EPA1352 Advanced Simulation (2021/22 Q3)
Lab Assignment 4: Network Model Analysis

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Summary

For this assignment, we use road conditions and traffic data to create a simulation environment that allows us to analyze the criticality and vulnerability of the Bangladesh road network. Furthermore, we increase the level of detail of our model to have a closer representation to reality. The model is run under different natural hazards conditions. Finally, the simulation output is analyzed to find the most critical and most vulnerable bridges.

1. Literature Review

Vulnerability in transport networks refers to the extent to which infrastructural components are vulnerable to natural hazards which include but are not limited to earthquakes, floods and fires (Balijepalli & Oppong, 2014). A common way to assess vulnerability is to rely on disaster exposure metrics (Jafino et al., 2019). Vulnerability analyses are helpful in preparing for disaster scenarios and in identifying components that require special attention—especially in terms of maintenance (Balijepalli & Oppong, 2014). In our analysis, to measure vulnerability of bridges, we will look at their condition as well as local exposure to four natural hazards that Bangladesh is exposed to: earthquake, erosion, cyclone, and flood.

Criticality, on the other hand, concerns the contribution that each component makes to the network (Jafino et al., 2019). Critical components are the ones with high benefit to the users and the society (Jafino et al., 2019). In our analysis, we will approximate criticality of a component as the economic value that flows through it. In that sense, it resembles Metric 8 from the work of Jafino et al. (2019).

2. Model and experimental setup

2.1. Vulnerability of bridges

To define the vulnerability of the bridges, we decided to consider the following natural disasters: earthquake, cyclone, flood, and erosion. Also, we considered a scenario where no natural hazard exists and the probabilities of the bridges breaking down is based solely on their condition. Initially, we found the probability of each of these hazards to happen in Bangladesh. These probabilities, available in Statista (2021), were given based on a 10-scale and were normalized. The only hazard for which such data was unavailable was the erosion. In that case, we assumed that its likelihood of happening is the same as the earthquake's, as by searching in the literature we found that many parts of the country are mainly susceptible to earthquake induced erosion (National Plan for Disaster Management, 2020).

By searching in the literature, we found hazard exposure of Bangladesh's districts and assumed that bridges have the same vulnerability as the division they belong to (we were able to use districts as they were corresponding to divisions in the BMMS_overview.xlsx file).

For division level cyclone, we used specific district level vulnerability scores as calculated by Hossain et al. (2019). For the rest of the disasters—namely earthquake, erosion, and flood—, we consulted on a technical assistance report commissioned by the Asian Development Bank (2018). In this report, exposure was defined based on a 5 categories-scale. These categories were *Very unlikely, Unlikely, Possibly, Likely and Almost Certain*. In this case, we decided to convert these categories into numerical values, where zero was given to the "*Very Unlikely*" category and 1 to the "*Almost Certain*" category. The probabilities for the intermediate categories were increased evenly by 0.25.

Finally, we considered the condition of the bridges, as bridges of different conditions differ in the probability of breaking down under natural hazards. Instead of using conditions A, B, C and D (like we did in the previous assignments) we decided to use the Bridges Condition Scores (BCS) given in the Bridges.xlsx file (BCS1TotalScore column), on which the classification of the bridges' conditions to A, B, C or D is based (Ministry of Communications Roads and Highways Department, 2005). We used this condition scores as our $score_{baseline}$.

To calculate the vulnerability scores of the bridges under different hazard scenarios, we assumed that in case a district is 100% vulnerable to a natural hazard, the probability of the bridge breaking down under this scenario is doubled. The formula that was used for earthquake is given in Equation 1. Same logic was applied for every hazard.

Equation 1 Earthquake vulnerability score

$$score_{vulnerability,earthquake} = score_{baseline} * (1 + exposure_{district,earthquake})$$

2.2. Breaking probability of bridges

After calculating the vulnerability scores, we discussed that these scores were reasonable approximators for the breaking probabilities. With this assumption, we initially used the formulation given in Equation 2.

Equation 2 Initial formulation for break probability

$$prob_{breaking,earthquake} = score_{vulnerability,earthquake}$$

We conducted the main body of analysis based on this equation. Nonetheless, we discussed that this approach might be lacking some aspects in the real life.

In our data, we have bridges with the perfect score of zero. In such cases, these bridges will have zero probability of breaking down. However, in real life, a bridge might break down even if it is in perfect condition.

Also, the impact of a unit change in this score might not correspond directly to a unit of change in breaking probability.

Motivated by these discussions, we argued that a better approach might be to have a linear regression equation for $prob_{breaking,earthquake}$, instead of directly using vulnerability scores. For this purpose, we also created some scenarios by experimenting with x_{min} and x_{slope} in Equation 3.

Equation 3 Expanded formulation for break probability

$$prob_{breaking,earthquake} = x_{min} + x_{slope} * score_{vulnerability,earthquake}$$

2.3. Delay time caused by broken bridges

To model the bridges' delay time, we used the paper by Zhu et al. (2010) where the delay time of a bridge over the Mississippi River was analyzed. In their results, delay time seems to follow an exponential distribution, as seen in Figure 1, and therefore we decided to simulate delay time by using an exponential distribution as well. In this analysis, the bridge of focus had an average delay time of 28 minutes, while its length is 580 m (Purdue University, 2020), corresponding to an approximated waiting time of 0.05 minutes per meter.

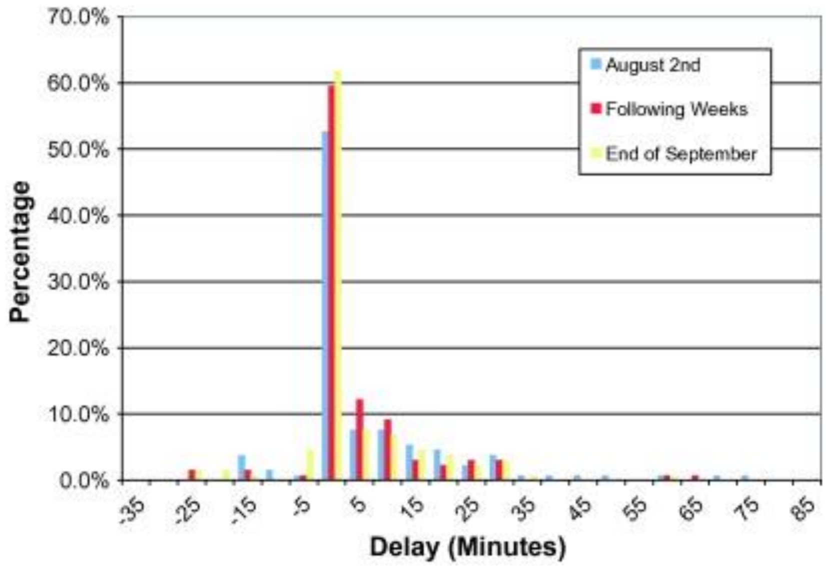

Figure 1 Delay time distribution of the I-35W bridge over the Mississippi River (Zhu et al.,2010)

Assuming that the delay time is proportional to the length of the bridge, we modeled the delay time of each bridge by an exponential distribution with the expected value of $delay\ per\ meter\ *\ length\ of\ the\ bridge$.

Furthermore, as we expanded the logic on delays on bridges by implementing a FIFO (First-In-First-Out) principle. This implementation is discussed in more detail in Section 3.3.

2.4. Traffic data

Traffic data has been utilized mainly to procure the generation probabilities of different categories of vehicles, which carry different amount of economical goods and have different velocities. This was done to ensure the fitness for purpose of the model during construction as it is more realistic to base the generation probabilities of different categories of vehicles on traffic data. However, the main assumption is that the most important among the categories of vehicles have been selected for analysis: these were Heavy Trucks, Medium Trucks, Small Trucks, Large Busses, Medium Busses. The choices of these vehicles were determined by the annual hours driven data that has been found in literature which will be further explained in Section 3.3.1. To find probabilities of generation in each source of the model, the total amount of all these vehicles were calculated per road. Then the total number of each vehicle category per road has been divided by the total amount of all the vehicles in the road. The distinction of the probabilities per vehicle category per road is important as it provides realism and insight into, for example, what roads are critical due to having vehicles with higher loads upon the road.

In simpler terms, the probabilities of generating different vehicle categories based on the road is about answering the question "if we take a random vehicle from this specific road, what is the probability that it is a large truck with respect to past traffic data?" The implementation of these ideas in python can be found under Section 3.2.

3. Implementation

3.1. Data cleaning

In this section, we describe the process we followed to prepared the data for the simulation runs.

3.1.1. Calculating vulnerability scores

- On the Bridges excel, we normalized the BCS scores to be between 0 and 1.
- BCS scores were not available on BMMS_overview; hence, we needed to match the bridges from Bridges dataset with BMMS_overview. Using excel formulas (all of which are documented on BMMS_overview), we implemented the following algorithm:
    - First, try to match by unique LRP (which is the road name and LRP number concatenated with an underscore in-between).
    - If no match is found by unique LRP, try to match the bridge name.
    - If no match is found, check for the bridge condition. If the bridge condition is A, then set the value to zero.
    - In case no match is found, leave the cell empty. These bridges will be removed from the data once the file is imported in cleaning_data.ipynb.
- We calculated vulnerability scores based on Equation 1 . The steps we followed for this purpose are as follows:
    - We created an excel file named natural_hazards and entered district level exposures per natural hazard based on studies by Asian Development Bank (2018) and Hossain et al. (2019).
    - We corrected some names in the natural_hazards file so that they correspond to the division names on BMMS_overview (Comilla vs Cumilla, Bogura vs. Bogra, etc.).
    - On BMMS_overview, we used excel formulas (as documented on the worksheet) to lookup for the divisions and match them from natural_hazards file.
    - If the district is not found, the vulnerability is inherited from the circle.
    - Once exposure levels to hazards were matched, Equation 1 was used to calculate the vulnerability score of the bridge under four hazard scenarios.
- After preparing BMMS_overview file, we ran the cleaning_data.ipynb to
    - merge bridge data with starting and ending points of the roads, intersections
    - calculate links from one component to the other.
- With that, we got five different csv's ready for runs: cleaned_roads_BCSscore (where no disaster happens), cleaned_roads_Earthquake (Earthquake), cleaned_roads_Erosion (Erosion), cleaned_roads_Cyclone (Cyclone) and cleaned_roads_Flood (Flood).
- For all bridges that are considered in simulation, vulnerability scores, as a weighted average based on likelihood of each hazard, are reported on bridges-scores file.

3.2. Traffic data

- Under Traffic data.ipynb, first the traffic files that are in .htm format have been read as dataframes.
- These dataframes have been made with respect to their column_names that are present in the .htm files and including only necessary information to resemble a .csv.
- Link no.s (which are a column present in the .htm files, signifying the road and the segment of it) have been seperated into a new column indicating only their respective roads. Also the start location and end location LRP names were concatenated with "-" in between. This was done to ensure that road segments (if needed) would be easy to track through LRPs and not only with the segment names that have been provided in the .htm files, concatenated to the road names.
- The data types have been corrected, previously being all objects, into floats and integers respectively.
- The list of names of the roads of interest have been utilized (starting with N).

- The probabilities of each category of vehicle for each road (adding up to 1 for each road) have been found by:
  - Finding the proportion of each category of vehicle traffic by dividing it by the total amount of traffic within that road.
- Lastly, these probabilities have been written into the traffic_probabilities.txt file to be read by the model.

3.3. Changes to the model

We extended the model to increase the level of detail of our simulation making it "more" realistic. But given our time constraint we still used many of the assumptions that the original model was built on (e.g., the velocity is constant throughout a single step) in order not to drastically change the model structure. We tried our best to develop the code following closely the modularity and information hiding principles, key to good model building.

3.3.1 New Vehicle classes

We introduced new types of vehicles that represent the most common transports in Bangladesh: we created new classes that extend the Vehicle one (extending the Vehicle class enabled us not to change the code of the model, except for when sources generate vehicles, *Source.generate_vehicle*). We added HeavyTruck, MediumTruck, SmallTruck, LargeBus and MiniBus because, since they have the highest number of annual hours driven (Bangladesh Road Research Laboratory, 2017, Table 4.1), we assumed these are the most common vehicles you could see on the road. When we save information about travel time and waiting time for the Vehicles, we also save the information about their type.

So far, these classes have different class attributes regarding their speed and length and the amount of goods that can be carried, but they have the same behaviour as the parent class. Instead of creating different instances of the general Vehicle class and assigning them a different speed, we decided to still implement different classes because it increases the reusability of our code in case in the future there would be the need to assign different behaviour to the various types of vehicles (e.g., the LargeBus needs to stop throughout their longer routes to let people on and off). Reusability should be pursued since it increases software quality (Sandhu, Kaur, & Singh, 2009).

The following table contains the characteristics that we implemented for each new class:

Table 1 Summary of the vehicles' characteristics. Average speed is taken from Bangladesh Road Research Laboratory (2017, Table 4.1): it is assumed to be the average speed in the overall network (so also considering other roads than the highways). Since the maximum speed on highway source is higher (Islam, 2018), we assumed that the vehicles would travel to higher velocity but not at the highest velocity allowed: we used 80% of the maximum speed as a good proxy of the normal speed of vehicles ($NS = MS * 0.80 \sim MS = NS * 1.2$. We used these proportions because we Vehicles can accelerate by 20% in case there is enough space on the road. See section 3.3.3). Source for Vehicles' length is Bangladesh Road Research Laboratory (2017, Table 2.11). For the three kinds of trucks, we used their gross vehicle weight as a measure of the goods they can carry: $WG = Gross\ Vehicle\ Weight - Unloaded\ Weight$. The data for these last two values is from Bangladesh Road Research Laboratory (2017, Table 2.11). For the two kinds of busses, we used an estimate of the weight of the maximum number of passengers they can carry: $WG = Maximum\ Number\ of\ Passengers * Average\ Weight\ in\ Bangladesh$. We used the representative model for each category (Bangladesh Road Research Laboratory, 2017, Table 2.9) to find the maximum seating capacity: for the Large Bus it was 52 ("Tata LPO 1316 Bus", n.d.) and for the Minibus it was 41 ("Tata LP 909 Starbus Specifications", n.d.).

The Average Weight in Bangladesh used for these computations was 52.3 Kg (World Health Organization, 2011, Table 6.1).

VEHICLE	AVERAGE SPEED (AS) [KM/H]	MAXIMUM SPEED ON HIGHWAY (MS) [KM/H]	NORMAL SPEED (MS) [KM/H]	LENGTH [MM]	WEIGHT OF GOODS (WG) [KG]
HEAVY TRUCK	31	50	41	9,010	18,700
MEDIUM TRUCK	31	50	41	8,395	10,770
SMALL TRUCK	29	50	41	5,000	3,720
LARGE BUS	37	55	45	11,080	2,720
MINIBUS	26	55	45	5,970	2,144

Each Vehicle will have a class attribute called *normal_speed* that will contain the normal speed as described in Table 1.

The Source class generates the different kinds of Vehicles according to different probabilities that depend on the road the Source belongs to (see *Source.generate_vehicle*). These probabilities, as discussed prior, are denoted per road per vehicle category, creating a more realistic model. It is also important to reiterate that this distinction makes it so that the criticality of certain roads is more explicit in the model: if there are more goods being carried through a certain road, then it means that that road is more critical. These probabilities are read from a csv file and passed as a parameter to the model creation method.

3.3.2 Finer description of delays on bridges

To ensure that the delay times are generated by exponential distributions with the expected value of $delay\ per\ meter\ *\ length\ of\ the\ bridge$, we made some changes on the *get_delay_time* function of the Bridge class.

To get a closer description of reality, in our model if a Vehicle that arrives at a broken bridge gets a waiting time that is inferior to the time the last Vehicle that arrived at the bridge has still left to wait, the former Vehicle has to wait the same amount as the latter plus 1 more minute (we add 1 minute as it is the smallest time constant that the model can deal with). This addition tries to implement a very basic and rustic version of the queues that would be developing in reality at broken bridges, according to the First-In-First-Out (FIFO) principle, used in queuing models of traffic flows (Jin & Li, 2006).

This addition is implemented by comparing the waiting times before assigning it to the new Vehicle in line and by taking track of the latest addition to the queue. Thus, changes affect only the *Bridge.__init__*, *Bridge.get_delay_time*, *Vehicle.step* and *Vehicle.drive_to_next*. We developed the new code according to a proper functional decomposition (Hofmann, 2004): the addition is mainly in a function, *Bridge.compare_to_least_waiting_time_and_fix*, that is called by *Bridge.get_dealy_time* and to restore the original behaviour commenting the function invoking is enough.

3.3.3 Changes in the speed of Vehicles because of traffic

Again, to get a closer description of reality, we implemented the impact of traffic on the Vehicles' velocity in a very simple manner.

Firstly, we assume that there is a need to slow down for a Vehicle if the length of the road segment the Vehicle is in is less than the average size of all the Vehicles (7,891, see Table 1) times the number of vehicles at that time in transit on that segment: this multiplication gives a rough estimate of the space occupied by the Vehicles in the segment. And, accordingly, we assumed that the Vehicles would go up if this appraisal would be smaller than half of the road segment's length.

To implement such dynamic:

- At each step of the Vehicles, we update the velocity according to how much room there is on the road segment. We do this at the beginning of the *Vehicle.drive* function, before computing the *distance* that the Vehicles will travel in the current step (here the original assumption of the model was kept: the velocity is constant for each step).
- Not to overcomplicate the code, we make sure that the velocity can't be decreased more than once per road segment. Same applies to increasing the velocity. Also, after changing road link, the speed of the Vehicle is set to be equal to *normal_speed* class attribute of their specific type.
- The velocity is increased by 20% and decreased by 50% if needed.

Since when creating the code, we used several functions to represent the different operations (deciding whether there is the need to change velocity, computing the increased velocity, computing the decreased velocity), we can easily increase the level of details of the single parts without affecting the rest of the code: this is an example of good functional decomposition (Hofmann, 2004).

3.3.4 Experimentations with break probability calculation

As discussed in 2.2, we experimented with different x_{min} and x_{slope} values in Equation 3. For this purpose, we added two parameters to the model: *break_prob_min* and *break_prob_slope*. Default values of these parameters are 0 and 1 respectively, making Equation 3 equivalent to Equation 1. When bridge objects are created, instead of passing the score immediately as read from the excel file, the model passes the value returned by get_break_prob function. This function simply makes a calculation based on Equation 3.

4. Results

This section presents the simulation results obtained from the experiments. The KPIs were computed for every run, for every scenario. The computation of the KPIs, as well as the graphs, can be found in the *data_visualization* notebook provided. We are mainly interested in the **throughput time**, which is the average elapsed time that inputs take to move through the whole process and become outputs (Slack et al., 2010), as well as the **waiting time**. In the case of this analysis, this would be the average time a truck takes to travel from the source (input) to the sink (output) and the average time the trucks must wait due to delays. Finally, we also analyzed the most vulnerable and critical bridges based on the simulation results.

Baseline Scenario

Average travel time: from the baseline scenario analysis, it's possible to see that Cyclone scenario has the highest average travel time, but only marginally above Earthquake or BCS values. Heavy truck and Large Bus are the vehicle types with mostly large Interquartile ranges (IQR) among the scenarios, with the Earthquake scenario being somewhat an exception. In contrast, Medium and Small trucks in general depict mostly small Interquartile ranges (IQR) among the scenarios, with also the Earthquake scenario being an exception (for Medium Trucks also Erosion and Flood scenarios have more widespread values). In general, one can observe that the Earthquake scenario shows opposite behaviour for vehicle types. Heavy Truck and Large Bus depict more condensed distributions, whereas the other vehicle types show more widespread distributions, suggesting that perhaps that the Earthquake scenario impacts in a more uncertain way the journey of Medium Truck, Mini Bus and Small Truck (sometimes bringing the travel time below what was observed for the BCS scenario, but also sometimes bringing it above).

Average wait time: the time trucks have to wait due to delays overall is very limited, with the highest outliers going to around 20min. Erosion scenario depicts the highest average values for every vehicle type, suggesting that this scenario makes the journey of every average truck type worst than the other natural scenarios (with Earthquake following next). However, even for the Erosion scenario, the average wait time remains around 4min to 6min. In contrast, for BCS, Cyclone and Flood scenarios, the average wait time stays below 2min.

Figure 2 below depicts the results for average travel time and wait time by scenario.

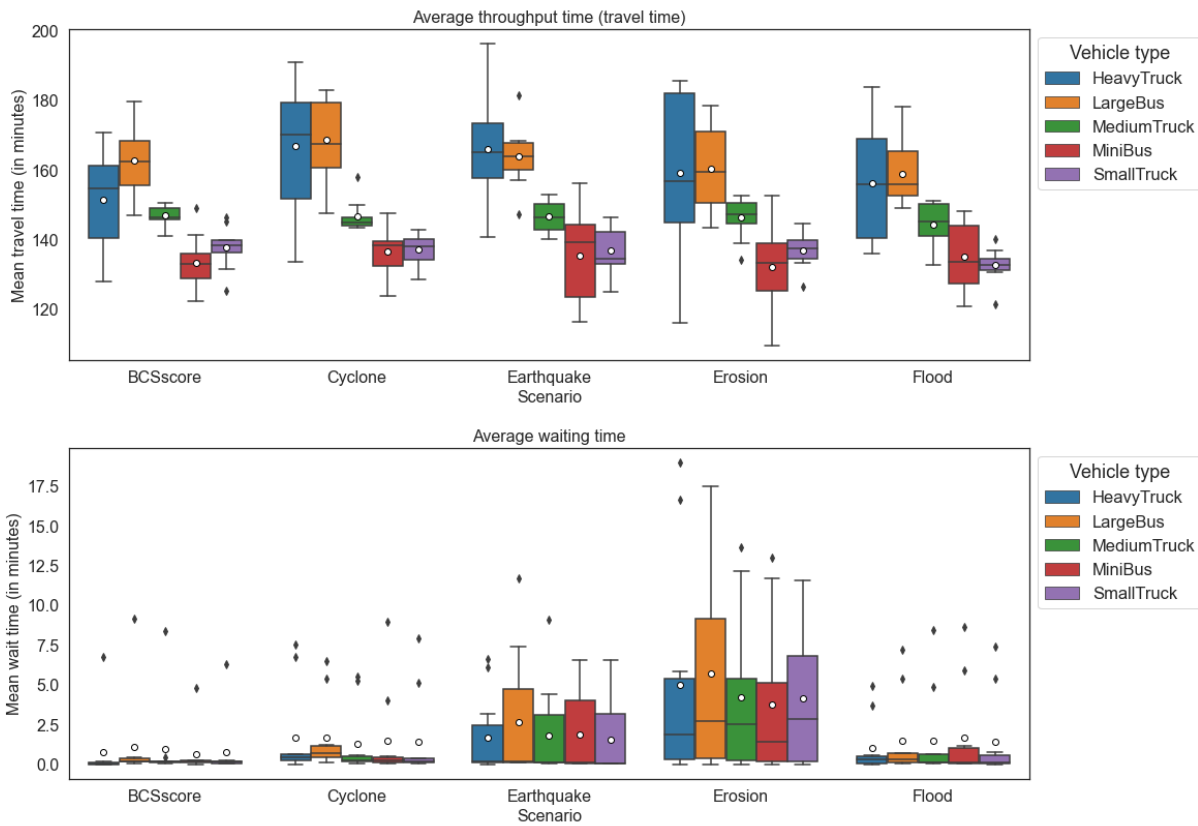

Figure 2 Average Travel time and Wait time results by scenario

Experimentations with break probability calculation

For the experiments results (Appendix A), it's possible to see that the average travel time remains relatively stable within the range of 60min to 100min for all experiments, with the same type of behaviour overall seen in Figure 2 for different vehicle types also being seen on the experiments. Regarding average wait time, it's possible to see that the highest outliers depicted in Figure 2 (around 20min) do not appear on the experiment scenarios, where the highest outliers are around 6min of waiting time. Appendix A presents all the boxplots for travel time and wait time for each experiment.

Most critical and vulnerable bridges

The results section ends with the analysis of the most critical and vulnerable bridges, following simulation results. To come up with the most critical bridges, we computed the number of trucks that went through each bridge (bridge's throughput), multiplied by the weight of goods (WG) information of each vehicle type (as depicted in Table 1). This result on the total weight of goods that moved through each bridge, which we used as an estimative of the criticality of the bridge. For the vulnerability, we used the Aggregated score for vulnerability (composition of the vulnerability to Earthquakes, Erosion, Floods and Cyclone), in which each bridge had its aggregated score normalized according to the highest score. The following figures depict the relationship between criticality and vulnerability of bridges, the top 10 most critical bridges and the top 10 most vulnerable bridges.

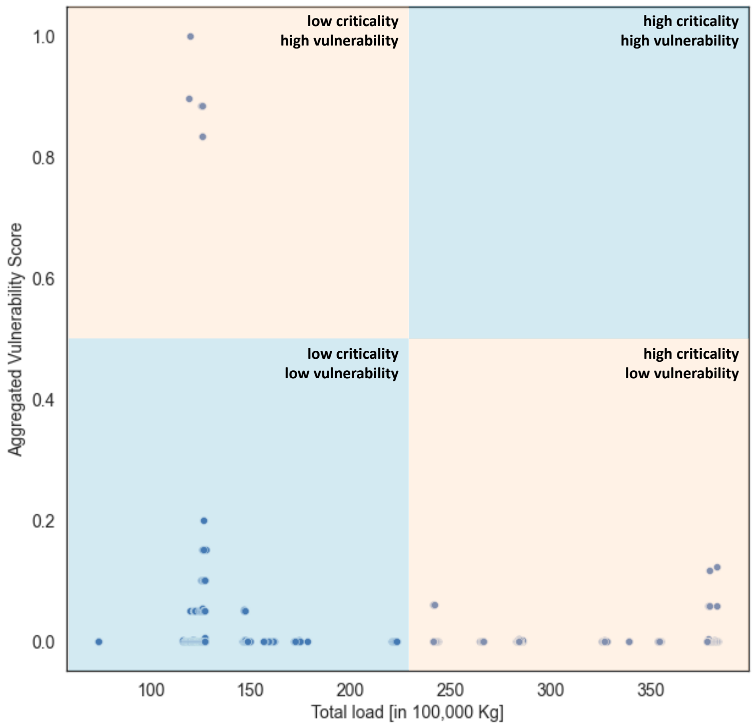

Figure 3 Criticality versus Vulnerability matrix. The majority of the bridges are either in the low-low or high-low quadrants of criticality x vulnerability.

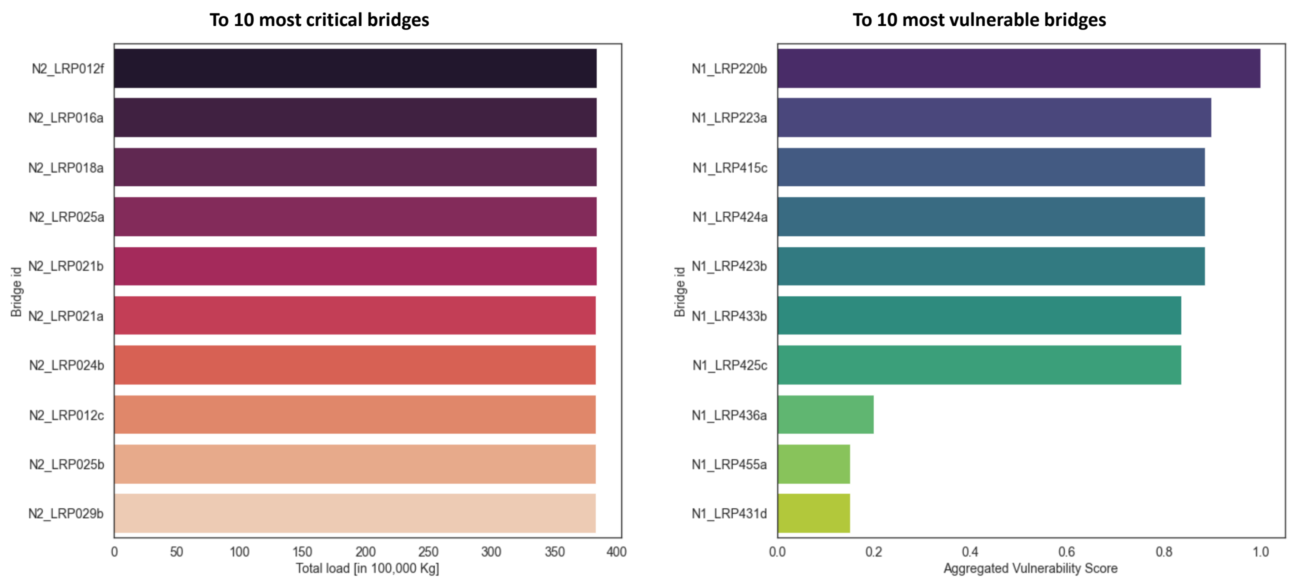

Figure 4 Top 10 most critical and top 10 most vulnerable bridges

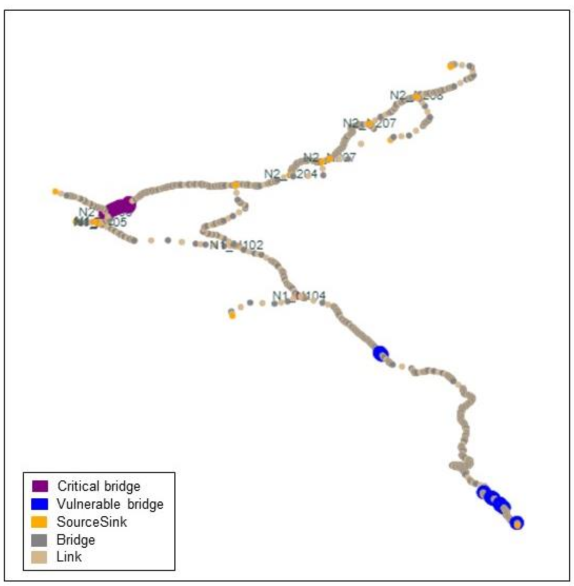

Figure 5 Visualization of the model developed. In blue the 10 most vulnerable bridges, in purple the 10 most critical bridges.

5. Reflection

- With the normalization we did on BCS scores, we assumed that the bridge with the greatest BCS will break down for sure. Nonetheless, this assumption is not unjustified considering that the bridges of condition D are described to have major structural damage by the Government of Bangladesh (Ministry of Communications Roads and Highways Department, 2005).
- With our additions to the model, we tried to have a finer representation of reality. But given our time constraints we still relied on the structural assumptions in the given model code (e.g., broken

bridges stay broken throughout each simulation; Vehicles' velocity is constant throughout the whole step): to have an even closer representation of the full traffic dynamics, we would have needed to make many changes that would impact the overall structure of the model. For example, to include traffic dynamics, key to assess the importance of links and bridges, we would need to have a closer representation of the location of where cars are on the various Links and based on the roads and vehicles size, we would need to understand the traffic conditions; also, traffics can cause incidents that should be modelled as well.

6. Limitations

- We didn't consider all the possible kinds of Vehicles (like motorcycles or rickshaws): if done, we would have a finer description of reality.
- Our additions to the model aren't perfect: we included some simplistic assumptions that could be removed to have an even finer description of the model. For example, vehicles change velocity according to the overall conditions of the link whereas in reality they change it based on how the closest vehicles behaves; Vehicles can't change more than once their velocity per link; Vehicles change their velocity always in the same way (increase by 20%, decrease by 50%); the Vehicles' speed in adjacent links is not correlated; bridges are assumed to have one lane when their broken.
- Our analysis on vulnerability of bridges relies heavily on BCS. However, there were some bridges for which condition classification was conflicting with BCS. In addition, we do not know to whether BCSs are up to date. Nonetheless, this was the only available data source that we had.
- Our calculation of the delay time distribution was based on the work of Zhu et al. (2010). We acknowledge that the I-35W Mississippi bridge might have different traffic flow dynamics or the incident that was discussed in the paper might be unique.
- Due to time constraint, we were not able to have a finer description of the *Bangladesh.get_route* function that determines what route the Vehicles will get: they can either go straight, to a random location or to the closest destination possible according to probabilities defined by us without correlation to reality. With more time we would have looked into the most probable routes for the Vehicles and change the method accordingly: for example, if we see that the vehicles tend to stay longer on N1 and N2 then we would have guaranteed that the probabilities of going straight a Vehicle at the SourceSink of these roads would be higher than the other options; if the Vehicles come from the side roads, then they would have higher chances of randomly choosing N1's or N2's SourceSinks as their destinations. We believe that using the probabilities describe in sections 2.4 and 3.3.1 can partially make up for it since we are describing with finer detail the real traffic conditions.

7. Ideas for further improvement

To conclude the following ideas could be suggested for further improvement:

- Road segments might have speed limits in real life. As we didn't have the data available per road segment, we couldn't implement this.
- We excluded the bridges for which we didn't have BCS score available. We could use an approximator logic for this case. For instance, we could fill this value by the average the BCS score of bridges with the same condition.

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Appendix A – Boxplots of experiment scenarios

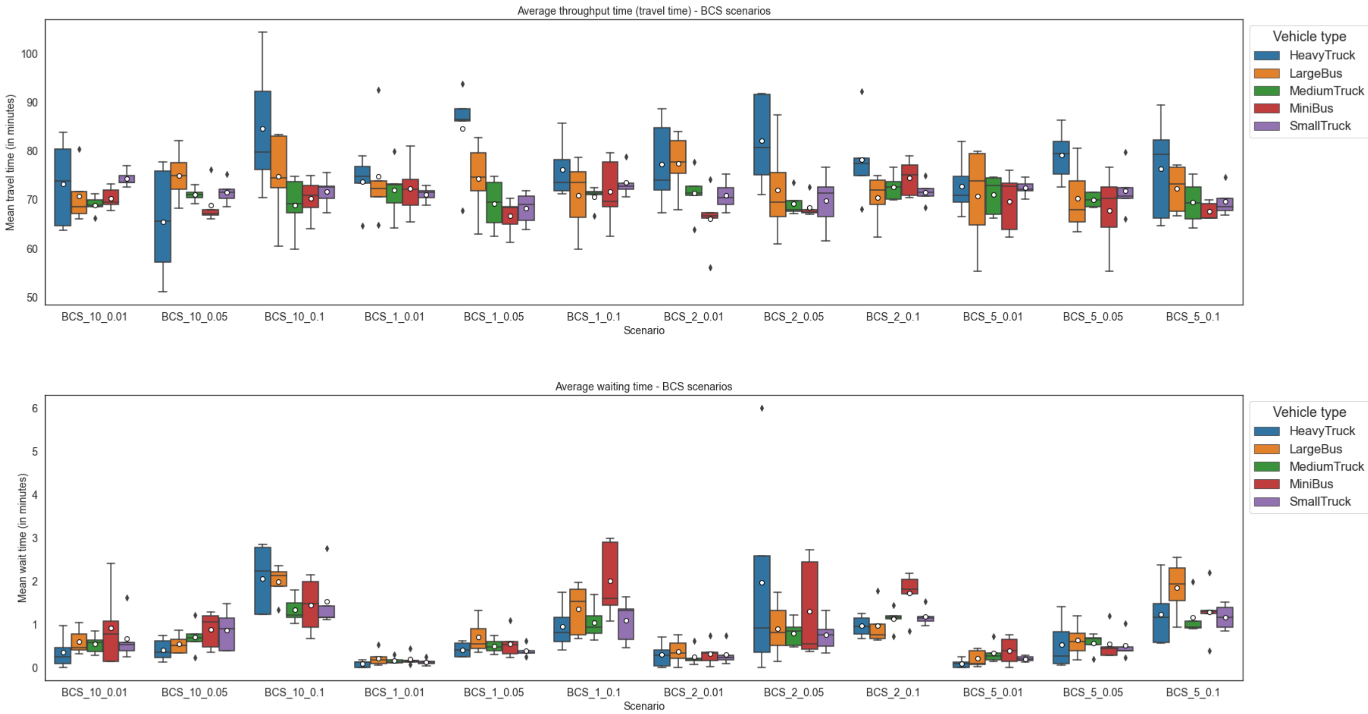

Figure 6 Average Travel time and Wait time results by scenario (BCS experiments)

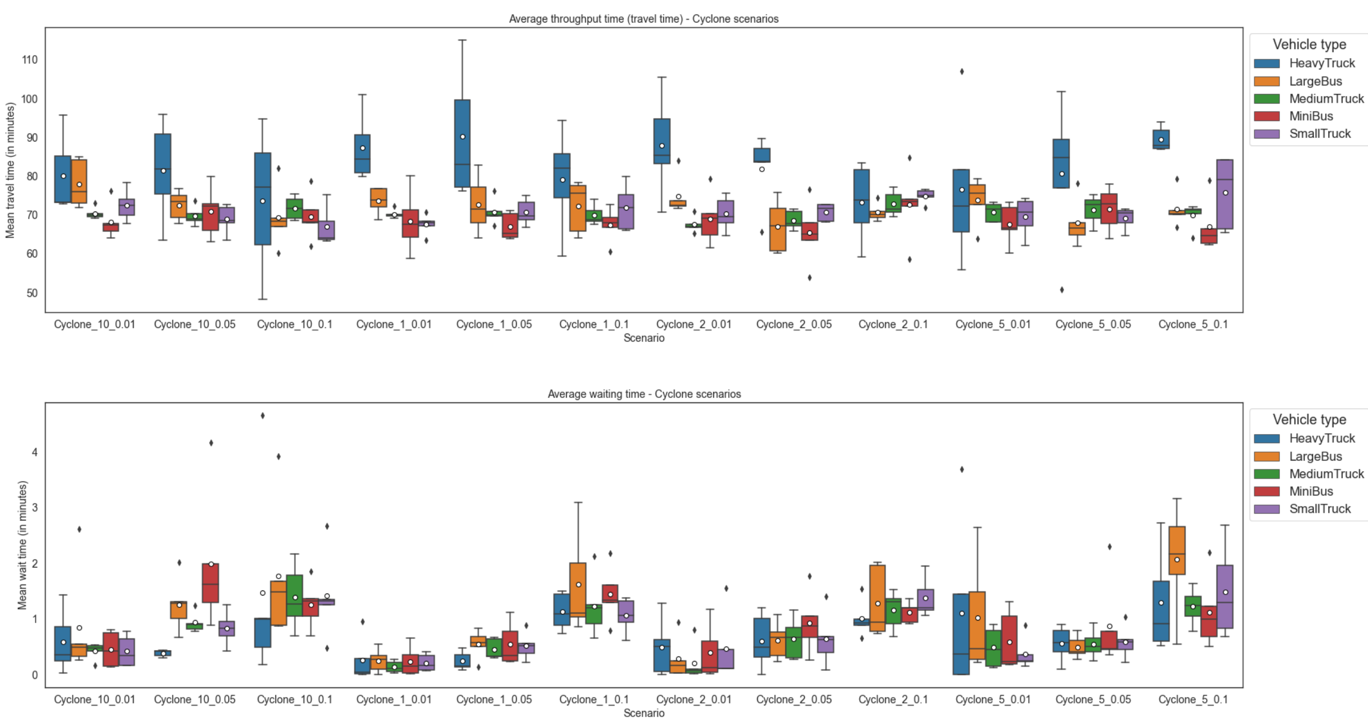

Figure 7 Average Travel time and Wait time results by scenario (Cyclone experiments)

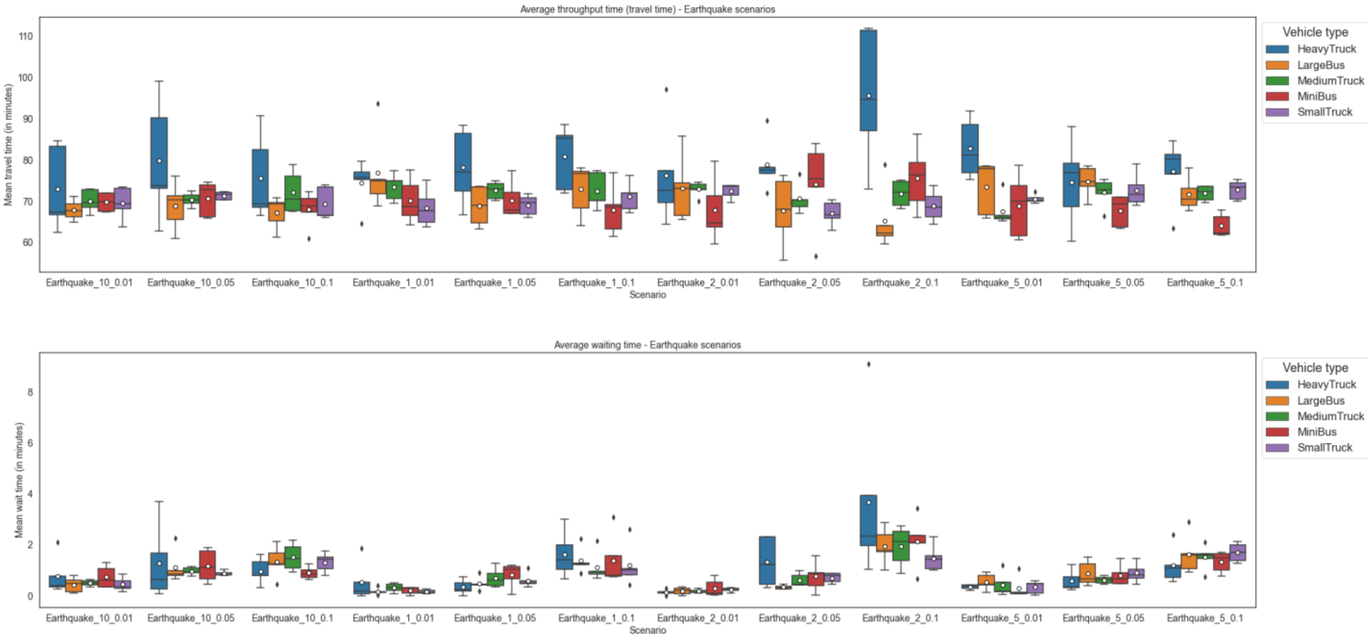

Figure 8 Average Travel time and Wait time results by scenario (Earthquake experiments)

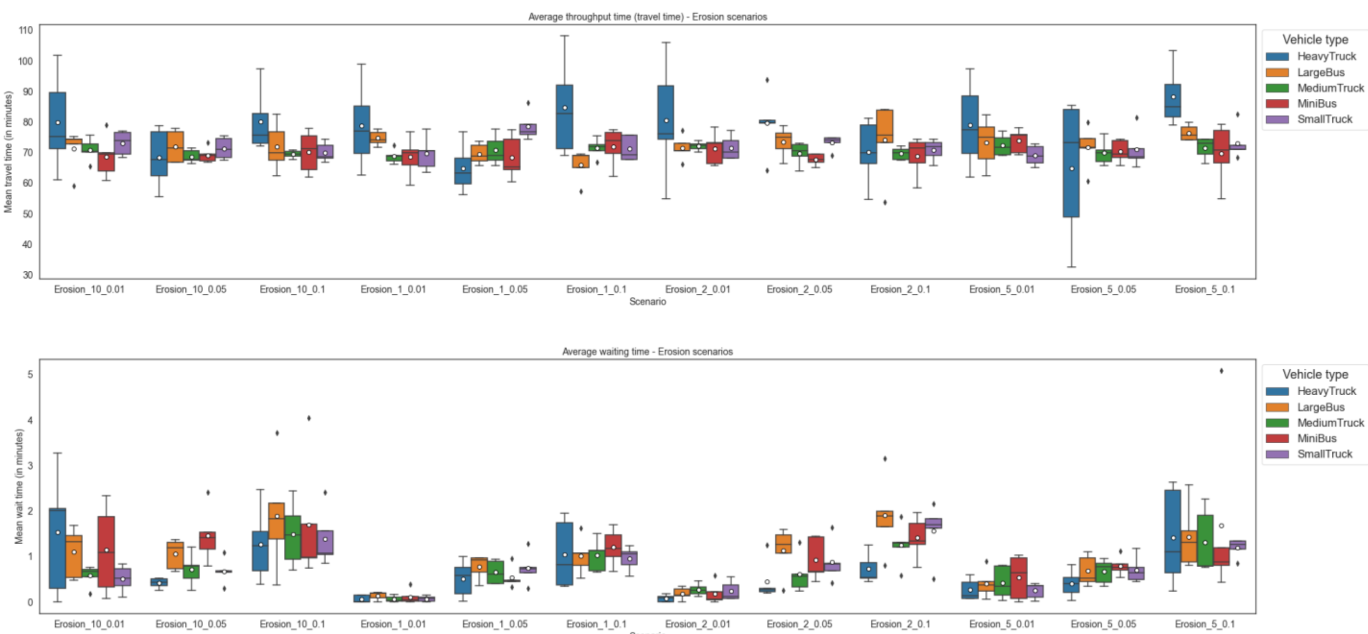

Figure 9 Average Travel time and Wait time results by scenario (Erosion experiments)

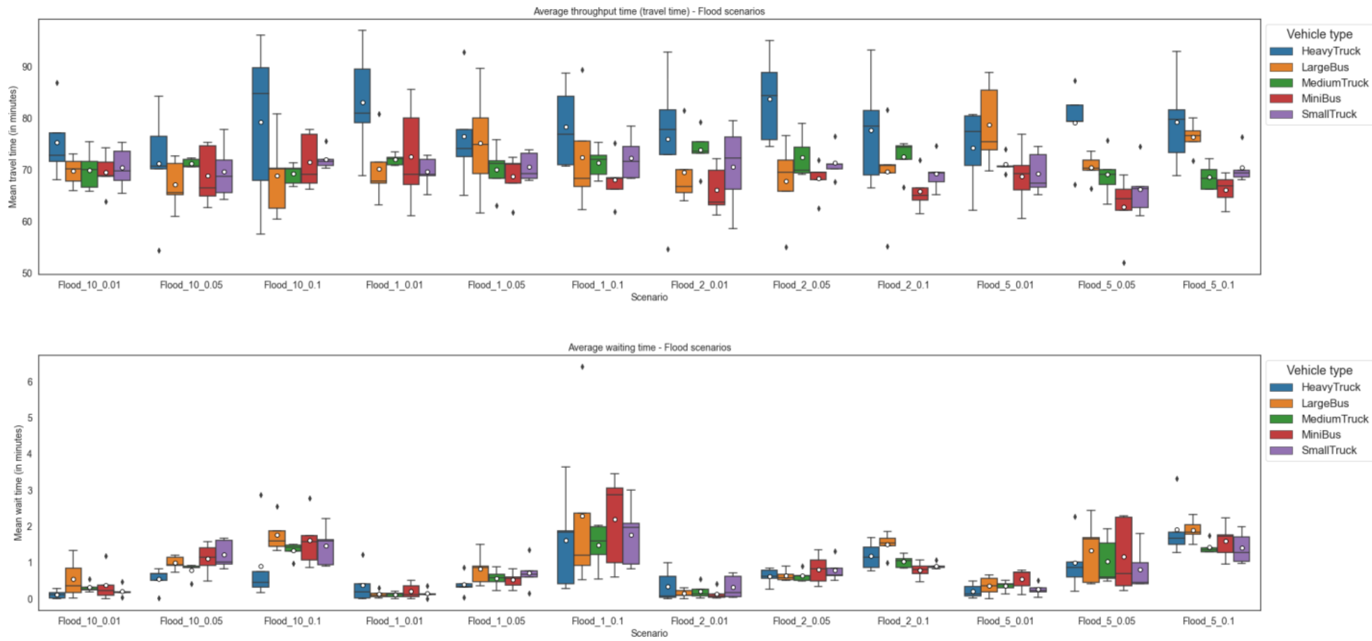

Figure 10 Average Travel time and Wait time results by scenario (Flood experiments)