex multi-objective optimization problem as they need to ensure network reliability and availability, minimise costs and environmental impact, and achieve safety requirements as defined by their organizations (Jensen, 2020).

Overcoming the barriers of considering bridges as parts of a network and of solving the caused multi-objective optimization problem has attracted the interest of research community. Orcesi and Cremona (2010) proposed a system which considers the position of the bridge within the network, visual condition inspections and interests of users and bridge owners. Another study worth mentioning evaluated the life-cycle performance of bridge networks, considering the time-variant nature of bridge reliability due to elements deterioration, complex network layouts and a correlation structure for the service state of each bridge (Bocchini & Frangopol, 2011b). The same authors presented a probabilistic computational method for the Pareto optimization of the preventive maintenance applications to networks of highway bridges (Bocchini & Frangopol, 2011a). Bocchini et al. (2013) formulated a Markov chain model that analyses the life-cycle of single bridges and bridge groups, taking into account deterioration, repair activities, failures and restorations. The work of Hu and Madanat (2015) formed an optimal maintenance, rehabilitation, and replacement schedule,
balancing an acceptable level of network reliability and the lowest possible life-cycle maintenance cost of individual bridges. The study of Hu et al. (2015) described a plan for maintenance of bridge networks, minimizing the additional travel distance caused by bridge failures under budget constraints and over a planning horizon. In addition, Moreu et al. (2017) formulated a consequence-based management model for taking maintenance decisions for bridge networks, relating service condition limit states to transverse displacement and minimizing total network costs. Yang and Frangopol (2020) determined probabilities of different bridge failures scenarios utilizing system reliability analysis, while for every scenario, network traffic flow was predicted in the damaged network. Liu et al. (2020) proposed a risk-based, network level methodology for optimal bridge adaptation management, taking into account scour and climate change. Finally, a recent research work analysed issues and proposed concepts for overcoming them in areas related to life-cycle analysis, risk, resilience, design and management of both independent bridges and networks of bridges, under independent and interrelated hazards (Akiyama et al., 2020).

Similarly, there is an increased research interest in the maintenance prioritisation of multi-system multi-component networks (MSMCN) in general and beyond bridges, with applications in transport infrastructure and others sectors. MSMCN are constituted by multiple systems that are in turn composed by multiple components. A bridge, for example, can be seen as a system of numerous components, while at the same time being part of a network of numerous bridges. Developments in infrastructure condition assessment and prediction using sensors (Hadjidemetriou & Christodoulou, 2019), as well as in data analytics, in recent years, have motivated researchers and asset owners to investigate the benefits of predictive maintenance of MSMCN, compared to reactive maintenance. Predictive maintenance is the decision-making for maintenance actions
considering the forecasted service life, aiming to decrease life-cycle cost. Combining predictive maintenance with a systematic approach (rather than an approach focusing on individual components) has the potential to further expand benefits by enhancing connectivity and reliability. Systematic maintenance approaches can be classified into: selective, opportunistic, and group maintenance.

The first class, namely selective maintenance, comprises of inactive time periods, while proposing which elements need to be maintained during active maintenance periods in order to assure system reliability. Liu et al. (2018) for instance, proposed a selective maintenance approach which targets the rise of the possibility of a following effective maintenance time period, using a tailored ant colony algorithm. The second class of systematic maintenance methods, termed opportunistic, concentrates on components maintenance meeting some condition- or age-based criteria, when there is an opportunity due to the maintenance of neighbouring elements. Aizpurua et al. (2017) for example, formed a prognostic-based maintenance policy for complex dynamic networks, using dynamic fault tree, while allowing maintenance of failed non-critical elements at the same time with maintenance of a critical element. The third category of systematic maintenance methodologies, called group maintenance, conducts multiple maintenance activities at the same time. It is the most challenging systematic approach, but it has the greatest potential in reducing costs by using shared setup cost and system downtime for groups of elements. Chalabi et al., for instance, implemented a Particle Swarm Optimization algorithm, applied in multi-unit series production systems, aiming to improve system availability and minimize preventive maintenance cost (Chalabi et al., 2016).

Despite the increasing number of research studies for maintenance prioritisation of bridges or MSMCN in general, only a small portion of them takes into consideration
bridge criticality. There are also several studies that define and estimate criticality, yet not using this information for bridge maintenance prioritisation. In addition, there is no standardised definition of criticality for transport infrastructure assets (e.g. bridges). For instance, Latora and Marchiori (2005) evaluated critical positions of transport networks by estimating the difference between the worst performance of a network under defined damages and the optimal network performance. Bush et al. (2013) focused specifically on the analysis of “critical” bridges, defining them as those with potential extensive failure consequences. A study worth mentioning assessed railway bridges based on vulnerability and criticality analysis (Aflatooni et al., 2014). New equations were developed, while the contribution of several “critical factors” was determined.

Summarising, predictive group maintenance of bridge networks is challenging due to the heterogeneity of bridges included in a network and the economic dependence in such hierarchical network configurations. Additionally, from a network perspective, bridge maintenance prioritisation should be matter not only of bridge condition, but also of bridge criticality within the network. The failure of each bridge will have different impact on traffic and on areas that are connected by the bridge. Although there are various methods on maintenance prioritisation of bridge networks, there is room for improvement in the area of predictive group maintenance, considering bridge criticality, uncertainty in elements deterioration and budget constraints. Given this, the current paper proposes a predictive group maintenance prioritisation method for networks of heterogeneous bridges, based on both bridge condition and criticality within the network. The developed method optimizes positive economic dependencies at both network and system levels. At the network level, the paper introduces a novel procedure for approaching bridge criticality. Bridge criticality analysis is based on a network
centrality measure, distinguishing the nodes of municipalities and bridges, and suitably adopted as a prioritisation method. The sections that follow describe the proposed methodology, the conducted case study, and finally the extracted conclusions.

2. Methodology

The presented methodology is a continuation and a significant improvement of a framework developed by the authors’ research group (Liang & Parlikad, 2020). The already developed general framework for the maintenance prioritisation of MSMCN is herein modified and applied on a network of bridges, while the new dimension of the criticality of a system within the network is added. The presented methodology emphasizes on the estimation of bridge criticality, while explaining how it is added to the general framework for bridge maintenance prioritisation. The hierarchical structure of the framework is classified into three levels, named component, system, and network, whilst it is formed under the following assumptions:

- The deterioration of bridge components is stochastic and thus a continuous-time Markov chain model is utilized for describing it. This multi-state stochastic process considers the time of remaining at a condition state (i.e. sojourn time) as exponentially distributed, while its parameterization is based on periodic bridge assessments.

- Bridge operating environment, which causes element deterioration, stochastically worsens over time.

- Maintenance is classified into minor and major. The former refines the deteriorating operating environment without disrupting bridge operations, while the latter restores element condition to the level of new.
When multiple elements of the same bridge are maintained at the same time, the element that requires more downtime (i.e. operation interruption) dominates, while the setup cost is shared.

Operation interruption (e.g. lane closure) of one bridge can affect the traffic on other bridges.

The presented condition- and criticality-based predictive group maintenance prioritisation model for networks of bridges follows six core stages, as illustrated in Figure 1.

2.1. Components deterioration model

Asset owners have their own indices, assessing components condition using discrete stages (e.g. 6 stages in the following presented case study). Additionally, the majority of asset owners have been saving data only for the last few decades, with their inspection rate ranging between one and five years (Jeong et al., 2018). Thus, the estimation of deterioration rate is challenging. The current method uses the equation defined by the Structures Investment Toolkit (SIT) (Hesketh et al., 2015) for calculating deterioration rate (stage 1, Figure 1). The input includes bridge location (e.g., rural, urban), bridge type and usage, the route supported, traffic, structure size (i.e. dimensions and number of spans), material and current components condition. This continuous-time multi-state discrete stochastic process for estimating components aging was selected due to its mathematical tractability, practicality, and generalizability when combined with a phase-type estimation. The deterioration mechanism is formed as a path that captures non-memoryless deterioration behaviours, in contrast with conventional models. The used model enables the heterogeneity of deterioration rates due to different operating environments.
More specifically, Figure 2 (Liang & Parlikad, 2020) illustrates the state transition of the element deterioration procedure with periodic condition assessments, as used in the presented framework. Elements are inspected periodically with a rate, and when their condition has passed a predefined threshold value, major maintenance is applied bringing the condition back to excellent. Additionally, minor maintenance can be applied to protect elements against external factors, such as increasing loading, prolonging their service life. The condition of an element \( u \) in a system \( v \) (i.e. bridge) is described by indices \( i \) and \( j \) with a state space \( S_{ui}^{(v)} \in \{(0^{(v)},0^{(v)}),\ldots,(i^{(v)},j^{(v)}),\ldots,(k_{ui}^{(v)},m_{ui}^{(v)})\} \). The index \( i \in \{0^{(v)},1^{(v)},\ldots,k_{ui}^{(v)}\} \) represents the element progressively deteriorating condition, where \( i=0^{(v)} \) denotes excellent element condition and \( i=k_{ui}^{(v)} \) designates failure. Similarly, \( j \in \{0^{(v)},1^{(v)},\ldots,m_{ui}^{(v)}\} \) indicates additional deteriorating mechanisms caused by the deterioration of other elements, growing loading or declining environment. Element deterioration rate is connected to the deterioration paths that demonstrate a non-memoryless deteriorating behaviour. The deterioration procedure is formulated as a continuous-time Markov chain model. It should be clarified that \( b_{ui}^{(v)} \) represents major maintenance threshold value; \( 1/\mu_{in_{ui}}^{(v)}, 1/\mu_{i_{ui}}^{(v)}, \) and \( 1/\mu_{M_{ui}}^{(v)} \) correspond to the durations of inspection, minor maintenance and major maintenance, respectively; \( \lambda_{n_{ui}(i,j)}^{(v)} \) denotes the element deterioration rate at the rated operating condition; \( \lambda_{d_{ui}(i,j)}^{(v)} \), indicates the element deterioration rate under detrimental impact of the operating environment; and \( \lambda_{f_{ui}(i,j)}^{(v)} \) represents the decline factor of the operating environment factor \( j \).

### 2.2. Optimal time for components maintenance

Two types of maintenance actions are considered and modelled, called major and minor maintenance. Components maintenance is conducted so that their condition will not
drop under predefined threshold values, arising major safety risks. The optimal
maintenance time for each component (stage 2, Figure 1) is calculated, based on
minimizing the life-cycle cost of the examined component, considering the latest
condition assessment, and outputs from stage 1 (Liang & Parlikad, 2020). Each element
at each condition state is associated with specific available maintenance practices. The
cost type of maintenance practices can be fixed (i.e. applied under specified conditions,
only at one point in time), constant (regardless of element condition); or variable (i.e.
dependent on the element condition). The asset owner needs to define these costs since
they differ between countries and organisations. A component can deteriorate at a
different rate than expected (i.e. slower or faster) due to the stochastic nature of
component deterioration. Stage 2 is recalculated when there is a change in component
condition state, after inspection.

2.3. Penalty cost function

The presented framework proposes maintenance of elements, belonging in the same
system (i.e. bridge), to be conducted simultaneously, when their optimal maintenance
times are similar due to the dual positive economic interdependencies within the bridge
network (Liang & Parlikad, 2020). Firstly, in the system level, the setup cost for
maintenance will be shared and thus lower in total, compared to separately maintaining
bridge elements. Secondly, in the network level and in a similar way, traffic will be
interrupted once, and consequently system downtime will be lower. The reduced setup
cost and traffic interaction can have a positive economic impact, saving money and time
for asset managers. Thus, the optimal maintenance timing for groups of elements may
differ from the one of the individual components (as calculated in stage 2) composing
the group. Hence, a penalty cost function (stage 3, Figure 1) (Hesketh et al., 2015;
Liang & Parlikad, 2020) is applied to estimate the cost of different scenarios for
advancing or postponing maintenance actions of elements. This penalty cost function is
designed within a predefined finite time horizon $T_h$ for every element. The expected
element cost in $T_h$ is a sum of: a. the cost of the expected inspection and minor
maintenance prior the first renewal time $t$ (i.e. application of a major maintenance); b.
the cost of major maintenance, setup, and operation interruption due to the major
maintenance; and c. the additional cost between the first major maintenance and the end
of the planning horizon (Equation 1).

$$h(t,a) \equiv t \left[ C_{\text{in},u}^{(v)} \mu_{\text{in},u}^{(v)} \tau_i^{(v)} \right]_{i=a}^{j} \pi \left( i, m_i^{(v)} + j \right) + C_{\text{c},u}^{(v)} \sum_{i=a}^{j} \pi \left( i, m_i^{(v)} + 3 \right) + \left( C_{\text{M},u}^{(v)} + C_s^{(v)} + \frac{c_l^{(v)}}{\mu M_l} \right) + \left( T_h - t - \frac{1}{\mu M_1} \right) C_u^{(v)\ast} \tag{1}$$

where: $a$ is the condition revealed by the latest inspected condition

- $C_{\text{in},u}^{(v)}$ is the inspection cost for element $u$ in system $v$
- $C_{\text{c},u}^{(v)}$ is the minor maintenance cost for element $u$ in system $v$
- $C_{\text{M},u}^{(v)}$ is the major maintenance cost for element $u$ in system $v$
- $C_s^{(v)}$ is the set-up cost for major maintenance of elements in system $v$
- $c_l^{(v)}$ is the per unit time penalty cost of level $l$ operating interruption in system $v$
- $C_u^{(v)\ast}$ is the additional maintenance cost between the first major maintenance and the end
of the planning horizon

The expected cost when the first major maintenance activity is conducted at time
$t$, within the planning horizon ($t \leq T_h$) is computed as:

$$H(t,a_u^{(v)}) \int_0^t f_a(\tau|a_u^{(v)}) \left[ \phi h(\tau,a_u^{(v)}) \right] d\tau + F_s(t|a_u^{(v)}) h_1(t,a_u^{(v)}) \tag{2}$$

In case of only one major maintenance activity happening throughout the
planning horizon, the penalty cost of shifting $\Delta t_1$ from the optimal element maintenance
time $t^\ast$ is expressed as follows:
\[ P_u^{(v)}(\Delta t_1) = H(t^* + \Delta t_1, a_u^{(v)}) - H(t^*, a_u^{(v)}) \]  

(3)

In case of the requirement for multiple major maintenance activities during the planning horizon, \( \Delta t \) represents the sequence of time shifts, while the overall penalty cost function is calculated as follows:

\[ P_u^{(v)}(\Delta t) = \sum_{i=1}^{\Theta} P_u^{(v)}(\sum_{j=1}^{i} \Delta t_j) \]  

(4)

where \( \Theta \) is the number of maintenance activities within the planning horizon \( T_h \).

Summarising, this cost function is designed for both scenarios of minor and major maintenance of components. It considers safety risks and the impact on loss of service. Safety risks are divided into structural integrity risk and public safety risk. The loss of service takes into account the availability impact (i.e. lane closure) and the impact on supported and/or crossed routes by the examined bridge.

2.4. Grouping components maintenance

The following stage, called grouping components maintenance (stage 4, Figure 1), exploits the positive economic interdependencies at both the network and system levels. Conducting maintenance activities simultaneously has the potential to reduce traffic interruption time and setup cost (Wildeman et al., 1997). Setup cost includes the design and resources preparation for maintenance activities, while it is shared for the joint activities. The considered traffic interruptions consist of lane closure, contraflow, or any other insignificant traffic interruption. Joint execution of maintenance shifts in maintenance timing of components, with penalty function estimating the cost (stage 3). This stage compares the penalty cost of shifting activities and the benefit from grouping. Grouping is conducted only if the penalty cost is lower than the saved amount of money due to the simultaneous maintenance of elements (i.e. decreased operational disruption and setup cost). For a group of elements (belonging in the same bridge) that
will be simultaneously maintained, the estimated total time for maintenance equals the duration of the longest element maintenance activity. For example, if the maintenance of an elements group of a bridge needs both contraflow and lane closure at the same time, the calculation will only consider the contraflow.

Optimising group maintenance policy includes a time complexity of $2^n$, using Landau’s “big-O” notation, where $n$ is the number of maintenance activities. Time complexity can be decreased to $n^2$, if every group of elements has consecutive activities, as proved by Wildeman et al. (1997). Time complexity for solving a given computation process can be defined as the amount of time taken by an algorithm to run as a function of the length of the input, and thus depends on the number of operations needed to solve or approach such a process (Rosen, 1999). “Big-O” notation has been extensively used to approximate the number of operations an algorithm uses as its input grows. Hence, this notation provides an indication whether a particular algorithm is practical to be used for solving a problem. Therefore, for optimizing the maintenance schedule of stochastic deteriorating bridge elements, a genetic algorithm is used to provide robust results with limited computational capability. The genetic algorithm effectively avoids local optimal points of the overall maintenance cost function.

2.5. Criticality-based bridge prioritisation
The fifth stage (Figure 1) of the presented method, which is the focus of the current paper, ranks bridges of the same network based on their criticality. This stage understands a roadway network as a complex network, containing nodes that represent bridges and municipalities, and links that symbolise roads (Herrera et al., 2020). This paper proposes the calculation of bridge criticality as a combination of a centrality measure in complex networks and the observed traffic passing by a bridge on a typical...
day. An antecedent of the used centrality measure can be found on the group-betweenness centrality (Kolaczyk et al., 2009).

2.5.1. ABA-Closeness vitality

From a network topology perspective, node criticality is related to the location of the node in the network structure (Oliva et al., 2019). The most widely used analyses for measuring the criticality of nodes have been based on centrality measures (Rodrigues, 2019). Among the extensive range of centrality measures available in the literature, we selected “closeness vitality” due to its capability of quantifying network accessibility to nodes that include essential services (Das et al., 2018; Koschützki et al., 2005).

Hospitals and fire stations were selected as essential services for the development of the described methodology and its application on a case study. A node vitality considers any network function, while calculating the difference of conducting such a function with and without the node in the network (Latora & Marchiori, 2007). Such an approach can effectively estimate the impact of a fully operational bridge in its network. The adaptation of the vitality-based measure to the bridge prioritisation problem requires a centrality index representing the distance between network nodes, also known as closeness centrality (Barthélemy, 2011; Crucitti et al., 2006). The use of closeness centrality herein is tailored to two types of nodes: bridges and municipalities. The described novel version of closeness centrality is named ABA-closeness since it is based on computing path distances starting from nodes belonging to a group of nodes, A (i.e. municipalities), passing by a second group, B (i.e. bridges), and finally ending up at a node belonging to the initial group, A (i.e. municipalities). Some of the municipality-nodes include essential services (i.e. hospitals and fire stations).

Given a graph representation of a road-network, $G = (V, E)$; where $V$ is a set of nodes (i.e. bridges, $V_B$, and municipalities, $V_M$) and $E$ is the set of links (i.e. roads), $A$ is
defined as the adjacency matrix with elements $a_{ij} = 1$, if node $i$ and $j$ are connected, and $a_{ij} = 0$ otherwise. The closeness of a node is defined as the inverse of the average distance from all other nodes. The higher a node closeness value, the lower its distance to the rest of the nodes in the network is. In this case, the closeness is computed by considering the distance (i.e. geographical distance in kilometres) between municipalities. Such a distance for the municipality-nodes $i$ and $j$ is noted by $d(i,j)$; and it represents the shortest-path between the nodes $i$ and $j$, ideally weighted by the links length. Equation (5) provides a general expression of closeness of node $j$, $C(j)$, serving as a basis for further adaptation required to approach ABA-closeness in this paper.

ABA-closeness is defined herein through a classification of the nodes in $V$ such that $V = B \cup M$; where $B$ is the set of bridge-nodes and $M$ is the set of municipality-nodes.

$$C(j) = \frac{n-1}{\sum_{i \in V \setminus \{i\}} d(i,j)},$$  \hspace{1cm} (5)

where $n$ is the number of nodes in the graph $G$, that is, the size of the set of nodes $V$.

Aiming to adapt the closeness centrality of a node to represent its criticality, $M$ is partitioned in categories depending on the criticality of the service provided by the municipality. Thus, the method considers the classification $M_0$ if no essential service is provided, and $M_i$ if the essential service $i$-th at node $i$ in $M$ is provided, with up to $K$ services. For the presented case study, $M = M_0 \cup M_1 \cup M_2$ is a partition of $M$ in presence of critical nodes, with $M_1$, $M_2$ and $M_0$ respectively representing hospitals, fire stations, and finally municipality-nodes with no level of criticality. The general partition $M = M_0 \cup M_1 \cup ... \cup M_K$ can be considered for further analysis. The distinction among the nodes criticality is justified by their different nature of service. Node criticality is a flexible concept since it may vary over time. For instance, the criticality of a node that includes critical facilities (e.g. hospitals, fire stations) can be increased due to the appearance of extreme events, such as natural disasters (e.g. flooding) or man-mad
events (e.g. accidents) (Dong et al., 2019). Another example of node criticality variation, is the criticality growth of a node comprising a hospital during a pandemic (e.g. COVID-19 in 2020/2021). To demonstrate node criticality variation, we use the seasonal criticality variation of a node including a fire station, which can be higher during summer when the possibility of appearance of wildfires is higher (Parente et al., 2019).

Equation (5) is adapted to consider distances only between municipality-nodes, while computing paths passing by any node in \( V \). Equation (6) implements this variation, approaching the closeness of node \( j \) along with a difference in the computation depending on the criticality classification of any node \( i, i \in M \), connected to node \( j, j \in V \).

\[
C^*(j) = \alpha_0 \frac{m_0 - \sum_{i, i \in M} d_{ij}}{\sum_{i, i \in M} d_{ij}} + \ldots + \alpha_K \frac{m_K - \sum_{i, i \in M} d_{ij}}{\sum_{i, i \in M} d_{ij}},
\]

where \( I_k(j) \) is an indicator variable of membership of the node \( j \) to the municipality of criticality type \( k \), as it is shown in Equation (7),

\[
I_k(j) = \begin{cases} 
1 & \text{if } j \in M_k \\
0 & \text{if } j \notin M_k 
\end{cases}
\]

In Equation (6), the subscript for the function distance, \( d_{ij} \), emphasises the fact that paths may pass by any node in \( V \), independently of being a bridge or a municipality; and \( m_k \) denotes the number of nodes in \( M_k \). The parameters \( \alpha_k \) weight the importance of each connection and they can be tuned into their sensitivity degree to better represent the distance to the critical nodes. For instance, in summer time, we can increase the distance to fire stations to be twice the distance to other critical nodes. Similarly, in case of increased demand for hospitals, we are interested in exacerbating the distance to the hospitals. By increasing the distance to a critical node \( k \) (augmenting the relative size of the corresponding \( \alpha_k \)), all routes reaching that node are longer, and thus criticality of
bridges, connecting these routes, is also increased. The parameters, $\alpha_k$, should follow the conditions of linear combination: $\alpha_k \in [0,1]$ as well as $\sum_{k \in K} \alpha_k = 1$. Both $M_k$ and $\alpha_k$ are considered for all the cases, $k = 0, 1, \ldots, K$. Equation (6) has a compact representation given by Equation (8),
\[ C^*(j) = \alpha_0 C^*(j; M_0) + \ldots + \alpha_K C^*(j; M_K), \tag{8} \]
where each item in the sum is explained by Equation (9),
\[ C^*(j; M_k) = \frac{m_k - l_a(j)}{\sum_{i \in M_k \setminus d_V(i,j)} d_V(i,j)} \quad \forall k = 0, \ldots, K. \tag{9} \]

The closeness vitality of node $j$ is therefore computed as the difference on closeness when this centrality measure is computed with and without the aforementioned node $j$ to approach the distance $d_V(i,j)$. This is represented by Equation (10),
\[ \Delta C^*(j) = \sum_{v \in V} C^*(v) - \sum_{v \in V \setminus j} C^*(v). \tag{10} \]

Equation (10) measures the increment on the overall ABA-closeness when it is computed for distances based on a previous removal of node $j$. This is, therefore, a measure of the vitality of such a node $j$ with respect to ABA-closeness. The higher the ABA-closeness vitality, the higher the impact of node $j$ in the ABA-closeness of the network is. Summarising, closeness has been proposed as a measure of the distance between municipalities and/or specific critical nodes. Closeness vitality computes the impact of each of the network nodes in such closeness measures, becoming suitable to approach a criticality ranking of the nodes. It should be clarified that the connectivity of a node (e.g. number of links connected to or emanating from it) is related to node criticality and it is included in the used measure of closeness vitality. Firstly, the measure of closeness centrality (on which closeness vitality is based on) is inversely
proportional to the average of the length of the shortest paths between the node and the rest of nodes in the network. Thus, if a node is poorly connected, it will likely have a low closeness value (since the lower the number of paths connecting it with the other nodes, the higher the expected distance between such a node and the other nodes is).

Secondly, following the concept of vitality, removing a bridge/node can decrease the number of routes (i.e. connectivity) leading to municipality/nodes. In an extreme case, a bridge removal can disconnect a municipality from the network (with the closeness value being infinitum), if the municipality is only connected to the rest of the network through that one bridge/node.

The proposed methodology estimates bridge criticality not only based on the ABA-closeness vitality ranking ($R_1$), but also on the observed traffic passing by a bridge. Thus, there is a second bridge ranking ($R_2$), with the bridge with highest traffic positioned first. A weighted arithmetic mean of the two rankings estimates the final ranking, as shown in Equation (11),

$$MP1 = \frac{w_1 R_1 + w_2 R_2}{w_1 + w_2},$$

where $MP1$ stands for Maintenance Prioritisation Index. A weighted arithmetic mean is calculated by data points which do not equally contribute to the final average. In case of all weights being equal (i.e. $w_1=w_2=0.5$), then the weighted arithmetic mean is the arithmetic mean. $MP1$ is a suitable index to serve as the basis for adding criticality to bridge maintenance prioritisation practices because: (a) it considers different perspectives of criticality (i.e. bridge connectivity and traffic served by bridges); and (b) it is flexible and generalisable since it allows further research in optimising the weights of the two rankings (Equation 11) and even in adding another ranking (i.e. $R_3$), if proved necessary. In practice, the weights are determined by decision makers, based on their organisation goals and requirements. However, there is a great research interest
about multi-criteria decision-making theory, and specifically on how the weights can be optimised with respect to one or multiple criteria (Fancello et al., 2019; Yannis et al., 2020). The current paper uses an equal contribution of the two rankings since the investigation on the criteria, set by a specific asset owner, along with the optimisation of the weights, is out of the scope of the paper.

To sum up, bridge criticality is approached from a complex network perspective since it can effectively represent the role of a bridge in a road network (Herrera et al., 2020). A bridge failure affects the traffic served by it (and this is why traffic is considered in our criticality evaluation), connected roads, other bridges and municipalities. Numerous centrality measures, such as variations of “betweenness” or “degree index”, can be tailored to assess bridge criticality (Jafino et al., 2020; Stergiopoulos et al., 2015). Amongst them, we have selected “closeness centrality” and “vitality” to form the novel measure of ABA-closeness vitality for the following reasons. The concept of “closeness centrality” is used due to its capability of estimating the distance from one node to the rest of network nodes and consequently its level of isolation (Barthélemy, 2011; Crucitti et al., 2006). In our case, it estimates the path distances from a municipality/node, passing by a bridge/node, and finally ending up at a municipality/node. The concept of “vitality” is selected due to its capability of considering different levels of importance amongst nodes. Thus, it can take into account the existence of critical services into municipality nodes (e.g. hospitals, fire stations) (Das et al. 2018; Koschützki et al. 2005).

2.5.2. Network traffic simulator

A network traffic simulator was also developed based on a discrete event simulation process (Yu et al., 2019) for calibrating the ABA-closeness weights, investigating different scenarios of traffic and of a bridge closure, and validating the prioritisation
procedure. The simulated traffic can model the operation of the network as a sequence of events in time. As the process is discrete, there is no consideration of any change in the system between consecutive events. Simulation of road network traffic has been used in the literature for a range of objectives, such as dynamic route guidance systems (Schreckenberg et al., 2001; Shi et al., 2015) and the study of network capacity and traffic congestion (Shi et al., 2019).

Network nodes which are classified as municipalities (i.e. source) generate vehicles traveling to another municipality node (i.e. destination) via shortest paths (Zhan & Noon, 1998). Traffic is generated randomly, with probabilities proportional to the population size of the municipalities and the observed traffic on a typical day. The traffic generation regime is a mixture of simple Poisson processes, with the Poisson parameter depending on the time of the day and the node-source population. Poisson processes are used given that this distribution function is naturally suitable to model the number of events in a time period (Buckley, 1968). Given a time $t$, the traffic rate $\lambda$ can be understood as $rt$, where $r$ is the number of events per unit of time. Following the Poisson distribution, the expected number of events per time unit is $\lambda$ and the probability of the occurrence of $k$ events in a time $t$, $P_k$, is expressed by Equation (12):

$$P_k = \frac{\lambda^k e^{-\lambda}}{k!} = (rt)^k e^{-rt}$$

where $e$ is the Euler constant $= 1.569$, and the symbol ‘!’ is the factorial operator, $k! = k(k-1)(k-2)…1$. A Poisson distribution considers the randomness of the events occurrence to generate traffic. Other circumstances are considered by changing the traffic rate based on the municipality size and the time of the day. By the nature of the Poisson distribution, the departure/arrival of vehicles occurs at a given rate, $\lambda$, independently of time. The network simulator basic workflow is the following:

- use NetworkX (Python) to define a network topology (Hagberg et al., 2008);
• convert network topology to a simulation model;
• run the simulation with SimPy (Python) (Team SimPy, 2020).

A range of network traffic scenarios, along with their repetitions, are simulated to validate the bridge-criticality prioritisation and to better understand its consequences in terms of traffic congestion and travel time. Besides, a simulation approach benefits from considering not yet observed traffic scenarios, which is essential to get an optimal tuning of the weights related to the ABA-closeness expression of Equation (11). This endows the ABA-closeness with a better adaptation to a range of scenarios beyond those already observed and for those the bridge-criticality is approached.

The basis for the simulator software is a Python library called ANX (Likic & Shafi, 2018). The main library and scripts are open-source and can be downloaded from https://pypi.org/project/anx/. Our modifications to ANX to achieve an adaptation to the road network problem and to the observed data are summarised in Table 1. Nodes are grouped and the characteristics of nodes and links are modified. Vehicles start from municipality/nodes, move in the network passing through bridge/nodes and municipality/nodes and arrive in municipality/nodes. During their trips, queueing is considered and the possibility of traffic jams is estimated. Hence, road/links congestion is computed via the possibility of traffic jam formation and the road_capacity condition, which is added as a feature of each link.

Table 1 contains instances of network elements used in the simulator system. More node types are defined for critical nodes, such as those including hospitals or fire stations. The links are extended in their domain, depending on the range of node types used in the simulation. The simulation generates traffic for each municipality-node (i.e. non bridge-node) at a certain rate following a Poisson distribution (i.e. node_traffic_rate at Table 1). The traffic is routed to another municipality-node following the shortest
path. The variable `node_traffic_delay` (Table 1) considers the possible natural delay at crossing a node (e.g. traffic-lights). Additionally, there is a maximum amount of traffic a node can handle at the same time. This is considered by the variable `node_queue_cutoff`. The current version of the simulator considers homogeneous features among all municipality-nodes, and similarly among all bridge-nodes. The model can straightforwardly scale in its resolution of the representation, by considering individual features for each node. The second column of Table 1 represents roads, which are the links of the network simulator connecting nodes (i.e. municipalities and bridges). Similarly with nodes, the current simulator version considers homogenous road characteristics, in terms of of `road_capacity` and `link_traffic_delay` (delay originated by the condition state of the road), but it can be easily modified to consider individual features.

In general, simulation models approximate a real-world system, without exactly imitate it. Thus, a simulation model should be verified and validated to the degree needed for intended purpose or application of the model. Following the recommendations of (Sargent, 2013), we used an “event validity” and an “internal validity”. The “event validity” compares the observed traffic with the simulated traffic at bridges. Then Person correlation coefficient is used (Equation 13).

\[
\begin{align*}
 r = \frac{1}{n-1} \sum_{i \in B} \frac{(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}}
\end{align*}
\] (13),

where \( B \) is the set of bridges, \( x_i \) and \( y_i \) are the observed and the simulated traffic, respectively, passing by the \( i \)-th bridge, \( i = 1, \ldots, n \); and \( \bar{x} \) and \( \bar{y} \) are the corresponding average values. This coefficient, \( r \), takes values in the range \([-1,1]\], with -1 representing the maximum of negative correlation and +1 the maximum of positive correlation between the 2 inputs. The Pearson correlation between the observed and simulated traffic load at bridges was 0.91, showing a strong positive correlation.
The second used type of validation, termed “internal validity”, investigates whether there is consistency amongst results after multiple simulation repetitions (i.e. plausibility in the variability related to the events generated by the simulation) (Sargent, 2013). After repeating the simulation (for the traffic in a single day) 20 times, the global average value of the simulated traffic data is 116040, with a 95% confidence interval (i.e. 95% z-score percentile of the Normal distribution) for such an average for the values (106250, 125830). Since the total observed traffic is 112711, the global average value of the simulated traffic data and its associated standard deviation are in a plausible range, therefore accomplishing the “internal validity”.

2.6. Scheduling

The final stage, termed scheduling (stage 6, Figure 1), utilizes rolling horizon that is an established methodology for reducing the scheduling computational complexity (Kreipl & Pinedo, 2004). It is a repeated process which disintegrates long-term scheduling into several smaller time planning periods and composes them in a rolling horizon manner. In each repetition, maintenance scheduling is executed only for the current horizon. If the available budget for a time period is not enough for all groups of elements, the ones belonging to bridges higher in the critical prioritisation list (stage 5) are maintained.

Components condition state at the end of the current planning horizon is calculated and updated so that maintenance of next planning horizon being able to be scheduled by re-running stages 2, 3 and 4. Summarizing, this technique conducts long-term maintenance planning with low computational complexity.

3. Case Study

The proposed condition- and criticality-based predictive group maintenance method was applied to a network of 21 bridges. The selected network of bridges belong to a wider
network of bridges, and thus the results will be different if more bridges are considered. Thus, the case study serves as an example on how the proposed methodology can be applied to bridge networks. The 21 bridges are composed of 296 components in total, which serve multiple functionalities (i.e., primary deck, abutment), are made of several materials (e.g., steel, concrete). These bridges are exposed to numerous environmental conditions, which can cause additional deteriorating mechanism for elements (accelerating their deterioration), as thoroughly described in subsection 2.1 and Figure 2. Such environment conditions can be the deterioration of other elements in the same structure or growing traffic loading. The data was processed in the MATLAB programming language and environment, on a PC with specifications as follows: Intel Xeon CPU E5-2680 v4, 2.40GHz, and 64 GB RAM. The processing time of this case study was 2 minutes. The presented method can efficiently process data from a large network of bridges since real-time data processing is not required. The data used for the case study has been provided by “Infraestruturas de Portugal”, which is a state-owned company, managing the Portuguese rail and road infrastructure. The used bridge components condition index is divided into six discrete states from 0 to 5, with 0 indicating excellent condition and 5 representing failure.

Life-cycle cost analysis of bridge components (stage 2) has three typical trends, as shown in Figure 3 that relates total life-cycle cost with the time of applying maintenance. The first diagram shows a monotonic increase trend, meaning that the sooner the component is maintained the lower the life-cycle cost. The monotonic decrease trend of the second diagram suggests no maintenance thorough the planning horizon. The third trend contains a minimum point of life-cycle cost, which is the optimal time for maintenance. After running the presented algorithm for the case study, the maintenance of 275 out of 296 components is proposed within the next 30 years of
the planning horizon, using a relatively high available budget. The fact that almost all
elements are proposed to be maintained shows that a lower budget, which is common in
transportation authorities, would delay the maintenance of more elements. Hence,
effective maintenance prioritisation becomes dramatically important for the operation
and safety of bridges. The proposed system dynamically adapts thresholds for different
components by the means of minimizing the average cost, and thus the maintenance-
related budget is reduced and outperforms the conventional fixed maintenance threshold
scheme.

Table 2 presents an example of the way different stages of the method are
connected. Only 13 components from four bridges (out of the 296 elements from 21
bridges that were used for the case study) were selected. The reason for selecting these
specific elements is their mutual proposed maintenance time (i.e. Year 1), after
grouping (stage 4). This section of elements assists the understanding of the connection
between the 6 different stages of the described framework. The deterioration model
(stage 1), combined with the life-cycle cost analysis (stage 2) proposed that the optimal
maintenance for each of these components is Year 1 or Year 2, with a planning horizon
of 30 years. The estimation of the penalty cost function (stage 3) assists the grouping of
components (stage 4). As already mentioned, the optimal maintenance time for all of the
four groups of components was Year 1.

Criticality-based ranking (stage 5), which is the main focus of this paper, is
conducted at the structure level (i.e. bridge), and thus the 21 bridges of the case study
were prioritised, as extensively presented in the following paragraphs, Figure 4, Figure
5 and Table 2. The higher on the list the more critical the bridge is. After applying
budget constraints, only 3 out of the 4 group elements can be maintained (stage 6), with
the maintenance of the fourth being moved to Year 2. Additionally, for all elements of
the case study, group maintenance, during the 30 years of planning horizon, caused an approximately 11% reduction in the maintenance cost, compared to SIT (Hesketh et al., 2015). Specifically, the total maintenance cost of every bridge, for a time horizon of 30 years, is calculated by both SIT and our proposed method and then compared. All costs (e.g. inspection cost, minor/major maintenance cost, setup cost) and safety threshold values (e.g. element condition threshold for application of major maintenance) are set to be the same for both methodologies. Thus, the only difference remains the proposed maintenance year for every element. SIT is a decision support system created by Atkins to allow Highways England to conduct lifecycle planning of their assets. It is one of the limited number of tools which makes calculations at the element level, taking into account external factors, such as traffic and other elements condition within the same system to estimate the deterioration rate.

The spatial location of the 21 bridges and municipalities of the area is illustrated in Figure 4. The spatial information provided by Figure 4 is the base for the creation of a complex network (Figure 5) that is used for the criticality evaluation of bridges. Figure 5 preserves the geographic coordinates of the nodes (i.e. bridges and municipalities). Network links (i.e. roads) inherit the distance between nodes from Figure 4. The nodes representing municipalities in Figure 5 are weighted to be visually proportional to their population size. The same nodes are also labelled with the village names. The critical points of hospitals and fire stations are marked with H and FS, respectively. Bridge-node size is again proportional to the observed volume of traffic passing by each bridge in a typical week day. In addition, bridge-nodes have a traffic-light colour code to represent their ABA-closeness vitality values. Red colour represents nodes with an ABA-closeness (vitality) value higher than the mean value plus 2 standard deviations. Orange colour stands for nodes with an ABA-closeness (vitality)
higher than the mean value plus 1 standard deviation but lower than the mean value plus 2 standard deviations. The rest nodes are coloured with green. Figure 5a presents these values using distance and connectivity of bridges to municipalities as a criterion. Figure 5b approaches ABA-closeness vitality by additionally considering distance and connectivity of bridges to the critical municipality-nodes that include a hospital or a fire station. After considering those critical municipality-nodes, a significant shift on ABA-closeness vitality is observed at the bridge-node 7, connected to Avelar (hospital). Similarly, ABA-closeness vitality is higher now for bridge-nodes 1 and 2, neighbouring to Alvares (fire station).

Table 3 presents the criticality-based ranking (stage 5) of the examined road-bridges. It consists of the ABA-closeness vitality ranking before considering the critical points of hospitals and fire stations, the ABA-closeness vitality ranking after considering the critical points, the traffic-based ranking, and the final ranking of the bridges combining the last two indices. It should be noted that bridges which are connected by the same road have similar traffic volumes and thus their traffic-based ranking is their mean value. For instance, bridges 4 and 5 have the same traffic, and thus they are both ranked as position 17.5. After combining the two indices and as presented in the last column of Table 3, the most critical bridges are: bridges close to Avelar (i.e. bridge 6, 7, 8 and 10) that has a hospital; bridge 14, which is a hub for the connectivity of the south area of the network and directly connects Vila Facaia and Outao; and bridge 20, that connects surrounded areas with Pedrogao Grande, which contains a fire station.

The traffic simulation, as explained in the Methodology section, is used as a validation of the results shown in Table 2. The simulation represents 3 hours of peak-time traffic (i.e. 7am-10am). The data collection frequency is 5 minutes. Therefore, the
simulation encompasses 60 time units. The procedure is repeated 100 times, allowing
the calculation of the mean of variables and producing statistically robust insights about
the traffic dynamics. The simulation uses part of the observed traffic data to provide
plausible results, useful for a decision-making support process.

The aim of the simulation is to compare traffic flow in municipality-nodes
having hospitals and fire stations, when a bridge suffers a disruption as well as under
normal conditions. The more important the bridge for a municipality-node, the larger
the decay in the traffic flow at that node is, after disruption of such a bridge. Table 3
shows the coherence of the final criticality ranking results. In addition, the simulation
results demonstrate how roads reaching to critical municipality-nodes have an
increasing average traffic-load after a bridge disruption. The higher the bridge in the
final criticality ranking, the higher the increment on the average traffic-load in the roads
connecting critical municipalities after disruption of such a bridge is. Both measures of
node traffic and average road congestion (Table 4) are taken in relative units to the
regular ones, considering the simulation with no bridge disruption. The last row of
Table 4 presents the numbers for this regular traffic case, used as a basis for the rest of
the table. Based in an observed traffic of approximately 6,000 units per day, we assume
that 3,000 of vehicles are before noon. Out of the 3,000 vehicles, we assume that the
traffic during the 3 peak-hours of the simulation (i.e. 7am-10am) is 2,500 vehicles in
circulation. The described process is used as the simulation seed for the results of Table
4. These simulation results for bridge-disruption scenarios are computed using the
expression of relative increase, as it is given by Equation (14).

\[ Impact = \frac{x_{\text{disrup}} - x_{\text{basis}}}{x_{\text{basis}}}. \]  

(14)
where \( \text{Impact} \) is the relative increase of the simulation results when a bridge disruption happens, \( x_{\text{disrup}} \), with respect to the basis simulation measures under regular conditions, \( x_{\text{basis}} \).

Overall, Table 4 shows a higher average congestion of roads reaching to critical municipalities in case any of a top prioritised bridge presenting a disruption. In such case, the traffic coming-in and going-out of a municipality is maintained stable since the lower number of traffic coming-in (given the difficulties to reach the node due to the disruption) is balanced by the lower traffic able to go out of the node. In our case study, the most affected municipality is Avelar (H) since most of the top-ranked bridges are almost directly connected to Avelar. The least affected municipalities are Castanheira (FS) and Alvares (FS) due to their long relative distance between them and the critical bridges. These 2 places therefore provide resilience on fire station services to the area under study.

4. Conclusions

Most bridges serve more traffic and are exposed to more intense extreme events than originally designed due to population growth and climate change. Asset managers have to solve a multi-objective optimization problem allocating the available budget and scheduling maintenance, while achieving safety requirements and ensuring network functionality. Given the aforementioned limitations, the current paper considers a bridge network as a MSMCN that contains bridges (i.e. systems) of different types and exposed to different environments, which are in return composed of different component types. Such a network has a dual-positive maintenance-related economic dependence, consisting of the setup cost at the system level and the operation downtime at the network level. Additionally, bridges have unequal levels of importance within a network since they serve different amounts of traffic, connect areas with various
characteristics and their failure has a different impact on the network. Presented herein is a predictive group maintenance model for bridge networks, exploiting the described dual-positive economic dependence and considering bridge criticality.

The proposed model can be applied to long-lifetime assets that are exposed to external risks. It proposes maintenance prioritisation of bridge elements, based on elements condition deterioration considering uncertainty, elements life-cycle cost analysis, the economic benefits from elements group maintenance (i.e. reduced setup cost and traffic interruption) and bridge criticality within the road network, using a specifically tailored version of closeness vitality and traffic simulation. Additionally, the model follows transportation authorities predefined thresholds for safety (e.g. element condition threshold for application of major maintenance) and functionality (e.g. number of lanes closed for maintenance), that can be adjusted according to stakeholders preferences for maintaining a particular level of operational safety and functionality. The model synthesizes several established concepts of reliability engineering, such as life-cycle cost analysis, predictive maintenance, condition-based and criticality based maintenance, and dynamic maintenance scheduling. It is characterized by some strong advantages, such as the maintenance grouping that reduces the operation downtime and setup cost, the formulation of different types of operation interruptions based on the components under maintenance, and finally the focus on the heterogeneity amongst elements in terms of deterioration rates, maintenance costs, and their operating conditions. The combination of the aforementioned with the use of a novel approach for bridge criticality analysis within a network summarize the contribution of the current paper. The presented research uses an adaptation of complex network centrality measure for solving the problem of maintenance prioritisation of bridges in a road network. This adaptation, named ABA-
closeness vitality, is a modification of the classical closeness centrality. Specifically, the
novelty lies in the ABA-closeness vitality that considers two groups of nodes to
calculate the closeness centrality. Groups A and B represent municipalities and bridges
respectively. The closeness distances are computed for nodes belonging in Group A,
where the traffic is generated. At the same time, the paths for A-A routes are allowed to
pass over nodes of the group B. The vitality computed over the new ABA-closeness
centrality measure is the result of percolation of one of the nodes. The ABA-closeness
vitality, after the removal of one of the bridge-nodes, provides a measure of bridge
criticality in maintaining the connectivity of the road network.

The novel ABA-closeness vitality measure considers different levels of
information related to the network. Firstly, a weighted graph is used based on the road
segments length. Secondly, a heterogeneous complex network, categorising nodes into
municipalities and bridges, is used, along with the connection between nodes. Thirdly,
municipality nodes are classified into “critical” (i.e. including essential services) and
“non-critical”. The distance of paths (which start and end to municipalities/nodes) is
weighted based on this classification (as already explained). This partition on the
computation of any relevant statistics provides an extra level of information for a
specific group of interest in the population (i.e. critical municipalities). Summarising the
proposed bridge criticality evaluation method is characterised by the advantages of: (a)
a heterogeneous complex network (i.e. separation of municipalities and bridges as well
as consideration of only municipality/nodes as origins and destinations), which can
effectively represent a road network; and (b) the capability of ABA-closeness vitality
measure to estimate the additional distance from one municipality to another if bridge is
out of service, while considering critical services in municipalities.
The proposed framework, which is not yet at the stage of commercialisation, has the potential to improve bridge management. Simultaneous application of maintenance activities to groups of elements, belonging to the same bridge, saves costs since execution of maintenance requires only one setup (Liang & Parlikad, 2020; Wildeman et al., 1997). The saved amount of money can then be used for maintaining some extra element groups of the same bridge network earlier (i.e. before passing safety threshold values), improving structural safety. As a result of the increased structural safety, network reliability is also improved since the possibilities of a bridge failure and consequently of a network disruption (due to degradation or closure of links and/or nodes) are both decreased. Another reason of improved network reliability due to group maintenance is the reduced number of times of traffic interruption (that causes additional time and cost for travellers, when happens). The metrics for evaluating bridge criticality have been successfully used to other industries (Das et al. 2018; Koschützki et al. 2005) and have been modified to be applicable to the problem of maintenance prioritisation of bridge networks to add extra knowledge for consideration when taking decisions for bridge management. The novelty of our framework regarding criticality evaluation lies in the consideration of the distance added to travel from one municipality to another due to a bridge closure as well as the consideration of bridge criticality variation due to extreme events or the season of the year.

However, the proposed method has room for improvement and work is currently under way to further enhance it. Elements deterioration is currently modelled by a discrete state stochastic practice, with the assumption that the holding time at each state is exponentially distributed. This assumption can be approximated by phase-type distribution or relaxed by using a semi-Markov model. Further study of the genetic algorithm under different contexts, such as constraints of maintenance resources, will be
conducted. Additionally, the current traffic simulator is a tool for reinforcement and validation of a complex system consisting of bridges, municipalities and roads. The level of detail of the traffic simulation is in accordance with the abstraction of the problem and the scope of investigating the relation of individual bridges belonging to the same network. A higher level of detail for simulating traffic will be potentially needed when developing in-depth an associated software, including traffic signal control system and probably road pavement condition that can cause congestion. Future work also includes the consideration of imperfect maintenance practices and their resulting type shift in the grouping policy. Additionally, the weights of the developed MPI will be optimised based on asset owners’ requirements. Vulnerability analysis, including the consideration of possibilities and impact of extreme events on bridge networks, will be added to the presented framework. Finally, the authors are in collaboration with several transport asset owners for modifying, expanding, and testing this approach in real-life networks of bridges and other assets.

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**Data availability statement**

The data that support the findings of this study are available from the corresponding author, [GH], upon reasonable request.

**Declaration of interest statement**
The authors declare no conflicts of interest in preparing this article.

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### Tables

#### Table 1. Node and link definitions used in the simulator system

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Links</th>
</tr>
</thead>
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<td>&quot;n0-n0&quot; : {</td>
</tr>
<tr>
<td>&quot;node_traffic_rate&quot;: [ &quot;poisson&quot;, 0 ], # bridge</td>
<td>&quot;link_traffic_delay&quot;: 0.0300,</td>
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<td>&quot;node_traffic_delay&quot;: 0.0000,</td>
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<tr>
<td>&quot;node_queue_cutoff&quot;: 100</td>
<td>}</td>
</tr>
<tr>
<td></td>
<td>&quot;n0-n1&quot; : {</td>
</tr>
<tr>
<td></td>
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</tr>
<tr>
<td></td>
<td>&quot;road_capacity&quot;: 1000</td>
</tr>
<tr>
<td></td>
<td>}</td>
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<td>&quot;n1&quot; : {</td>
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<td># similarly, defined the links: n1-n1, n1-n0</td>
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#### Table 2. Scheduling of bridge components

<table>
<thead>
<tr>
<th>Bridge ID</th>
<th>Component ID</th>
<th>Components maintenance year</th>
<th>Groups of components maintenance year</th>
<th>Bridge criticality-based ranking</th>
<th>Scheduling - year</th>
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#### Table 3. Criticality-based maintenance prioritisation of bridges

<table>
<thead>
<tr>
<th>Bridge ID</th>
<th>ABA-closeness vitality ranking, without critical points</th>
<th>ABA-closeness vitality ranking, including critical points</th>
<th>Traffic-based ranking</th>
<th>Mean ranking</th>
<th>Final ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>5</td>
<td>3</td>
<td>20</td>
<td>11.5</td>
<td>10</td>
</tr>
<tr>
<td>1</td>
<td>6</td>
<td>5</td>
<td>21</td>
<td>12.5</td>
<td>12</td>
</tr>
<tr>
<td>2</td>
<td>18</td>
<td>6</td>
<td>19</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>3</td>
<td>21</td>
<td>21</td>
<td>16</td>
<td>18.5</td>
<td>21</td>
</tr>
</tbody>
</table>
Table 4. Simulation results: relative impact of disruption at the top 5 ranked nodes as proposed in Equation (14)

<table>
<thead>
<tr>
<th>Bridge ID</th>
<th>Avelar (H)</th>
<th>Castanheira (FS)</th>
<th>Pedrogao G. (FS)</th>
<th>Alvares (FS)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Node traffic</td>
<td>Road congestion</td>
<td>Node traffic</td>
<td>Road congestion</td>
</tr>
<tr>
<td>6</td>
<td>-0.03</td>
<td><strong>disc.</strong></td>
<td>0.02</td>
<td>0.20</td>
</tr>
<tr>
<td>7</td>
<td>0.00</td>
<td>0.36</td>
<td>0.01</td>
<td>0.11</td>
</tr>
<tr>
<td>10</td>
<td>0.06</td>
<td>0.19</td>
<td>0.08</td>
<td>-0.09</td>
</tr>
<tr>
<td>14</td>
<td>0.01</td>
<td>0.22</td>
<td>0.01</td>
<td>-0.09</td>
</tr>
<tr>
<td>8</td>
<td>0.02</td>
<td>0.36</td>
<td>0.08</td>
<td>0.18</td>
</tr>
<tr>
<td>Basis</td>
<td>800</td>
<td>67</td>
<td>800</td>
<td>94</td>
</tr>
</tbody>
</table>
Figure captions

Figure 1. Main stages of the developed methodology

Figure 2. State transition diagram for element u in system v (Liang & Parlikad, 2020)

Figure 3. Trends of life-cycle cost analysis

Figure 4. Bridges location

Figure 5. ABA-closeness vitality of case-study complex network: a. before considering critical points; b. after considering critical points (i.e. hospitals, fire stations)
Figure 1

129x28mm (300 x 300 DPI)
Figure 3

45x11mm (300 x 300 DPI)
Figure 4

54x30mm (300 x 300 DPI)
Figure 5

148x81mm (300 x 300 DPI)