Analyzing the Structural Health of Civil Infrastructures using Correlation Networks and Population Analysis

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Abstract — **Traditional Structural Health Monitoring (SHM) methods require bridge inspectors to manually inspect each bridge periodically (usually every two years) and recommend maintenance or rehabilitation services to the bridge if necessary. As limited manpower and budget constraints are the two major shortfalls in traditional SHM methods, in addition to potential human errors and lack of consistency, more rigorous and frequent solutions are needed to assess the health levels of bridges and provide needed recommendations. In this work, we process a new population-based approach that employs the concept of Correlation Networks to evaluate the status of each bridge based on general parameters as well as how it compares to other similar bridges. We propose a Correlation Network Model (CNM) that builds a network of bridges, based on time-series data on sufficiency ratings, for a population of 9,546 "steel bridges with stringer/multi-beam or girder design," taken from the U.S. National Bridge Inventory (NBI) database. We apply Markov Clustering Algorithms to produce clusters of bridges with similar features associated with their fitness ratings over user-defined periods of time. The top five clusters are identified and further analyzed using population analysis algorithms. We were able to identify three clusters with lower fitness ratings and suggest that the bridges in these clusters need to be serviced sooner than those included in the other clusters. Experimental results show that the proposed model provides an efficient approach that allows domain experts to assess the structural health of bridges/civil infrastructures in a robust way that can guide rehabilitation services for all bridges and identify potentially unsafe bridges that need urgent attention.**

Keywords — Structural Health Monitoring; Population Analysis; Correlation Networks; Markov Clustering; Sufficiency Rating; National Bridge Inventory database.

I. INTRODUCTION

The National Bridge Inventory (NBI) database consists of information on more than 600,000 bridges of the United States of America (USA), with each bridge dataset comprising 116 parameters. After each inspection cycle, usually every two years, the bridge inspectors develop condition ratings of the bridges as specified by the U.S. Federal Highway Administration (FHWA) [1]. Sufficiency Rating (SR) is an outcome parameter/measure which reflects the overall fitness rating of the bridge and is derived from over 20 NBI data fields/parameters grouped in four factors, i.e., Structural Evaluation, Functional Obsolescence, Essentiality to the Public Use, and Special Reductions as described in the FHWA coding guide [2]. SR ranges between 0% and 100 % or between 0 and 1000. Lower percentages/ratings indicate that the bridge fitness is low and higher percentages/ratings indicate that the bridge is highly fit. SHM is a process of implementing a damage detection and characterization strategy for engineering structures [3]. Traditional SHM methods require bridge inspectors to manually inspect each bridge over a period of time and recommend maintenance or rehabilitation services to the bridge if necessary. As limited manpower, budget constraints, and lack of consistent and continuous monitoring are the major shortfalls in traditional SHM, research communities are interested in new solutions to assess the structural health of civil infrastructures while taking advantage of the massive data available in the NBI database. In this work, we propose the use of Correlation Network Models (CNMs). CNM is a powerful big-data tool that has recently been used to analyze and visualize complex systems having large data with multiple dimensions/parameters in various domains [12], [17], [18]. We propose to employ CNM to create a correlation network of bridges, based on the time-series data of bridges' overall fitness rating, such as SR for a population of 9,546 "steel bridges with stringer/multi-beam or girder design" obtained from the NBI database. These bridges are taken from three US states: California, Iowa, and Nebraska, which come from three different climatic regions as shown in Figure 1. We then apply a Markov Clustering algorithm, such as MCL to obtain clusters of bridges that have similarity in their fitness ratings (such as SRs) over a certain period of time.

Our basic hypothesis is that the bridges with similar fitness characteristics are included in common groups or clusters. MCL is a graph-based efficient algorithm designed based on the random walks property of the graphs. As every clustering method groups elements with similar attribute values together [16], when applied to the bridge correlation network, MCL finds clusters of bridges with similar behavior in terms of SRs. We identified the top clusters produced by the algorithm for further analysis. We were able to identify clusters with lower fitness ratings that need to be serviced relatively soon compared to bridges in other groups. Our experimental results show that the proposed approach provides a new efficient tool that allows bridge owners to evaluate the structural health of bridges/civil infrastructures and identify the structures that need immediate attention. This may serve as the main component of a new SHM decision support system.

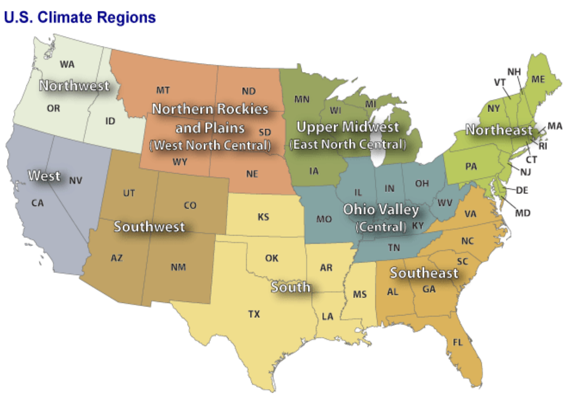

Figure 1. Map of nine USA climate regions (image courtesy NOAA). [8]

The remainder of this paper is organized as follows. Section II provides a general background, where the need for creating a Correlation Network of bridges with time-series data of SRs is discussed. Section III discusses the key concepts used for creating Correlation Networks and the population analysis approach, followed by a discussion on how network models are used in various application domains. Section IV includes the complete methodology used to implement the proposed approach. Section V discusses the experimental results of the study. Conclusions and future directions are summarized in Section VI.

II. BACKGROUND

Several researchers have recently attempted to develop deterministic and stochastic deterioration models for various bridge components, such as Deck, Superstructure and Substructure, and Average Daily Traffic [4]. Several studies have used Two-Step clustering, a powerful data mining tool, to study concrete deck parameters in the NBI database to identify the order in which bridges need to be serviced [5]. While there are some deterioration models that are based on temporal data [4], [6], but they usually consider only one or few input ratings, such as Deck Rating or Superstructure Rating, for their analysis. Since they did not consider a holistic approach or compound rating measures such as SR (which is a complex measure based on multiple parameters), their models are somewhat limited and lack robustness and consistency. For example, such models can explain how Deck Rating changes over a period of time but fail to measure the overall safety of bridges as a whole. To estimate the overall fitness ratings of bridges, we are proposing a population analysis model that is based on the complex SR measure. Again, as various models consider temporal data of selected input ratings, they are useful in estimating ratings of individual elements but fail in estimating the overall fitness ratings of bridges [4], [5], [6].

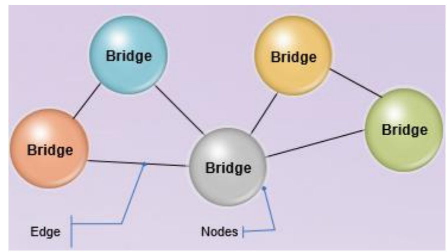

Figure 2. Graph model representation with bridges.

On the other hand, there are models, that could consider the overall fitness rating as their measure in predicting the health of civil infrastructures [7], [18], but they do not utilize time series data. Hence, obtained predictions may not be accurate or do not really characterize the overall behavior of the bridges over a period of time. Therefore, there is a need for a model that considers bridges' overall behavior or fitness ratings over a period of time and identifies the categories of bad bridges with respect to their fitness ratings.

A. *Correlation Network Model (CNM)*

As mentioned earlier in the introduction section, the NBI database has information on more than 600,000 bridges, each with 116 parameters. The big-data associated with these bridges can easily be analyzed or visualized using a powerful tool such as CNM. CNM [17], [18] is a graph- based model which would allow the correlated bridges to be connected by an edge in the Correlation Network Graph. Creation of a Correlation Network is explained in our methodology section. CNM is relevant for this research as the highly correlated bridges or bridges with dense connections (usually we call them clusters) would give us information about bridges that have the same kind of behaviors or characteristics.

For example, bridges with similar patterns in their SRs over a long period of time may be highly correlated and will have an edge between them in the CNM. Hence, all the highly correlated bridges will have dense edges among them and form as a cluster. The population analysis allows us to compare two or more clusters of bridges with respect to one or more enrichment parameters. This analysis will allow us to discover what parameters are significantly affecting a

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particular cluster. For example, if one particular cluster is highly enriched by Structurally Deficient (SD) bridges, then we can identify other parameters that are similar to these bridges and hence, we can control them. If this structural deficiency is due to the deterioration of deck rating, then we can advise the bridge authorities to implement deck-related rehabilitation measures.

B. *Correlation Networks in Various Disciplines*

In the past decade, Correlation-based Network Analysis has become a powerful analysis tool in biological studies and have been used by other researchers in various disciplines because of their ability

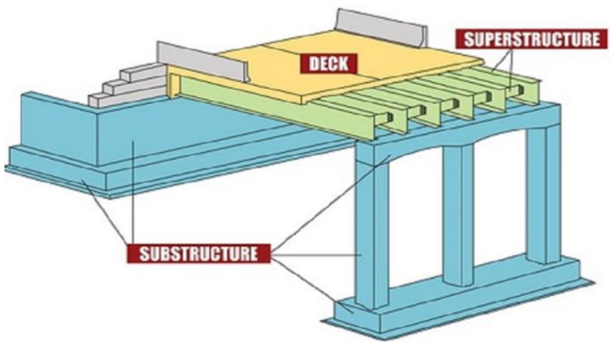

Figure 3: Structural elements of a bridge [21].

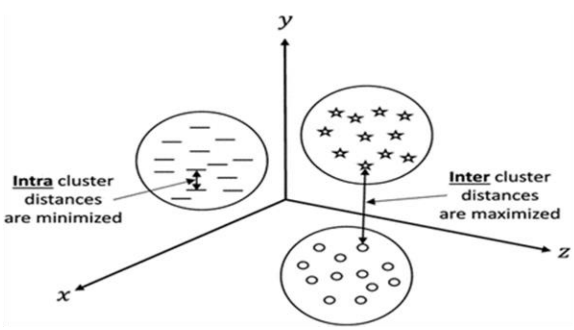

Figure 4. Representation of clustering.

to show generalization, visualization, and analysis capabilities [12]. CNA was successfully applied in biological systems to determine plant growth and biomass in Arabidopsis thaliana Recombinant Inbred Lines (RIL) and introgression lines (IL) [13], [14]. It was also applied to evaluate the effects of hypoxia on a tumor cell biochemistry [15]. Correlation networks are powerful and provide us the opportunity to measure changes in temporal datasets, and there are clusters which are highly enriched by a few Gene Ontology (GO) terms [17].

C. *Correlation Networks to Monitor Structural Health*

Recently, researchers have applied CNM to monitor the structural health of civil infrastructures and have also analyzed the safety issues with respect to various parameters such as inventory rating and deck rating [18]. One of the advantages of using CNM in civil infrastructures is that the bridges can be clustered based on some similarity, and visualized as healthy and unhealthy clusters of bridges [18], using any existing visualization tools, such as Cytoscape [19] and Gephi [20]. As CNM is a new approach for SHM, it can be used to display critical bridges and find an efficient way to improve bridge inspection schedules [18]. However, one of the limitations of the latter study is that it did not consider the temporal-data of SRs; hence, it cannot accurately predict a future overall fitness rating behavior of the bridges. Hence, creating a Correlation Network model that could deal with temporal-data is one of the objectives of this paper. The motivation of this paper is to develop a CNM that could consider bridges' overall behavior (i.e., SR) over a period of time and analyze highly correlated clusters of bridges to predict bridges' future behavior. The research question of this paper is to determine what parameters are enriched for each cluster of bridges in the population, if the bridges are clustered using the correlations of temporal data of SRs. The research objective of this paper is to provide a CNM-based Decision Support System for bridge owners to enable them to find out which bridges need to be serviced first. As a result, we developed a novel CNM that considers the temporal data of SRs of the bridges for the last 25 years (from 1992 to 2016), so as to exactly characterize the overall fitness behavior of the bridges over a period of time and hence, predict the future fitness behavior accurately.

III. GRAPH MODEL, CORRELATION COEFFICIENT, AND CLUSTERING

This section talks about the graph model, correlation coefficient and Markov clustering.

A. *Graph Model*

The graph model (denoted by G= (V, E), where V is a set of vertices/nodes, and E is a set of edges) used in this paper is undirected and unweighted. An example of an undirected and unweighted graph is shown in Figure 2 with five vertices and six edges, where every vertex represents a bridge/civil infrastructure and any two bridges are connected by an edge if and only if they have some correlation. Various colors of bridges may represent various status of bridges while visualizing them. For example, a green-colored bridge may represent a structurally sufficient bridge, whereas a red-colored bridge could be a SD bridge.

B. *Correlation Coefficient*

A Pearson's correlation coefficient [10] between any two variables is a real value that ranges between -1 and +1, and which expresses the strength of linkage or co-occurrence. This strength is called Pearson's *r* or Pearson product-moment correlation coefficient if the correlation is between two continuous–level variables [10], [11]. This paper uses

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bivariate (Pearson's) correlation analysis to show the relationship between any two bridges.

C. *Markov Clustering*

Clustering groups objects with similar attribute values together [16]. The objects are grouped together in such a way that distances among the clusters are maximized and the distances within the clusters are minimized, as shown in Figure 4. The MCL algorithm [9] with default parameters is used in this paper to cluster the bridges, as the MCL is more suitable to graph-based networks. MCL is a fast and efficient algorithm that is designed based on the random walks property of the graphs. A random walk in a strongly connected cluster usually visits almost all the nodes in the cluster. MCL was applied on various protein-protein interaction networks and proved to be remarkably robust to graph alternations and superior in extracting complexes from interaction networks [26]. Since our correlation network with civil bridges is also a kind of protein-protein interaction network, we used MCL to extract the clusters of bridges that behave similarly.

IV. METHODOLOGY

The following are the four phases of the CNM we are proposing.

i. Data acquisition and filtering
ii. Creating a correlation network and applying MCL algorithm
iii. Analyzing various clusters with respect to both input parameters, and output parameters, and comparing various clusters (population analysis)
iv. Developing a decision support system

The first two phases are explained in this section and the last two sections are explained as part of the next section. The novelty of this method is that the similar bridges are connected together into one cluster and the individual clusters are analyzed to see what input or output ratings are highly enriched for that cluster. The population analysis allows us to compare various clusters with respect to various rating parameters and then the decision support system allows us to make decisions about various clusters.

A. Data Acquisition and Filtering

Bridge data of California, Iowa, and Nebraska, from the years 1992 to 2016, was obtained from the NBI database. Each bridge description is an alpha-numeric string of 432 characters in the database. There are 45,397 (California-15123, Iowa-16513, and Nebraska-13761 bridges) common bridges from 1992 to 2016 (based on the structure number entry in the database) in these three states. A total of 7,038 bridges out of 45,397 are culverts (Alpha-Numeric character string position 262! ='N') and 38,359 are non-culverts, according to the 2016-database. As the data was processed for any kind of anomalies, we found that there are 2,285 of these 45,397 common bridges that have inconsistent entries. In some years, they were recorded as culverts and in some years they were non-culverts. These 2,285 bridges were omitted from consideration. The remaining 43,112 common bridges consisted of 5550 culverts and 37,562 non-culverts (bridges). The majority of non-culverts (9,546 out of 37,562) were coded with main-structure type-302 (Item 43 from the NBI coding guide). In the coding 302, the first digit 3 represents the kind of material, i.e., "Steel," and the last two digits, 02, represent the type of design, which is, "Stringer/Multi-beam or Girder."

Our method takes a population of this 9,546 steel-stringer/multi-beam or girder bridges across three states of the USA (California, Iowa, and Nebraska), which come from three different climatic regions (as shown in Figure 1). The following items/parameters extracted from the FHWA coding guide [2] were considered for our analysis.

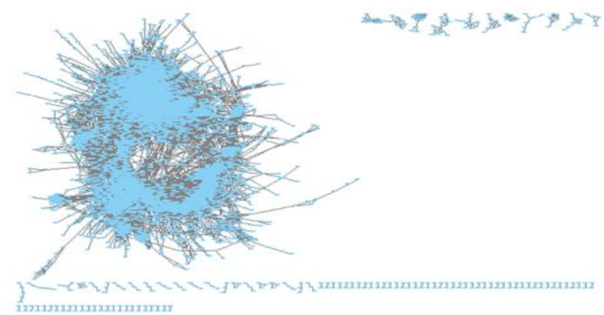

Figure 5. Correlation Network (correlation $\rho>=.90$) with 9,546 nodes and 767542 edges (Average degree=89.14, and 101 Connected components).

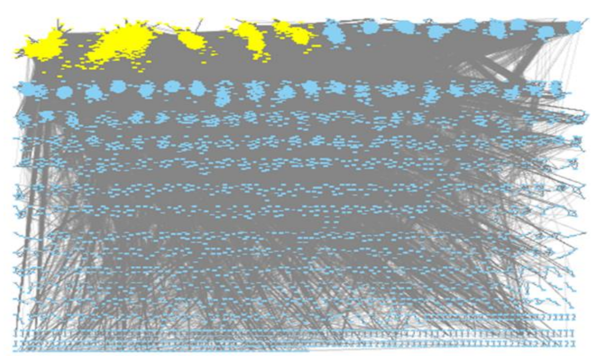

Figure 6. Clusters produced by MCL algorithm. Top-5 clusters are indicated by yellow color. Figure 5 and 6 were generated using Cytoscape [19].

i. Item 58 - Deck Rating (DR)
ii. Item 59 - Superstructure Rating (SPSR)
iii. Item 60 - Substructure Rating (SBSR)

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iv. Item 67 - Structural Condition Rating (SCR) / Structural Evaluation Rating (SER)
v. Item 71 - Water Adequacy Rating (WAR)
vi. Status of the bridge as defined in [22]
vii. Sufficiency Rating

B. Creating a Correlation Network

The SRs of each of the 9,546 bridges from 1992 to 2016 (25 years) are recorded as an input matrix (say, SR matrix) with each row (i.e., each bridge) of the matrix having 25 years' SRs in it. So, there are 9,546 rows in the matrix, with each row as a vector of 25 years' SRs. A Pearson correlation coefficients matrix (say, Correlation-matrix) was then obtained over the SR matrix. The resultant Correlation-matrix is of size 9546 times 9546. Assuming each bridge as a node (vertex) in the graph model, two nodes are connected by an undirected edge if and only if their correlation coefficient $\rho >= 0.90$ and significance value $p <= .01$. This creates a Correlation-Network with bridges as nodes along with highly correlated nodes connected by edges as shown in Figure 5. We applied the MCL algorithm with all default parameters in Cytoscape [19] on the obtained Correlation Network, in order to produce clusters. These clusters are basically sub-networks of nodes and edges. Each cluster was further analyzed to see which input parameters were enriched for that cluster. As the clusters are formed with high correlations among the nodes, we can infer that the overall behavior of the nodes within each cluster is the same. This is the hypothesis of this research. MCL has produced 8610 nodes in various clusters and 3865 nodes are present in the Top 5 clusters and shown in Figure 6. These Top 5 clusters are considered for further analysis. Various experiments are conducted on the Top 5 clusters produced by the MCL algorithm, and the results are shown below.

V. EXPERIMENTAL RESULTS

This section demonstrates various experimental results with respect to various network properties of the Top-5 clusters, SR, and other input ratings.

A. Network Properties of Top 5 Clusters

Figure 5 shows the correlation network (correlation $\rho >= 0.90$) formed with 9546 nodes, 767542 edges, and 101 connected components. This is a scale-free network and follows a power-law node degree distribution. In a power-law node degree distribution, there are many nodes with fewer degrees and fewer number of nodes with more degrees. The top 5 clusters (yellow colored clusters) produced by the MCL algorithm are shown in Figure 6. These clusters' statistics are shown in TABLE 1, with the top- most cluster having the highest number of nodes 1496 and 354939 edges, and the least cluster having 255 nodes and 13922 edges. The lower the diameter, the closer the nodes are. Hence, almost all the nodes in all the clusters are around the center node(s). The higher the clustering coefficient [23], the higher the degree to which nodes in a graph are inclined to cluster together. The higher values of the average clustering coefficient for each cluster / subnetwork indicate that the nodes inside each cluster tend to be part of that cluster only. Therefore, the Top 5 clusters with higher clustering coefficients are considered for further analysis. TABLE 1 shows that cluster 5 has the highest clustering coefficient, which is 0.838. The cluster density describes the potential number of edges present in the sub-network compared to the possible number of edges in the sub-network. From TABLE 1, we see that cluster 3 has the highest density (0.533) among all the Top 5 clusters.

TABLE 1. NETWORK STATISTICS OF TOP 5 CLUSTERS PRODUCED BY THE MCL ALGORITHM.

Cluster Number	#Nodes	#Edges	Avg. Degree	Density	Avg. Clust. Coeff.	SR Avg.
Cluster1	1496	354939	474.51	0.317	0.775	623.7
Cluster2	1180	99000	167.79	0.142	0.674	489.3
Cluster3	634	106955	337.39	0.533	0.823	801.9
Cluster4	300	13377	89.18	0.298	0.812	818.5
Cluster5	255	13922	109.19	0.43	0.838	577.5

B. Analysis of Bridge Behavior with Respect to Sufficiency Rating

We selected two bridges from cluster5 for our analysis to look at their behavior in terms of their overall fitness ratings (i.e., SRs) as shown in Figure 8. These two bridges are highly correlated (correlation $\rho >= 0.94$) with each other and hence, connected by an edge in the network. The first bridge (say Bridge1, shown in red color) has an initial SR value of 615 in the year 1992, and maintained almost the same value until the year 2013. After then, there was a sudden drop in the SR value from almost 600 to below 500, ending at a SR value of 490 in the year 2016. Similarly, the second bridge (say Bridge2, shown in green color) started with a SR value of 970 in the year 1992 and steadily maintained it until 2013. There was a sudden drop in the year 2013 to a SR value of 860 and ended at that value itself. Though the first bridge was constructed in the year 1969, and the second bridge in the year 1988, both of these bridge had almost similar SR curves from 1992 to 2016. We have also observed that the current status of the first bridge is SD, and the second bridge is structurally good.

As SR is an overall fitness rating of the bridges, and as both of these bridges had the same kind of SR curve for the last 25 years, if the first bridge is SD, the second bridge may also have a high probability of becoming SD in the near future, as both bridges are highly correlated and in the same cluster. Estimating after how many years the second bridge will become SD is not the scope of this paper. Some of the bridges' SRs comparison is given in Figure 9. In fact, all these bridges are connected to the bridge CA-B06422 (Bridge names are partially anonymized. That means the first two letters in each bridge name may indicate the state but the remaining sequence in the name does not reflect the original bridge name as it is given in [1]). This means all these bridges are adjacent bridges of the bridge CA-B06422. This figure clearly shows that the SRs pattern is almost the same for adjacent bridges as they are highly correlated. It also clearly shows that all these bridges are sooner or later going to become SD, as all bridge SRs are deteriorating. Immediate maintenance may be required for this kind of bridges. Figure 10 shows that both clusters 3 and 4 have higher SRs at the end (year 2016), while all the remaining bridges have lower averages of SRs. We can also observe that for clusters 4 and 3, there was a maintenance (in terms of reconstruction) took place in the years 1997 and 2007 respectively. Hence, these clusters have higher SRs in the year 2016 (as shown in Figure 10) and do not need immediate maintenance.

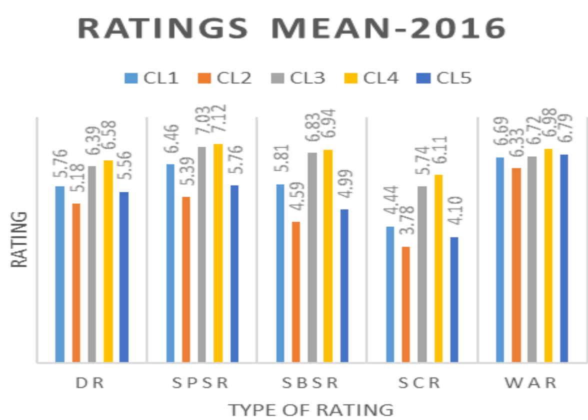

Figure 7. Ratings comparison for top 5 clusters (year 2016)

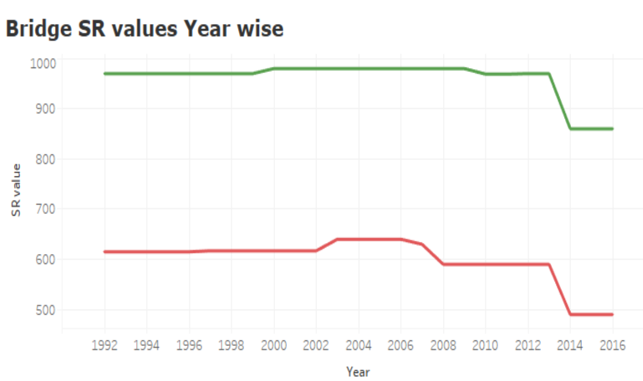

Figure 8. Comparison of SR values of two bridges from Cluster-5.
(The image was generated in Tableau [25]).

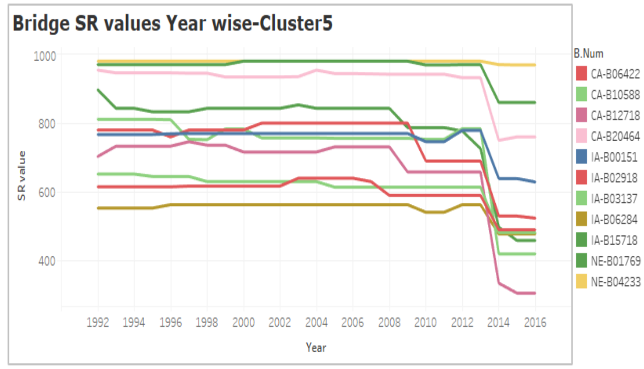

Figure 9. Ten adjacent bridges of the bridge--CA-B06422 from Cluster5 (Bridge names are partially anonymized).

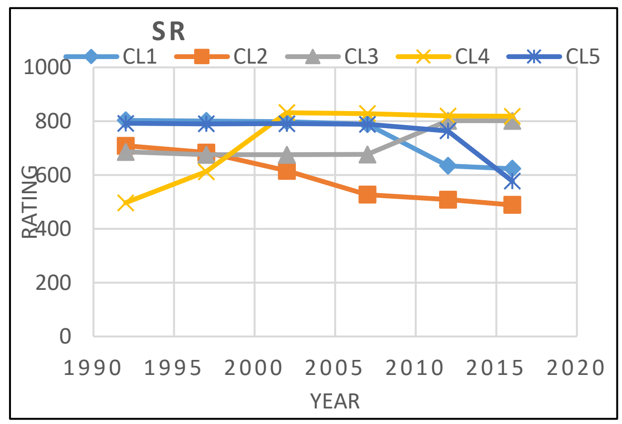

Figure 10. Comparison of Top 5 clusters' averages (dataset years 1992, 1997, 2002, 2007, 2012 and 2016) with respect to SRs.

C. Analysis of Top 5 clusters with respect to input rating parameters

Various input rating parameters of output ratings, such as SR, are considered for cluster enrichment analysis. Figure 7 shows the comparison of Top 5 clusters' average input ratings, such as DR, SPSR, SBSR, WAR, and SCR of the NBI-dataset-2016. From this figure, we can see that all the ratings of both cluster 3 and cluster 4 are higher compared to all the remaining clusters. Similarly, from Figures 11 through 15, we see how different input ratings vary for all the Top 5 clusters. For example, from Figure 11, we find that both cluster 1 and cluster 2 are enriched with DR = 5. This indicates that the deck (as shown in Figure 3) is in "Fair Condition" (as specified in the FHWA coding guide [2]). If we see cluster 4 from the same Figure 11, DRs ranging from 5 through 8 are equally distributed and hence, these higher ratings led to the higher SRs as shown in Figure 16. We can also see that both cluster-3 and cluster-4 have higher input rating values as shown in Figures 11 through 15. Figure 12 shows that Cluster-2 is highly enriched with Superstructure Rating <= 5. Once these bridges' Superstructure Ratings drop from 5 to 4, then the bridges will fall into the SD bridge

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category. Hence, the improvement in the Superstructure Rating in terms of reducing the live load is required. This can be done by reducing Average Daily Traffic and implementing required rehabilitation services on these bridges. Cluster 2 from Figure 13 also shows that the Substructure Rating is critical, as most of the bridges' Substructure Ratings are <= 5. From Figure 14, we see that Water Adequacy Ratings are good for all the clusters and no Water Adequacy improvement measures are required for these clusters. As shown in Figure 15, most of the bridges in clusters 1, 2, and 5 are enriched with SCR value <=4, which indicates that most of the bridges in these clusters are either SD or will soon become SD. Hence, they have lower SRs as shown in Figure 16. The same can be observed from Figure 10, where the average SRs for every 5 years' interval are shown. From this graph, Clusters 1,2 and 5 are showing higher deterioration patterns as compared to Clusters 3 and 4. Hence, our decision support system recommends various bridge authorities to provide immediate attention or service to the bridges in clusters 1, 2 and 5.

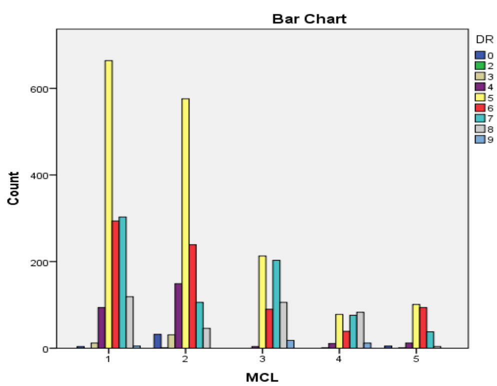

Figure 11. Comparison of Top 5 clusters with respect to Deck Rating (DR)

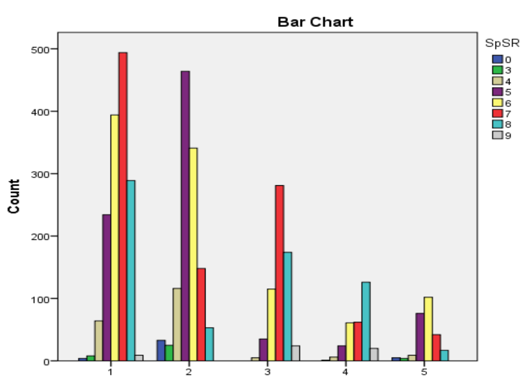

Figure 12. Comparison of Top 5 clusters with respect to Superstructure Rating (SpSR).

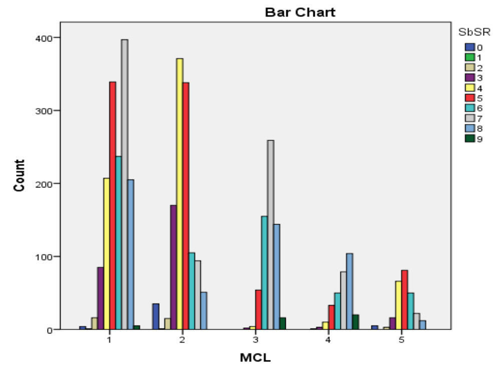

Figure 13. Comparison of Top 5 clusters with respect to Substructure Rating (SBSR).

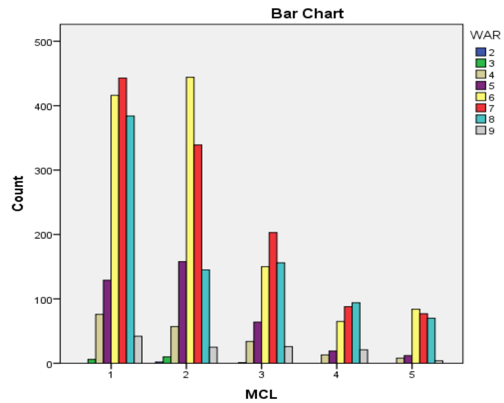

Figure 14. Comparison of Top 5 clusters with respect to Water Adequacy Rating (WAR).

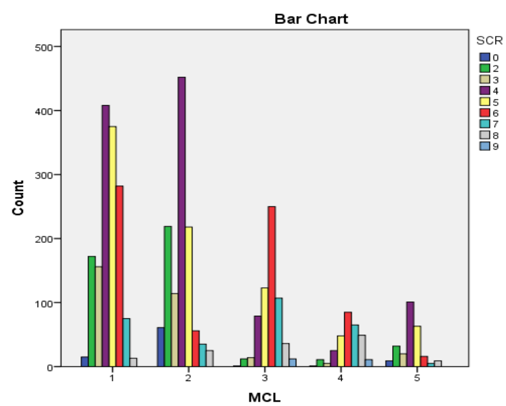

Figure 15. Comparison of Top 5 clusters with respect to Structural Condition Rating (SCR).

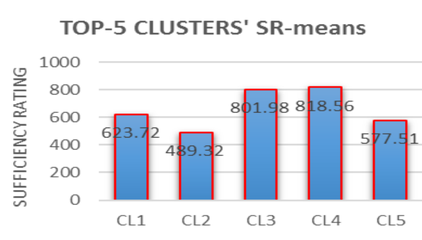

Figure 16. Averages of SRs of Top 5 clusters for the year 2016.

VI. CONCLUSIONS

In this paper, we presented a new Correlation Network Model for analyzing civil infrastructures with a focus on the assessment of safety of bridges. We employed the network model to provide a population analysis approach to extract useful information for publicly available bridge data. The proposed method allows highly correlated bridges to be identified and form a cluster of bridges with similar safety-related characteristics, such as the overall fitness rating. The population analysis makes it possible to compare different clusters with different enrichment parameters and ratings. We conducted a pilot study with a group of bridges from three states. We were able to use the constructed correlation network to identify several groups of bridges with different safety measures. Based on the obtained classifications, we identified bridges that exhibit a higher rate of deterioration and need to receive a higher priority for receiving maintenance. With these findings, we showed that the CNM enables domain experts to categorize clusters of bridges based on their safety. CNM as a decision support system allows SHM inspectors to have a risk-based schedule for servicing bridges, and allocate funds to inspect bridges with low safety patterns. As a future step, we plan to study the effect of specific parameters, such as Average Daily Traffic, on SRs and provide a risk assessment to various groups of bridges based on their deterioration patterns.

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