ROAD NETWORK LAYOUT PLANNING BASED ON EVALUATION OF CONNECTIVITY AND ASSET CRITICALITY

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ABSTRACT

State of the art research in ensuring transport infrastructure resilience focuses on adopting a network perspective. However, there is no comprehensive, widespread method for evaluating connectivity and proposing alternative routes to improve it. Presented herein is a framework that: assesses road network connectivity, using a "closeness" measure and focusing on routes passing by the vulnerable asset of bridges; and proposes the development of optimal alternative routes, using a genetic algorithm. The results showed a significant improvement of network connectivity and the potential of the method to serve as the basis for updated transport infrastructure planning practices.

INTRODUCTION

Transport networks are a vital requirement of any country's economic progress, which is associated with the accessible resources to the public and the effectiveness of their usage (Ivanova & Masarova, 2013). Transport networks serve human mobility and productivity contributing to public prosperity (Chan et al., 2010). Transport infrastructure assets constantly deteriorate over their lifetime. Their deterioration can be accelerated by heavy traffic or inadequate maintenance and eventually lead to failure. The failure may not be gradual but instant in case of extreme events appearance that can be classified into natural hazards (e.g. landslides droughts, wildfires, windstorms, floods) and man-made events (e.g. negligence, terrorism, accidents). Compared to their design estimations, most assets are exposed to more frequent and intense events due to climate change, while caring more traffic due to population growth (Yang & Frangopol, 2019). A transport infrastructure asset 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). Specifically, an asset disruption affects network traffic flow and it can cause the isolation of an area from the main network. This can sequentially lead to the loss of access to critical services (e.g. hospitals, fire stations).

Resilience is defined as the capability of a network to prepare for, absorb, recover from, and adjust to disturbances (Linkov et al., 2014). Transport resilience is the capability of the transport network to maintain its operational level of service or to re-establish itself to that service level in a specified timeframe, as defined by Freckleton et al. (2012). Another definition, set by Pant (2012), described transport resilience as the ability of the network to minimise operational loss. Reggiani et al., (2015) highlighted the positive correlation between transport network resilience and connectivity. Achieving transport network resilience and effective connectivity require management of existing infrastructure and planning for development of new infrastructure, if needed. Management of existing infrastructure includes asset monitoring, condition prediction and maintenance prioratisation. In practice, management and planning of transport infrastructure assets is conducted in different ways by decision-makers, who follow their organisations' guidelines and attempt to effectively use their available budget (Hadjidemetriou et al., 2020a). Assets are assessed either manually by inspectors or automatically with the aid of sensors and novel monitoring technologies, which can be based on computer vision and artificial intelligence (Christodoulou et al., 2018; Hadjidemetriou et al., 2015; Zhu et al., 2020). Asset monitoring along their lifetime facilitates the development of predictive models, which in turn assist the development of maintenance prioritisation strategies (Dhada et al., 2020). In case a transpor network cannot serve traffic demand or in case of resilience improvement, new infrastructure is developed based on socio-economic and in some cases political criteria.

Despite the clear purpose of each described step, current practices in infrastructure management and planning are characterised by major limitations and challenges. An asset failure affect its network since traffic needs to be served by alternative routes (Nakil et al., 2015). However, maintenance prioritisation and infrastructure planning is not always conducted from a network perspective. Another limitation is the lack of a standardised strategy for evaluating the criticality of each asset within the network. Assets criticality varies significantly due to different amounts of traffic served and impact of failure.

The current paper focuses on the asset of bridges in road networks due to their importance and high vulnereability and consecuently their association with network resilience. Bridges are mainly located at intersections of roads, with their fialure significantly affect their network. In some cases bridges connect isolated areas with the rest of the network. Only in the U.S., there are over 600,000 bridges, from which 40% are over 50 years old and 9.1% are structurally deficient (ASCE, 2017). The sections that follow describe: the state of knowledge in a adopting a network perspective for transport infrastructure management and planning; the proposed methodology; the conducted case study; and finally the extracted conclusions.

BACKGROUND

Overcoming the challenge of managing bridges as parts of a transport network has attracted the interest of researchers. For instance, Orcesi & Cremona (2010) developed a maintenance prioratisation method based on the location of bridges within a network, visual condition evaluations and stakeholders' interests. In addition, Bocchini & Frangopol (2011) assessed the life-cycle performance of bridge networks based on the time-variant nature of bridge reliability due to elements degradation and complex network layouts. Another research work worth mentioning formulated a Markov chain model that examines the life-cycle of groups of bridges groups, considering deterioration, maintenance actions and failures (Bocchini et al., 2013). Hu et al. (2015) also considered bridges as part of a transport network to design their maintenance plan that aimed to minimise travel distance caused by bridge failures. Another related work designed a model for predictive group maintenance for multi-system multi-component networks, enabling various representations of dependences at the network and system levels (Liang & Parlikad, 2020). This model was applied to a network of bridges, constituted by multiple heterogeneous components, showing potential for a considerable reduction in maintenance costs (Hadjidemetriou et al., 2021; Hadjidemetriou et al., 2020b). Yang & Frangopol (2020) estimated bridge failure probability for various scenarios and the traffic flow in the damaged network for each scenario. Another recent study, considering bridges as parts of a network, developed a risk-based model for optimal adaptation management, in case of scour and climate change (Liu et al., 2020). Finally, Akiyama et al. (2020) identified problems and proposed solutions in the areas of life-cycle risk analysis, resilience, design and management of both independent bridges and bridge networks.

Besides maintenance, transportation authorities are also responsible for planning new infrastructure for improving their transport networks. Traditional examples of infrastructure planning methods include "scenario planning" and "cost-benefit analysis" (Malekpour et al., 2015). State of the art research proposes adaptation and flexibility to respond to uncertainties, such as climate change, population growth and technology development. In this context, Sánchez-Silva (2019) firstly identified issues in existing processes of infrastructure design and management and secondly proposed a framework based on the ability of a network to change over time. Furthermore, Sadatsafavi et al. (2019) presented a scenario planning approach to recognise driving forces that influence transport infrastructure networks and explained how policy-makers can use these scenarios for assessing their plans and enhance network resilience.

Adopting a network perspective in transport infrastructure management and planning implies an understanding of the different levels of criticality of nodes and links, composing the network. Bush et al. (2013) evaluated bridge criticality, assigning each bridge to one out of three possible levels. For every level, their framework provides assistance on the type of data needed, the required accuracy in data acquisition, the frequency of evaluation and the appropriate evaluation practices. Gauthier et al. (2018) used resilience stress testing and a dynamic mesoscopic simulator to rank road network links according to traffic and day-to-day disruptions. Moreover, García-Palomares et al. (2018) classified road sections of the Spanish high-capacity road network into five levels of criticality, using existing accessibility indicators. Lastly, Oh et al. (2013) evaluated the criticality of infrastructure systems based on their zone of influence, activity analysis and socioeconomic impact.

Summarising, state of the art research in transport infrastructure management and planning highlights the importance of examining assets as elements of networks and of considering asset criticality within the network, when taking decisions. However, there is no comprehensive widespread method for assessing road network connectivity, considering the criticality of bridges, and proposing alternative routes to improve it. Given this, the current paper aims to develop a method that evaluates network connectivity and proposes the optimal development of new road sections to improve it.

METHODOLOGY

The methodology is divided into three main phases, termed spatial network extension, network connectivity evaluation, and optimal road sections selection.

Spatial Network Extension

The existing road network is analysed here as a complex network, with links corresponding to roads and nodes demonstrating bridges and municipalities. The existing road network is extended by adding all plausible new road sections (represented by dummy links). The addition of dummy links should meet the requirement of preserving the planarity condition. Thus, the dummy links do not cross with the existing links. Once the extended network is designed, network connectivity can be evaluated (in the following step) considering the existing network or a novel network, consisting of the existing road links and a set of dummy links (that represent the proposed new road sections).

Network Connectivity Evaluation: ABA-closeness

The network connectivity is evaluated by a variation of closeness centrality measure, termed ABA-closeness. Closeness centrality can approximate the distance between a node and the rest nodes of a network, and therefore the level of isolation of the examined node (Barthélemy, 2011; Crucitti et al., 2006). ABA-closeness is based on calculating path distances, beginning from nodes belonging to a specific group of nodes, A (i.e. municipalities), passing by a second specified group, B (i.e. bridges), and finishing at a node that belongs to the initial group, A (i.e. municipalities). As already explained, bridges were selected as the asset of interest for this case study due to their high vulnerability within a transport network. Similarly, the criticality of other assets (represented by nodes or links) can be evaluated, along with the way they affect network connectivity.

In the current case study, assuming a graph representation of a road network, $G = (V, E)$, where: E is a set of links (i.e. roads); V is a set of nodes (i.e. municipalities, V_M, and bridges, V_B); and A is the adjacency matrix with elements $a_{ij} = 1$, in case of nodes i and j being connected, and $a_{ij} = 0$ otherwise. The "closeness" of a node is defined as the inverse of the average distance from all other nodes of the network. The lower the distance of a node to the rest nodes, the higher the node closeness value. The closeness herein is calculated by considering the geographical distance between municipalities in kilometres. This distance between the municipality-nodes i and j is noted by $d(i,j)$, expressing the shortest-path between the two nodes. Equation (1) offers a general expression of closeness of node j, $C(j)$, serving as a foundation for further adaptation required to approach ABA-closeness. ABA-closeness is defined through a classification of the nodes in V such that $V=B \cup M$, where M is the set of municipality-nodes and B is the set of bridge-nodes.

$$C(j) = (n-1) / \sum_{i \in V \setminus i} d(i,j) \qquad (1)$$

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

Optimal road sections selection

After designing the spatial network extension and defining the way network connectivity is evaluated, the proposed method attempts to find the optimal combination of new potential links. A genetic algorithm (GA), as proposed by Holland (1992), is modified and applied to solve the optimisation problem of minimising ABA-closeness in the network extension, after adding a limited number of road-links. A GA procedure begins with settling a set of solutions, named population. Each individual in a population is characterised by a set of parameter values that completely describe a solution. GAs are selected to solve the presented problem because they can solve problems with large solutions-space and they use a binary alphabet (i.e., 0 and 1) to form chromosomes. In our case, existing and new potential road sections are represented by 1 and 0 respectively.

The main steps of the GA are summarised in Figure 1. The initial population of solutions is randomly selected. This population will evolve over a number of generations until reaching an optimal (or close to optimal) solution. A maximum number of generations can be used as a stop criterion for the GA. Each generation evolves towards the optimisation of a fitness function computed globally and for which every individual of the population has an input. Based on their fitness values, individuals are selected from the population and recombined, producing offspring that comprises the next generation. This is the recombination operation, which is generally referred to as crossover because of the way that genetic material crosses over from one chromosome to another. The expected results from this methodology is a set of new roads to be developed so that the ABA-closeness measure is minimised, and hence improving the network resilience. The new roads are chosen among the exhaustive set of all new potential roads (i.e. dummy roads), designed at the first stage of the methodology. This selection is the result of the combination of up to k new built roads. Such a number k is chosen based on budget and/or physical or environmental constraints.

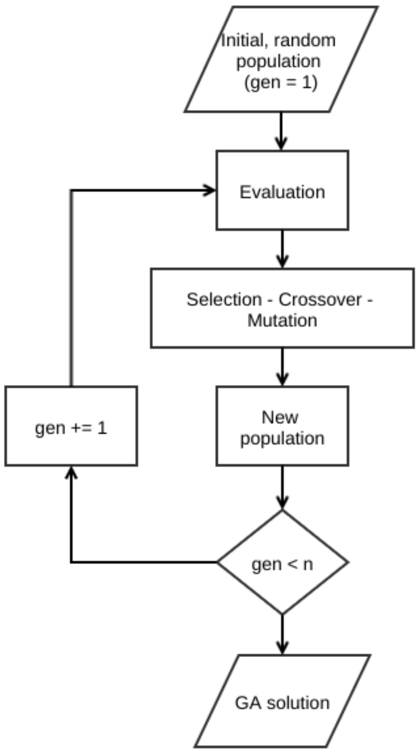

Figure 1: Main steps of the GA

CASE STUDY

The proposed method for network connectivity evaluation and new road sections development proposal to improve connectivity and consequently resilience was applied to a real road network that includes 21 bridges. The selected network belongs to a wider transport network, and thus the results will be different if more road sections and bridges are considered. Therefore, the case study serves as an example on how the proposed methodology can be applied to road networks. The data was processed in Python programming language and environment, using NetworkX library and a tailored version of a GA specifically developed for this problem. The specifications of the PC used were as follows: Intel Xeon CPU E5-2680 v4, 2.40GHz, and 64 GB RAM. The processing time of the presented case study was 2 minutes. The data has been provided by “Infraestruturas de Portugal” that is a state-owned company, managing the Portuguese roadway and railway infrastructure.

Figure 2 shows the spatial location of the bridges and municipalities of the area, along with the road sections connecting them. The spatial information provided by Figure 2 is the base for the formation of a complex network (Figure 3) that is used for the network connectivity evaluation. Figure 3 preserves the geographic coordinates of the nodes (i.e. bridges and municipalities), along with the links (i.e. roads) length. The nodes illustrating municipalities in Figure 3 are weighted to be visually proportional to their population size. The same nodes are also labelled with the municipality names.

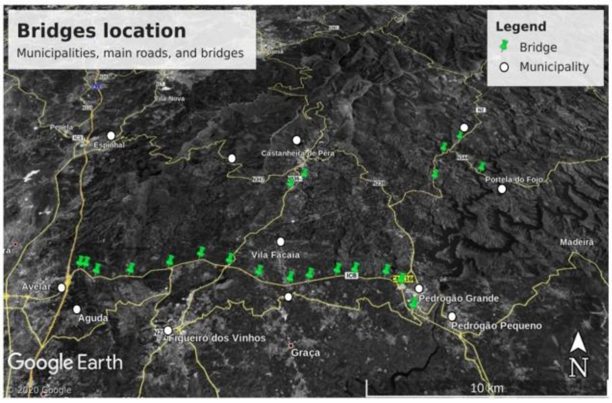

Figure 2: Location of bridges and municipalities

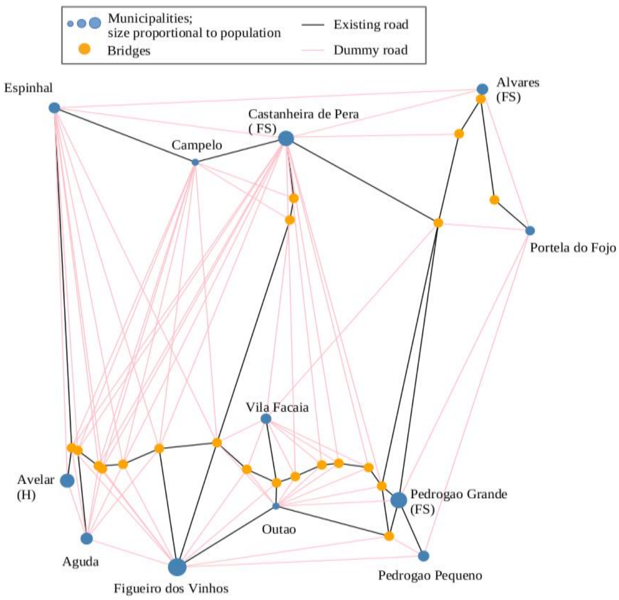

Figure 3: Formation of complex network, including existing and dummy road sections.

All dummy road sections, illustrated with grey colour in Figure 3, provide alternatives that can improve connectivity. However, decision-makers normally have budget constraints, and thus they can develop only a limited number of new road sections, if needed. The algorithm user can select the maximum number of new sections. We run the code twice, for a maximum number of newly developed sections of 5 and 3. The optimisation process maximises network connectivity by minimising ABA-closeness, as explained in the Methodology section, due to the addition of the novel sections, whose status changes from 0 to 1.

The procedure for tuning the GA parameters was based on an exhaustive search of their optimal combination. This was feasible by a reduction of the solution space to a limited number of plausible choices for each parameter. The examined values for the maximum number of generations were equal to 100, 200 and 500 or until convergence (that appears when a solution does not improve after a sequence of consecutive iterations). The examined values for: the GA population size were equal to 30, 50 and 80; for the crossover percentage were equal to 0.6, 0.7 and 0.8; and for the mutation rate were equal to 0.01, 0.02 and 0.05. Based on these options, the GA was computed with n=100 generations for a population encompassing 50 individuals. Each individual is a sequence of binary chromosomes and has a length equal to the number of dummy links. The crossover percentage was set to 0.8, and the mutation rate was set to 0.02. The objective/fitness function to be optimised (i.e. minimised) is the ABA-closeness that considering the distance between municipalities in the road network.There are up to 10,424,128 ways to select k = 5 new roads out of the 68 dummy, candidate roads. The results showed that the optimal road sections addition to the current layout (Figure 4) are those connecting: Avelar and Aguda; Aguda and B.076; Figueiro dos Vinhos and B.074; Campelo and B.076; and Espinhal and B.078.

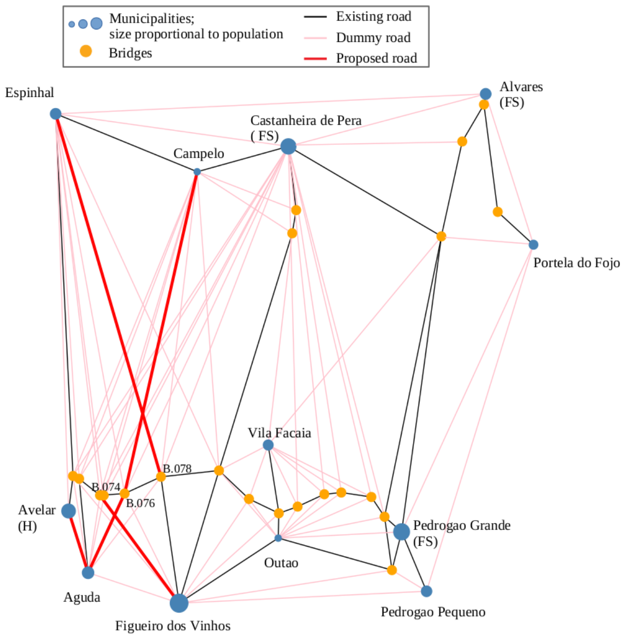

Figure 4: Optimal selection of 5 new road sections to improve network connectivity

ABA-closeness value of the existing network was 0.57, being decreased to a value of 0.31 thanks to the addition of the 5 new road sections. The proposed new links indicate the need for adding alternative routes in the southwest area of the network to enhance connectivity and consequently resilience. As it can be observed in Figure 4, two of the proposed road sections are crossed. Road intersections can include a roundabout, a beridge or traffic lights, significantly increasing the cost for improving network connectivity. Thus, the algorithm was run for a second time with a maximum number of proposed roads of 3 to investigate how the connectivity can be improved with a lower-cost solution. This solution reduces ABA closeness measure from 0.57 to 0.35, without causing crossing between sections. The optimal road sections addition (Figure 5) are those connecting: Avelar and Aguda; Aguda and B.076; as well as Campelo and B.076.

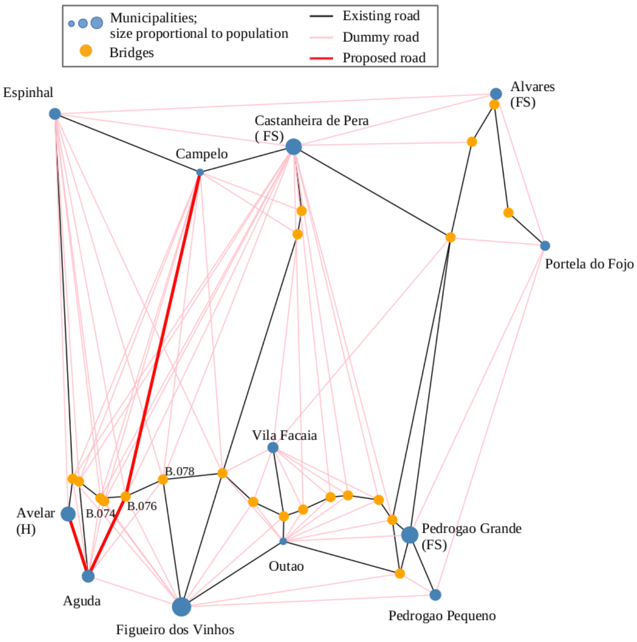

Figure 5: Optimal selection of 3 new road sections to improve network connectivity

CONCLUSIONS

Transport infrastructure assets are exposed to increasingly frequent and intense extreme events due to climate change and serve more traffic than originally designed due to population growth. An asset failure can have catastrophic results to the transport network. It is critical for a transport network to have alternative routes, connecting municipalities, in case of an asset failure. Consequently, network connectivity is directly connected with resilience. The current paper examines routes connecting municipalities, passing by bridges, due to bridge importance and vulnerability within a transport network. The case study, examining road network connectivity, shows that the addition of a limited number of new road sections can provide alternative routes that improve connectivity. Additionally, it shows that even with a limited budget (e.g. proposing the addition of 3 new road sections instead of 5 in our case study) the connectivity is significantly enhanced.

The development and use of ABA-closeness measure for the evaluation of network connectivity and the modification of the GA for proposing the optimal road sections to be developed for improving connectivity summarise the contribution of the current paper. The proposed framework can form the basis for transport networks connectivity evaluation, assisting decision-makers in infrastructure planning. As a result of improving connectivity, network resilience will be improved and thus road network users will also be benefited. The impact of an asset failure to users will be reduced due to the decrease in traffic delays and associated costs.

The proposed method has room for improvement and work is currently under way to further enrich it. The focus of the current paper is on routes connecting municipalities, passing by bridges. Future work aims to consider more links and nodes of a transport network. In addition, traffic served by nodes and links will be taken into account for criticality and connectivity evaluation. The method will also be adjusted so that the optimal proposal of novel roads development in terms of connectivity will consider their cost and the available budget. Future work also contains vulnerability analysis that will be based on the possibilities and impact of extreme events on transport networks. Lastly, the authors are in cooperation with transport asset owners for modifying, expanding, and testing this framework in real-life transport networks.

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