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AI/ML-assisted Analysis of the IABSE Bridge Collapse Database

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ABSTRACT: Former statistical analyses of bridge collapse data show that concrete bridges collapse significantly less frequently than bridges made of steel or wood. Since the main causes of bridge collapses worldwide are floods and associated fluvial processes, such as scouring, debris flows, etc. and impacts, it is reasonable to assume that the high dead load of concrete bridges leads to an overall more robust behavior in these events. This paper will examine whether the IABSE collapse database confirms this hypothesis and whether indications of further causes can be identified. For this purpose, the IABSE collapse database is examined using artificial intelligence and machine learning (AI/ML) methods. However, the AI/ML analysis does not confirm the previous thesis. Possible reasons for the rejection of the thesis, such as the representativeness of the data, are also discussed. An extension of the database for events with large numbers of collapses is recommended.

1. INTRODUCTION

Modern construction standards ensure sufficient safety of bridges based on probabilistic approaches. A check of this approaches can be done by evaluating collapses.

In Proske (2018) several databases on bridge collapses were listed. Statistical evaluations of such databases can be found e.g., in Wardhana & Hadripriono (2003), Cook (2004), Lee et al. (2013), Taricska (2014), Zhang et al. (2022). The statistical evaluation showed clear differences in the collapse frequency depending on the construction material (Table 1).

The interpretation of this result leads to the thesis that concrete bridges are more robust against floods and impacts due to their high dead weight. Floods are the main cause of bridge collapses (Proske 2018). The thesis of robustness in floods will be tested with the present IABSE database and by means of artificial intelligence (AI) and machine learning (ML).

2. DATABASE

In this paper, the IABSE database of bridge collapses will be used. This database was created within Task group 1.5 of the International Association of Bridge and Structural Engineering (IABSE). The database used contains data on 834 bridge collapses from 1966 to 2020. For each bridge collapse, the database records up to 48 parameters, although not all information is available for each bridge. Parameters include span width, year of construction, country in which the bridge is located, date of collapse, or construction material.

Table 1 allows a comparison of the number of collapses based on the IABSE database and other references. The collapse ratios of bridges are related to the inventory of bridges and normalized to the ratio of concrete bridges. Bridge ratios are based on U.S. as-built data, with the number for masonry bridges adjusted to European conditions.

The composite bridges show lower collapse frequencies in both the IABSE database and

Taricska (2014). However, these bridges are reported separately in Taricska (2014), while they are mixed with steel bridges in the IABSE database.

Table 1: Normalized number of bridge collapses; related to concrete bridges and to the number of bridges with a specific construction material in several databases, I: IABSE, T: Taricska, L: Lee et al.; W. & H.: Wardhana & Hadrpriono

Material	*I.*	*T. (2014)*	*L. (2013)*	*W. & H. (2003)*
Masonry	*0.78*	*6.80*	*1.74*	*2.43*
Concrete	*1.00*	*1.00*	*1.00*	*1.00*
Steel, Composite	*1.50*	*5.67*	*5.15*	*9.93*
Wood	*5.40*	*6.67*	*7.59*	*14.9*

3. APPLIED METHODS

The application of artificial intelligence (AI) or machine learning (ML) to the IABSE database promises to identify new relationships and confirming or falsifying the above-mentioned thesis.

First, both implicit and explicit feature engineering was performed. Feature engineering is generally understood as the selection and preparation of raw data into features or parameters that can be used for supervised learning in AI/ML procedures.

Furthermore, the data was checked for erroneous or incomplete information. For example, for some bridges the exact date of collapse is available, for others only the year of collapse, for some bridges the main cause responsible for the collapse is given, for others not.

As mentioned above, flooding, or fluvial processes are the main cause of bridge collapses. Therefore, an additional variable for failure due to flooding was introduced. This was chosen as the target value. Since the proportion of collapses due to flooding is lower in the IABSE database than in other databases or publications, the SMOTE procedure for “Imbalanced Data” was applied. In the SMOTE (Synthetic Minority Oversampling Technique) procedure, collapses due to flooding were synthetically expanded.

The testing and processing involved a considerable amount of time for the present database. Overall, this step dominated the total amount of work time.

Subsequently, the dataset was divided into a part for training the AI/ML and a part for checking the quality of the AI/ML model: 80% of the data was used for training and 20% of the data for quality checking. The data were sampled using Statified k fold Cross Validation Method.

For the evaluation of such datasets, several bindings of AI/ML tools to higher level computer languages are available today, e.g., the Python library Keras, PyCaret or Imbalanced Learn can be used. Therefore, a large number of AI/ML procedures has been applied in this investigation, such as K Neighbors Classifier, Decision Tree Classifier, Support Vector Machine, Gaussian Process Classifier, Multi-Layer Perceptron Classifier, Ridge Classifier, Random Forest Classifier, Quadratic Discriminant Analysis, Ada Boost Classifier, and others. Classification was used because the target value flood is binary.

The AI/ML methods Random Forests Classifier and Extra Tree Classifier proved to be particularly successful in the study. Both methods are based on decision trees.

For the evaluation of the prediction capability of the AI/ML methods, various procedures are available and were used, such as the Confusion Matrix with sensitivity, specificity, precision and accuracy, the area under the receiver operating characteristic (ROC) curve, recall and negative prediction value.

4. RESULTS AND INTERPETATION

First, the correlation matrix was investigated. This is necessary to check whether the AI/ML can and should be used meaningfully at all. If different factors show a high positive or negative correlation value, then a unifactorial statistical correlation is present, which must be checked for causality in the following. The use of AI/ML is more suitable for highly multi-factorial correlations.

The correlation matrix already showed the impact of data quality on the analysis. There is a strong negative correlation between the "start of construction" or the "year of commissioning of the bridge" and the "age of the component responsible for the collapse". In fact, for 85 % of all collapses, no value was available for the age of the structural element, and when values were available, they often referred to the failure of falsework. Presumably, the age of the falsework was then used, which leads to the negative correlation. In this respect, therefore, the interpretation of this correlation matrix already requires background information on the data. The large positive correlation between "traffic volume" and "roadway width" or "number of lanes" seems reasonable. The collapse cause "flood" showed only low correlations with the other parameters listed. This observation forms the basis for the analysis using AI/ML.

The IABSE database has already been investigated by means of ANOVE in Hingorani et al. (2022) related to different models for the estimation of casualty numbers of bridge collapses. Thus, the correlation for the number of persons on a bridge at collapse and the span or bridge area was compared. The correlation values in Hingorani et al. (2022) ranged from 0.12 to 0.22. Using the current IABSE-database, a correlation between casualty numbers and span length of 0.10 is computed which seems plausible.

An initial test of the AI/ML model is performed using the Confusion Matrix. This matrix shows the frequency in which the model was correct as well as the false-positive and false-negative predictions. The matrix shows that in 82 % of the collapses, the AI/ML correctly predicted that the collapse was not caused by flooding (specificity). In 1 % of the cases, the AI/ML incorrectly predicted that the collapse was caused by flooding. In 7 % of the cases, the AI/ML predicted a collapse due to flooding, which had other causes. In about 10 % of the cases, the AI/ML correctly predicted a collapse due to flooding (sensitivity). Especially the second row of the Confusion Matrix shows the high uncertainty of the results. In approx. 50 % of the cases the AI/ML was correct, in about 50 % of the cases the AI/ML was wrong!

In Naser (2021) an AI analysis of a bridge collapse and damage database with 299 datasets was presented. The AI methods Deep Learning, Decision Trees, Genetic Algorithms and Genetic Programming were used. As a result, similar error values were obtained for Deep Learning and Decision Trees as in the present case (40 % to 60 %).

In the next step, the weighting of the individual input variables for the two methods, Extra Tree and Random Forest are discussed.

The variable "Crucial Human Error, Force Majeure, Inspection Testing Error during Operation" is named as the most important input variable for both methods. However, design errors should then also occur. Unfortunately, these are underrepresented in the IABSE database compared to other studies on human errors in the design and construction process. A detailed interpretation of the error proportions in the IABSE database can be found in Galvao et al. (2021). "Foundation failure" is recognized as the second most important input variable in extra trees. In connection with the importance of scouring, this finding confirms the thesis stated.

The second parameter in the random forest models is the "year of construction". This could be an indication for more stringent design requirements regarding floods for bridges. However, other studies show the independence of collapses due to flooding from age (Montalvo and Cook 2017). The third parameter, the "number of injured persons", is also understandable. In Hingorani et al. (2022), it was shown that, on the one hand, the number of fatalities in bridge collapses due to flooding is low because the bridges are usually closed during such events. However, it was also shown that the probability of survival when people are present during flood-induced bridge collapse is practically zero. Neither relationship was directly evident in the correlation matrix.

5. PLAUSIBILITY CONSIDERATION

The importance of “Crucial Human Error, Force Majeure, Inspection Testing Error during Operation” as the most important input variable for bridge collapses during floods for both ML methods does not seem plausible. According to Johnson (2012), Cheng et al. (2019), the condition of bridges has little influence on the resistance of bridges to natural hazards, such as floods or fluvial processes. For earthquakes there are studies which indicate a relationship between bridge conditions and seismic fragility (Zanini et al. 2013).

Inspection failures appear 96 times as an indirect cause of collapse in the IABSE database and are thus likely overrepresented for the overall bridge collapse population. The weightings allow for several interpretations:

1. Correlations between inspection and bridge condition and flooding occur only at extreme values; a so-called tail dependency may exist. Therefore, the correlation was not recognized, e.g., in Johnson (2012), because mainly damages and not collapses formed the data basis.
2. The parameter of inspection failures is an unspecific parameter. The data quality, sensitivity, and specificity of this parameter are not sufficient for the investigation carried out.

Only a small proportion (about 20 %) of bridge collapses in the IABSE database relate to floods and fluvial processes, although flood data was mathematically extended. In fact, however, floods are the main cause of bridge collapses, as confirmed by an overwhelming number of publications (Proske 2018, 2022). A proportion of 50 % of all collapses is often cited.

Without citing the references in detail, Table 2 lists several natural events with numerous bridge collapses and damages per event as evidence. Overall, Table 2 lists approximately 10,000 bridges damaged or destroyed. The specific bridge details of such major events are rarely or never found in bridge collapse databases.

The destruction of a large number of bridges during singular flood events is not a peculiarity of the last decades as shown in Table 2. In Switzerland and Austria, flood events that destroyed dozens of bridges can be traced back over centuries. In Graubünden for example, floods in the years 1570, 1772, 1834, 1839, 1868, 1871, 1910, 1927, 1951 destroyed in total hundreds of bridges (Weidmann 2018).

Table 2: Large scale natural events with heavy bridge losses (grey: flood)

Year	*Country*	*Description of Bridge damages and losses*	*Cause*
1947	*USA*	*Heavy Losses*	*Flood*
1952	*U.K.*	*28 destroyed or damaged*	*Flood*
1964-1972	*USA*	*383 destroyed or damaged*	*Flood*
1970	*East-Pakistan*	*924 destroyed or damaged*	*Typhoon and Flood*
1976	*Japan*	*233 destroyed or damaged*	*Typhoon and Flood*
1985	*USA*	*73 destroyed*	*Flood*
1987	*USA*	*17 destroyed*	*Flood*
1989	*USA*	*< 10 destroyed or severely damaged*	*Earthquake*
1993	*USA*	*110 destroyed; 2,400 damaged*	*Flood*
1994	*USA*	*170 on highway destroyed or damaged*	*Earthquake*
1995	*Japan*	*27 with severe damages and partial collapses, 60 % in the area with small/median damages*	*Earthquake*
1998	*Bangladesh*	*400 damaged*	*Flood*
1998	*Central America*	*up to 92 on main routes and at least 200*	*Hurricane Mitch*

		small in Honduras destroyed, 126 in Costa Rica damaged, 300 in Peru severely damaged	*und Flood*
2000	*Zimbabwe*	*26 destroyed or severely damaged, furthermore in Mozambique, Botswana und South Africa damaged*	*Zyklon Eline, Flood*
2002	*Saxony*	*> 15 destroyed, > 450 damaged*	*Flood*
2004	*Indonesia, Southeast Asia*	*Destruction of many in coastal areas, hundreds washed away, many in Banda Aceh destroyed, 70 to 100 in North Sumatra destroyed*	*Tsunami*
2005	*USA*	*70 destroyed*	*Storm Katrina/ Flood*
2008	*China*	*Large number destroyed (landslides), 4,840 damaged*	*Earthquake*
2009	*U.K.*	*7 destroyed; 72 damaged*	*Flood*
2009	*Taiwan*	*> 20 destroyed; 200 on highway damaged*	*Typhoon Morakot/ Flood*
2010	*Chile*	*30 closed, severe damages on 19, slight damages on about 100*	*Earthquake*
2010-2011	*Australia Queensland*	*89 severely damaged*	*Flood*

2011	*USA*	*326 to 389. damaged, 40 destroyed,*	*Flood*
2011	*Japan*	*> 300 destroyed, approx. 3,200 hit by wave*	*Earthquake und Tsunami*
2012	*Afghanistan*	*400 destroyed*	*Flood*
2013	*USA, Colorado*	*40 on highway destroyed, further 20 damaged*	*Flood*
2013	*India, Uttarakhand*	*21 destroyed*	*Flood*
2014-2019	*Papua-New Guinea*	*285 destroyed or damaged*	*Flood*
2015	*U.K.*	*131 to 244 destroyed or damaged*	*Flood*
2016	*Japan*	*128 damaged*	*Flood*
2016	*Neu Zeeland*	*904 affected; 2 severely damaged*	*Earthquake*
2017	*Peru*	*>100 destroyed*	*Flood*
2017	*Nigeria*	*> 10 destroyed*	*Flood*
2018	*Turkey*	*12 destroyed*	*Flood*
2019	*Iran*	*84 destroyed*	*Flood*
2019	*Zimbabwe*	*9 accesses and 4 on main roads washed away, on local tracks approx. 100 damaged or destroyed*	*Cyclone Idai und Flood*
2019	*Japan*	*one on railway collapsed, scour on several, at least 8 collapsed*	*Typhoon Hagibis/ Flood*
2020	*Japan*	*10 on roadway and 3 on railway destroyed*	*Flood*

2020	*Greece*	*Unknown number destroyed, at least 15 damaged*	*Tornado/ Flood*
2021	*U.K.*	*2 destroyed*	*Flood*
2021	*Germany*	*62 destroyed, 13 severely damaged*	*Flood*

It is true that cases of bridge collapses with the same date can be found in the IABSE database. However, sometimes the collapses occur on the same date but in different countries on different continents. Nevertheless, the database contains seven bridge collapses on November 20, 2009, in the United Kingdom, two bridge collapses on April 27, 2015, in Russia, and five bridge collapses on November 22, 2019, in Kenya, with all bridge collapses caused by floods. The events in Russia and Kenya are not part of Table 2, showing that the table is also not complete. However, the data in the IABSE database include only a fraction of the approximately 10,000 damaged or collapsed bridges mentioned.

This underreporting is partly due to the collection of data based on daily media, but also due to different ownerships of the bridges and the related problems in collecting the data by third parties. Only in a few cases, such as the 1970 typhoon in East Pakistan, does the World Bank have concrete damage figures for individual bridges.

Assuming that the 10,000 bridges damaged or collapsed over a period of 50 years, approximately 200 bridges worldwide are destroyed or severely damaged by earthquakes and floods each year. Using the estimate that floods causing about 50 % of all collapses, these 200 bridge collapses result in approx. 400 bridge collapses per year worldwide.

Sasidharan et al. (2022) cite 6,000 bridge collapses in the U.S. due to scouring for a period of about 150 years. This results in about 40 collapses per year in the U.S. alone. Assuming that the U.S. contains about 15 % of the world's bridge inventory and that the ratios are comparable worldwide, the result is approx. 270 collapses per year worldwide due to scouring. According to the meta-analysis of collapses and the graphical representation in Proske (2018), the proportion of collapses due to scouring is about 20 %. Applying the factor of 20 % to the 270 annual collapses, one arrives at up to 1,350 bridge collapses per year.

Ashraf et al. (2022) estimates annual bridge collapses in the U.S. due to scouring of between 20 and 100. Using the same assumptions as in the previous paragraph, this would yield worldwide annual bridge collapses between 667 and 3,333.

According to the German Federal Statistical Office (Destatis 2022), an average of 406 natural catastrophes occurred worldwide per year between 2000 and 2020. Most of these natural disasters were floods, which accounted for the largest share of 36.6 percent. This results in approximately 160 floods per year worldwide. If we assume that on average 2 to 4 bridges are destroyed per flood, this results in 320 to 640 bridges collapses. Floods account for half of all bridge collapses, thus yielding 620 to 1,280 collapses.

Neither the IABSE databases nor Table 2 reflect these numbers. Therefore, factors for underreporting of bridge collapses are introduced in various publications (Vogel et al. 2009). Taking such a factor into account, gives a collapse frequency of 2×10^{-5} per year per bridge with respect to Switzerland. This corresponds to about one bridge collapse every three years in Switzerland.

Spector & Gifford (1986) state that at least 100 small old bridges collapse per year. Assuming this statement refers to the U.S. and that about 15 % of the world's bridge inventory is located in the U.S., this results in 667 bridge collapses worldwide per year. Such local collapses on minor roads also occur in Europe. Considering, for example, the collapses due to regional debris flows or flash floods, such as in Carinthia and Tyrol, Austria, in 2022, with more than 4 bridge collapses, and in Grugnay and Val Stabelchod in 2018 and Bondo in 2017, Switzerland, with together more than 6 bridge collapses, this probably results in more than one collapse per year on average also for Switzerland.

Thus, correcting the figure of 2×10^{-5} per year per bridge with these collapses of small bridges results in a collapse frequency of 1 to 2×10^{-4} per year worldwide (Proske 2018, 2022). Applying this to the worldwide inventory of 5 million bridges yields between 500 and 1,000 bridge collapses per year. This agrees remarkably well with the previous values and with the value of 1.2×10^{-4} per year per bridge in Proske (2018, 2022). Even the best databases with more than 1,000 collapses over several decades thus cover only a fraction of all collapses. Therefore, the authors suggest linking databases of individual bridge collapses with data from events with many collapses.

For bridge collapses in municipal areas or small bridges, the question is whether these structures still fall under the definition of bridges or are already considered culverts. In the latter case, the sample size would change. However, even then the denominator still contains a significantly lower uncertainty than the numerator.

6. CONCLUSION

Various databases on bridge collapses exist worldwide. Evaluations of these databases allow conclusions to be drawn about the causes of bridge collapses. Possible causes can be related to different loads or different resistance properties, e.g., the bridge material.

In the context of this paper, the thesis was discussed whether a significant difference of the collapse frequency of bridges exists depending on the building material, especially for concrete bridges. This thesis resulted, for example, from the statistical analysis of the data of Lee et al. (2013), Wardhana & Hadipriono (2003), Taricska (2014). With the data of the IABSE database this thesis could not be confirmed directly - except for bridges made of wood. There are several possible reasons for this, such as:

- The thesis is wrong because the data in the databases of Lee et al. (2013), Wardhana & Hadipriono (2003), Taricska (2014) are incomplete or not representative.
- The thesis is correct, but the data in the IABSE database are incomplete or not representative.
- The thesis is correct, but the methods used are inappropriate.

Whether the three databases Lee et al. (2013), Wardhana & Hadipriono (2003), Taricska (2014) statistically confirm the thesis independently cannot be determined beyond doubt, because the databases are probably not independent. Nevertheless, the data will not correlate completely, so that the three databases allow a stronger support of the thesis. As explained, the data in all databases, including the IABSE database, are also unlikely to be representative. For this reason, local databases, such as Cook (2004) are probably better able to provide evidence for the hypothesized relationship. The method itself should be able to identify correlations. This was also tested on a second database which is not part of this paper.

For the future, the goal must be to link the databases of individual bridge collapses (meso level) with the statistics of large-scale bridge losses (macro level), e.g., the IABSE database with the data from Table 2. The question here will be how to collect the relevant information. One possibility would be to ask the cost centers for reconstruction, e.g., state budget, municipal budget, or parliamentary inquiries.

Furthermore, more detailed data may be required which is not directly related to the bridges, such as flow velocity, flow depth, distance between abutments and the water, slope etc. Such parameters are already used in bridge risk assessments (Pregnolato 2019, Kattell & Eriksson 1998) and may be available.

Whether the higher dead load is the actual cause for the apparently significantly lower collapse frequency of concrete bridges could not be shown with the procedure. It would also be conceivable, for example, that concrete bridges are on average younger than steel, timber or stone bridges and were thus designed according to more modern standards with higher actions. However, Montalvo and Cook (2017) have shown that bridge collapses due to flooding are relatively independent of bridge age. This is true even with the observed decreasing number of bridge collapses.

Thus, further studies are needed. The paper shows that the successful application of AI/ML methods is limited by data quality.

Other publications, such as Pregnolato (2019), Kattell & Eriksson (1998), mention other highly specific variables for determining the vulnerability of bridges to flooding and scour, such as flow velocity, distance of river to abutment.

This means that the databases must be expanded not only in terms of the scope of bridge collapses, but also in terms of the scope of the hydraulic variables. For such extremely extensive databases, evaluation by AI/ML would be virtually predestined.

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