On the Robustness of Correlation Network Models in Predicting the Safety of Bridges

Prasad Chetti[1] and Hesham Ali[2]
[1]*Northwest Missouri State University, U.S.A.*
[2]*University of Nebraska at Omaha, U.S.A.*

Keywords: Bridge Safety, National Bridge Inventory, Correlation Network Model, Deterioration Rates, Risk Management.

Abstract: The problem of assessing the safety of bridges and predicting potential unacceptable deterioration levels remains one of the major problems in civil engineering. This work provides a comprehensive evaluation of the Correlation Network Model (CNM) in safety assessment and the prediction of potential safety hazards of bridges. The study applies a population analysis approach to compare individual or cluster performance against a larger set of peers. The CNM outcomes were validated using a linear regression model and a robustness analysis, resulting in a high level of consistency in identifying bridge clusters with different deterioration rates, and thereby identifying clusters with high- risk and low risk bridges. This process allows for the detection of significant parameters affecting bridge deterioration. The findings affirm the CNM's capability in capturing complex relationships between input parameters and bridge deck conditions, which exceeds the capabilities of simple linear regression models. Furthermore, the CNM's robustness, under various conditions and assumptions, is confirmed. The study demonstrates the potential of CNM as an effective tool for strategic planning and for efficient resource allocation, enabling focused maintenance and repair interventions on bridge infrastructures that could potentially extend their service life.

1 INTRODUCTION

Every year, the U.S. Federal Highway Administration (FHWA) collects data on the condition ratings of more than 600,000 bridges. The data document over 100 parameters for each bridge in the National Bridge Inventory (NBI) database (FHWA ASCII format, 2023) and the definitions of these parameters are given in the "Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges" (FHWA coding guide, 2023). This wealth of data presents a significant big data challenge, requiring effective analysis techniques. One essential parameter is the condition rating, which is represented by a numerical value ranging from 0 to 9. A rating of 9 signifies excellent bridge condition, while a rating of 0 indicates that the bridge has failed. Ensuring public safety and promoting economic growth are crucial drivers for governments to prioritize the maintenance and safety of transportation infrastructure, particularly bridges. However, the current state of bridges in the United States has raised concerns. According to the American Society for Civil Engineers (ASCE, 2021) report card, U.S. bridges received a 'C' grade, indicating the need for sufficient funds to ensure safety and optimal distribution of those funds to address critical bridges first (ASCE report card, 2021). With 42% of bridges being 50 years or older, 7.5% are classified as structurally deficient, and an estimated $125 billion is required for backlog bridge repairs, making it essential to allocate funds effectively. To achieve this, a comprehensive understanding of factors influencing bridge safety is necessary, including structural condition, age, materials used, design, exposure to environmental factors (e.g., corrosion, weathering), vulnerability to natural hazards (e.g., earthquakes, floods), maintenance needs, traffic volume, functional importance, socio-economic impacts, available resources, budget constraints, stakeholder preferences, and decision-making tools. Additionally, accounting for geographical, material, and design effects on bridge deterioration rates is crucial. Various bridge deterioration models were developed in the past to assess bridge performance (Hatami & Morcous, 2011). However new data driven approaches, such as the correlation network

Chetti, P. and Ali, H.
On the Robustness of Correlation Network Models in Predicting the Safety of Bridges.
DOI: 10.5220/0012692800003708

In *Proceedings of the 9th International Conference on Complexity, Future Information Systems and Risk (COMPLEXIS 2024)*, pages 107-113
ISBN: 978-989-758-698-9; ISSN: 2184-5034

models, have recently been developed by researchers to identify the similarities in the bridge deteriorations with respect to various bridge parameters (Chetti & Ali, 2020; Chetti & Ali, 2019; Fuchsberger & Ali, 2017; Chetti et al., 2021).

Correlation network models (CNM) have demonstrated their effectiveness in various domains such as social networks and finance. In the context of social networks, CNM has been used to identify early opinion leaders on platforms like Twitter during the COVID-19 pandemic (Hatami et al., 2021). Similarly, in finance, correlation networks, combined with population analysis, have been employed to analyze the impact of crises on different sectors (Hatami et al., 2023). In recent years, several researchers have leveraged CNM and population analysis to highlight the advantages of using population analysis for identifying enriched parameters and estimating inspection frequencies of bridges within specific clusters parameters (Chetti & Ali, 2020; Chetti & Ali, 2019; Fuchsberger & Ali, 2017). Additionally, it has been emphasized that smart big data pipelines are necessary to tackle the challenges associated with civil infrastructure in the United States (Gandhi et al., 2018). Existing literature indicates that the combination of CNM and population analysis serves as a robust, big data model for visualizing clusters of bridges and their deterioration rates parameters (Chetti & Ali, 2020; Chetti & Ali, 2019; Fuchsberger & Ali, 2017; Chetti et al., 2021).

CNM was introduced by Chetti et al., (Chetti et al., 2021) for analyzing safety and performance factors in civil infrastructures, specifically focused on highway bridges from the United States. The study utilized correlation network models within population analysis to understand the impact of various parameters on bridge safety and deterioration rates. In their study, Chetti et al. proposed a population analysis approach, which involves assessing the performance of an individual element or community/cluster in comparison to a group of peers or communities. The methodology they proposed includes identifying significantly enriched parameters for different bridge communities, as illustrated in Fig. 1. The process consists of three main steps: dataset preparation, population analysis, and validation. Within the population analysis, three specific steps are involved, namely creating a similarity/correlation network, identifying candidate clusters (CCs), and applying enrichment analysis.

Using a Spearman ranking correlation coefficient of at least 0.90, a correlation network was created for the condition ratings data, with bridges as nodes and condition rating relationships as edges. The threshold of correlation coefficient .90 is taken to capture the clusters with bridges that have very high similarity in their deterioration behavior. The Markov clustering (Dongen, 2000) method was used to discern CCs, and an inflation value of 1.9 was chosen for its modularity and average deck condition rating differences. Of the initial 17 clusters, 10, with a median size of 10 or above, were viewed as CCs, constituting 233 out of 268 bridges as shown in Fig.2. Enrichment analysis revealed a significant overrepresentation of input parameters in seven CCs, as shown in Table 1. These clusters were further divided into above-average and below-average groups, each associated with geographical regions, materials used, and factors indicating high traffic usage and maintenance effectiveness. However, a common limitation of CNM for civil infrastructures is its validity. This current study extends the work done in (Chetti et al., 2021) with a validation step, where the validation is done by comparing CNM produced results with a linear regression model and through a robustness analysis.

2 METHODOLOGY

The verification of outcomes from a CNM, using a population analysis strategy, can be undertaken in three distinct ways. Initially, it can be accomplished by scrutinizing existing scholarly works to identify recurring themes or corroborating evidence. The second technique contrasts the findings generated by the CNM against those obtained from a linear regression model by looking for alignment between the two. Finally, implementing a robustness analysis provides a means to assess the consistency and reliability of the results under various conditions or presumptions. This article primarily concentrates on the latter two techniques, as the results were validated using the existing literature about the durability of concrete decks using the study done by Chyad et. al. (Chyad et al., 2018).

2.1 Validation Using Simple Linear Regression Model

Simple linear regression model can also be used to validate the deterioration patterns of the candidate clusters. The dependent variable (Y) is the condition rating, and the independent variable (Age) is the time in years. So, the regression equation is:

$$Y = b0 + b1 * Age \tag{1}$$

Using the extrapolation from the regression equation, one can estimate how a bridge could go to a structural deficiency status (deck condition rating that is <=4 is said to be structurally deficient (ASCE report card, 2021).

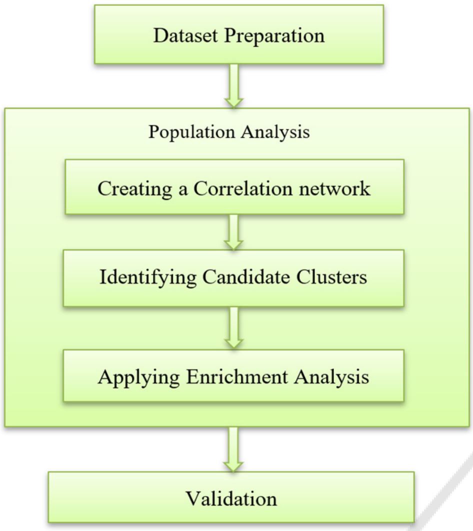

Figure 1: Methodological Steps of Population Analysis with Correlation Network Model.

2.2 Validation Through Robustness Analysis

Robustness analysis tests a model's stability by evaluating its performance under data perturbations or variations (Watts & Strogatz, 1998). It ensures that significantly enriched parameters aren't overly reliant on selected correlation coefficients. The analysis was conducted by randomly selecting a percentage of bridges (90% in this case) to identify the significant input parameters. This robustness underscores CNM's reliability in predicting bridge deterioration and identifying clusters requiring maintenance and repair, irrespective of differing correlation coefficients.

3 RESULTS

This section examines the outcomes obtained from the application of the CNM, and its validation using simple linear regression models, and robustness analysis. These results highlight the capability of CNM in predicting future bridge deterioration and informing effective maintenance planning.

Table 1: Significant parameters of candidate clusters for the Robustness Analysis with 90% bridges selected and with >= .90 correlation.

Parameter	CC pair	End Avg. Condition Rating
Steel * Midwestern	CC24	5.714
HighPlains	CC64	6.333
Prestr'CncrtCont	CC6	6.5
BxBm_GrdrSnglSprd	CC23	6.555
Prestr'CncrtCont * BxBm_GrdrSnglSprd	CC23	6.555
HighPlains	CC23	6.555
Northeast	CC51	6.576
Prestr'Conc * Northeast * ADT_C	CC51	6.576
Prestr'Conc * Southern	CC3	6.933
Southern	CC1	7
Prestr'Conc * Stgr_Ml'bm_Grdr	CC4	7
Prestr'Conc * Southeast	CC4	7
StateTollAuthority	CC4	7
CncrtCont's * Southeast * ADT_D	CC4	7
Prestr'Conc * Southeast * ADT_D	CC4	7
CncrtCont's * Slab * ADT_D	CC4	7
Prestr'Conc * Stgr_Ml'bm_Grdr * ADT_D	CC4	7
Prestr'Conc * Stgr_Ml'bm_Grdr * Southeast	CC4	7
CncrtCont's * Slab * Southeast * ADT_D	CC4	7
Prestr'Conc * Stgr_Ml'bm_Grdr * Southeast * ADT_D	CC4	7

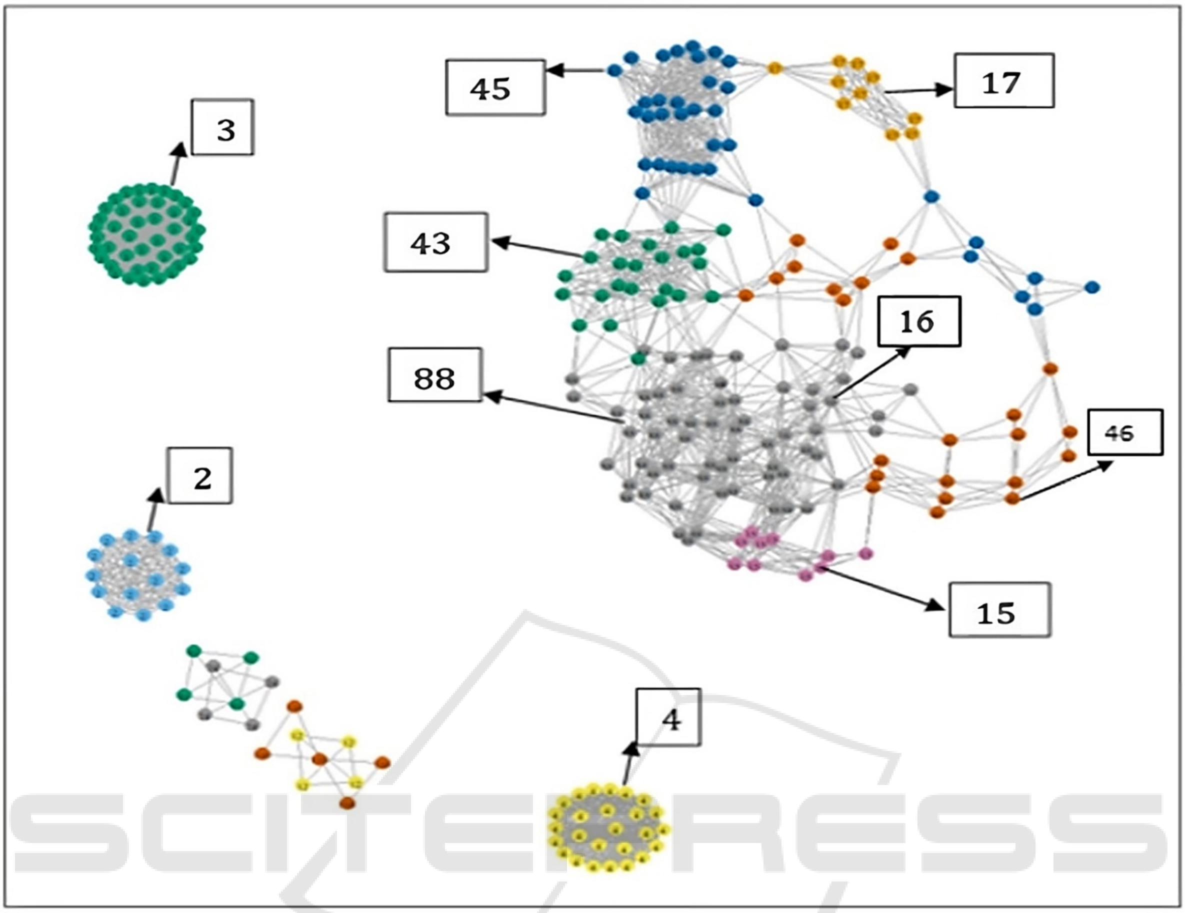

Figure 2: Correlation network of 268 bridges. Clusters with different numbered labels are generated using MCL clustering algorithm (Chetti, 2023).

The regression models for each significant cluster gave specific coefficients and statistical measures that helped understand the lifespan and maintenance requirements of bridge decks within each cluster. As seen in Table 2, the β0 coefficient was the mean response or average deck rating at age zero, indicating the baseline value of the dependent variable before age-related changes. The β1 coefficient denoted the mean response change or average deck rating when age increased by one unit, suggesting the relationship's direction and magnitude between independent and dependent variables. The adjusted R-Square value measured the regression model's strength and predictive power and assessed the model's data fit.

3.1 Validation Using Simple Linear Regression Model

It is worth noting that all bridges in this study started with an initial deck condition rating of 9, with the rating scale being 0-9, and 4 indicating a structurally deficient status. Thus, the study bridges were initially in good shape, deteriorating over time. Fast deteriorating clusters were identified as CC43 and CC88, with CC43 expected to reach structural deficiency within the next 12 years, and CC88 within the next 14 years (as the data started 26 years ago (Chetti et al., 2021). These bridges are classified as high-risk bridges based on their deterioration rate. This data is crucial for prioritizing maintenance and repairs. Other clusters, like CC15, CC45, CC17, CC4, and CC3, displayed negative relationships between age and average deck rating, with varying strength and predictive power. The predicted timelines for these clusters to reach structural deficiency ranged from 49 years to over 100 years. These bridges are classified as low-risk bridges.

Fig. 3 displays the deterioration curves of significant clusters using simple linear regression. It illustrates the relationship between average deck rating and age for each cluster. The x-axis denotes bridge deck age in years, and the y-axis indicates the average deck rating on a 0-9 scale. The figure highlights the swift decline of CC43 and CC88 as their average deck ratings decrease rapidly with the age of the bridge deck. This finding aligns with earlier predictions suggesting that these clusters will likely reach structural deficiency status within the next 12 and 14 years, respectively. Other clusters present a slower decline, demonstrating a more gradual decrease in their average deck ratings.

3.2 Comparing CNM with Linear Regression Model

The CNM results were validated by comparison with linear regression outcomes. The significant input parameters identified by the CNM were found consistent with the significant coefficients of the linear regression models. This consistency underscored the utility of the CNM in predicting bridge deterioration and recognizing clusters needing maintenance and repair.

Both models identified swiftly deteriorating candidate clusters, specifically CC43 and CC88, predicted by the linear regression model to reach structural deficiency within 12 and 14 years, respectively. These clusters were also identified as underperforming by the CNM, signifying their faster deterioration, potentially due to certain enriched input parameters. Additionally, prior literature affirmed that certain geographic regions, like the Midwest, suffer from inferior bridge deck conditions (Chyad et al., 2018), reinforcing the need for specific maintenance and repair interventions. Besides validating CNM usage, the study illuminated several CNM benefits over the linear regression model. These include capturing complex relationships between input parameters and bridge deck deterioration, identifying aberrant performance clusters, pinpointing significantly enriched input parameters in clusters, and informing efficient resource allocation for bridge owners and managers by identifying key clusters and input parameters contributing to deck deterioration. The robust validation of the CNM's use in predicting future bridge deterioration and pinpointing maintenance and repair intervention clusters was further enhanced by its comparison with other models and existing literature.

3.3 Robustness Analysis

Robustness analysis is a technique used to check the stability of a model by evaluating its performance when subjected to perturbations or variations in the data (Watts & Strogatz, 1998). In this study, robustness analysis was performed on the same set of deck condition ratings of bridges by taking 90% of the existing set of bridges with a .90 and above correlation. The resultant candidate clusters, the ones with significant parameters, are shown in Table 1. There are seven candidate clusters with significant parameters, and the comparison of the main dataset (the previous dataset with all the bridges) with the dataset with 90% of the bridges considered for the robustness analysis indicates that both have the same number of candidate clusters and similar significant parameters.

Furthermore, robustness analysis was also performed by checking other correlation coefficients, such as >=.70 and >=.80. with correlation coefficient >=.70. It is observed that there are only two candidate clusters, indicating that the Midwestern region is significantly enriched in the low rating cluster category, while Southern and Southeast bridges are still in the high-performing candidate cluster category.

Table 2: Years to get to structural deficiency status.

Cluster	β0 coefficient	β1 coefficient	Adjusted R-Square	Structural Deficiency Years
CC43	8.962	-0.131	0.899	38
CC88	9.147	-0.13	0.927	40
CC15	9.802	-0.107	0.643	54
CC45	8.63	-0.096	0.654	49
CC17	8.303	-0.071	0.502	61
CC4	7.868	-0.047	0.278	83
CC3	7.597	-0.033	0.181	>100

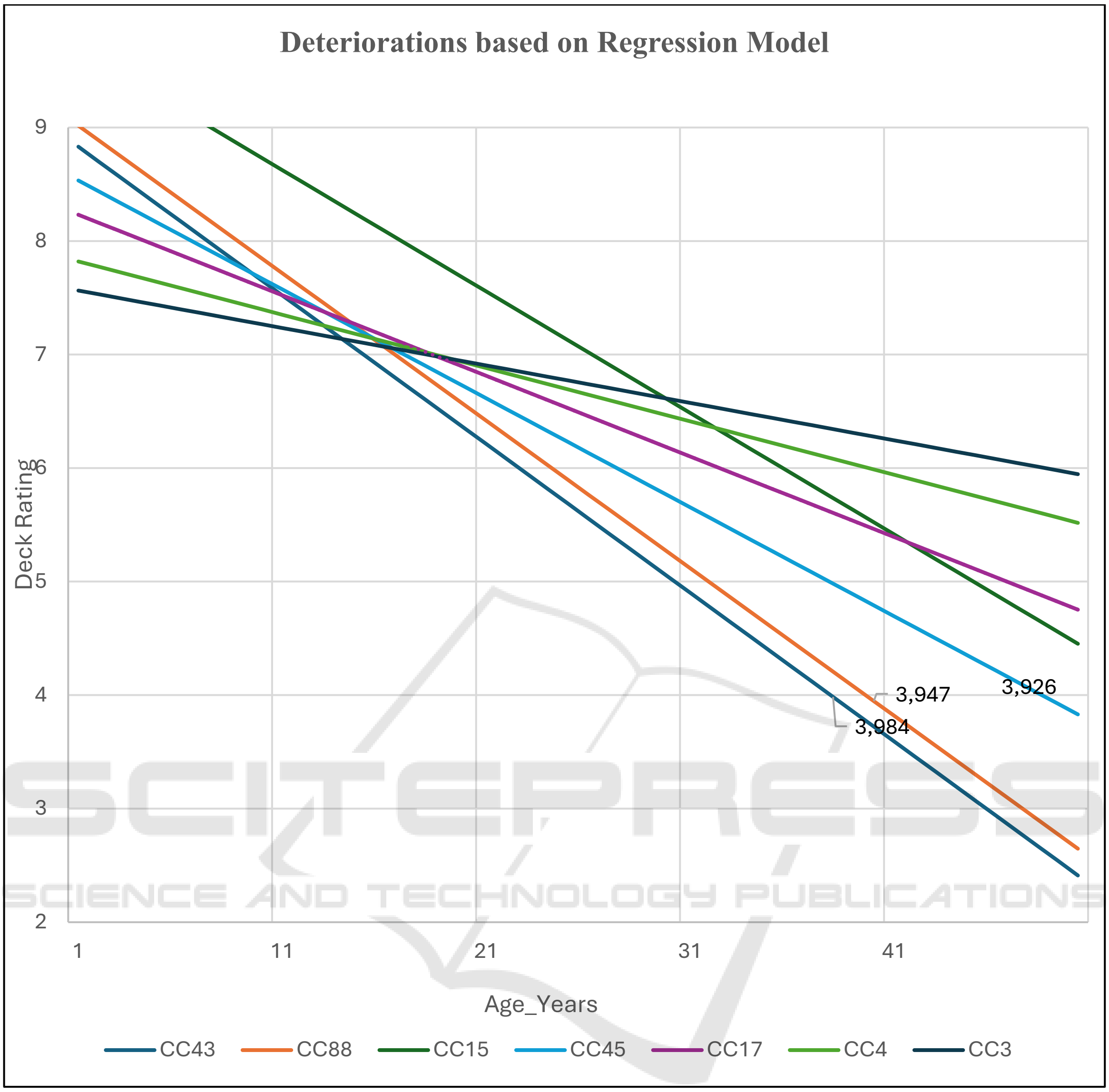

Figure 3: Deterioration curves of the significant clusters using simple linear regression.

Similar results were obtained with correlation coefficient >=.80. The results show that there are four candidate clusters with significant input parameters, with the Steel parameter significantly enriched for the low-performance cluster, such as CC20, while Southern and Southeast bridges (along with other parameters) are still in the high-performing candidate cluster. These results suggest that the CNM is robust and consistent in identifying candidate clusters with significant parameters across different correlation coefficients, and therefore demonstrating its reliability in predicting future deterioration of bridges and identifying clusters in need of maintenance and repair interventions.

4 CONCLUSION

In conclusion, this research validates the effectiveness of the CNM in predicting future deterioration of bridges by using a population analysis approach. Through the comparison with linear regression models and robustness analysis, the study has confirmed the CNM's ability to consistently identify high and low risk bridge clusters with different rates of deterioration. In addition, it has been revealed that the CNM can detect significant parameters influencing bridge deterioration and outperforming simple linear regression models in this regard. Furthermore, the study has demonstrated the CNM's robustness across different conditions and assumptions. These findings have considerable implications for strategic planning and resource allocation in bridge infrastructure management. The ability of the CNM to predict future bridge deterioration, and highlight clusters that require maintenance and repair interventions, could potentially enhance the efficiency of these operations and extend the service life of the bridges. This study has thus underscored the value of the CNM as an innovative tool for bridge infrastructure management, deserving further exploration and application in this field.

REFERENCES

ASCE report card on US bridges. https://www.infrastructurereportcard.org/wp-content/uploads/2021/01/Bridges-Final.pdf (2023, August 15).

Chetti, P., & Ali, H. (2020). Estimating the inspection frequencies of civil infrastructures using correlation networks and population analysis. International Journal on Advances in Intelligent Systems, 13(1&2), 151-162.

Chetti, P. (2023). Analyzing Structural Health of US Bridges Using Correlation Networks and Population Analysis (Doctoral dissertation, University of Nebraska at Omaha).

Hatami, Z., Hall, M., & Thorne, N. (2021). Identifying early opinion leaders on covid-19 on twitter. In HCI International 2021-Late Breaking Papers: Design and User Experience: 23rd HCI International Conference, HCII 2021, Virtual Event, July 24–29, 2021, Proceedings 23 (pp. 280-297). Springer International Publishing.

Hatami, Z., Chetti, P., Ali, H., & Volkman, D. (2024). A novel population analysis approach for analyzing financial markets under crisis-a focus on excess returns of the US stocks under 9/11 and COVID-19. Applied Economics, 56(9), 1063-1076.

Chetti, P., & Ali, H. (2019). Analyzing the structural health of civil infrastructures using correlation networks and population analysis. In Proceedings of the Eighth International Conference on Data Analytics, Porto, Portugal.

Federal Highway Administration. (2023, August 15). https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm

Federal Highway Administration. (2023, August 15). https://www.fhwa.dot.gov/bridge/mtguide.pdf

Hatami, A., & Morcous, G. (2011). Developing deterioration models for Nebraska bridges (No. SPR-P1 (11) M302). Nebraska Transportation Center.

Dongen, S. (2000). A cluster algorithm for graphs. CWI (Centre for Mathematics and Computer Science).

Fuchsberger, A., & Ali, H. (2017). A correlation network model for structural health monitoring and analyzing safety issues in civil infrastructures.

Chetti, P., Ali, H., Gandhi, R., Ricks, B., Ghersi, D., & Najjar, L. (2021). A new approach for analyzing safety and performance factors in civil infrastructures using correlation networks and population analysis. Will be Coming in the Proceedings of the 13th IWSHM.

Chyad, A. M., Abudayyeh, O., Zakhil, F., & Hakimi, O. (2018, May). Deterioration rates of concrete bridge decks in several climatic regions. In 2018 IEEE International Conference on Electro/Information Technology (EIT) (pp. 0065-0068). IEEE.

Gandhi, R. A., Khazanchi, D., Linzell, D., Ricks, B., & Sim, C. (2018, May). The hidden crisis: Developing smart big data pipelines to address grand challenges of bridge infrastructure health in the United States. In Proceedings of the... International ISCRAM Conference.

Watts, D. J., & Strogatz S. H. (1998). Collective dynamics of ‘small world’ networks. Nature, 393(6684), 440-442.