Multi-Scale Classification of Ontario Highway Infrastructure: A Network Theoretic Approach to Guide Bridge Rehabilitation Strategy

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"All my success is not but through Allah" (The Quran, Hud, 88)

Abstract

Highway bridges are among the most vulnerable and expensive components in transportation networks. In response, the Government of Ontario has allocated $26 billion in the next 10 years to address issues pertaining to aging bridge and deteriorating highway infrastructure in the province. Although several approaches have been developed to guide their rehabilitation, most bridge rehabilitation approaches are focused on the component-level (individual bridge) in a relative isolation of other bridges in the network. The current study utilizes a complex network theoretic approach to quantify the topological characteristics of the Ontario Bridge Network (OBN) and subsequently evaluate the OBN robustness and vulnerability characteristics. These measures are then integrated in the development of a Multi-Scale Bridge Classification (MSBC) approach—an innovative classification approach that links the OBN component-level data (i.e., Bridge Condition Index and year of construction, etc.) to the corresponding dynamic network-level measures. The novel approach calls for a paradigm shift in the strategy governing classifying and prioritizing bridge rehabilitation projects based on bridge criticality within the entire network, rather than only the individual bridge's structural conditions. The model was also used to identify the most critical bridges in the OBN under different disruptions to facilitate rapid implementation of the study results.

Keywords: Bridge Rehabilitation; Complex Network Theory; Network Topology; Robustness; Vulnerability Index.

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Notation

k = Degree centrality
P_k = Degree centrality distribution
N_k = Number of nodes with k degree
N = Total number of nodes
BC = Betweenness centrality
$\rho(j,k)$ = Number of shortest paths connecting nodes j and k
$\rho(j,i,k)$ = Number of shortest paths between nodes j and k that pass-through node i
NBC = Normalized betweenness centrality
C = Capacity
α = Tolerance parameter
CC = Closeness centrality
s = distance-sum
$d(i, j)$ = Shortest path distances
R = Robustness
N'= Number of nodes in the giant component
VI = Vulnerability index
$\langle k \rangle$ = Degree centrality average
$\langle k^2 \rangle$ = Degree centrality variance

List of Acronyms

ABC: Accelerated Bridge Construction
BC: Betweenness Centrality
BCI: Bridge Condition Index
BMS: Bridge Management System
CC: Closeness Centrality
EV: Extreme Vulnerability
GIS: Geographic Information System
HB: High Betweenness
HC: High Closeness
HV: High Vulnerability
LB: Low Betweenness
LC: Low Closeness
LHRS: Linear Highway Referencing System
LV: Low Vulnerability
MB: Moderate Betweenness
MC: Moderate Closeness
MSBC: Multi-Scale Bridge Classification
MTO: The Ministry of Transportation of Ontario
MV: Moderate Vulnerability
NBC: Normalized Betweenness Centrality
OAGO: The Office of the Auditor General of Ontario
OBI: Ontario Bridge Inventory
OBN: Ontario Bridge Network
ORM: Ontario Road Map
R: Robustness
VHB: Very High Betweenness
VHC: Very High Closeness
VI: Vulnerability Index

1. Introduction

The transportation network is one of the most vital physical infrastructure in modern societies. In fact, some might argue that it is an essential human need, as it facilitates the delivery of goods (e.g. food) and people. For example, the Canadian highway network accounts for almost 72% of the trade corridors and facilitates the transportation of most of the Canadian population (Transport Canada, 2016). Therefore, any disruption in the transportation network might result in a cascading economic, social, and health negative impacts on both the surrounding communities and the national/regional level.

In the Canadian province of Ontario, most of the highway network was built post World War II, while more than 70% of the province highway bridges were constructed between 1950 and 1980 (OAGO, 2009). As such, many of which have already reached their design life (MMM Group, 2007). More specifically, 20% of the bridges and culverts are considered to be in a poor condition and require major rehabilitation in the next five years (OAGO, 2016). The urgent need for a comprehensive rehabilitation strategy is demonstrated by the fatigue failure arch hanger rode of Latchford arch bridge in Ontario in 2003 and the abutment shear failure of the De la Concorde overpass in Quebec (Government of Quebec, 2007). The fact that even a single bridge failure can cause a disproportionate economic impact is best exemplified by the sudden bearings failure of the Nipigon River Bridge in Ontario (Torrie et al. 2016). The closure of this fairly new bridge resulted in blocking an estimated daily traffic of 1,300 trucks carrying $100 million worth of merchandise (The Globe and Mail, 2016) and left them with only the option of detouring though the United States as the Trans-Canada Highway was essentially completely severed at a critical bottleneck.

The aging transportation infrastructure and the accelerated deterioration due to winter maintenance activities, coupled with the unexpected issues of new bridges, resulted in the Ontario government developing and improving a provincial highway infrastructure rehabilitation strategy, by which the Ministry of Transportation-Ontario (**MTO**) aims, through rehabilitation, of having 85% of the province's highway bridges in *good* structural condition in the near future (Ministry of Infrastructure, 2017). An approximate $84 billion 10-year investment plan geared towards the transportation sector was approved in 2013, with a third of the investment ($26 Billion) allocated specifically to highway and bridge infrastructure (Ministry of Finance, 2017).

Currently, the MTO utilizes a Bridge Management System (**BMS**), originally developed in 2000 (Thompson et al. 2003) that requires a biennial inspection of all bridges, by a licensed engineer, to assess the bridge's structural integrity and serviceability condition (Ministry of Transportation, 2015). A key result from the inspection's is the Bridge Condition Index (**BCI**), which quantifies the bridge structural condition (Ministry of Transportation, 2015). Other factors, along with the BCI, guide the decision maker in prioritizing and scheduling bridge rehabilitations and/or replacements (Ministry of Transportation, 2006). Despite all considered factors, (i.e., construction; detour length around the bridge; traffic on bridge; pedestrian requirement; bridge width; hydrology; geometrics, and economic importance on the bridge) the MTO assessment framework, falls short in considering the cascading effect associated with the closure of any highway bridge.

This is because the current assessment strategy does not extrapolate the impact of a component-level (single bridge) vulnerability on the network-level performance.

The literature of bridge condition assessment and bridge rehabilitant planning can be broadly classified under two research themes. The *first* theme focuses on assessing the traffic impact on bridge rehabilitation. A comprehensive review of this research stream is provided in Zhu et al. (2012). More recently, Alam et al. (2016) developed a dynamic traffic assessment model to investigate the impact of bridge closures on its neighbouring bridges, and subsequently proposed a traffic diversion plan to optimize the traffic flow on the network. Furthermore, an optimum bridge rehabilitation plan was proposed by Guo et al. (2017) that consider the post-disaster traffic demand using the network topology and the characteristics of traffic flow. This research theme facilitated the understanding of traffic assignment dynamics associated with the bridge rehabilitation plans. Traffic assignment is mainly geared towards quantifying the level of congestion associated with a specific bridge closure, and, as such, is frequently implemented to study the micro-level traffic impact. Such established approach, is not the focus of the current study, which aims at quantifying the network-level (macro-level) cascading effects resulting from the dynamic redistribution of load demands associated with different bridge closure scenarios.

Table 1: **Recent Studies on Bridge Networks**

Study	Context	Sample Size	Main Modeling Approach	Objective
Dong et al, 2014	California, USA	10 bridges 4 nodes 5 links	Optimization	Pre-earthquake rehabilitation plans
Liu et al. 2006	Colorado, USA	13 bridges 5 nodes 6 links	Optimization	Rehabilitant under uncertain measures

Study	Context	Sample Size	Main Modeling Approach	Objective
Zhang et al. 2017	Hypothetical network	37 bridges 30 nodes 37 links	Optimization	Post disaster bridge recovery plans
Guo et al. 2017	California, USA	75 bridges 20 nodes 33 links	Network-level assessment	Assessment of traffic demand after a seismic event
Rokneddin et al. 2013	South Carolina, USA	515 bridges 515 nodes*	Optimization	Ranking and identifying critical bridges for seismic retrofit
Chang et al. 2012	Tennessee, USA	12821 nodes 15758 links 616 bridges	Optimization,	Developing rehabilitation program to maximize the evacuation capacity under post disaster event
Kurtz et al. 2015	California, USA	1738 bridges*	Network-level assessment and Optimization	Reliability analysis under seismic events
Current Study	**Ontario, Canada**	**1835 nodes 1995 links 1486 bridges**	**Complex network theory**	**Multi-scale assessment at the network-level**

* Number of nodes and/or links are not identified in the corresponding study

The *second* research theme focuses on investigating the bridge condition, to inform bridge rehabilitation decision makers, which is further categorized as micro- and macro-levels. In the micro-level studies, bridges are investigated at the component-level using a variety of methodological approaches. Siddiquee et al. (2017) developed an inventory of the bridges in the Canadian province of British Columbia by assessing the bridge's current condition followed by a prediction of the bridge's future rehabilitation plans through statistical models. Chandrasekaran et al. (2015) developed a multi-objective genetic algorithm-based approach, to optimize the repair options of bridges piers jacketing under different natural disaster scenarios. Unlike the micro-level studies, the interdependence between the different bridges is considered at the macro-level. For example, Liu et al. (2006) presented an analytical method considering the existing and future bridge conditions using genetic algorithms. These algorithms were then used to develop an optimal rehabilitant schedule to the bridge concrete decks. Subsequently, Dong et al. (2014) proposed a probabilistic approach to schedule bridge retrofitting plans after an earthquake, utilizing a multi-criteria optimization method. In addition, some macro-level studies utilized network-level approach to present effective bridge rehabilitation plans. In this respect, Kurtz et al. (2015) applied a network-level assessment to improve the seismic resilience of deteriorated bridges. Moreover, Chang, et al. (2012) proposed a bridge rehabilitant plan to maximize post-disaster evacuation capacity by simulating earthquakes, optimizing seismic rehabilitation plans, and modeling the network evacuation flow. Table 1 provides a summary of previous literature on bridge networks using different modeling approaches and, if applicable, considering different risk types.

Unlike the existing network-level models that have been utilized in the literature, we contend that the application of complex network theoretic model offers an innovative classification approach to assess the correlation between component-level data and their corresponding dynamic measures. In this respect, Bush (2014) defines complex network theory as “*the study of network representation of physical, biological, and social phenomena leading to predictive models of these phenomena*” (pp.203).

The objective of this study is to develop, and further apply, a comprehensive Multi-Scale Bridge Classification (**MSBC**) approach that integrates complex network-level modelling with component-level bridge assessment indices. This subsequently enables the quantification of possible cascading effects and dynamic vulnerability indices under different rehabilitation scenarios. Such integration provides a new lens to quantify the robustness and vulnerability of network components, which provides the mean to identify the most critical components in the network under different disruptions. Following the introduction, Sections 2 and 3 details the data collection process and the mathematical formulation of complex network measures; Section 4 presents the results of the developed model with emphasis on the Ontario Bridge Network topological characteristics, robustness, and vulnerability; in Section 5 the MSBC approach is proposed and discussed; and Section 6 concludes the study and highlights avenues for future research.

2. Methodology

2.1. Data Collection and Processing

Two primary datasets were combined to simulate the Ontario Bridge Network (**OBN**). The first dataset is the 2013 Ontario Bridge Inventory (**OBI**) that includes all the bridges owned and maintained by the MTO. This inventory contains details of 2,802 bridges and provides information on their location, year of construction, deck width, and Bridge Condition Index (**BCI**). The BCI score ranges between 0 to 100, where 100 places a bridge in an excellent condition bin. Other classification bins include good (70-100), fair (60-70), and poor condition (<60) (Ministry of Transportation, 2015). To fit the scope of study, the OBI data were filtered as follows: 1) all underpass (local roads) and subway bridges (rail lines) that traverse major roads were not considered during the analysis as the rehabilitation impacts of these bridges on the highway network are minimal (e.g. over weekend night closures); and 2) all multi-bridge interchanges and multi-bridges that carry highway traffic in different directions were represented as one bridge. To simulate this in the analysis, average values of the bridges' BCI and age were considered, while their widths were lumped.

The second dataset is the Ontario Road Map (**ORM**), obtained from MTO's Linear Highway Referencing System (**LHRS**), which contains the entire road network of Ontario. Therefore, this dataset was also filtered to exclude local and municipal roads, while the MTO owned roads and highways were kept. Finally, three major highways that are not owned by MTO (i.e. Gardiner Expressway in Toronto, Lincoln M. Alexander Parkway in Hamilton, and the 407 Highway that runs from east of Toronto to Hamilton) and their comprising bridges were added to the two primary datasets. The resultant MTO roads and highways network contains 19,550 nodes and 19,713 links associated with unique identifiers of location (longitudes and latitudes). It should be noted that these nodes and links represent only the geographical identifiers of the ORM, which are used to profile the ORM data on a geographical interface.

The processed OBI and ORM datasets were compiled in a single dataset representing the OBN. In this respect, a two-step sequential fitting process was carried out using Qgis and Python. First, Qgis is utilized to merge both datasets into one Geographic Information System (**GIS**) file, which resulted in an un-fitted overlay of the two datasets. The second step focused on developing a Python code to relocate all highway nodes to their closest bridge nodes in a single dataset. At this point, the dataset contained high level of details resulting in an unnecessary computational complexity. To address this issue, the additional highway nodes between the bridge nodes were eliminated, as they do not contribute to the proceeding analysis. Figure 1 presents a detailed illustration of the OBN fitting stages.

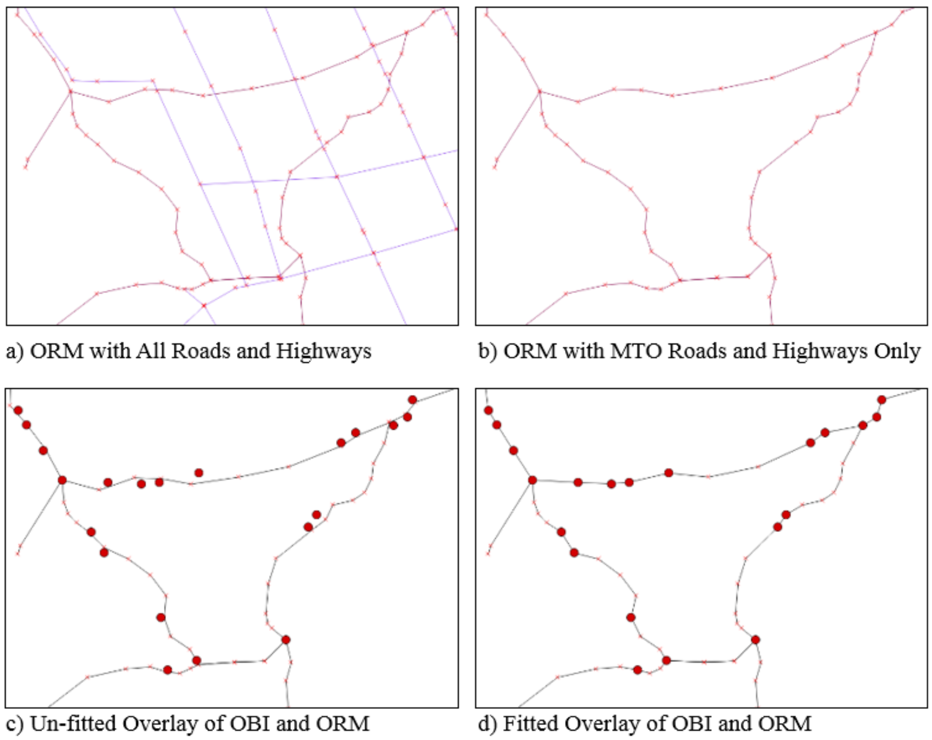

Figure 1: OBN Dataset Fitting Process

The resultant total number of nodes and links used in the current study for the OBN is 1,835 and 1,995, respectively. These nodes represent bridges and highway intersections (in case no bridge exists in the intersection), while highway segments that connect these bridges and intersections are represented by links. Figure 2 shows a flow chart representation of the OBN generation process.

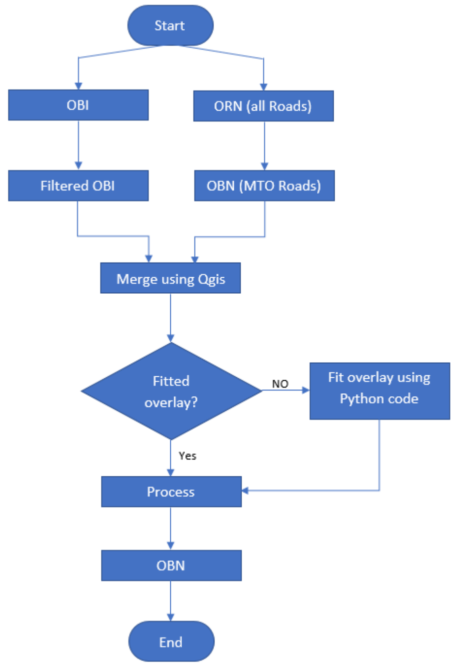

Figure 2: Illustration of OBN Dataset Development

The generated OBN nodes and links are shown in Figure 3. As illustrated in Table 1, this dataset is one of the most comprehensive bridge datasets in relevant literature. Although the work of Chang et al (2012) contained 12,821 nodes and 15,758 links, they have only analyzed a total of 616 bridges.

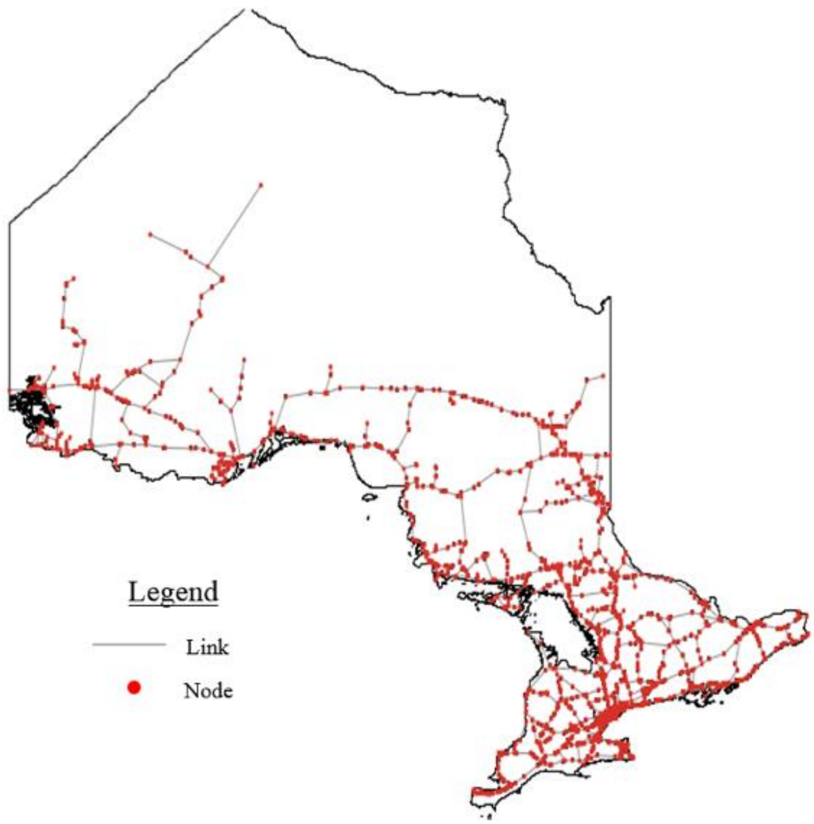

Figure 3: The OBN Dataset

Lastly, the OBN is considered to be an unweighted and undirected network, as traffic loads are assumed to run equally in both directions. In addition, bridge rehabilitation is considered to be performed under a full bridge closure condition, simulated as a single node removal strategy in the current study.

3. Methods and Measures

Different complex network measures are utilized to study the OBN. The OBN topological characteristics are identified by evaluating the network centrality measures. This is followed by different node removal strategies to investigate the robustness of the OBN under different scenarios. The node removal strategies continue to evaluate the vulnerability of each bridge in the network. To accommodate the computational processes of such a comprehensive dataset, a Python code is developed comprising all the mathematical formulae. The analytical processes are detailed in the following subsections.

3.1. Network Topology measures

The degree centrality (*k*) represents the number of direct links connected to this node, while the degree centrality distribution (P_k) presents the percentage of nodes with a degree *k* (Newman, 2010) that can be evaluated as (Barabási, 2016):

$$P_k = \frac{N_k}{N} \quad \text{(Eq. 1)}$$

Where N_k is the number of nodes with *k* degree and *N* is the total number of nodes. While, the betweenness centrality (*BC*) measures how nodes exist in the shortest paths between other nodes in the network (Newman, 2010). The *BC* can be expressed as:

$$BC_i = \sum_j \sum_k \frac{\rho(j,i,k)}{\rho(j,k)}, \quad i \neq j \neq k \quad \text{(Eq. 2)}$$

Where $\rho(j,k)$ is the number of shortest paths connecting nodes j and k, and $\rho(j,i,k)$ is the number of shortest paths between nodes *j* and *k* that pass-through node i. The shortest path between any pair of nodes in the network is defined as the path that comprises the least number of links between this pair (Barabási, 2016). As such, higher BC_i value of a node is an indication of a frequent occurrence of this node in the overall network paths (Li et al. 2017). The *BC* is often normalized to allow for a direct comparison between nodes as expressed in Equation (3).

$$NBC_i = \frac{BC_i}{\max(BC_i)} \quad \text{(Eq. 3)}$$

Noting that the load demand (variable) on each bridge (defined as the total number of shortest paths passing through the bridge) stems from the node *BC* value, the capacity *C* (defined as the largest load demand a node can accommodate before it becomes nonoperational) of each bridge is assumed to be a function of the corresponding load demand as expressed in Equation (4). This is following the approach proposed by Motter et al. (2002). Therefore, the model utilizes a design tolerance parameter of 20%, α, to sustain additional load demands due to any accidental disturbances within the network. The capacity *C* can be expressed as:

$$C_i = (1+\alpha)BC_i \tag{Eq. 4}$$

The closeness centrality (*CC*) measures the proximity of nodes to one another (Newman, 2010). The *CC* in the network is evaluated as:

$$CC_i = \frac{N-1}{s_i} \tag{Eq. 5}$$

Where, the distance-sum s_i is calculated from the shortest path distances $d(i, j)$ as:

$$s_i = \sum_j d(i, j) \tag{Eq. 6}$$

3.2. Disruption Analysis

As mentioned earlier, the analysis assumes that bridge rehabilitation is carried out under a full closure condition, which can be represented by a node removal strategy. A node removal strategy is performed by stressing (i.e. removing from the network) one node at a time. During this process, the overall load demand on the network is redistributed among all other nodes based on the shortest path (Motter et al. 2002). If the new load demand exceeds the capacity, the corresponding node becomes nonoperational. Hence, the extent of nonoperational network bridges caused by the cascading failure is quantified. In the context, *robustness* is defined as the ability of a network to maintain its basic operations even when some of its components (nodes and/or links) are disrupted, while *vulnerability* evaluates the cascading impacts on a network when a single node or link is disrupted. Both measures are critical to identify the negative consequences on the network performance under bridge rehabilitation scenarios.

3.2.1. Robustness

The present study quantifies the robustness (R) of the OBN under three node disruption strategies: 1) random removal of nodes, where sequential random node removal simulations are applied on the network to simulate a random failure; 2) sequential targeted removal of nodes with the highest k values; and 3) sequential targeted removal of nodes with the highest BC values.

Under each node removal strategy, the fraction size of the *giant component* is compared to the network size, which could be mathematically described as in Equation (7). Wang et al. (2017) defines the *giant component* as "*the size of the largest connected component of the remaining network is equal to a predetermined fraction of the size of the original network.*" (pp. 24).

$$R = \frac{N'}{N} \qquad \text{(Eq. 7)}$$

Where *N'* is the number of nodes in the giant component. In the targeted node removal simulations, and in the presence of multiple nodes exhibiting the same *k* or *BC* value, one node is removed randomly among them.

3.2.2. Vulnerability Index

The network vulnerability index (*VI*) is quantified by individual node removal (Deng et al. 2015). and assessing the subsequent cascading impacts (defined as the number of nonoperational nodes) due to that node removal. The *VI* can be expressed as:

$$VI = \frac{N - N'}{N} \qquad \text{(Eq. 8)}$$

4. Results

This section presents the results and facilitate a better understanding of the OBN topological characteristics. The OBN topological characteristics are first identified through a series of centrality measures. These measures include the degree, betweenness, and closeness centralities. Afterwards, the OBN robustness and dynamic vulnerability indices are quantified through several bridge rehabilitation scenarios as detailed in the methodology section.

4.1. Network Topology

The degree centrality (*k*) distribution of the OBN (Figure 4) shows that 93% of the bridges have a degree $k = 2$. This was expected as most of the bridges are along the highways with only few interchanges with *k*-value higher than 2. In the OBN, bridges linked to minimum (i.e. $k = 1$) and maximum (i.e. $k = 4$) number of highways represent only 1.1% and 1.5%, respectively, of the OBN. As such, it could be argued that the OBN falls under the *random* *network* classification, because both the average ($\langle k \rangle =$ 2.1) and variance ($\langle k^2 \rangle = 0.34$) values are finite (Barabási, 2016). This classification also indicates that the OBN is vulnerable to any type of bridge rehabilitant scenario. However, the degree centrality distribution of the OBN does not provide information about its robustness and the location of different vulnerable bridge. Figure 5 shows a scaled representation of the OBN map to identify the geographical distribution of the bridges and their corresponding *k* value.

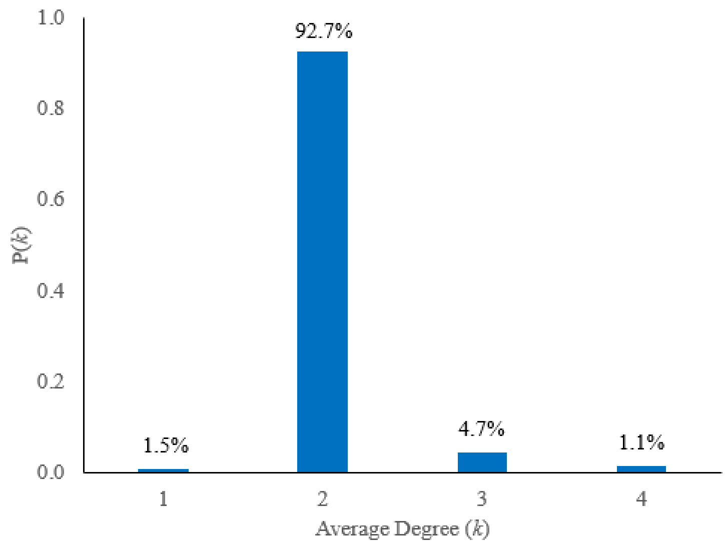

Figure 4: The Degree Centrality Distribution of the OBN

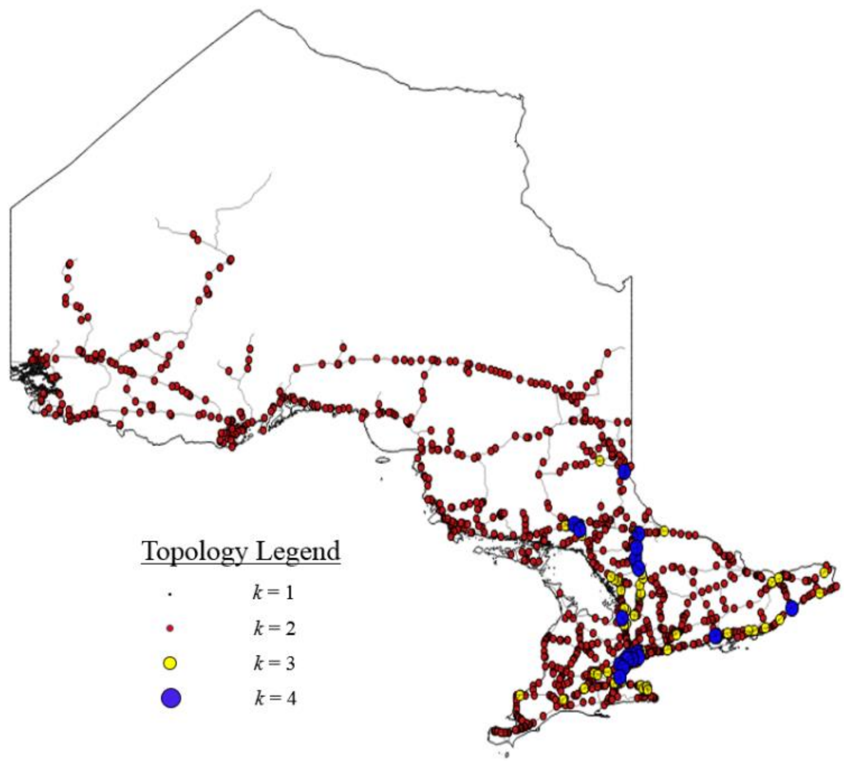

Figure 5: Scaled Representation of the OBN Degree Centrality

To quantify the *BC* distribution of the OBN, Figure 6 classifies the probability of occurrence in four *BC* categories ranging from low to very high. Figure 7 shows a scaled representation of the OBN map to identify the geographical locations of the bridges and their corresponding *BC* categories. As illustrated in Figures 6 and 7, bridges under the Low Betweenness (*LB*) category represent the majority (88.1%) of the OBN bridges. This indicates that most bridges exhibit similar load demands. On the other hand, there are only 4.2% and 1.2% of bridges under High Betweenness (*HB*) and Very High Betweenness (*VHB*) categories, respectively. Being under these categories indicates that the load demands on these bridges are relatively high. It is also observed from Figure 7 that these bridges are scattered throughout southern Ontario, but more apparent in the eastern part of the province.

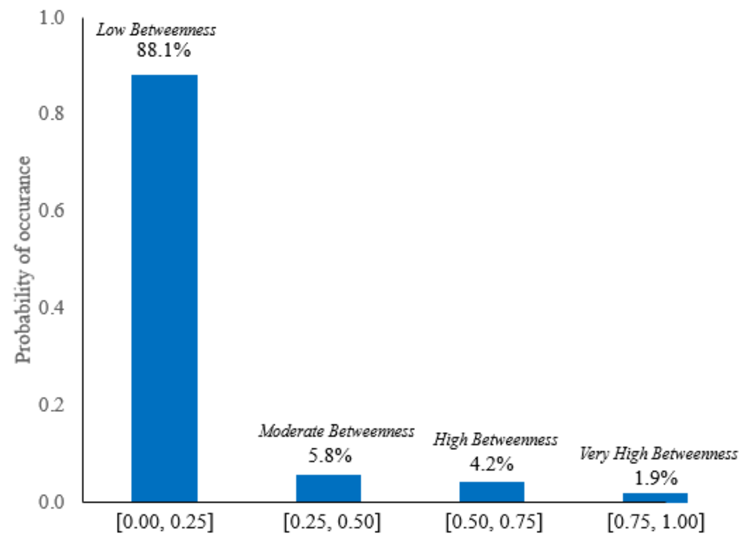

Figure 6: The Betweenness Centrality Distribution of the OBN

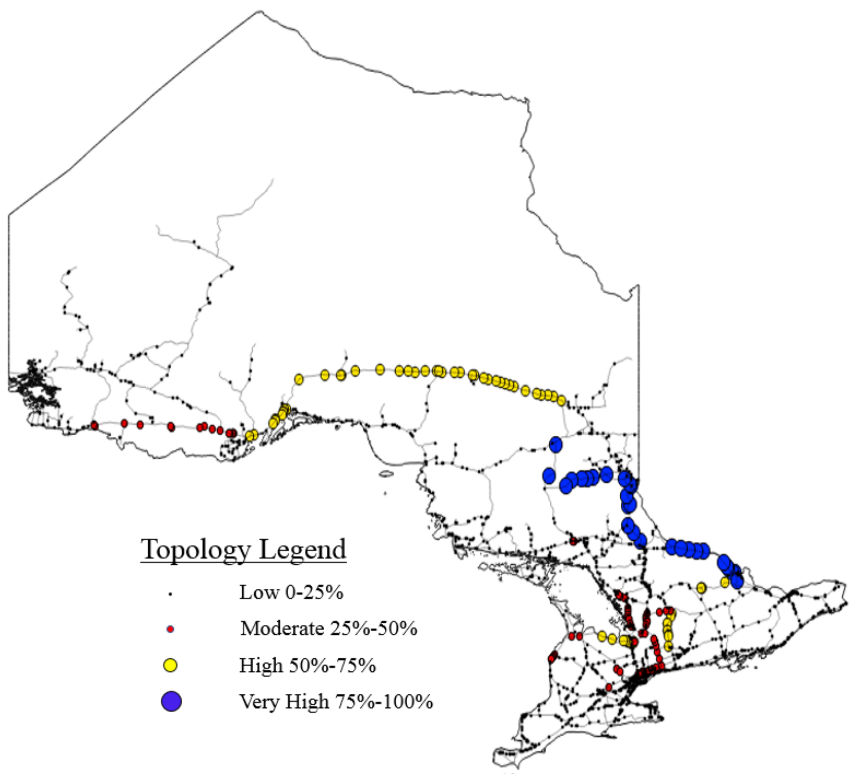

Figure 7: Scaled Representation of OBN Betweenness Centrality

Similar to Figure 6, the distribution in Figure 8 classifies the *CC* under four categories. The results highlight an equal distribution of bridges under Very High Closeness (*VHC*), High Closeness (*HC*) and Moderate Closeness (*MC*) with values of 28.9%, 29.5% and 28.9% respectively. Whereas, the Low Closeness (*LC*) represents 12.7% of the OBN Bridges. This indicates that the bridges are geographically well distributed in the network. The scaled map representation of the four *CC* categories in Figure 9 shows that bridges in the southcentral and southeastern part of Ontario have the highest *CC* values, while bridges in the North, where bridges are distant from one another, have the lowest *CC* values.

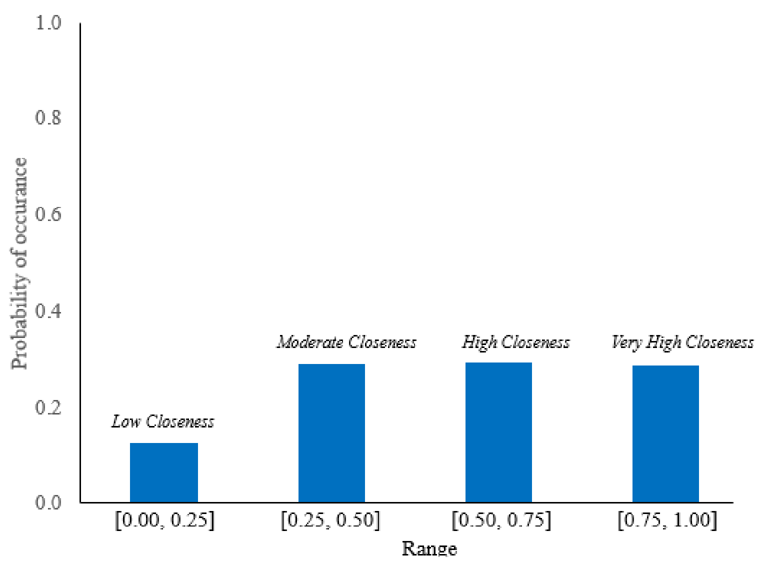

Figure 8: The Closeness Centrality Distribution of the OBN

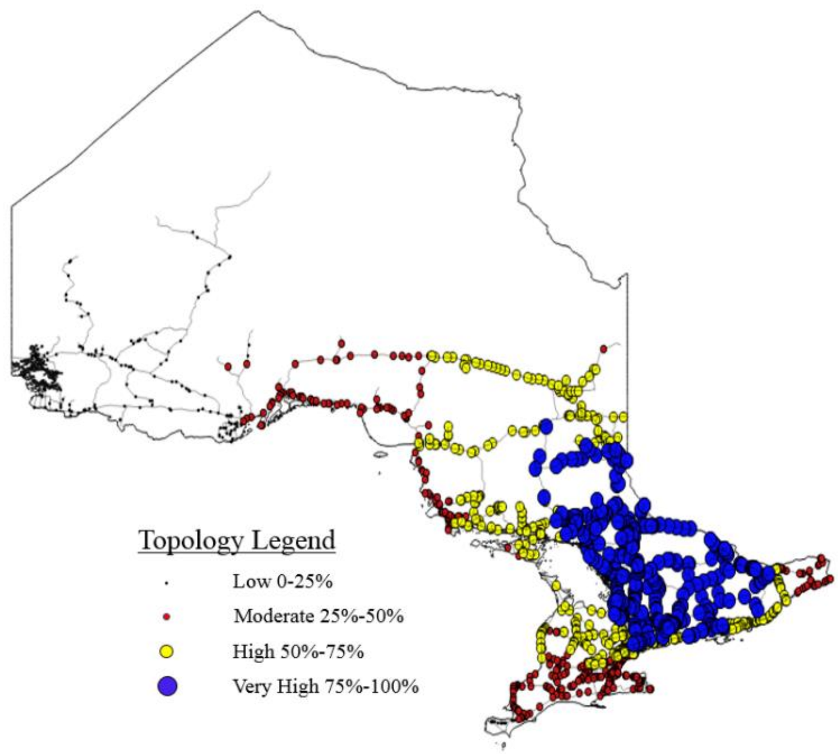

Figure 9: Scaled Representation of the OBN Closeness Centrality

4.2. Network Robustness

Figure 10 shows the robustness of the OBN under random selection of bridges for rehabilitation, and under *k*-based and *BC*-based attacks. It shows that the OBN exhibits similar behaviour to the *k*-based bridge rehabilitation. For example, only 6.6% and 7.3% of bridges need to be removed from the OBN to have robustness value of less than 10% under both random and *k*-based bridge rehabilitation, respectively. This is mainly attributed to the fact that, with most bridges having a $k = 2$, the probability of randomly stressing such bridges is relatively high. Conversely, the *BC*-based bridge rehabilitation shows distinct robustness behaviour. The robustness value drops to less than 10% when only 1% of the bridges are removed. This indicates that failures of bridges with high *BC* values have a more severe impact on the OBN robustness than those with high *k* values.

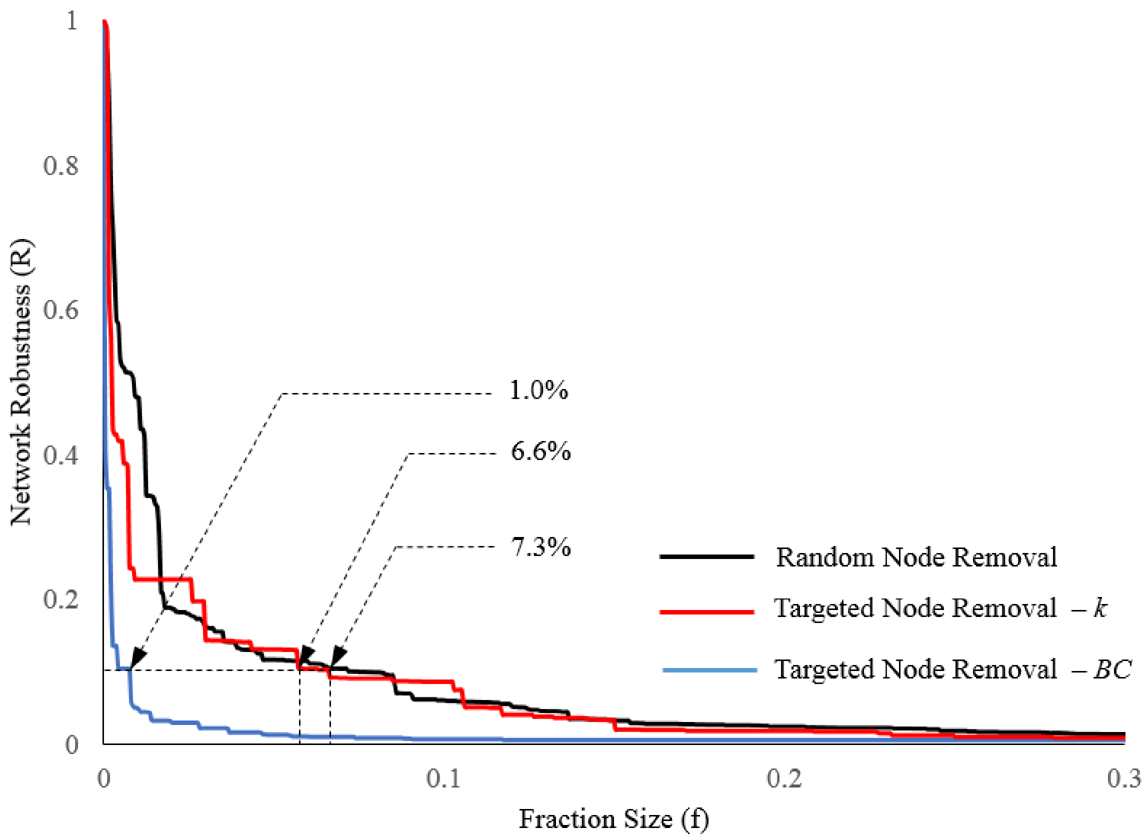

Figure 10: Robustness of the OBN

In light of the above robustness measures, it is observed that setting up multiple bridge rehabilitation construction projects simultaneously could lead to significant impacts to the OBN. More specifically, selecting multiple bridges for rehabilitation, randomly or with high centrality values, could cause the phenomena of giant component to rapidly diminish (see section 3.2.1), and therefore, cause more severe multiple disconnections. This is confirmed by the drastic drop in the OBN robustness value, shown in Figure 10, as it requires performing only a few bridge rehabilitation projects simultaneously, even if they are low in *k* or *BC* values, for the load to spread. This load propagates along neighbouring nodes in the network and subsequently turns into a cascading failure that causes clustering in smaller components within the network.

4.3. Network Vulnerability Index

Vulnerability analysis quantifies the importance of different bridges by considering the possible cascading impacts once they are closed for rehabilitation and evaluating the subsequent OBN performance. The index provides direct measures to identify bridges that require special consideration not only because of their actual load demands, but also due to their geographical and topological locations on the OBN. Figures 11 presents the distribution of the *VI* for all bridges (top right) and the probability of occurrence is classified into four *VI* categories: Low Vulnerability (*LV*), Moderate Vulnerability (*MV*), High Vulnerability (*HV*), and Extreme Vulnerability (*EV*).

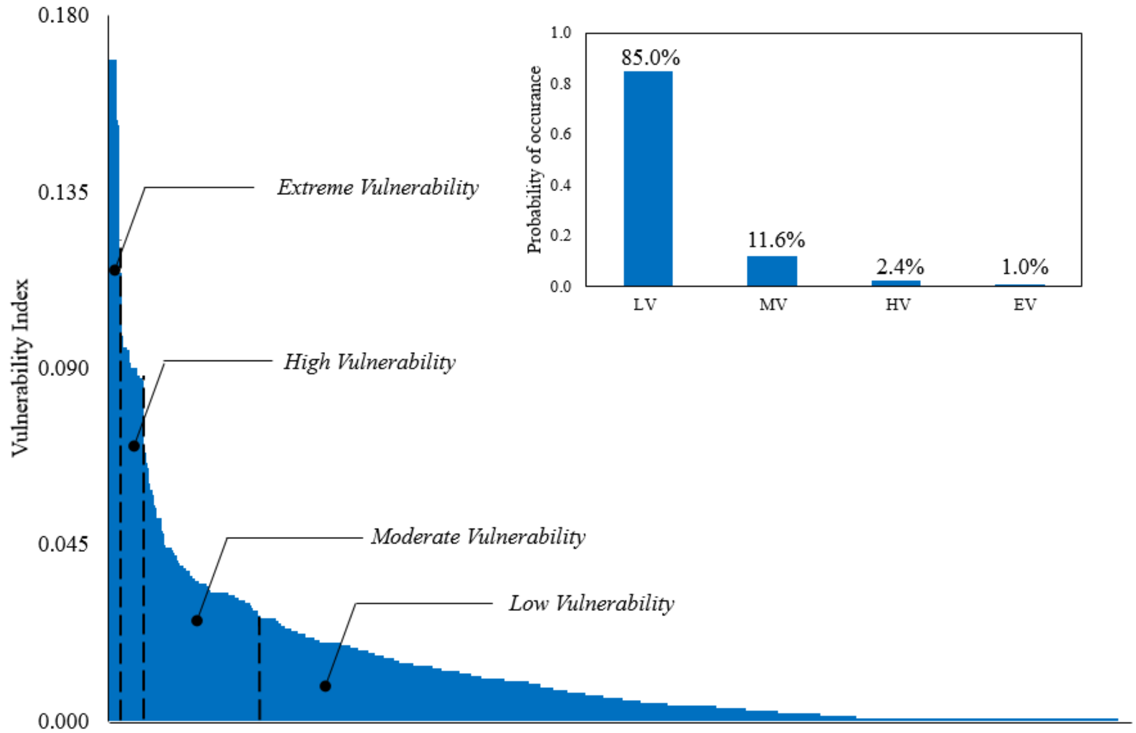

Figure 11: Vulnerability Index of the OBN

The analysis indicates that there is a small percentage of vulnerable bridges in Ontario. As shown in Figure 11, the highest two vulnerability groups (i.e., *EV* and *HV*) represents only 2.4% (i.e. 50 bridges) of the OBN, while 85.0% of the OBN lie under *LV* category. The high percentage of *LV* bridges indicates that rehabilitation of these bridges will not cause a significant impact on the network. However, despite the small percentage of the *EV* and *HV* bridges, any closure of these bridges for rehabilitation imposes major impacts to the network. To illustrate such an impact, the rehabilitation of one of bridges (represents 0.067% of the OBN) with the highest *VI* value triggers a disproportionate cascading impact that result in 237 non-operational bridges (represents 16% of the OBN) in the network.

The *VI* map of the OBN in Figure 12 shows that bridges that hold or surrounded with higher *BC* (see Figure 7), have higher *VI* than those elsewhere in the map. Moreover, most of *EV* and *HV* bridges lie in the southcentral and southeastern parts of Ontario, where one-third of Canada's population lives (Ministry of Finance, 2017). As such, it is clear that the impact of the bridges with high *BC* values would severely impact the other surrounding bridges, and would therefore, trigger cascading effects due to the spread of high load that cannot be sustained by the other network bridges.

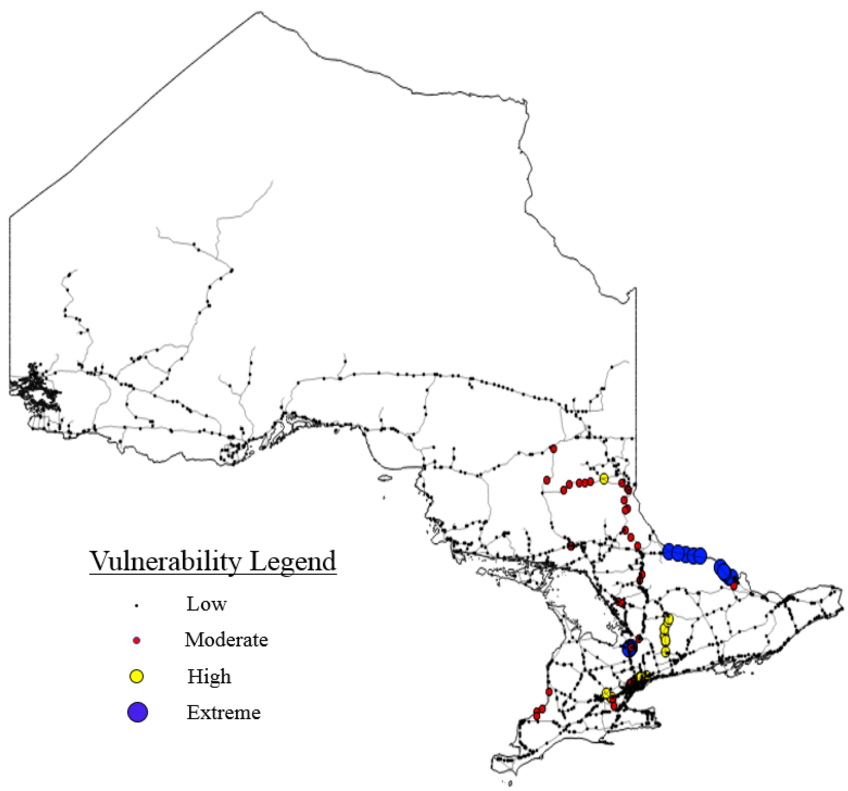

Figure 12: Scaled Representation of OBN Vulnerability Index

5. Discussion of the Multi-Scale Classification Approach

As stated earlier in the introduction, most of the bridges in the OBN were constructed post World War II. This indicates that there are several bridges older than 50 years, that potentially require major rehabilitation or replacement. By plotting the *VI* value of each bridge in the OBN against its corresponding construction year as shown in Figure 13, a vivid illustration when integrating both component and network level measures starts to emerge. It should be noted however that such illustration should be interpreted carefully due to the fact that several bridges in the network have already benefited from regular rehabilitation cycles. Therefore, to paint a more comprehensive illustration, Figure 14 shows a plot of the *VI* against the BCI, as the BCI reflects the actual status of the bridge, which in turn presents a more comprehensive classification approach.

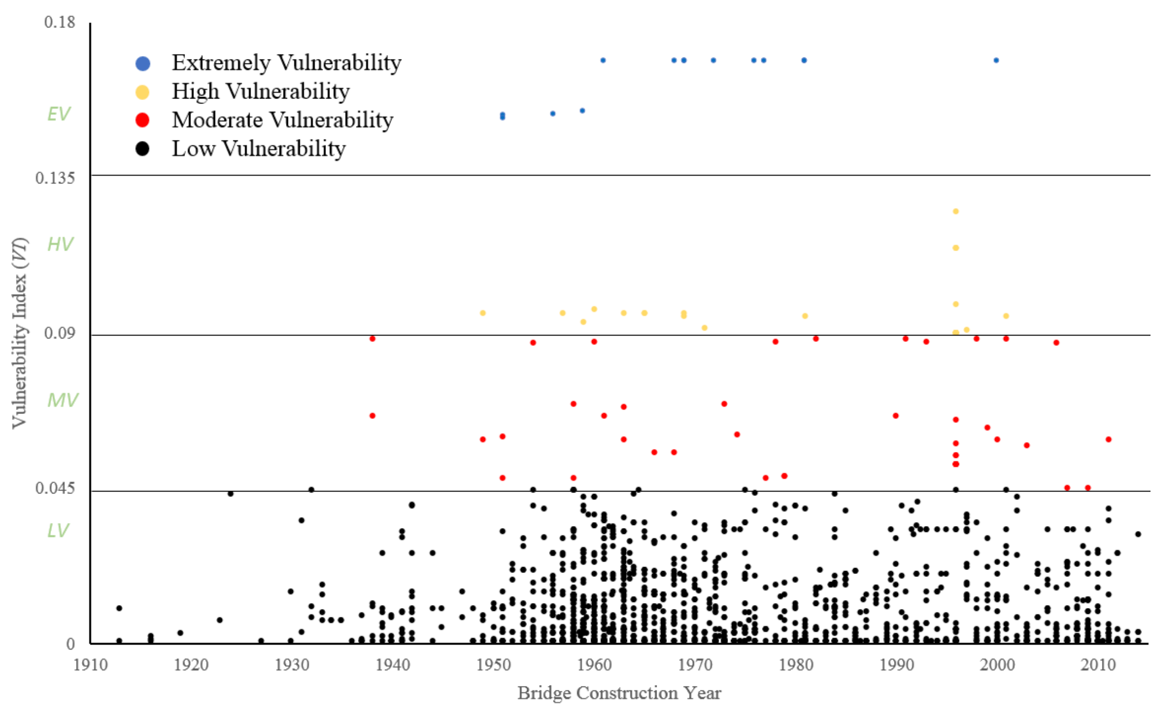

Figure 13: Bridge Vulnerability as a Function of its Age

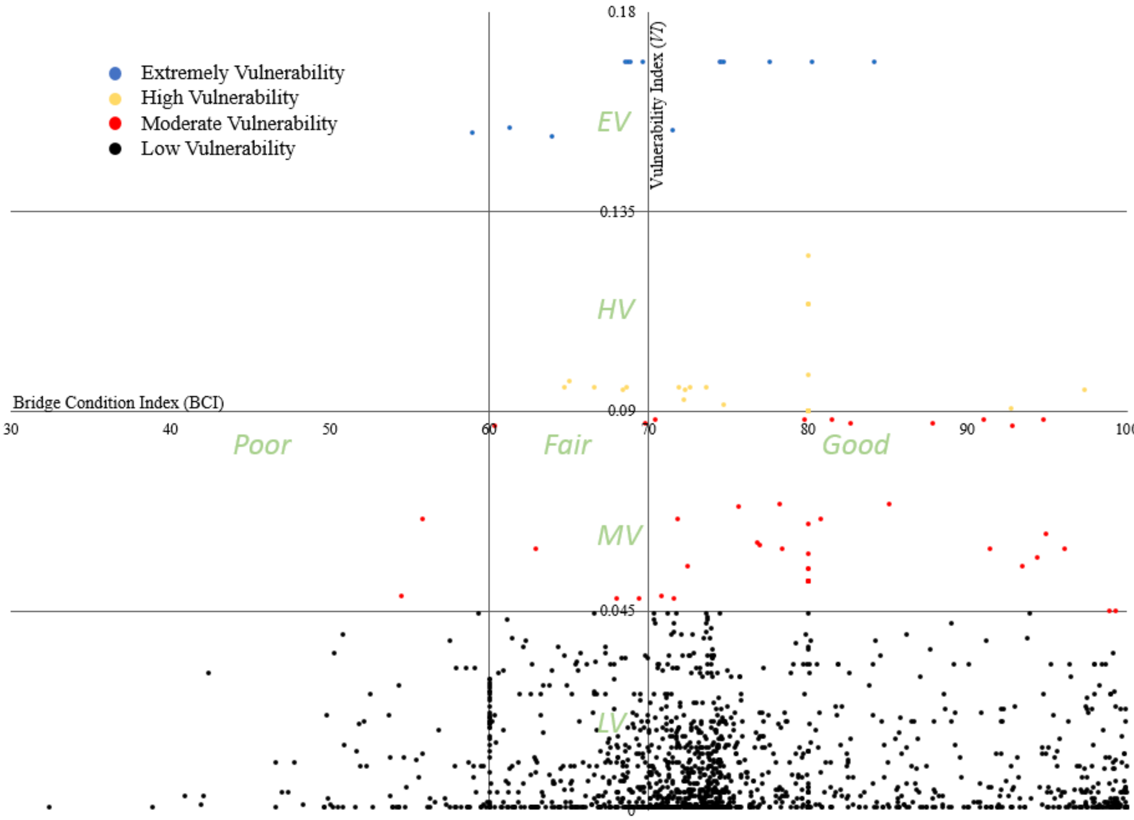

Figure 14: Bridge Vulnerability as a Function of its Condition

Figure 14 categorizes the BCI based on the MTO classification (excellent, good, fair and poor) and categorizes the *VI* as Low, Moderate, High, and Extreme Vulnerability. As can be seen in Figure 14, there is no direct correlation between the *VI* and the bridge status, when the BCI is considered. In contrast, Figure 15 shows that the *VI* increases as the *NBC* increases. It confirms that the bridge *NBC* along other topological features are the main factor for the *VI* since the vulnerability measures is initiated based on network *BC*. This reinforces the importance of considering the different network-level characteristics (e.g. *BC*) for bridge rehabilitation plans.

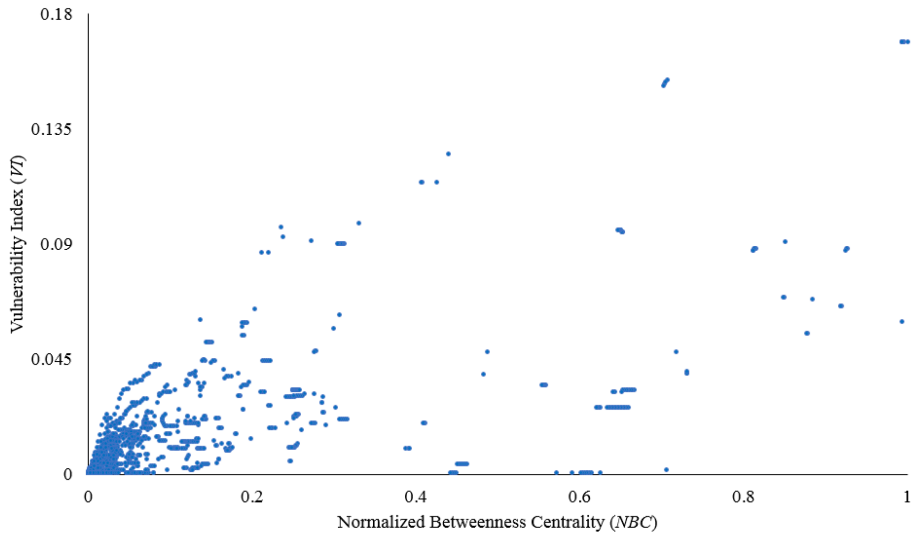

Figure 15: The Vulnerability Index with Normalized Betweenness Centrality of the OBN

To identify the critical bridges by applying the MSBC on OBN Vulnerability Index map (Figure 12), the *EV* bridges can be recognized on two main highways within the network. Any unplanned rehabilitation to these bridges can trigger substantial cascading impacts to the major routes in the province of Ontario. This is because the Highway 17 is a freight corridor for goods and people movement between two major Canadian provinces: Ontario and Quebec, while Highway 400 links Toronto (Canada's financial capital) to the northern part of the province. Therefore, any future rehabilitation plans should consider these bridge repair needs separately given the highlighted disproportionate cascading effects.

Overall, the bridges under the *LV* category populate 85.0% of the OBN (Figure 10). Under this category most of the poor and fair condition bridges lie under the *LV* category. Since those bridges (i.e., bridges under *LV* category) do not impose significant cascading impact to the network, the bridges under the *LV* category could be rehabilitated based on their structural condition while giving the bridges with higher *VI* the priority. Furthermore, they can be considered in the rehabilitation plan by combing bridges from different vulnerability categories after confirming that the cascading impacts are within an acceptable range. The network robustness should be also considered when more than one bridge is scheduled for rehabilitation, and to confirm the absence of any potential cause of multiple cascading effects.

As bridges advance higher in the *VI* scale, it is recommended that higher priority should be given to the bridges under each category based on their condition and should avoid combining more than one bridge at a time. As presented above, the impact to the network due to rehabilitation of one of the *EV* bridges causes significate cascading failures to the OBN. Therefore, special measures should be considered to prevent and minimize such considerable impact. The prevention measures should consider more frequent site inspections and faster response to repairs. Minimizing the disturbance to the network during rehabilitation should consider construction methods like Accelerated Bridge Construction (ABC) to complete the construction work in a reduced amount of time. In general, The ABC methods should be assigned to bridges with *EV* nature by default to reduce network disturbance. Furthermore, to enhance the sustainability of the network, the bridge design codes should consider more stringent durability requirements to offer a longer design life when replacing any of the bridges in the *EV* and *HV* category.

6. Conclusion

The transportation network in Ontario is very crucial for the social wellbeing of Ontarians, and Canada's overall economy, since about 40% of Canada's population lives and works in Ontario (Ministry of Finance, 2017). In highway networks, bridges are the network's most vulnerable and expensive components. As such, if a bridge is closed for rehabilitation, there is a potential of encountering a cascading disturbance throughout the network. The Ministry of Transportation of Ontario currently adopts a framework to guide bridge rehabilitation using the provincial budget to improve aging infrastructure. Integrating the findings of this study with the existing framework measures will provide a practical solution within the available budget. The Ontario Bridge Inventory (OBI)currently includes various information pertaining to its comprising bridges at the component-level with no consideration to the network-level. More specifically, the OBI does not consider the negative cascading impacts that a bridge closure (for scheduled for a rehabilitation) can have on other bridges. Conversely, the dynamic vulnerability indices quantify the impact of the rehabilitation plans of the Ontario Bridge Network (OBN) at the network-level.

The current study utilizes complex network theory to analyze the OBN. Such a comprehensive approach has never been comprehensively studied before in literature for bridge networks. Previous literature considered a network-level assessment and optimization based analysis, with exception of the work of Rokneddin et al (2013) where a preliminary effort of utilizing network bridge topology was presented. Given the lack of studies utilizing complex network theoretic measures in bridge networks, this study provides the seminal work for future studies through this field. This study focuses on measuring the overall behaviour of the OBN based on its topology, and the robustness and vulnerability of bridge rehabilitation scenarios. It also integrates available bridge information with the vulnerability measurements obtained from complex network theory.

To that end, the study integrates the network Vulnerability Index and Bridge Condition Index (BCI) in a Multi-Scale Bridge Classification (MSBC) approach in order to identify critical bridges in the network and, and subsequently guide rehabilitation strategies of the OBN.

Overall, the OBN exhibits acceptable levels of centrality, but the robustness and vulnerability reveal cascading impacts if bridges are closed for rehabilitation. Any rehabilitation of bridges designated as highly vulnerable should be evaluated considering possible cascading impact, and rehabilitating more than one of these bridges simultaneously should be avoided. Alternatively, the Low Vulnerability bridges, which populate most of the OBN, could be rehabilitated at the same time or in conjunction with bridges of high/extreme vulnerability, but only after ensuring the network robustness for such scenarios. Finally, special attention should be given to the bridges with high vulnerability (i.e., Extreme- and High Vulnerability Index) as they should be inspected more often, their repair needs should be addressed in a timely manner, and replacements might require expedited construction methods. Applying the suggested techniques will assist the MTO to achieve its goal (i.e. 85% of bridges in good condition) efficiently with reduced disturbance to the OBN.

Future studies may extend the proposed approach to accommodate traffic flow data. This was both outside the scope of the current study and also not feasible due to the lack of access to traffic flow data. The availability such data will also enable the examination of staged rehabilitation (partial bridge closures).

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