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A Review of Artificial Neural Networks (ANNs) as a Potential Predictive Tool for the Performance of Scissor-Type Deployable Bridges

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Abstract: After a severe disaster, some places may be unreachable for rescue operations due to bridge destruction. A scissor-type deployable bridge is a novel rescue technology that enables a lifeline to be quickly recovered during a catastrophic event. Several structural analysis approaches have been used to predict the structural behavior of deployable bridges, yet none of the prior studies have used Artificial Neural Networks (ANNs) to predict the structural behavior of scissor-type deployable bridges. This research explores the potential of ANNs to predict the performance of a scissor-type deployable bridge. The study aims to leverage the capabilities of ANNs in modeling complex relationships to forecast key parameters related to the bridge's functionality. ANNs can assist engineers in optimizing the design parameters of scissor-type deployable bridges by predicting how different configurations affect total deformation and stress levels. The analysis involves training the neural network with relevant data to learn and generalize patterns, enabling more informed predictions for diverse scenarios. Lastly, the application of ANNs in simulating bridge behavior contributes to advancing research in structural engineering, particularly in the field of deployable structures, by providing insights into complex structural responses that are challenging to model analytically.

Keywords: Deployable Bridge, Mobile Bridge, Scissor-Type Bridge, Aluminum Alloy, Artificial Neural Networks (ANNs), MATLAB

1. Introduction

One of the most important aspects contributing to nations' quick growth and stability is the development of their transportation infrastructure networks. Bridges are the primary components of the infrastructure transportation network, and they are frequently regarded as lifelines for connecting communities and regions [1]. Natural and human-caused calamities, including tsunamis, hurricanes, earthquakes, floods, and inadequate designs, have seriously threatened bridge infrastructure safety in recent decades. Statistical studies predict a five-times rise in severe natural disasters over the next 50 years [2]. For example, Typhoon Morakot in 2009 triggered 88 floods in Taiwan, damaging over 200 bridges and destroying over 100 [3]. In the Philippines, the October 2013 earthquake in Bohol is regarded as the strongest and most catastrophic natural event to hit the nation, costing over Php 2 billion in infrastructure losses [4] and resulting in 41 bridges being reported destroyed.

To survive calamities like these, we need to create a new rescue structure. We must examine how to repair a damaged structure or establish a new sort of rescue system as quickly as possible after a disaster because time is of the essence when trying to save lives. A temporary or mobile bridge is a structure that allows a lifeline to be quickly recovered after a tragedy [5]. The mobility, adaptability, and standard of a mobile bridge are more demanding than those of a regular bridge, and the bridge must be delivered and erected quickly. In addition, a bridge must be built to support the weight applied across its width.

The design and production of emergency bridges began in the 1940s. The Bailey Bridge, which is made up of modular panels and was created by British engineer Donald Sie Bailey, is the most noteworthy. It is still in use in many places of the world and is particularly significant due to its military tactical status and performance [6]. As technology evolves, emergency response bridges are foldable and may expand to a fixed size; the extended construction is strong enough to withstand loads [7]. One of the notable research that focuses on the Mobile Bridge (MB), a specific type of emergency response bridge, explored its design and application for natural disaster response. A scissor-type mechanism is the fundamental component of the bridge's design that enables rapid deployment. Many test MBs of different sizes were constructed and evaluated. The moveable bridge was successfully deployed over the real river in less than an hour, with no technical problems, and the simulation results demonstrated that it was operational and could be utilized by vehicles [8]. Moreover, a study on deployable scissor-type bridges used numerical models based on Finite Element (FE) analysis to approach a simpler design. The experimental strain variations are found to be compatible with the FE numerical model, with deviations of less than 5% on the safe side. The method is considered reliable [9]. Furthermore, influence line diagrams and equilibrium equations were used in another study to provide a unique design approach for scissor-type bridges. By examining changes in the live load distribution on the structure, the suggested methods could precisely calculate each member's size and provide the minimum and maximum values of the influence line border when carrying light vehicles [10]. However, no research has examined using Artificial Neural Networks (ANNs) for predicting scissor-type deployable bridge performance through structural analysis. ANNs can assist engineers in optimizing the design parameters of scissor-type deployable bridges by predicting how different configurations affect total deformation and stress levels.

ANNs have been applied in structural engineering to address diverse issues and provide novel solutions. One related research conducted is the structural reliability assessment of steel four-bolt unstiffened extended end plate connections using ANNs [11]. Another study utilized an ANN as the basis for creating a prediction capacity model and seismic fragility estimation for reinforced concrete (RC) bridges. The capability measures were trained, validated, and tested using an ANN model, yielding an excellent agreement between experimental data and predicted results, as demonstrated by the high correlation [12]. Hence, this proves that ANNs could serve as a better alternative in structural analysis, as they are more convenient to design and implement with enough training data.

2. Materials and Methods

This research will review the potentiality and reliability of Artificial Neural Network (ANN) to predict the performance of scissor-type deployable bridges. The datasets needed for training the ANN model will be based on the chosen reference scissor-type deployable bridge from recent studies. The deployable bridge model will be then subjected to Finite Element Analysis (FEA) using ANSYS static structural function. The numerical results gathered from FEA will be utilized for the development of ANN. Accordingly, the datasets will be trained using a back-propagation algorithm in a feed-forward architecture. The design of the ANN architecture will define the number of inputs, outputs, neurons, and hidden layers. The input datasets include the length, width, height, deck thickness, Gross Vehicle Weight Rating (GVWR), modulus of elasticity, density, Poisson's ratio, yield strength, and ultimate tensile strength, whereas, the output datasets are the maximum deformation and maximum stresses.

The design and training of the ANN for the scissor-type deployable bridge will be done using the Neural Network Fitting Tool in MATLAB. In the field of neural network modeling, the Neural Network Fitting Tool in MATLAB, known as the "nftool" is a valuable resource for beginners and professionals, providing an extensive range of functionalities for the design, training, and validation of neural networks for data fitting applications. During the training process of the network, the Levenberg-Marquardt Algorithm (LMA) will be implemented. When solving non-linear least squares problems, the LMA, sometimes referred to as the Damped Least-Squares (DLS) approach, is an effective numerical optimization technique. It works especially well for fitting least squares curves, where the objective is to determine a model curve's parameters that minimize the sum of the squares of the discrepancies between the observed data points and the model predictions. If the error percentage of the trained ANN is not acceptable, the trained ANN will be optimized and retrained, continuing in a loop until the least possible error percentage is achieved. Mean Squared Error (MSE) will be used to check how close estimates or forecasts are to actual values. The value ranges from 0 or greater, with lower values indicating higher model accuracy. Finally, the coefficient of determination, often known as R-squared, quantifies the fraction of the variance in the dependent variable that can be explained by the independent variable. It quantifies the extent of diversity within the provided dataset, with R-squared values ranging from 0 to 1, indicating the extent to which the dependent variable can be predictable.

After developing and training the ANN model, the final phase is the prediction of the outcome based on the input datasets. The model will continuously carry out iterative procedures until the ANN gives the predicted output, which includes the maximum deformation and maximum stresses. These output parameters are essential for evaluating the safety and structural performance of the scissor-type deployable bridge, which helps engineers make well-informed decisions for optimization and improvement. Subsequently, the effectiveness of the developed ANN model is examined by comparing the model's predicted outputs with the outcomes derived from FEA.

The proposed methodological process in this study is presented in Figure 1.

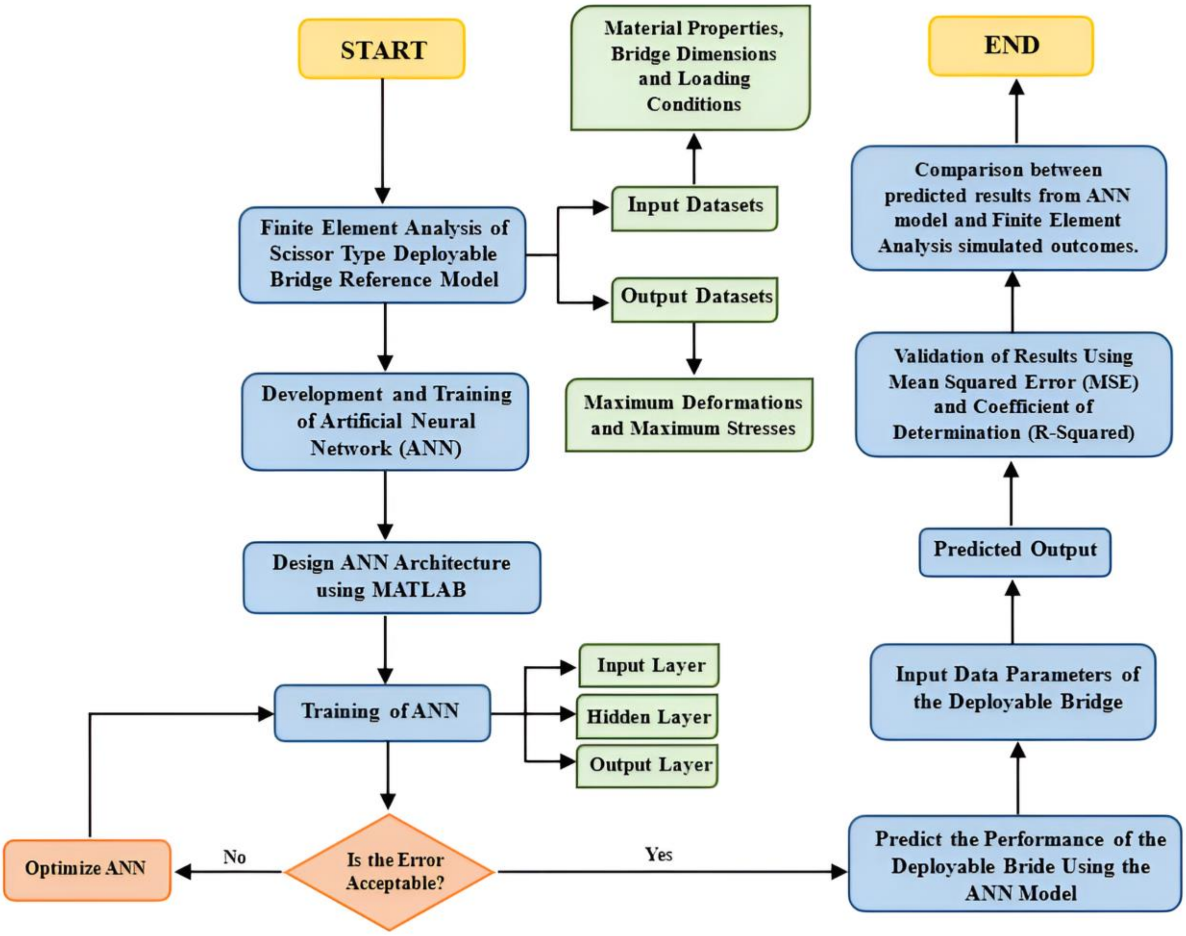

Figure 1. Flowchart of Artificial Neural Network (ANN) as a Predictive Tool in the Performance of Scissor Type Deployable Bridge

3. Results and Discussion

This section of the research paper gives a summary of previous research and literature that is pertinent to concerns about disaster operations by developing a rescue system in the form of deployable bridges as a solution. This paper will address several kinds of deployable emergency response bridges and their uses, materials for scissor-type bridges, and the use of Artificial Neural Networks (ANNs) for predictive modeling in structural analysis of bridges.

3.1 Structural Forms of Deployable Bridges.

Modern post-disaster rescue equipment, such as emergency deployable bridges, makes it possible to access the disaster site, which will facilitate rescue efforts and resulting in the saving of more lives [14]. A deployable structure's ability to exist in two distinct stable states—the fully folded state and the fully unfolded one—is its most distinctive characteristic. The deployable structure is smaller and convenient to transport and store when it is fully folded. The structure is durable and capable of supporting weights when completely extended [15]. Likewise, to facilitate launching, retracting, transporting, and storing, a lightweight bridging system is required [16].

3.1.1 Arch Type Deployable Bridge.

In the course of the deployment procedure, deployable structures show inconsistencies in the member lengths at intermediate geometric configurations. The corresponding snap-through event "locks" the structures in their deployed position by generating second-order strains and stresses. To take on this limitation, a geometric design approach that takes into consideration the discrete joint size and is suitable for deployable arches with any curvature has been proposed. The semi-elliptical arch's geometric design has been successfully implemented using this type of approach. A preliminary structural design shows that the “arch” is generally feasible for light loads and short to medium-span structures [17]. Recent studies demonstrate the advantages of deployable arch bridges, such as it is built with a simple configuration and may be deployed quickly. The deployable arch bridge has good adaptability; depending on the need, the number of bridge span modules can be increased or decreased to fulfill the needs of crossing various obstacles. It is very convenient to transport and unfold the arch bridge design [15]. However, the increased number of joints may increase the amount of maintenance required. Long vehicles with low clearances (such as tractor-trailers) may be unable to cross due to the arch's curvature, which might be solved by constructing ramps to lessen the slope at the extremities. Finally, when the arch's height is combined with significant wind loads, the arch may overturn in the transverse direction [18].

3.1.2 Scissor Type Deployable Bridge.

The scissor mechanisms are most commonly used in the field of temporary dome architecture. Organizing the scissor units as a geodesic grid or maximizing the scissor components' sectional area improves their strength and stability. To enable safe passage for people and vehicles, an emergency bridge's design must ensure construction speed and structural strength [19].

The idea of multi-folding microstructures and earlier research on deployable structures have led to the proposal of a novel kind of emergency bridge known as a Mobile Bridge (MB) [20]. Although the upper and lower chords are the primary elements that resist sectional stresses in a typical truss bridge, the MB lacks chords but can be carried and built rapidly utilizing a scissor mechanism [21]. In its most basic form, the scissors mechanism is made up of two straight linear elements. A pivot connects the pieces at their centers, forming a hinge connection. The two members are in the shape of the character “X” in the fully deployed state. As seen in Figure 2, two hinges connect one unit to the next. The structure can be deployed and has a big length-to-width ratio from the expanded to the folded state. There are two types of compacts: non-deployed and deployed. In its current state, the construction is easily transportable and may be kept for future use. In this way, this method is particularly effective for systems that need to be moved and kept in a small amount of space at a time [8].

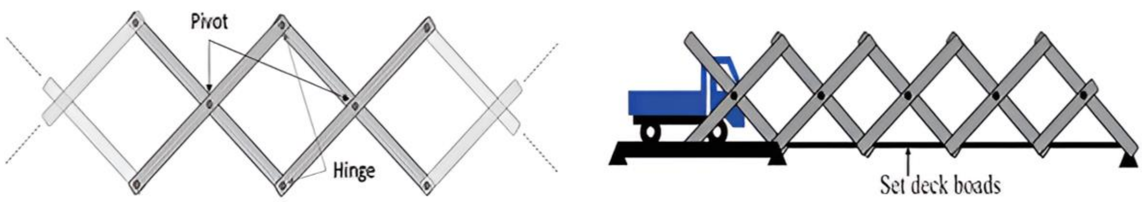

Figure 2. Basic Concept of Scissor-Type Bridge

When the scissors mechanism is successfully applied to the bridge structure, the structure should have the following features: it should be easier to deploy and fold with just one control force, have a shorter transport time than a more conventional temporary bridge, and be more efficient in terms of size when comparing its deployed and folded states. The scissor-type mobile bridge has a smaller live load capacity and span than other bridge types due to the lack of upper and lower chord elements, which, when present, resist bending forces. As a result, the lighter bridge may be erected more rapidly and its components carried in a light vehicle [9]. Although it offers several advantages, research studies have identified drawbacks with the scissor-type bridge mechanism. Due to the coupled stiffness of these bridges, the vibration of scissors-type movable bridges is more sensitive in the horizontal rather than vertical direction [22].

3.2 Materials Used in a Scissor-Type Deployable Bridge.

The selection of materials for the building of scissor bridges is a complex procedure that involves considering several elements, such as the length of the span, environmental circumstances, load-bearing capacity of the bridge, and financial limitations. Pursuing ideal materials has emerged as a catalyst for innovation in scissor bridge building, as engineers and researchers persistently explore novel design possibilities.

3.2.1 Structural Steel.

The selection of structural steel for bridges should take into account the required material attributes or stress state, the construction site's environmental factors, the corrosion protection system, and the building method [23]. The fundamental factors involved in designing and constructing steel bridges are the physical attributes of structural steel, which include strength, ductility, toughness, weldability, weather resistance, chemical composition, shape, size, and surface features [24]. One of the research studies explores the use of A36 structural steel as the main material for scissor-type deployable bridges. The deployable bridge is designed to fit in the trunk of a 4 × 4 pick-up truck; therefore, its overall dimensions are 2.2 m (width), 2 m (height), and 14m (length). Stress analysis is simulated using ANSYS Workbench's static structural function. It was discovered that one of the limitations of the steel deployable bridge design is the overall weight of the bridge. An emergency deployable bridge should be as lightweight as possible without losing strength to be easily transported and deployed during a natural disaster. Therefore, research and analysis on bridge weight reduction techniques involving the use of lightweight materials may take into consideration the significance of material selection in further studies [25].

3.2.2 Fiber Reinforced Polymer (FRP).

Although composite materials are less ductile than traditional materials like structural steel in applications, they have several advantages, such as high specific stiffness and strength, lightweight material, excellent corrosion resistance, and low maintenance costs, which make them very appealing for use in the construction industry in certain circumstances. These benefits have prompted the examination of Fiber Reinforced Polymer (FRP) as a bridge-building option. The following applications have been taken under consideration thus far: (a) bridge component repair and upgrade retrofitting schemes; (b) design of replacement bridge components; and (c) design and construction of new bridge structures for pedestrian or highway use [26]. However, the disadvantages of using FRP in a composite bridge application are as follows: (a) a large deflection of the structure caused by the low modulus of materials (compared to steel) and low stiffness of the FRP components; (b) the need to simplify the joints and connections; and (c) the high cost of composite materials necessitates the solution of cost-effective problems [3].

In general, carbon fiber is the most desirable reinforcing due to its extremely high strength compared to other fibers. Due to its high modulus of elasticity, carbon fiber reinforced polymer (CFRP) is the material most suitable for deployable bridges. The less material deflects, the higher the modulus of elasticity. This attribute is necessary to guarantee that the bridge will not deflect excessively. Fiber-reinforced composite (FRP) is highly beneficial for building deployable bridges [27]. A study was conducted to analyze the mechanical properties of a lightweight FRP scissor-type bridge using the finite element method to identify its strength and durability [28]. The findings indicate that FRP scissor bridges can be designed to withstand the same loads as traditional steel scissor bridges. The results suggest that FRP composites are a better choice for bridge construction than traditional materials [29].

3.2.3 Aluminum Alloy.

As a lightweight material, aluminum alloy provides an alternative for deployable bridges. Additionally, experiments conducted in a research laboratory have shown that aluminum alloy has superior corrosion resistance, eliminating the need for any protective coating [30]. According to theoretical and practical research, it was reported that aluminum alloy has the best mechanical and anticorrosive qualities. This might be very advantageous for applications involving bridges, such as the restoration of bridge decks, deployable bridges, and military bridges [31].

According to a current study, a scissor-type Mobile Bridge (MB 4.0) made of aluminum alloy with improved mobility, functionality, and a lighter weight was created. Consequently, the MB4.0 is now more easily transportable and can be set up at temporary construction sites without requiring heavy machinery or foundation work. It is therefore also far more economical [8]. However, experimental findings reveal that vibrations in the horizontal direction are significantly more pronounced than those in the vertical direction. Reinforcing elements added to the bridge's upper level resulted in higher horizontal and vertical eigenvalue frequencies compared to the unreinforced bridge. This suggests that reinforcing components enhance the stiffness of the MB4.0 bridge, thereby reducing the influence of bending moments on the primary structural members. The application of appropriate reinforcement can improve both the bridge's stability and safety [32].

3.3 The Artificial Neural Networks (ANNs) Capabilities

Artificial Neural networks (ANNs) are capable of producing extremely accurate predictions when provided with a substantial quantity of training data. Neural networks can be emulated in digital systems, even though they are more frequently connected to analog computers. They use a series of algorithms that are inspired by the structure of the human brain [33]. These algorithms involve an array of numerical learning methods and consist of a large number of nonlinear computational units, known as network nodes, which are interconnected by weighted links. ANNs can effectively solve a wide range of complex problems, from small to large scale. This is due to their massively parallel distributed structure, which allows them to learn and generalize. Additionally, they can produce reasonably accurate outputs for inputs not used during the learning phase, also known as “training” [34].

ANNs are used to predict how materials with similar properties will perform under different testing scenarios, based on experimental data. They are used as predictive tools, forecasting certain outputs based on input values. Engineering predictions are the main use for the backpropagation network model. One or more continuously valued outputs and several continuous-valued inputs can be connected through this efficient method to create nonlinear transfer functions. The network is named for the way it handles mistakes during training and essentially employs a multi-layer perception architecture [35].

Feed Forward Neural Networks (FFNN) are the most widely utilized artificial neural network technique for dealing with various engineering limitations. A layer in the FFNN technique is entirely linked to the layer before it by weights [36]. The typical three-layer feed-forward type of an ANN is shown in Figure 3. Currently, this backpropagation architecture-based interactive network has gained popularity, value, and ease of learning, especially for complex models like multi-layered networks. The ability of ANNs to handle nonlinear solutions to indefinite problems is their greatest strength. There are three layers in the professional backpropagation network: input, output, and at least one hidden layer [37].

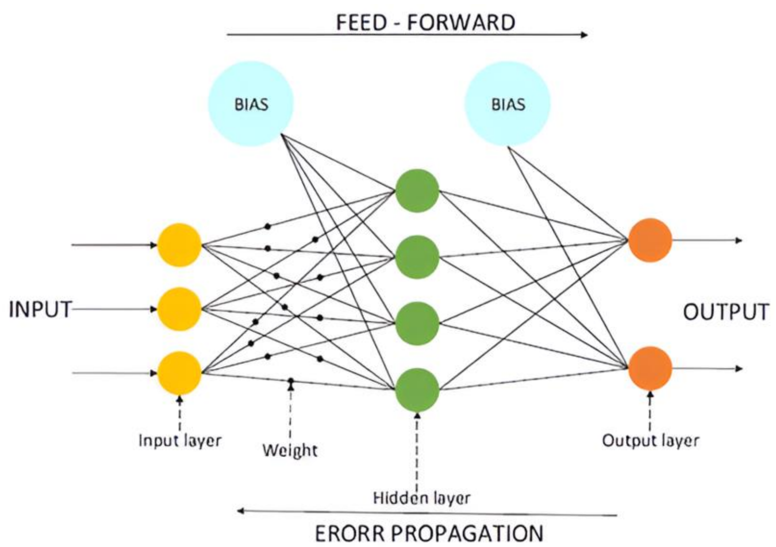

Figure 3. Three-layer Feed Forward Artificial Neural Network Schematic Representation [37]

Nowadays, ANNs have garnered growing interest in civil engineering. They have been used to address numerous structural analysis and design problems. These types of problems are most suited for ANN applications: the problem domain is rich in examples or historical data; the data set is incomplete or contains errors; the function to find solutions is unknown; and applications are data-intensive and dependent on numerous criteria. The amount of research being done on using ANNs to solve civil engineering problems is expanding quickly. The application of ANNs in structural engineering has developed as a new paradigm for computing, despite its continued extreme limitations. It has been used in a variety of applications, including finite element analysis, structural design, material behavior modeling, damage assessment, and structural analysis [38].

3.3.1 Application of Artificial Neural Networks (ANNs)on Bridge Performance.

Artificial Neural Networks (ANNs) have been applied in structural engineering to address diverse issues and provide novel solutions [39]. The following applications of ANNs in structural analysis and design could be emphasized: topology optimization (based on the removal of ineffective structural members), joint location, size optimization of structural members, shape optimization of structural types (e.g., truss geometry), structural analysis of systems with large degrees of freedom, and maximum stress identification and location [40]. From past studies, numerous research findings confirmed the efficiency and accuracy of the proposed ANN models as a successful predictive modeling technique for assessing the structural behavior of structures, especially bridges.

Table 1. Application of Artificial Neural Networks (ANNs) on Bridge Behaviour

Application of ANNs on Bridges	Research Methods and Findings	Reference
Estimation on Dynamic Displacements due to Dynamic Loads on Bridges	- This study made recommendations on how to make perception of the limited data on individual girder points to understand the overall behavior of bridges. - To replicate real-world traffic scenarios, dynamic vehicle load assumptions using the Pearson Type III distribution of traffic theory were created. - Ultimately, the ANN allowed us to reasonably precisely estimate the vertical dynamic displacement, which had been influenced by FEM results from loads based on actual conditions.	[41]
Bridge Damage Identification	- An ANN-based bridge behavior model was formed. By using this technique for damage identification and localization, bridge performance trends may be obtained, early inspections can be triggered, and inspectors can be directed toward the regions of the bridge that are most likely to sustain damage. - The study's initial findings show that engineers may find it useful in the future to quickly ascertain a bridge's baseline performance and obtain automated weekly updates on the bridge's condition.	[42]
Developing Bridge Deterioration Models	- ANN models with diversified configurations were developed and used to provide predictions on the degradation of the superstructure, substructure, and bridge deck. - The National Bridge Inventory (NBI) database provided the information needed to create the deterioration models for bridge structures. - As a result of this study, a bridge deterioration model was created using the proposed ANN models to predict deterioration in all bridge systems.	[43]
Identification of Flexural Structural Damage in the Girders of a Vehicle Bridge	- A Neural Network (NN) based model was created, performed, and assessed to identify flexural structural damage in the girders of a vehicle bridge. - Based on the findings of this study, it can be concluded that NN models trained using modal strain energy differences can be used to accurately determine the position and extent of damage in a bridge's girders.	[44]

3.3.2 Training of Artificial Neural Network (ANN).

Artificial Neural Networks (ANNs) can be worked with a variety of software programs. One of these is TensorFlow, a comprehensive open-source machine-learning platform that offers an extensive set of customizable tools, libraries, and community offerings [45]. When it comes to ANN software, one of the best in Neural Designer, a desktop tool for data mining that employs neural networks, a key machine learning paradigm; however, one of the drawbacks is its high cost [46]. The Neural Lab is another software used to construct models, which allows for the creation of custom ANN-based application by combining the C++ classes within its object-oriented implementation. This modeling tool was created and implemented using a variety of optimization methodologies. The model supports multi-layer feed-forward networks, as well as probabilistic neural networks, and it has been used in previous research due to its user-friendly coding and versatility [46]. Lastly, MATLAB is a program that gives an interactive environment where users may collaborate and visualize ideas in a variety of domains, including computational finance, communications, control systems, signal and image processing, and computational imaging. A collection of tools and applications for building, training, and modeling neural networks can be found in MATLAB's Neural Network Toolbox. Neural network development for tasks like clustering, pattern recognition, and data-fitting (including time-series data) is made simple by the software [47]. When using MATLAB to solve a problem, prototype solutions are typically produced more quickly than when employing other programming languages [48].

4. Conclusions

Scissor-type deployable bridges are ideal for disaster operations due to their rapid deployment capabilities and simplified assembly processes, which require fewer personnel. Various structural analysis methods have been utilized to forecast the structural behavior of deployable bridges. These are the Coefficient Technique, Kutzbach Equation, ANSYS Workbench, well-known Finite Element Analysis (FEA), and Influence-Line based design. However, none of the previous studies utilized Artificial Neural Networks (ANNs) to predict the structural behavior of scissor-type deployable bridges. This technique has the potential to be a highly effective tool in predicting the structural behavior of scissor-type bridges. When dealing with complicated structures like scissor-type bridges, ANNs shine because of their ability to detect patterns and trends in data. ANNs can learn from new data and adapt as needed. This means that the ANN model can be updated and improved as additional information about the efficiency of scissor-type bridges becomes available. ANN has been applied to several bridge applications, such as the detection of bridge damage, flexural behavior, as well as deterioration. ANNs can assist engineers in optimizing the design parameters of scissor-type deployable bridges by predicting how different configurations affect total deformation and stress levels. Overall, leveraging ANNs for simulating deformation and stresses in scissor-type deployable bridges enhances both the understanding and management of their structural performance, leading to safer, more cost-effective, and resilient infrastructure solutions.

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Conflicts of Interest

The authors declare no conflict of interest.

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