EPA1352. Advanced Simulation

Assignment 4. Criticality & Vulnerability in Network Analysis N1 - N2

Group 17

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Content

1. Introduction

Bangladesh, with its population of 172 million people living in just 147,000 square kilometres, faces a significant challenge due to its status as one of the most densely populated countries on the planet (WPR, 2023). The country is also highly vulnerable to the detrimental impacts of climate change, which include natural disasters that frequently ravage the nation. As a result, Bangladesh is classified as one of the world's most vulnerable countries to climate change (Azam et al., 2022). Considering this, there is a pressing need to enhance the country's resilience and reduce its vulnerability through effective infrastructural policies and projects.

To strengthen the resilience of Bangladesh's road network, funds need to be allocated to the most important bridges and road section – in the following called network components. This paper investigates the network through a computer simulation, to identify these most important network components. We will use metrics of criticality and vulnerability to assess importance.

In the next chapter we put forward metrics to assess criticality and vulnerability. Since the choice of indicators is heavily influencing what components are being identified as important, we will elaborate briefly on our choice of indicators based on economic and ethical considerations. Methodology behind simulation and experiment will be elaborated on in chapters 3, and 4. We will present and briefly discuss results in chapter 5, based on which we will formulate policy recommendations in chapter 6. Limitations will be discussed in chapter 7.

2. Criticality and Vulnerability

The concepts of criticality and vulnerability are widely used in studies and literature across many different disciplines. In this variety, definitions appear to differ strongly. Furthermore, within the areas of study (e.g. road networks and transport infrastructures) criticality or vulnerability can be assessed through various methods. In this section, literature on both concepts - within the context of network analysis – will shortly be reviewed to clearly define the concepts and metrics of criticality and vulnerability used in this analysis.

Even inside the context of transport network analysis definitions differ significantly. For instance, Korosh Mahmoodi (2018) defines criticality as a potential traffic capacity of the network components and vulnerability as a likelihood of a network component becoming untraversable. On the other hand, Jenelius and Mattsson (2015) define criticality as the combination the likelihood of components becoming untraversable and the impact of such disruptions to the entire network's traffic. The latter definition of criticality can be interpreted as encompassing both criticality and vulnerability as defined by Korosh Mahmoodi. Choosing metrics thus has a strong impact on the final policy recommendation, just as much as choosing indicators. Considering different philosophical approaches to make that decision is important. Simulation design, the available input data, and the decision on what results data to capture are also limiting the choice of metrics.

2.1. Criticality

We will work with Jenelius & Mattson's (2015) definition of criticality, as introduced above. We will compute the metric as follows:

(1) Criticality = probability of bridge collapsing * traffic flow per bridge

We chose to focus on bridges as the underlying assumption regarding the probability of a bridge collapse is predicated on a natural disaster of some kind. These bridges are the most vulnerable part of the model as we assume that the roads themselves will be intact enough to use for basic transport. In case a bridge collapses, it will necessitate a rerouting for the trucks. However, since we have only modelled the bridge being damaged and causing a delay, we chose not to model the process of rerouting of trucks.

The probability of a bridge collapsing captures the disruption probability of a network component. The traffic flow on each bridge captures the impact that a disruption at that component has on the network's global traffic. The higher traffic is on a node, the more impact potential traffic rerouting will have on all other components of the network. In order to measure traffic flow at each bridge, the number of vehicles traversing each bridge are being counted, regardless of scenario and probability of collapse.

By incorporating disruption probabilities, we conceptually follow the suggestion made by Jafino et. al. (2020), to "use … disaster exposure indicators to analyze the vulnerability of the network to natural disasters. Note that vulnerability is here not following the strict definition that we laid out for this paper. Note also that the presented criticality metric does capture which neighboring components will be most impacted by rerouting. In some parts of the network circumnavigating collapsed links is easier due to the high number of alternative routes available.

(2) betweenness centrality = number of shortest paths at through each component / total number of shortest paths

To also capture this characteristic, we decided to incorporate betweenness centrality as an additional measure of criticality. Components of high centrality will be regarded as components of high criticality.

2.2. Vulnerability

According to Jenelius & Mattsson (2015), vulnerability in road network systems refers to the risk that society faces in terms of transport disruptions and degradations. They suggest that vulnerability should not be viewed solely from the perspective of the transport network, but rather from the perspective of the people, services, and businesses that use the network. By working with this indicator definition, our vulnerability analysis can assist the management of potential risks that could arise, leading to better mitigation of the impacts of disruptions, and ultimately, enhancing the performance of transportation networks (Esfeh et al., 2022). Lives are at stake. Therefore, it is of pivotal importance that no citizen of Bangladesh is left behind by our recommendation for infrastructure projects when it comes to crisis mitigation.

We chose to measure vulnerability through delay times and number of delayed vehicles.

(3) Vulnerability1 = Relative delay of each source * probability of bridge collapsing

(4) Vulnerability2 = Share of delayed trucks of each source * probability of bridge collapsing

By using relative, rather than absolute values, the average delay of trucks from the same source and the proportion of trucks from the same source being delayed are considered. This removes population size from the importance of a source, thus making all cities weight equally in the metric.

2.3. Utilitarian and Egalitarian perspective

In their 2020 study, Afino et al. draw a distinction between two viewpoints, namely the utilitarian and egalitarian perspectives, when assessing vulnerability in a network. The utilitarian perspective recognizes that elements in a network are not equal and considers factors such as population density when evaluating the vulnerability of components within a particular area. Conversely, the egalitarian perspective assumes that all elements are equal and does not take such factors into account. Both perspectives are relevant for analysing vulnerability, leading to the categorization of vulnerability into two types: Utilitarian vulnerability and Egalitarian vulnerability. While the Utilitarian viewpoint prioritizes maximizing societal well-being without considering fairness or equity, the Egalitarian perspective places a greater emphasis on ensuring a fair distribution of welfare throughout society. For this reason, we chose to work with relative values in equations 3 and 4.

3. Simulation design

This report aims to expand on the analysis conducted in assignment three on the impact of delays caused by damage to bridges combined with delays caused by traffic at bridges as well as roads. In this assignment, the previous mesa model is updated with traffic data for individual nodes and links of the NetworkX model, and the simulation is conducted on the N1 and N2 highways and their side roads of length greater than 25km. To reduce the influence of modeller bias (Keller & Hu 2019), a data-driven modelling approach was employed in this study.

3.1. Dataframe size and merging

The Dataframe was created using the BMMS_Overview.xlsx file and the _roads3.csv files. Data cleaning involves creating a DataFrame of relevant roads and bridges, assigning unique IDs and agent types. Intersections were located and placed based on documented data and uses euclidean projection to fill in missing intersections. The resulting DataFrame includes bridges, intersections, and road elements with unique IDs and agent types. Two new additions were made to the data cleaning process. Firstly, traffic data from the htm files was added to the Dataframe for each road segment. It only considers the total amount of traffic on the road, hence only the information in the AADT column is considered. While adding the traffic data to the file, special consideration was given to making the code generalised to allow for scaling.

Furthermore, for every SourceSink, was given an incoming and outgoing traffic. To calculate the proportion of outgoing and incoming traffic for each SourceSink, we used the absolute traffic numbers from the corresponding X.traffic.htm file. The SourceSink is determined using the road and chainage. The outgoing traffic is the proportion of total trucks generated at the SourceSink, while the incoming traffic is the proportion of total trucks destined for the SourceSink. We calculate the total number of trucks on the road using these proportions and overwrite the absolute traffic numbers. The resulting Dataframe is the final output of this process. For more information on the procedure please consult the *Data_Processing.ipynb* file.

3.2. SourceSink and NetworkX

To enable vehicles to move over the road network, the SourceSink components generate a vehicle, set a path for the vehicle and direct it to a random sink location in the network. To facilitate this, a NetworkX model of the road network is generated. In this model, each bridge is presented as a node, each road as an edge and can return the shortest path between two nodes.

To optimize the process of determining the shortest path between an origin and a destination, the discovered paths are saved into dictionary path_ids_dict_complex. This reduces the need for repetitive calculations and speeds up the process of determining the shortest path for a vehicle.

3.3. Batch Run

The *batchrunner.py* file was added to the project, which utilizes Mesa's batchrunner to run all scenarios sequentially. Each scenario runs 10 iterations for a period of 5 days. The probability of bridges breaking according to category is passed to the batchrunner. The output is saved for every scenario and combined in the file, called *scenarios.csv.*

4. Experimental design

The traffic simulation model has been updated to improve the realism of traffic flow on the N1, N2 and their sideroads by adjusting the creation of trucks at each source and the assignment of destinations. To accurately assess the criticality of bridges and the vulnerability of cities/bridges, it is necessary to have a realistic breakdown probability for each bridge category. Unfortunately, there is no available data on how each bridge category behaves relative to the others. As a result, the model was executed under various scenarios, each with a distinct probability of breakdown for each bridge category, as shown in Table 1. To ensure accuracy, each scenario was run 10 times.

Scenario	Cat A %	Cat B %	Cat C %	Cat D %
0	0	0	0	0
1	0	0	0	5
2	0	0	5	10
3	0	5	10	20
4	5	10	20	40

Table 1: Delay times across simulations.

Scenario 0 serves as a control, representing a day without any bridge breakdowns. Scenario 1 to 4 have progressively increased breakdown probabilities for lower-quality bridge categories, with the difference in probabilities growing with each scenario.

5. Results

This section will cover the presentation and discussion of the results. To begin with, a broad performance measure, the average driving time per scenario, will be introduced for the purpose of interpretation and validation. Subsequently, the model's output concerning the pre-defined network metrics will be showcased.

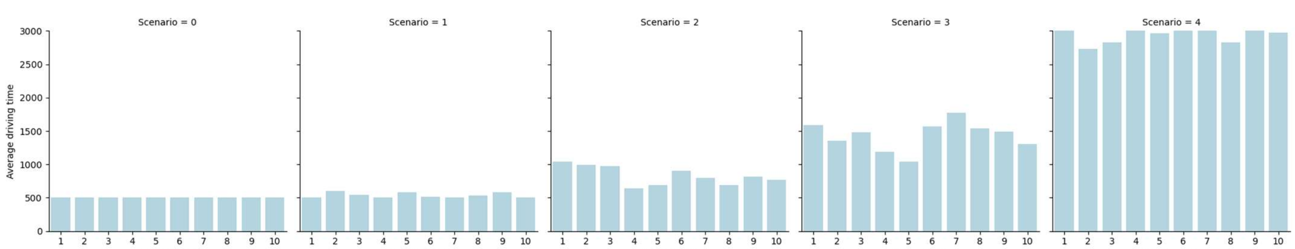

Figure 1: Driving time across scenarios.

Although there are slight differences in driving times between scenarios 1 through 4, they are not as significant as initially anticipated. This is unexpected, given the drastic impact of breakdown probabilities on scenarios. However, upon examining the data in Table 2, it becomes clear what is responsible for this behaviour.

Condition	Occurrence
Condition A	970
Condition B	249
Condition C	179
Condition D	13

Table 2: Occurrence of bridges per category.

Most of the bridges in the network belong to category A, making the other categories less prominent. As a result, delays for category A bridges largely influence the scenario output. Since the breakdown probability for category A bridges remains constant at 10% in scenarios 1-4, the average driving times for each scenario are very similar. Going forward, we will thus focus on insights from scenario 4, while the outputs of the other scenarios can be found in the Data_Analysis.py notebook.

5.1. Criticality

Bridges that are significant and pose a high risk of failure are categorized as critical bridges. Such bridges are responsible for causing the most severe delays. Table 3 depicts the bridges identified as most critical, following formula 1 (see chapter 2.1). Table 4 depicts the bridges identifies as most critical, following betweenness centrality (see formula 2, chapter 2.1).

Bridge
Bridge at id 1000004
SHAMMOTI PARA
AMIR GOAN SLAB CULVERT
BARIPOLE BOX
MIRPUKUR CULVERT

Table 3: Most critical bridges as computed by formula 1.

Component
1000374
1000208
1000019
1000204
1000199

Table 4: Most critical components as computed by formula 2.

5.2. *Vulnerability*

This metric provides insights into the most susceptible bridges within each source-sink when all cities are considered equivalent. The partial betweenness centrality of a specific source-sink towards all bridges is multiplied by the weighted relative delay of each source, leading to the identification of the most vulnerable bridges for each source-sink. The determination of vulnerable bridges is based on the analysis of delay frequencies (Figure 2) and delay durations (Figure 3) for each source-sink.

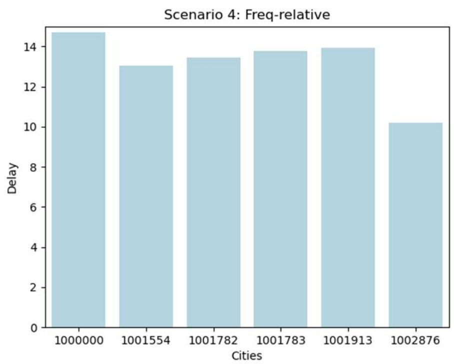

Figure 2: Frequencies of delays across source-sinks in scenario 4.

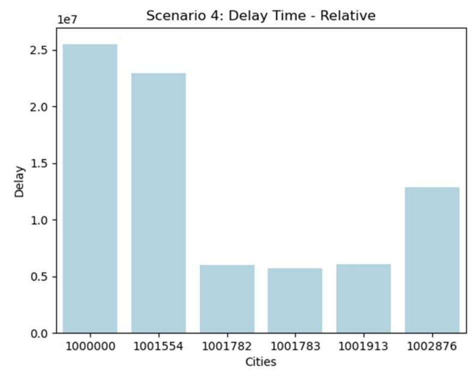

Figure 3: Delay times across source-sinks in scenario 4

6. Recommendation

Since there is little overlap of identified network components between all four employed metrics, it is not possible to give a general recommendation as to what component should require most urgent attention by policy makers. The here presented analysis shows some limitations, as elaborated on in the following chapter. However, it is also possible that there are no components in the network under analysis that add significantly to the network's performance. In that case each component has a roughly similar effect on overall traffic. Focussing on specific components would then not significantly increase overall network performance in case of a natural disaster.

7. Limitations

Metrics 1, 3, and 4 are using collapse probabilities of bridges. These metrics could have also incorporated further information such as water data, historical data on storms, etc. This would have helped to extrapolate results, since collapse probabilities are defined artificially and are not based on past real-world natural disasters.

Incorporating more metrics would have helped in drawing a more complete picture. Jafino et al. (2020) is discussing 17 different metrics of criticality in the context of transport networks, which can be roughly categorized into travel costs, traffic flow, accessibility, centrality, exposure disaster, and redundancy. We selected only one of these 17 metrics. Including too many metrics, on the other hand, increases complexity in choosing network components. In. hindsight, the following metrics might have been a better choice for our purpose, nevertheless.

Firstly, we could have selected a weighted betweenness centrality. Derived from network theory, this metric measures the number of shortest paths going through each network component. The component that is part of shortest paths, is of highest betweenness centrality. Unlike unweighted betweenness centrality, this metric allows us to assign weights to each component. We could have used traffic data from the simulation results as basis to compute weights. In this way, we indirectly incorporate the information gained from the proposed travel cost metrics as well. Secondly, we could have used the metric of nearby alternative elements, which is “based on the availability of other elements that are geographically close to that element” (Jafino et. al. 2020). Thirdly, we could have chosen exposure disaster for assessing vulnerability. Exposure disaster is “often used jointly with other metrics to narrow down potential interventions” (Jafino et. al. 2020).

One major limitation we encountered was the computational complexity of this model. The model ran for 5 hours and 20 minutes on the first batch run. This severely limited the number of iterations we could perform to improve the model. This problem would also limit the number of iterations we can perform to get statistically significant results. The small sample size may result in observation bias and affect the output of the analysis.

As mentioned earlier, when coming across a damaged bridge, we could have made the trucks change their routes. This would require considering a broken bridge as a broken edge and recalculate the path after the truck reaches that point. This would then add additional travel time for the truck as well as delay time on the partially damaged bridges. However, for this task we would need to involve the entirety of the road network of Bangladesh. With the current time constraints and computational limitations this is not possible.

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