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Application of machine learning in bridge engineering: A state-of-the-art review

M.R. Karim
Military Institute of Science and Technology, Dhaka 1216, Bangladesh

K. Islam
Polytechnique Montreal, Montreal, QC, Canada

K.S. Ahmed
Military Institute of Science and Technology, Dhaka 1216, Bangladesh

Q. Zhang & M.S. Alam
The University of British Columbia, Kelowna, BC, Canada

ABSTRACT: At present, with the prospect of being able to access a large database of information, the bridge engineering industry has begun to explore the potential of applying artificial intelligence and machine learning in diverse fields, as machine learning is capable of handling complex problems with high computational efficiency and assisting with decision making for stakeholders. To date, reported works on the use of artificial intelligence and machine learning in bridge engineering have focused on preliminary design, classification, safety, structural health monitoring, and maintenance, with areas such as bridge deterioration model and load-capacity rating system having yet to be addressed. The present study offers a comprehensive review of the developments and challenges with respect to the application of machine learning in bridge engineering. First, an overview of the commonly used machine learning algorithms is provided. Then, the application of machine learning to the design, construction, operation, monitoring, and maintenance of bridge systems is discussed. Finally, the extent of machine learning applications in the load rating, damage detection, decision making, and replacement tasks involved in the lifecycle of bridges is summarized.

1 INTRODUCTION

In machine learning (ML), understood as a subset of artificial intelligence (AI), machines attain the ability, through computer algorithms and data science, to learn without being explicitly programmed, and to improve automatically through experience(Samuel 1959). Figure 1 illustrates the field of ML within the domain of AI, and also depicts deep learning(DL), which is considered a subset of ML. Over the last several decades, ML has played a crucial role in various sectors of engineering, business, and communication. Numerous studies have been carried out on the application of ML tools in different disciples of civil engineering. Initially, ML in civil engineering focused on simple problems such as the testing of various existing tools (Arciszewski et al. 1987, Stone et al. 1989, Ghaboussi et al. 1991). It then came to be applied to more difficult and complex practical problems (Borner et al. 1995, Hani 1996) and, more recently, has been explored as a promising solution to multifarious applied engineering problems (Zhang et al. 2019, Xie et al. 2020),such as structural system identification, design optimization, construction engineering, environment and geotechnical engineering, vibration control, and health monitoring (Amezquita-Sanchez et al. 2016).

Various ML techniques and methods pertaining to bridge engineering in particular have also been developed in recent decades. Bridge classification (Jootoo et al. 2017), construction control and monitoring (Feng et al. 2011), bridge health prediction, monitoring and condition evaluation (Peng et al. 2017), bridge deformation application, abnormality detection, bridge structural damage identification (Neves et al. 2018, Gonzalez et al. 2015), and damage classification (Malekjafarian et al. 2019), are just some of the recent examples of applications within this domain. To date, various ML methods have been used in different areas of bridge engineering. Artificial neural networks (ANNs), for instance, have been successfully implemented to many bridge related problems (Wei et al. 2011, Xie et al. 2020). Structural health monitoring and deterioration of various bridge components, meanwhile, have been successfully assessed by the application of support vector machine (SVM) (Bao et al. 2013).Decision tree (DT) mainly has been used for bridge classification, design, functionality, and assessment (Sabarethinam et al. 2020).In the case of seismic applications in bridge design, control, and damage estimation, load capacity rating use of random forest (RF) or hybrid method (Jia et al. 2020) has been seen. Other notable ML methods, such as response surface model (RSM), logistic regression (LR), Naive Bayes, K-nearest neighbor (KNN), and K-Mean have been less common in bridge engineering, other than in applications involving independent component materials.

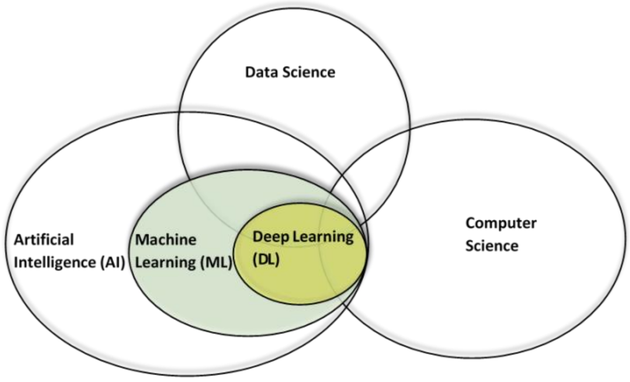


Figure 1. Venn diagram displaying components of AI (Good fellow et al. 2016).

Although, as mentioned, some studies have been conducted on the application of ML in bridge engineering, a detailed review of the literature is not yet available. However, it is clear to what extent the concept of ML has utilized in the domain of bridge engineering or helping engineers/owners to apply ML techniques in the design, construction, operation, monitoring, maintenance, and replacement of bridges. Therefore, a comprehensive review is needed in order to further study the following questions:

– What are the ML algorithms that have been most widely adopted in bridge engineering?
– What are the aspects of bridge engineering that have most commonly been the subject of ML applications to date, and what is the potential of other areas for application of ML algorithms?
– What trends can be identified with respect to the scope of future research in the bridge engineering field?

The main objective of this paper is thus to provide a comprehensive and structured state-of-the-art review of the scientific literature on the application of ML in bridge engineering in order to address the above research questions. This review will aid researchers, practicing engineers, and decision-makers in understanding the progress to date and future prospects of ML applications in bridge engineering.

2 METHODOLOGY

The process of literature retrieval followed in this article has been illustrated in Figure 2. It shows the method used to identify relevant literature which are publicly available, especially by e-access. Titles and, or keywords having ML in bridge engineering sector were used to identify the research articles in prominent academic databases, namely ASCE library, Web of Science, Google Scholar, Scopus, and Engineering Village. Few other keywords have also been searched relevant to the background study of the paper. Searching parameters and key words are displayed in Table 1. More than 100 relevant could be sorted out finally for grouping and referencing the paper. The sequence of this paper includes the commonly used ML algorithm in bridge engineering, state-of-the-art research conducted so far in bridge engineering, and its potential future scope. Table 2 provides a summary of various topics where ML applications have been implemented in the context of bridge engineering.

Table 1. List of searched key words.

No	Focus	List of searched keywords	Connectors
1	Background and overall engagement of ML in bridge engineering	Machine learning, bridge, bridge engineering, civil engineering, structural engineering, earthquake, bridge performance	and, or, review, impact, use, model, assessment, application, state of the art, trend
2	ML and its application in various components of bridge and sectors of bridge engineering	Machine learning, deck, bridge, pier, railway bridge, bridge classification, design, health monitoring, damage evaluation, failure mode prediction, load capacity rating	
3	ML Methods applied in bridge engineering	ANN, Back propagation, SVP, DT, RF, LR, RSM, KNN, naïve Bayes bridge, bridge engineering	

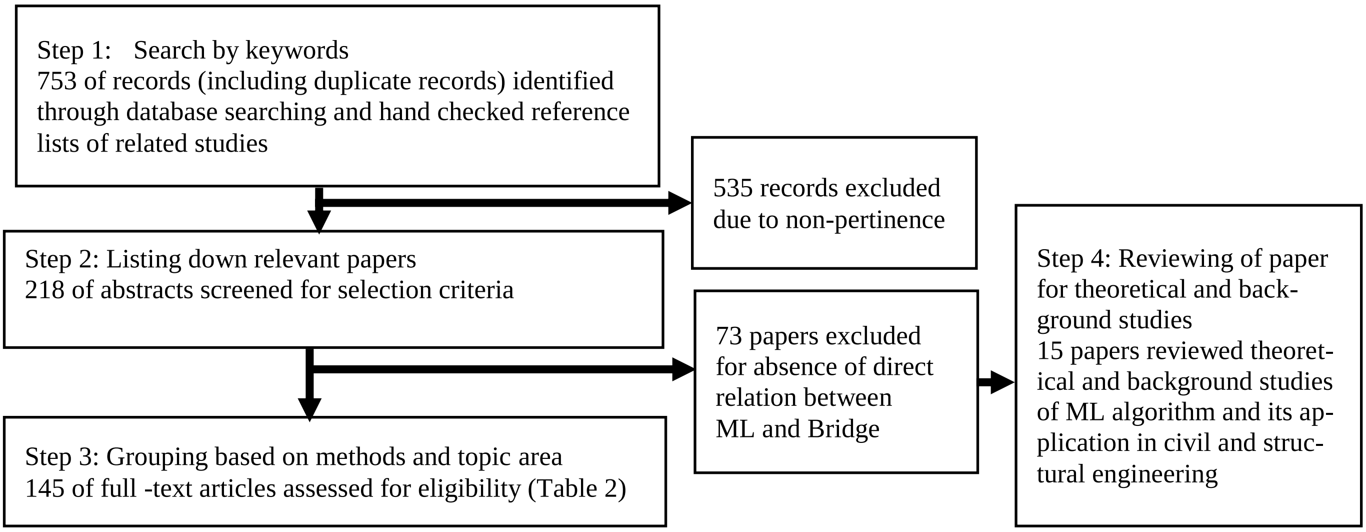


Figure 2. Literature retrieval process (Ganbatet al. 2018).

Table 2. List of research articles on various topic area of bridge engineering.

Topic area	ML methods				
	ANN	SVM	DT and RF	Hybrid	Other
Bridge design and classification	12	4	5	3	2
Construction monitoring	7	3	8	2	4
Structural health monitoring, prediction, evaluation	12	9	2	4	3
Abnormality, deterioration, damage detection	11	4	5	2	0
Failure mode prediction	6	7	6	1	1
Load capacity evaluation	7	4	5	3	3

3 ML METHODS USED IN BRIDGE ENGINEERING

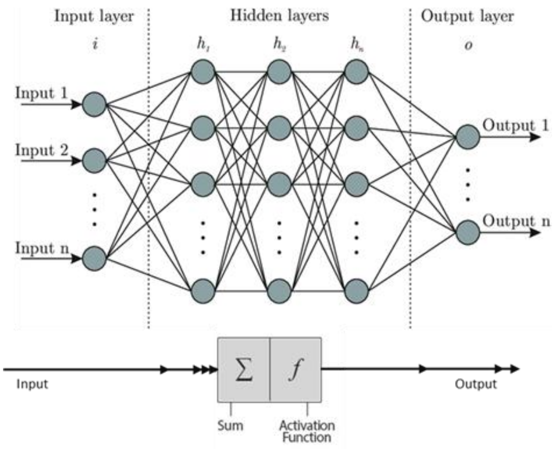
To date different ML schemes have been used for various bridge engineering applications; such as design and component level analysis (Hong et al. 2002, Sirca&Adeli2004, Rizzo et al. 2020), detection and structural health monitoring (Gordan et al. 2020) and a wide range of studies applicable for bridge engineering design input (Malik et al. 2020). A short overview of these methods is presented below.

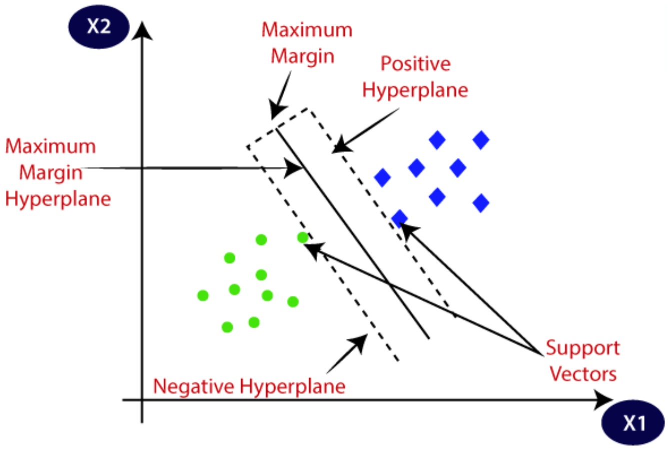
3.1 *Artificial Neural Network (ANN)*

ANNs are inspired by the interconnected biologic neural structure of the human nervous system and brain for learning-analyzing (Aleksander & Morton 1993, Arbib 1995, Anderson 1995, Wang et al. 2014, Deng et al. 2014). A simplified ANN is composed of an input layer, several hidden layer, and an output layer as shown in Figure 4 (a). The functionality of an ANN thus varies with its topology consisting of its weighting systems and the activation functions ANNs are used to solve complicated pattern recognition and classification problems in numerous applications. Commonly used ANN models include: Feed forward neural network, Recurrent Neural Network (RNN), Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), and Radial Basis Function Neural Network (RBFNN). There also exist some hybrid ML methods combining ANN with other algorithms, such as fuzzy logic, adaptive neuro-fuzzy inference system, probabilistic and wavelet analysis.

3.2 *Support Vector Machine (SVM)*

SVM algorithms were developed by Boser, Guyon and Vapnik (Boser et al. 1992), and then generalized for a non-linear state in 1995 by Corinna Cortes and Vapnik (Mirmohammadi et al. 2014, Vapnik1999, 2000). SVM became popular choice for classification, regression, and outliers detection particularly for high-dimensional and non-linear problems in bridge engineering. The SVM algorithm (see Figure 4(b)) separates the classes using a hyper-plane and the margin of this hyper-planeis at a maximum distance from the labeled classes where the margin is calculated as the sum of the distances of the hyper-plane from the nearest point of the labeled classes.

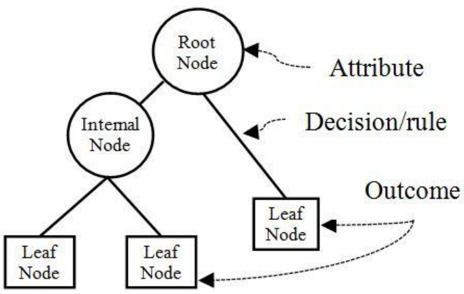


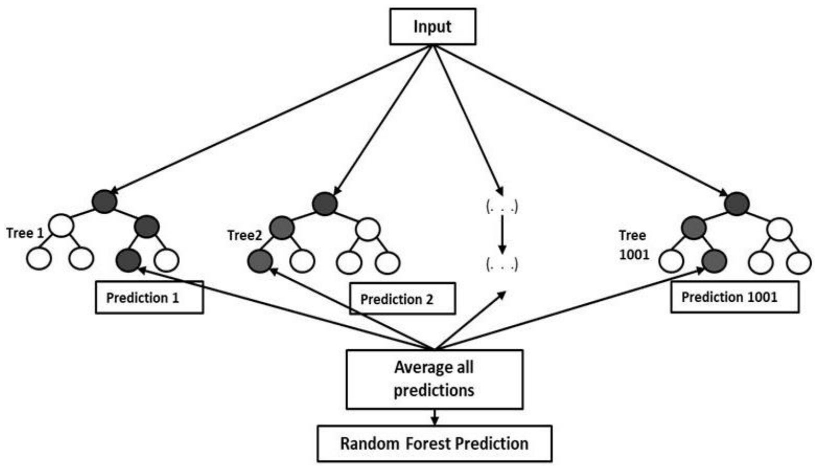


(a) (b)
Figure 4. Basic structure of (a) ANN (Bre et al. 2017) (b) SVM (Vapnik 2000).

3.3 *Decision Tree (DT)*

DT is basically a nonparametric regression method resembling (Figure 5 (a)) a tree structure, where each node displays an attribute, each branch displays a decision, and each leaf indicates an outcome (Jadhav & Channe 2016). DT method is used to subdivide the characteristics at any node to identify whether subdivision is best for that individual segment. Basing on the values of the splitting characteristic, the training data are divided into several subsets until all cases in a subset fit to the same class. In civil engineering, DT is commonly used for classification, cost and utility management and decision-making process based on the event outcomes.





(a) (b)
Figure 5. Basic structure of (a) DT (Jadhav & Channe 2016) (b) Random Forest (Breiman 2001).

3.4 *Random Forest (RF)*

Random Forest (RF) is supervised learning algorithm developed by Leo Breiman (Breiman 2001) which was used in modeling predictions and behavior analysis. In RF, a regression tree is generated from the random selection of training data sets. Then the prediction is made by accumulating of the instances individually, taking the one with the majority of votes for classification or averaging for regression as the selected prediction as shown in Figure 5(b). So as compared to single tree classifier, RF generally shows a significant performance improvement. A comparative picture of the ML methods discussed so far is given below (Goodfellow et.al. 2016, Bishop 2016).

4 ML METHODS USED IN DIFFERENT AREAS OF BRIDGE ENGINEERING

4.1 *Preliminary Design and Decision Making*

Preliminary design is one of the most important components of a project. It determines the feasibility and budgeting of one or more proposed options. Iterations between engineers and owners are often required to come up with a feasible solution to which both parties are agreeable. Hong et al. (2002) conducted a study on preliminary structural design for cable-stayed bridges in which ANN-based ML methods were adopted as a component of the design phase. Sun et al. (2015) presented a statistical Bayesian inference-based method, applying the model to a truss bridge for the purpose of confirming and regularizing it (and finding it to be accurate). Wang & Adeli (2015) presented an adaptive control algorithm, which is a combination of wavelet neural network and adaptive fuzzy sliding mode control approach, for vibration control of a large structure under dynamic loads. Jootoo et al (2017) explored the suitability of SVM, Bayesian networks, and DT as preliminary design aids for design engineers seeking the most suitable bridge type. These studies have expanded the horizon for bridge engineers, allowing them to consider a wider range of design options.

Table 3. Comparison of commonly used ML methods.

Method	Key Advantages	Key Disadvantages
ANN	Workable with any number of inputs and layers, for both regression and classification problems	Requires sufficient amount of training data, can become “black boxes” without functional visibility
SVM	Effective in high dimensional space, memory efficient, versatile as different kernel functions can be used	Do not provide probability estimates, with higher features regularization gets challenging
DT	Does not require normalization or scaling of input data, ideal for discrete regression	Higher complexity and time requirement, inadequate for continuous regression
RF	Robust to outliers, automatically handle missing values	Higher complexity and time requirement

4.2 *Construction and Operation*

Construction cost estimate is a crucial part of project management. Traditional cost estimates are either based on detailed drawings or data from other similar projects. There has not been a systematic algorithm that well utilizes a large amount of existing data in the industry. Juszczyk (2020) used successfully an SVM-based approach to develop a cost prediction model of a bridge. The input was the basic information of the bridge available at the beginning of the projects (physical dimension, material category, location etc). They investigated SVM-based ML models considering the data from different bridge construction projects. The result of SVM gave an output of an actual model of the bridge which help estimate the construction costs with reasonable accuracy.

Zheng et al. (2020) adopted RF algorithm as a computer aided tool for predicting and controlling the displacement of bridge piers during the construction of two overlapped earth-pressure-balanced machine (EPBM) tunnels. They successfully identify the control variables of the EPBMs required to safely pass through under the bridge. An ANN-based model presented by Lee et al. (2008) proposed a method for condition ratings of existing bridges from the limited field measurement data which reduce the inspection efforts significantly.

4.3 *Monitoring and Prediction*

Bridge health monitoring usually involves the processing of a large amount of data, which can be efficiently dealt with using ML. Bulut et al. (2005) prescribed a SVM and wavelets based algorithm for real-time non-destructive structural health monitoring instrumented by integrated wireless sensors lodged on the target area. The efficacy of the approach was validated with a satisfactory result using a numerical model of the Humboldt Bay Bridge, California.

Boller et al. (2009) showed that required data for ANNs can be obtained from information available from the various database, and it can be generalized and sorted out for various relationship circumstances from the complex systems with noisy data. They presented that this ANN data can provide a non-mechanistic framework for monitoring and evaluating baseline characteristics of bridges for both long- and short-term assessment. Shu et al. (2013) also used ANN for monitoring the structural condition of a 3D truss-type structure of a model railway bridge subjected to dynamic excitations by a moving train. Kromanis & Kripakaran (2014) studied the structural response of bridges due to temperature variation by ML. They used ANN and SVM to generate data to predict the relation between temperature variation and relevant tilt measurements in a pedestrian bridge design. Ye et al. (2017) proposed wavelet multi-resolution analysis and SVM based data reconstruction approach for bridge health monitoring. The data imputation was done from recorded data of a prestressed concrete cable-stayed bridge. The result of the study verified the effectiveness of the proposed data reconstruction approach by imputing missing data and affirmed that it can accurately evaluate the safety of bridge structures. Using hyperspectral images of steel surfaces of Sydney Harbour Bridge, Huynh et al. (2015) conducted an assessment of paint condition by multi-class SVM. The result displayed a high degree of matching performance between human expert judged assessment and that of ML classifier generates one. Condition assessment of concrete structures also done by Alamdari et al. (2017) applying unsupervised SVM. They have developed the method to detect small crack at the early stage of its occurrence and tested this on the replicated structure of Sydney Harbor Bridge. Alipour et al. (2017) introduced a data-driven solution for cost-effective, rapid, automatic load postings evaluation for large infrastructure networks by RF classification. They used it for automated screening and the assessment of infrastructure of the national bridge inventory by pattern recognition.

Mangalathu et al. (2019) conducted a comparative study to predict various failure mode (e.g., flexure, shear, flexure-shear failure) recognition using various types of ML approach. They found that ANN based ML exhibits better performance amongst all (i.e., quadratic discriminant analysis, KNN, DT, RF, naive Bayes, and ANN) the ML methods they used to compare the findings. Morcous (2005) used DT algorithm to model bridge deck deterioration. This ML algorithm was utilized to compare the accuracy of the condition of different bridge components of existing bridge management systems with that of Markov chain models. Malik et al. (2020) predicted scour depth around bridge piers in tandem arrangement using M5 and ANN regression models and discussed the effect of spacing on scouring around piers in a tandem arrangement using experimental as well as modeling techniques. Rizzo et al. (2020) used ANN based model to predict the critical flutter velocity of suspension bridges, while Venkat et al. (2009) used SVM based aerodynamic analysis to predict the same for the case of a cable-stayed bridge. They estimated the probability distribution of critical flutter velocities by synthetically generating a larger dataset by this ML method. Sharafi et al (2016) developed SVM algorithm using different kernel functions to predict the scour depth near to bridge piers. Liu and Ni (2019) also found their SVM based evaluation method is convenient and viable for safety evaluation of bridge bearing observed by real-time monitoring devices.

4.4 *Maintenance*

Nguyen et al. (2019) collected a large database of 2,572 bridges from the National Bridge Inventory (NBI) in order to develop an ANN-based ML model. The datasets were used for training and testing of the ML algorithms for predicting bridge deck condition. They showed that the ANN models can effectively predict the deterioration curve of the deck and can also assist in condition rating of the deck and thereby inform planning of future bridge maintenance work. Cheng &Hoang (2014) utilized the LS-SVM method for risk score interpretation in bridge maintenance, an approach which can be further applied for decision-making purposes. Arong et al. (2020) utilized SVM to develop a practical method for the assessment of bridge soundness by evaluating the degree of the structural health condition of a bridge’s superstructure. They examined the maintenance priority evaluation of bridge integrity of small- and medium-span bridges using SVM as a way of supplementing or supplanting engineer judgment in distinguishing the health rating for the purpose of bridge maintenance decision making.

5 PROSPECTIVE APPLICATIONS OF ML METHODS

5.1 *Load Capacity Rating*

Because of increasing traffic loads, damage during service, material deterioration, and revised code requirements, assessing the load capacity of older bridges is an important issue for bridge owners(Moses and Verma 1987). One way to accurately assess the bridge capacity rating is to develop a numerical model introducing the modified geometric parameters of the bridge elements in such a way that the updated model’s vibration properties comply with the field data. Conventional reliability analysis can be another option for a rational assessment strategy. These safety indices have been shown to correlate closely to the risk or probability that the loading to which a given bridge member is subjected will exceed its corresponding strength or capacity. In evaluating the performance of highway bridges, the load intensity, load effect analysis, and strength parameters are in most cases not known with certainty. In this regard, ML algorithms can perform several statistical methods that describe the equation of probability failure for a bridge conditioning assessment,

$$P_f = \sum_i P(R = r_i) \text{ x } P(S > r_i) \qquad (1)$$

where, *P(S)* is the probability of load, and *P(R)* is the probability of resistance. Given that the rating depends on the load and resistance factors selected, which, in turn, depend on the site traffic volume and potential truck load overweight conditions, the girder analysis used, the observed deck smoothness, and the inspection effort and maintenance, training can be performed to identify the model that best fits the curve as shown in Figure 6 (referring to the potential probabilistic failure curve for determining bridge rating). This method can be an effective solution for efficient resource allocation in that it supports expeditious maintenance-related decision-making through rapid identification of candidate bridges requiring further observation.

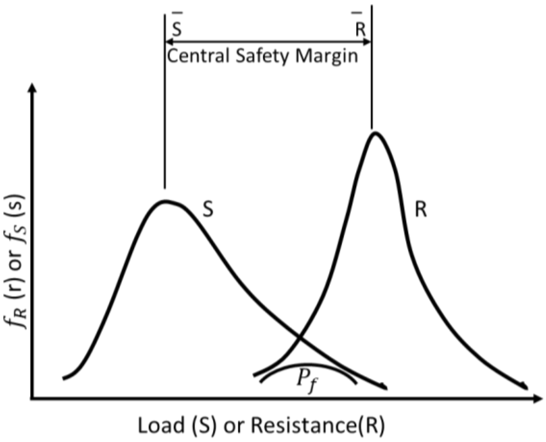


Figure 6. Failure probability model (Moses & Verma 1987).

In the literature, a few studies can be found related to load capacity evaluation of bridges. Alipour et al. (2017) successfully applied DT and RF for load capacity rating of different bridges across the United States. Datasets for over 40,000 concrete slab bridges, obtained from the National Bridge Inventory database, were trained in DT and RF classification models. The authors thus presented an approach for load capacity evaluation of different bridge classes, and established relationships between their load capacity ratings and bridge characteristics. Sirca & Adeli (2004) also used a counter-propagation ANN for quantifying the cross-sectional properties of girders. They demonstrated that their proposed model can accurately produce the section properties of the steel girders, a functionality that can further help with evaluating the bridge load rating. Lee et al. (2008) developed an improved ANN model using very limited existing inspection data of historical bridges for load capacity ratings. In this model, traffic volume, pedestrian volume, and weather data were incorporated with the limited inspection records available. Yu et al. (2012) developed an improved response surface method based on SVM and uniform design method for reliability analysis of suspension bridges. Their method was tested on a typical self-anchored suspension bridge, the Liede Bridge in Guangzhou, China, and the result affirmed that the method is reliable and feasible. Feng et al. (2013) utilized finite-element model and SVM to develop a method that can identify the scour safety level for a bridge system. They used variations in the modal properties of the bridge to determine the deviation status.

5.2 *Failure Mode Prediction Following an Earthquake*

Bridges are a critical component of a nation's infrastructure system and communication network. Depending on the extend of seismic damage following an earthquake event, visually locating, detecting, identifying, and categorizing damage to individual bridge components require significant investment of time and personnel, and may require a longer period of time after the event. This will eventually disrupt communication and transportation arteries and may impede various sectors of disaster management or economic activities. The United States Geological Survey Tools developed several tools, such as Shake Map (Wald et al. 2005) and Shake Cast (Wald et al. 2008) in the past to get reliable and pertinent information about the intensity of an earthquake and damage to specially distributed infrastructure after an earthquake. However, these tools are not entirely suited to bridge infrastructure, as bridge damage or failure mode assessment requires parameters for more specific components compared to the assessment of buildings. With the recent advancements in information technology, application of AI and ML to predict post-earthquake damage or failure to bridges can be used as an alternative tool to seismic vulnerability assessment based on fragility curves. Jia et al. (2020) conducted research on RF and ANN-based rapid assessment methods for seismic damage prediction. They used data from the Wenchuan earthquake of 2008 as a training set and data from the Tangshan earthquake of 1976 as the validation set and demonstrated that their proposed approach performs reliably in assessing damage to bridges in the wake of an earthquake event.

They concluded that their method can be applied forresource allocation and decision making in a rapid bridge repair and maintenance program. Mahmoudi et al. (2016) showed that SVM-based fragility curves offer accurate predictions compared to the component-based fragility curves developed by Monte Carlo simulations. As a part of vibration-based damage identification and SHM, Jianan et al. (2019), meanwhile, developed a method for identification of seismic damage to bridges based on transmissibility function and SVM.

6 CONCLUSIONS

The review of the state-of-the-art application of ML algorithms in bridge engineering in recent decades shows that numerous studies have been published in this field demonstrating the applicability of ML to such areas of bridge engineering as design optimization, condition assessment and prediction, structural health monitoring, damage detection, construction, maintenance, and monitoring. From this study it is observed that, among the various ML methods described in the literature, primarily ANN, SVM, DT, RF and various hybrids of two or more such algorithms have been applied in bridge engineering. This study finds that the critical task in generating any ML algorithm is to manage or collect a sufficient amount of reliable data by which to establish suitable metrics, with the majority of this data being used for training while the remainder is used for testing or validation purpose. Moving forward, then, the development and practical use of ML in the applied bridge engineering sector will demand the generation of or access to large database. With the emergence of big data technology, thus, the use of ML algorithms in various subdomains of bridge engineering has been accelerated in recent years. In fact, the present study shows that ML in conjunction with big data has driven recent breakthroughs with respect to load-capacity evaluation and failure mode prediction, among others. These recent advancements in the application of ML signal the potential growth of ML within the bridge engineering sector.

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