Bridge Health-Informed Route Planning: Challenges and Promises

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ABSTRACT

Ensuring bridge safety is crucial for transportation in many countries, including the US. In fact, the ASCE gave an overall cumulative grade of C– for US infrastructure, in large part due to deteriorating bridges. Unsafe bridges within transportation routes pose significant challenges to stakeholders including traffic safety concerns, environmental hazards, and economic implications. The collapse of Minneapolis I-35W bridge highlights these issues. Our research encourages stakeholders to make informed decisions by taking into account bridge risk factors and the sensitivity of transported materials (e.g., hazardous materials, heavy equipment). This approach enables strategies like load balancing, rerouting enforcement, and prioritizing maintenance tasks to be applied effectively. We generated a bridge-health enriched geographic information system (GIS) dataset that integrates bridge information from the National Bridge Inventory (NBI) with GIS data from OpenStreetMap. We analyzed example origin-destination (O-D) pairs in Nebraska to demonstrate how different routes in Nebraska exhibit, besides differences in travel distance, varying statistics on bridge health scores. We also introduce a simulation platform for route planning and visualization currently in active development. We finally discuss the challenges we faced and opportunities ahead in combining these distinct datasets for sustainable route planning and infrastructure maintenance.

1. INTRODUCTION

Infrastructure development has been an integral part of human progress throughout history. From ancient civilizations to modern-day transportation systems, infrastructure has played a vital role in shaping society and driving economic growth [1]. Multiple reports have highlighted the strong correlation between infrastructure development and the economic development of countries [2, 3, 4]. Transportation infrastructures in particular, bridges specifically, are vital components in facilitating the movement of goods and people across different locations. However, the safety and sustainability of bridge infrastructures face multiple challenges such as deterioration and eventual collapse due to factors like aging infrastructure, lack of maintenance, and design flaws [5, 6, 7, 8]. These challenges have significant consequences including traffic accidents, environmental hazards, and economic implications. For instance, the collapse of the I-35W Bridge in Minneapolis in 2007 claimed the lives of 13 people, injuring more than hundred, and caused widespread damage to vehicles and the surrounding area [6]. Another recent example is the collapse of Fern Hollow Bridge, a 52-year-old bridge in Pittsburgh that had a poor condition rating [6]. These incidents highlight the need for developing innovative solutions to address the challenges posed by bridge health concerns. However, for a large country like the US with over 600,000 bridges spread across the country including in rural areas with a median age of approximately 44 years, keeping all of them in optimal condition is challenging [9]. The ASCE further reports that 7.5% of the nation's bridges are considered structurally deficient [9].

One way to tackle these challenges is by integrating bridge health information into route planning systems. By utilizing bridge health condition data and rerouting enforcement strategies, we can reduce the likelihood of bridge collapse incidents, facilitate informed maintenance, and ensure safer and more efficient transportation systems. Unfortunately, most popular route planning systems including Google Maps do not offer bridge health condition information in route planning or in suggesting alternative routes. We propose that incorporating such vital bridge health information in route planning is crucial in various settings. These include maintaining a sustainable road infrastructure, transportation of goods and services that require high attention including transportation of hazardous materials, or the movement of heavy and military equipment, or in disaster scenarios with a requirement for offline accessibility. In light of this, we leveraged a GIS data and a separate bridge health condition information from two distinct sources to generate a bridge health condition enriched GIS dataset that can be used in bridge health-informed route planning. We look at the state of Nebraska as a case study and used OpenStreetMap as our source of GIS information. The National Bridge Inventory (NBI) [10], an open data from a database maintained by the Federal Highway Administration (FHWA) with a rich information about bridges in the US was used as our source of bridge health information. The NBI dataset includes health condition ratings of different bridge components such as super-structure, sub-structure, and bridge deck, among others [10]. Using this data, we demonstrate how different routes exhibit varying statistics on bridge health scores and distances. Our results show that shortest route is not necessarily safest route and vice versa.

The remainder of this paper is organized as follows: in the next section, we discuss related work about bridge health, transportation networks, and bridge collapse of investigation. In Section 3, we discuss our approach of enriching the GIS data with bridge health condition information from NBI and the challenges in merging these distinct datasets. In Section 4 we demonstrate the usability of the generated dataset by taking sample Origin-Destination (O-D) pairs and generating alternative routes using the Dijkstra algorithm by iteratively taking out bridges from previous best routes.

The case-studies presented in this paper include O-D pairs that represent routes between two cities and a remote town in Nebraska: Omaha, Lincoln, and Scottsbluff, NE. We will show that routes between cities and to a remote town involve bridges with a poor deck condition rating of 4.

In Section 5 we discuss implications of our results and their potential applications while also stating limitations of our work. In Section 6 we highlight a visualization platform being developed that enables simulation of route planning in presence of various scenarios including bridge health condition, convoy capacity, and presence of adversaries. Finally, Section 7 concludes the paper.

2. RELATED WORK

The study of bridge health and its impact on transportation networks has been a focus of extensive research over the years [5, 6]. One such paper is a recent work by Crawford [6], which provides a comprehensive overview of bridge deterioration and failures. This work highlights the importance of understanding the causes that contribute to bridge collapse and the need for ongoing maintenance and monitoring to prevent such incidents and bridge failures in general. The study also emphasizes the economic and social consequences of bridge collapses, including disruption to transportation networks, loss of life, and damage to property. Another related study by Morgese et al. [7], conducted a post-collapse analysis of the Ponte Morandi bridge in Genoa, Italy which showed that the bridge did not receive proper maintenance despite being in service for over 50 years. These studies highlight the importance of understanding conditions of bridges and their impact on transportation networks.

Various studies have investigated impact of bridges on transportation networks [11, 12, 13, 14]. In [11] Researchers framed transportation networks as lifeline systems and studied network level consequences of bridge closures with a framework and resilience index they proposed. Their results showed that closure scenarios on 10 bridges incurred significant regional resilience losses. Zhu et al. [12] studied the travel impact of the I-35 bridge on the society assessing its impact both during the collapse and reopening of the bridge. Other works have shown that machine learning algorithms can be used to understand and predict the likelihood of a bridge needing maintenance based on factors such as age, type, and usage [15, 16, 17]. In a loosely related work to this paper, situation aware military convoy routing algorithms for military applications were also proposed [18]. The algorithms proposed considered 10 input parameters including route width and length, threat, hostility, and infrastructure type [18]. Simulation results on a grid with UAV threats and up to 18 edges show how to avoid threats using multiple parameter configurations. This body of literature shows the importance of detailed route information in planning and maintenance activities and the impact of bridge health condition on overall routing.

3. ENRICHING OSM WITH NBI DATA

Our aim in this paper is to show the importance of incorporating bridge health information in route planning. With this in mind, we first need to find a large, openly available, offline accessible, and detailed GIS dataset that can ideally provide detailed bridge information including its name, health condition, and coordinates providing a comprehensive coverage.

3.1 Openstreetmap Gis Data

OpenStreetMap [19] is the largest open geographic information dataset that can satisfy most of our requirements. Various research works and applications have leveraged this large geographic database for a range of problem domains [20, 21, 22]. Despite its limitations, such as presence of incomplete or inaccurate data [23], the OpenStreetMap project has seen exponential growth since its inception, providing a free and global map coverage that can serve as alternative to its commercial counterparts like Google Maps.

However, bridge information is one of the least covered pieces of information on OpenStreetMap (OSM). Although most bridges are labeled correctly, these bridges may miss fields such as type of bridge, construction material, year built etc. These fields are superfluous to the average OSM user, but are vital when performing bridge-aware routing. Besides, more authoritative information such as health condition rating of bridge components is not available. Despite the shortcomings, the ease of access and comprehensive GIS coverage make OSM the most suitable data source for GIS research and offline applications.

When working with OSM data, there are several different file formats available. Two formats in particular, OSM XML and PBF (Protocol buffer Binary Format), are most common. The OSM

XML format can be considered a “raw data” format, listing all entries in a human-readable XML format. OSM in this format is generally larger in size compared to other OSM formats and is slower to work with due to the nature of its XML structure. To increase performance when reading and writing OSM data, we use the PBF format. The PBF format is much faster and more compact than XML format but it is not human readable [24]. Therefore, we opt to use the OSM XML format for correctness checking and data analysis, and the PBF format for data parsing and editing when possible, with tools.

OSM data, regardless of the file format, comprises of a collection of objects: Nodes, Ways, and Relations. In OSM, Nodes are fundamental data items in OSM. A Node has latitude and longitude coordinates and an ID, describing a single point on a map. Ways are a collection of Nodes, that can describe objects such as roads, buildings, highways, and importantly, bridges. Relations can contain Ways and Nodes and are used to define geographical relations between OSM objects. All OSM objects can have tags with a key-value pair used to define metadata for the object such as street name, highway number, bridge information, etc. In OSM, bridges can be identified as a Way object with a bridge tag, and key-value pair "bridge"="yes". Name tags are applicable to most OSM objects and are stored similarly, e.g. "name"="Highway 72".

3.2 National Bridge Inventory Data

The National Bridge Inventory (NBI) is a database created and managed by the Federal Highway Administration that contains a detailed record of bridges and bridge repairs in the United States. Though the dataset is publicly available, only the Federal Highway Administration can update it, and most bridges are only updated biannually or longer.

The NBI database is vast, containing data on nearly all bridges in the United States over 20 feet long used for traffic [25]. It contains over 600 thousand entries, having over 100 fields. Each entry describes a single real-world bridge including year constructed, health ratings, material types, etc. Since bridges will be matched between the datasets by location and name, the most crucial matching fields are latitude and longitude for location and carried-by for street name. It is important to note that in NBI, a bridge is represented by a single point coordinate only. This record could be at any point on or near the real-world bridge. NBI entries are provided by the bridge’s owning agency and several standards put in place by the Federal Highway Administration must be followed when collecting bridge data. Unfortunately, these standards enforce little when collecting a bridge’s location; It is fully up to the bridge’s owning agency to best decide how the bridge’s latitude and longitude should be measured [26, 27]. A standard from 1995 indicates a required amount of precision, but does not describe which point of the bridge to use for data collection [25]. This means it is difficult to be certain how this data is collected and consequently, how to correct any inconsistencies in latitude and longitude. A bridge’s positional data is collected at the time of the bridge’s initial inspection, and is rarely updated afterward [26].

Though NBI data is frequently used for bridge health analysis, inaccuracies occur frequently in the data due to the lack of standards during the data collection process. This is especially apparent when inspecting NBI positional data against the OSM dataset. In some cases, the positional data of NBI was found to be invalid in 28% of entries [28]. Inaccuracies in NBI have even led to the collapsing of some bridges that may not have been properly inspected [29]. Our implementation must find a novel method of avoiding these inaccuracies. We do so by relying on the strength and accuracy of OSM to find placement errors in NBI and determine where they lay.

(a) Reverse geocoding **(b) Query matching** **(c) Q-H matching** **(d) Query matching (FP)**

Figure 1. Example scenario and approaches, where a bridge coordinate from NBI (blue) is matched against bridges from OSM using different approaches: (a) Reverse geocoding mismatch with parallel ways in OSM, (b) Query matching using Overpass with false positives (FP), (c) Q-H matching method yielding multiple matches, filtering out FP, (d) Multiple FPs for a single NBI entry when query matching alone is used.

3.3 Challenges Combining the two Datasets

As described above, the two datasets (i.e. NBI and OSM) are of varying quality and format. Hence, it is important to understand the nuances of each. As the datasets are disparate with distinct coding techniques the process of adding a highly accurate NBI data to the OSM should not be considered “merging” or “combining” in a traditional sense, rather these words imply all data across each dataset is put together to create a new dataset via a certain key. This also generally means that the two datasets are similar in format and content. In our case, not all data can be used, nor are the two datasets similar. The process here should be considered “data enrichment,” where the OSM data is selectively enriched with bridge information from a vastly different data source, NBI. Via this data enrichment process, detailed bridge data is added to corresponding OSM bridges in the form of tags. Matching is confirmed if and only if an OSM way has a bridge tag and is a roadway. NBI data is added as tags. For example the tag “nbi:sub-cnd=5” can be added to denote a score of 5 for a bridge’s NBI sub-structure rating. Given that Openstreetmap is a community effort, uniform coverage of areas is inherently a challenge, especially for areas like Nebraska where 72% of its communities have populations below 800 people [30].

3.4 Q-H Approach to Reduce False Positives

As shown in Figure 1, multiple way objects are in proximity to an NBI point coordinate (colored blue). A successful query using different methods results in different possible matches. Using the popular reverse-geocoding approach with Nominatim API results in a match of just one way object closest to the point coordinate ignoring the other valid way point, as shown in figure 1.a. This approach resulted in only 4,697 matched roadway bridges out of 15336 NBI and 10384 OSM bridges in Nebraska, i.e. less than a third (30.6%) of NBI entries. The second approach used is query matching using overpass API, this approach returns more than one match giving the possibility of to consider multiple matches even when the closest way object is invalid. The disadvantage of this approach is the fact that it returns false positives (fig 1.d).

To address the above challenges a heuristics-based query matching referred to as query-heuristics (Q-H) was introduced. With this approach a scoring mechanism is used to pick OSM objects that maximize confidence and reduce false positives. This approach enabled us to match 56.9% of entries from NBI onto the entries in OSM, excluding culverts. The heuristic part involves average of two scoring mechanisms: distance scoring, and name scoring. With distance (geodesic distance) scoring we measure the proximity of the candidate objects with the following formulation.

$$dist\_score = \frac{t}{d+t}$$

Where d is the closest geodesic distance between an NBI point and any point within the bridge polygon, as opposed to centroid of the polygon, and t is a threshold value (we found t=20 a suitable threshold). We considered matches with a distance score above 0.5 as candidates prioritizing bridges found within 20 meters of the NBI entry.

Name scoring uses Sørensen-Dice string matching [31] to measure similarity between a bridge's name in OSM vs a name in NBI (e.g. Sa = "654 AV-707 / 708 R" in OSM vs in Sb= "654 Avenue" in NBI) as follows.

$$sd\_score = \frac{2|A \cap B|}{|A| + |B|}$$

Where A and B are the sets of characters found in strings Sa and Sb respectively, and |A| and |B| are the cardinalities of sets A and B respectively. Table 1 summarizes the results.

4. ROUTE GENERATION AND ANALYSIS USING THE ENRICHED DATASET

We now demonstrate the use of NBI-enriched GIS data in route generation. For this purpose we first selected three sample points in Nebraska representing the cities Omaha (OM) and Lincoln (LN), and a remote location called Scottsbluff (SF). After identifying the coordinates of these locations we generated a graph with the GIS data, which gives us vertices (V) and edges (E) as is common in traditional graph theory G(V,E). We then proceed to generate ten iterations of finding the shortest route between pairs OM-LN and OM-SF, identifying and extracting tagged NBI bridges, taking out all these identified bridges, and recomputing the graph G. The iterative methodology is diagrammatically described in Figure 2.

Figure 2 illustrates the Iterative process of route planning, in which the best route is determined at each stage. Figure 2.a displays 5 different routes that can be taken as alternatives. Applying Dijkstra shortest path algorithm between s and t results in s->A0->t as best route, after taking out bridge A0, i.e. removing p2 from a way point (P1, P2), and recomputing the graph shows the previous route is no longer viable and results in the route shown on figure 2.b, iterating over this process until the last bridge on E0 as shown on Figure 2.f. In our experiment on the actual GIS data, we performed ten iterations for the two O-D pairs. In the following we will discuss results in applying our method on the actual GIS data from Nebraska.

Table 1: Comparison of the matching techniques on 11,122 non-culvert NBI entries and 10,384 OSM bridges. The table shows the improvement in Q-H matching over RG matching (4,483 added vs 6,329), while reducing false positives introduced in Query matching (7,905 vs 6,509 received).

Iteration Match Rates				
	NBI		OSM	
Iteration	Entries	Added	Entries	Received
RG Matching	11,122	4,483	10,384	4,483
Query Matching	11,122	6,329	10,384	7,905
QH Matching	11,122	6,329	10,384	6,509

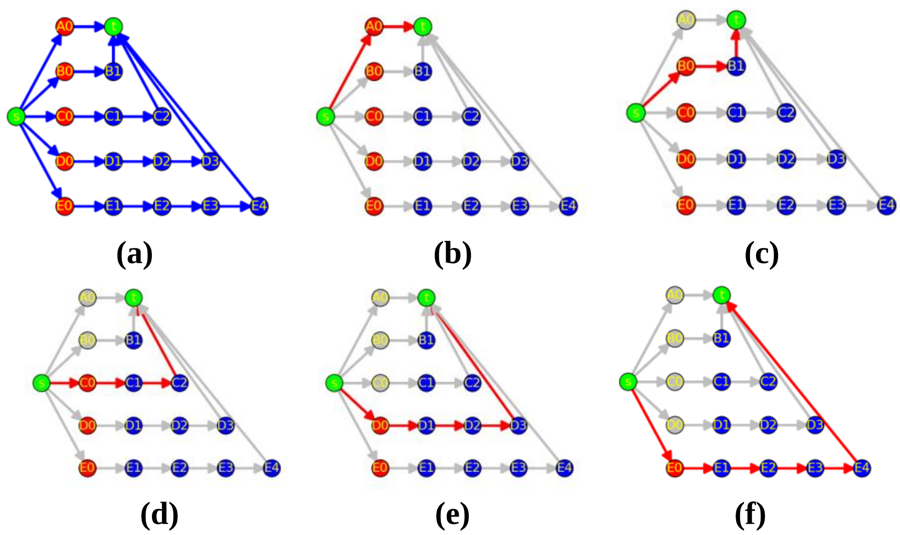
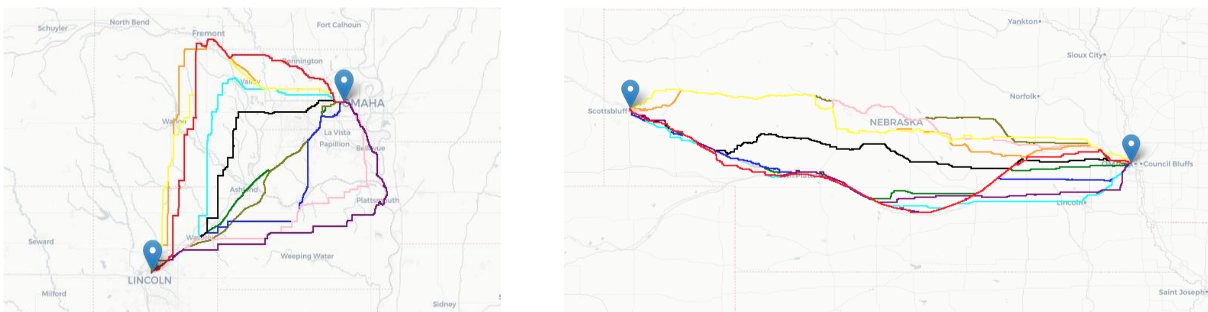


Figure 2. Route planning with iterative graph regeneration. The green circles labeled s and t represent source and destination nodes (S-D), the red circles represent bridges, blue arrows represent possible routes forming edges, while red arrows show selected best routes at each iteration using Dijkstra algorithm. Gray circles represent taken-out bridges after each iteration.

4.2 Results with Sample O-D Pairs

The generated ten alternative routes between OM-LN and OM-SF pairs are shown on Figure 3. As shown on Figure 3 the shortest routes tend to drastically change as the bridges are removed from the graph. We performed preliminary analysis of these routes consisting bridges to study the length of the routes, number of identified bridges, and their health condition rating taking the deck condition rating (nbi:deck-rating) from our enriched GIS dataset. Note that this method can be extended to other components of the bridge such as super-structure and sub-structure as they are already integrated. From the results in Figure 3, we can visually inspect that bridges alter routes. Further analysis on Figure 4.a shows that the length of routes between OM-LN pairs (nearby and two most populous cities in the state) also drastically increases as we iteratively remove bridges.

An interesting observation here is that the condition rating denoted by the minimum deck condition rating of bridges along the routes does not follow a predictable pattern where the best route and the tenth route both involve a deck condition rating of 5 (FAIR CONDITION - all primary structural elements are sound but may have minor section loss, cracking, spalling or scour), while intermediary routes have a condition rating as low as 4 (POOR CONDITION - advanced section loss, deterioration, spalling or scour). Given the distance between OM-SF pairs is significantly longer than the previous pairs there seem to be more alternatives with fairly more equivalent distance. An interesting observation in the second pair is that the best route involves a bridge with a POOR condition rating. In both cases we can see that bridges are critical components in creating connections while best routes did not show better condition rating. Figure 5 shows a more detailed result on the distribution of deck-condition rating of routes with corresponding colors on Figure 3.



(a) Set of iterative shortest routes between Omaha and Lincoln.

(b) Set of iterative shortest routes between Omaha and Scottsbluff.

Figure 3. Results of iterative graph generation and route planning taking out bridges identified in each shortest route. The figure shows the shortest path in the first iteration (green) tends to change gradually, finally taking the routes colored red on the tenth iteration.

5. DISCUSSION

The results from the generated ten alternative routes with between the OM-LN and OM-SF pairs mainly demonstrate the importance of bridge health information. A notable observation from Figure 3 is that the computed shortest routes undergo significant changes as bridges are removed from the graph. Our results further acknowledged the fact that bridges play important roles in connecting communities. We have also demonstrated the ease of identifying the health condition rating of bridges in route computations, this demonstrates its potential for bridge health-informed route planning applications. As results on Figure 4 suggest best routes in terms of distance are not safest nor did receive special treatment to improve their condition rating. This is further demonstrated in Figure 5 where we can observe condition rating as low as 4 in some of the best routes, while also observing a top condition rating among the last routes. While the results are preliminary, we can see the potential of enriching GIS dataset with highly up to date and highly accurate bridge health information for route planning. This will have a profound impact in special transportation scenarios such as transportation of hazardous materials [8, 32] or designing routes for military convoys. For example, a route planner with the objective of avoiding bridges based on their condition rating can easily incorporate condition rating of the desired component(s) as a weight (cost) function in route computation [33]. This information is also valuable for policy makers. Taking the Omaha-Lincoln pair as an example, a load balancing recommendation system can be implemented to alternate traffic between route 0 and route 1, which have fairly closer travel distances. A maintenance prioritization system can also be developed to identify the risk level of a route based on assessment of involved bridges.

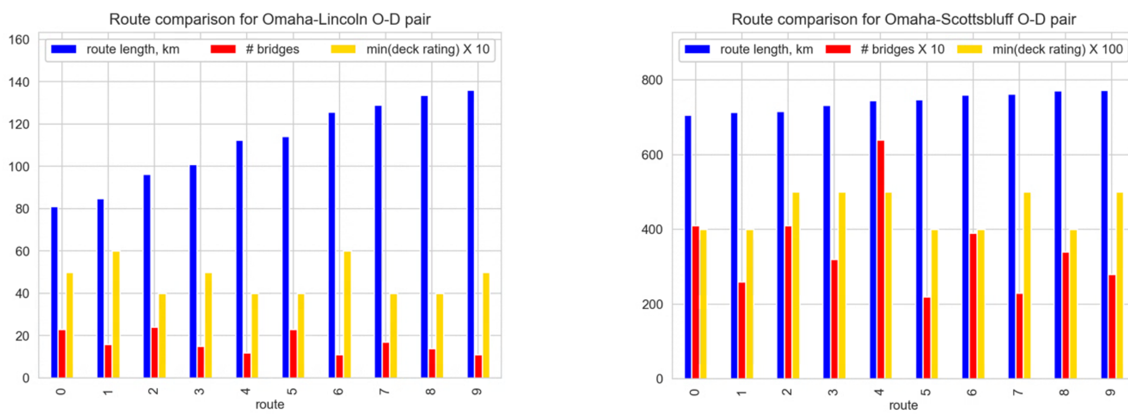


Figure 4. Comparison of identified routes on each iteration. The blue color shows the length of route in Kilometers, while the red and yellow colors represent number of bridges and minimum deck condition rating of bridges along the routes. The red and yellow bars are scaled for ease of visualization as shown in the legend boxes.

However, our proposed approach is not without limitations. First, the bridge health data from NBI is a less frequently updated inspection database. This brings timeliness limitations. Second, matching the two disparate datasets might not be reliable because of multiple reasons. These include unavailability of datasets on remote locations, and the problems due to inconsistencies we already discussed. The first limitation of our approach can be addressed by using a more reliable and frequently updated bridge health dataset such as continuous measurement-based approaches with sensors, though this solution might bring scalability issues. Future work can address second limitation of our approach with different approaches, such as crowdsourcing to properly tag remote bridges in OSM and using more finetuned matching approaches that take advantage of computer vision, NLP, and related machine learning techniques.

6. VISUALIZATION AND SIMULATION PLATFORM

With the objective of advancing bridge-health informed routing methods, we have been developing a route planning and visualization system that can work offline (in lieu of Google maps). This standalone system takes convoy information with desired source and destination locations as inputs and visually shows the selected routes including the health condition of each bridge along the computed routes. Future iterations will include presence of adversarial conditions [18] which will affect computation of route costs. The UI of current status of this project developed with react framework is shown on Figure 6.

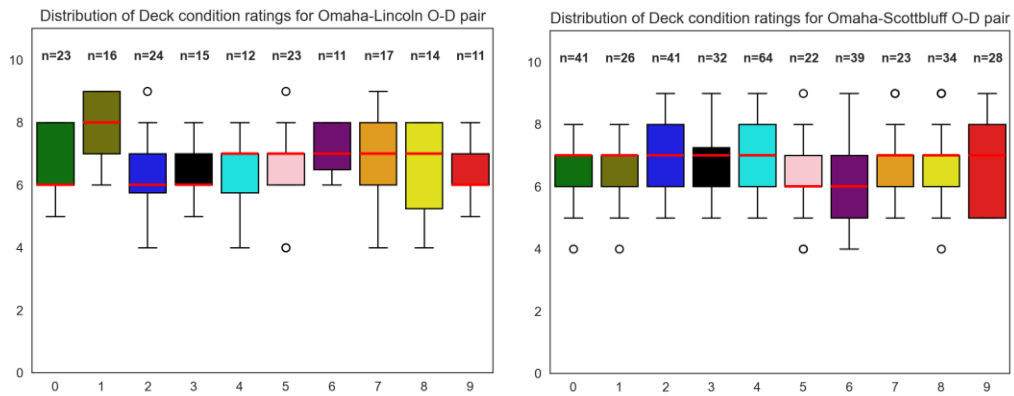


Figure 5. Distribution of condition rating of the decks of bridges along the selected best routes in each iteration ranging from zero to nine. The figure on the left shows the distribution for Omaha-Lincoln pair, while distribution for Omaha-Scottsbluff is shown on the right. The number of bridges is denoted by n on top of each distribution. The colors correspond to the routes shown on figure 3.

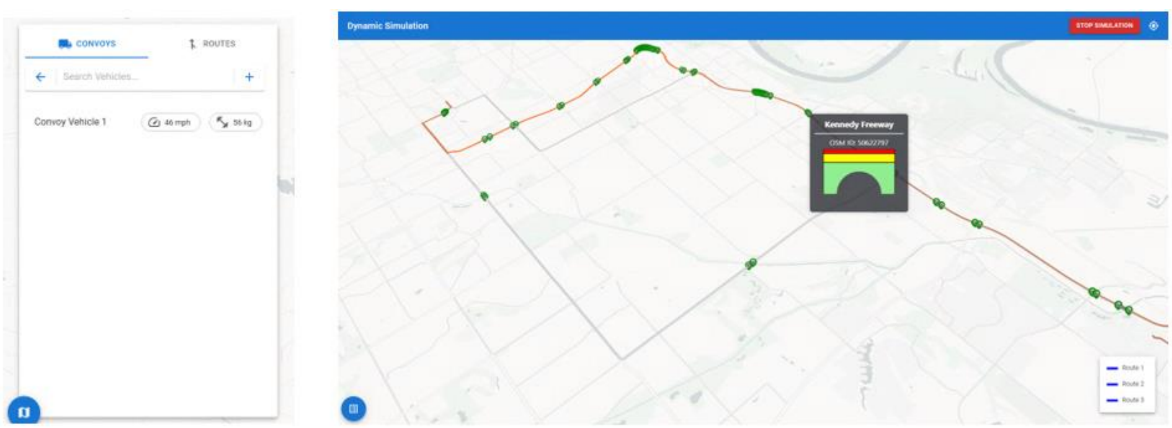


Figure 6. screenshots showing the simulation platform in development. The left figure shows the specification of a convoy for simulation, the right figure shows the alternative routes for an S-D pair of the convoy providing a detailed bridge information.

7. CONCLUSION

In this study we call for improving route planning and maintenance in transportation networks via enriching GIS data with bridge health information from external authoritative sources such as NBI. With real experiments we show that best routes computed with common shortest path algorithms do not necessarily mean safest routes. We showed promising opportunities of leveraging these distinct datasets to improve safety and logistics of transportation networks. We also showed limitations of our proposed approach which include the availability of datasets on remote locations, inconsistencies in data quality, and reliability of health information sources. We also indicated how future work can address these limitations with approaches such as using alternate bridge health datasets, crowdsourcing to properly tag remote bridges in OSM, and improving the matching approach with emerging AI techniques including computer vision. Our study contributes to the existing literature by providing a methodology for enriching specific elements of GIS graph with bridge health information for transportation networks. We hope this research lays the groundwork for a safer and more efficient route planning, offering potential applications in advanced traffic management systems and optimized infrastructure investment plans.

ACKNOWLEDGEMENT

This work is partially supported by contracts W912HZ21C0060 and W912HZ23C0005, US Army Engineering Research and Development Center (ERDC), and Award Number 1762034 from the National Science Foundation.

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