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Structural monitoring of movable bridge mechanical components for maintenance decision-making

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Abstract. This paper presents a unique study of Structural Health Monitoring (SHM) for the maintenance decision making about a real life movable bridge. The mechanical components of movable bridges are maintained on a scheduled basis. However, it is desired to have a condition-based maintenance by taking advantage of SHM. The main objective is to track the operation of a gearbox and a rack-pinion/open gear assembly, which are critical parts of bascule type movable bridges. Maintenance needs that may lead to major damage to these components needs to be identified and diagnosed timely since an early detection of faults may help avoid unexpected bridge closures or costly repairs. The fault prediction of the gearbox and rack-pinion/open gear is carried out using two types of Artificial Neural Networks (ANNs): 1) Multi-Layer Perceptron Neural Networks (MLP-NNs) and 2) Fuzzy Neural Networks (FNNs). Monitoring data is collected during regular opening and closing of the bridge as well as during artificially induced reversible damage conditions. Several statistical parameters are extracted from the time-domain vibration signals as characteristic features to be fed to the ANNs for constructing the MLP-NNs and FNNs independently. The required training and testing sets are obtained by processing the acceleration data for both damaged and undamaged condition of the aforementioned mechanical components. The performances of the developed ANNs are first evaluated using unseen test sets. Second, the selected networks are used for long-term condition evaluation of the rack-pinion/open gear of the movable bridge. It is shown that the vibration monitoring data with selected statistical parameters and particular network architectures give successful results to predict the undamaged and damaged condition of the bridge. It is also observed that the MLP-NNs performed better than the FNNs in the presented case. The successful results indicate that ANNs are promising tools for maintenance monitoring of movable bridge components and it is also shown that the ANN results can be employed in simple approach for day-to-day operation and maintenance of movable bridges.

Keywords: monitoring; maintenance; movable bridges; artificial neural networks; anomaly detection

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1. Introduction

Heavy movable structures comprise of mechanical and electrical components as well as structural components. A main objective of the bridge owners is to have timely and proper maintenance of the mechanical components to mitigate unexpected failures. Therefore, the mechanical components such as gear boxes, open gear, electrical motors are frequently inspected and maintained. Evaluation and assessment of machines is very critical in order to increase reliability of the machinery and to decrease possible loss of production due to breakdowns. Such problems have been studied mainly for mechanical structures in industrial and manufacturing environments such as factories and plants. The operation, monitoring and assessment of heavy movable structures in the context of civil infrastructure monitoring have not been fully studied and presented in the literature. The objective of this study is to track and assess the condition of some of the critical components (e.g., gearbox and rack and pinion/open gear) of an operating movable bridge with the help of Artificial Neural Networks (ANNs) by analyzing continuous Structural Health Monitoring (SHM) data. While ANN methods have been used extensively for machinery, mechanical components or fixed structures (Castejon *et al*. 2010, Rajakarunakaran *et al*. 2008, Rafiee *et al*. 2007, Yeung and Smith 2005, Kowalski and Kowalska 2003, Maier and Dandy 2000, Li *et al*. 2000, Feng and Bahng 1999, Barai and Pandey 1995), the implementation on a large scale heavy movable bridge is quite unique.

Movable bridges are used as a way for land traffic to cross a waterway and at the same time, ensuring a path for the waterborne traffic. Moving components of these bridges are operated by various types of machinery to open the passageway for waterborne traffic. Movable bridges have long been known; the first handbook for movable bridges was published as early as late 19th century (Fränkel 1882). Since then, scarce documentation compared to fixed bridges has been dedicated to identify the most common issues and response characteristics of movable bridges. Movable bridges are viable alternatives to high fixed bridges over a waterway; however, they also present significant drawbacks and problems associated with the operation, and performance such as rapid deterioration, the frequent breakdowns, high maintenance costs, difficulty in repair works (Catbas *et al*. 2007, Catbas *et al*. 2010, Gul *et al*. 2013). A minor malfunction of any component can cause an unexpected failure of bridge operation. In this context, SHM offers promising tools for tracking the performance of these structures to address such problems.

SHM can be defined as the process of implementing a monitoring strategy for aerospace, mechanical and civil structures by combining different technologies such as sensing and data acquisition hardware and damage detection algorithms. It is possible to observe the long-term structural behavior with continuous or discrete intervals of monitoring from an array of sensors, capturing seasonal and environmental changes that are not readily apparent from intermittent tests. Health monitoring concept uses integrated local and global non-destructive experimental technologies together with advanced analysis and modeling techniques to complement inspections and provide continuous information regarding state parameters, loading environment, and state of health (Aktan *et al*. 2000). Such a system on a movable bridge can be used to monitor critical components of a movable bridge and generate warning flags to indicate a worsening in certain conditions. Infrastructure owners may use these flags as a mechanism to assess maintenance performance (Gul *et al*. 2011, Catbas *et al*. 2012). In addition, the data may be used by the contractors in scheduling preventive maintenance to maximize the service life of the equipment and the structure. Finally, the root causes of the structural and mechanical problems can be determined, and future designs can be improved using the information generated by the monitoring system (Catbas *et al*. 2014).

In this study, the inherent operational behavior of two mechanical components of an existing movable bridge is modeled with two different neural networks using the SHM data. A Multi-Layered Perceptron Neural Network (MLP-NN) and a Fuzzy Neural Network (FNN) are used for an efficient and practical determination of the current state of the health of the gearbox and rack-pinion/open gear assembly, which are critical for the opening and closings of movable bridges. They are monitored using accelerometers for healthy condition for a sufficiently long period of time. With the unique opportunity to artificially induce reversible damage scenarios on these components in a controlled manner, these components are also monitored in the damaged states to acquire data representing the unacceptable bridge mechanical condition. Damage-sensitive features are extracted from the statistical properties of acquired vibration signals. These features are then utilized to train the neural networks to establish the pattern between the statistical parameters and damaged/undamaged cases. Once trained successfully, the networks are used to predict output values for new input data from the continuous monitoring of the bridge components. Results are presented in a comparative fashion.

2. Brief review of Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) have been developed as computing methods for modeling complex relationships between inputs and outputs or for finding patterns in data sets. ANNs learn from the existing patterns capturing the subtle functional relationships among the patterns and then make a prediction for the patterns, which are not considered during learning. The success of a network is measured by its generalization performance. If the difference between the actual and computed output by an ANN is within the acceptable levels, then the network can be used for prediction in the similar domain, which exhibits certain common characteristics with the existing patterns. The prediction performance of a network usually depends on the network parameters, the training process, the complexity of the underlying process represented in the training data set and the topology chosen. The best performance is generally achieved by a series of parametric studies on the different networks using a trial and error approach. At each trial, performance of network is evaluated. This process is repeated until the best architecture with the right network parameters is achieved. In this study, two different types of ANNs are used: Multi-Layer Perceptron Neural Networks (MLP-NNs) and Fuzzy Neural Networks (FNNs). Brief reviews of these networks are given in the following sections.

2.1 Multi-Layer Perceptron Neural Networks (MLP-NNs)

Multi-Layer Perceptron Neural Networks (MLP-NNs) are one of the most commonly used neural networks in structural engineering applications and have demonstrated various degree of success. These types of neural networks consist of multiple layers of computational units interconnected in a feed-forward way (Fig. 1). The input vector distributes the inputs to the input layer. The input layer does not involve any processing; rather it can be conceived as a sensory layer, where each neuron receives a sole component of the input vector “U”. The last layer is the output layer which outputs the processed data. The output of each neuron in this layer corresponds to a component of the output vector “X”. The layers between the input and output ones are referred as hidden layers. Hidden layer(s) may have any number of neurons; however they should be chosen carefully for each application (Maier and Randy 2000).

Each neuron in a layer is connected to all the neurons of the previous and next layers by weighted connections. Each neuron performs a nonlinear transformation of the weighted sum of the incoming inputs to produce the output of the neuron which is given to other neurons or outside the network. Eq. (1) shows the basic algebraic equation for each layer.

$$a_j = f(\sum w_{ij} u_i + \theta_j) \quad (1)$$

where a_j is the output of neuron j; w_{ij} represents the weight from neuron i to neuron j; u_i is the input signal generated for neuron i; θ_j is the bias term associated with neuron j; and the nonlinear activation function f is assumed to be a sigmoid function as $f(x) = (1 + e^{-x})^{-1}$ (Rafiee *et al*. 2007).

The most popular learning technique for these types of networks is the Back-Propagation (BP) algorithm. In the BP algorithm, the output values are compared with the desired answer to compute the value of some predefined error-function. Then, the error is fed back through the network by various techniques. The back-propagation neural networks are basically a gradient descent method, and two parameters called as the learning rate η and the momentum factor α; are usually introduced in the iterative calculation process as in Eq. (2).

$$w_{ij}(n+1) = w_{ij}(n) + \eta(\delta_j u_i) + \alpha \Delta w_{ij}(n) \quad (2)$$

where δ_j is the error signal for neuron j; $\Delta w_{ij}(n)$ denotes the adjusting weights between neurons i and j; meanwhile the symbols (n + 1) and n are the current and the most recent training step, respectively. Furthermore, to evaluate the effectiveness of the network, the coefficient of correlation (R) may be used and defined as in Eq. (3) (Rafiee *et al*. 2007).

$$R = \frac{\sum_{i=1}^{S}(x_i - \bar{x}_i)(t_i - \bar{t}_i)}{\left[\sum_{i=1}^{S}(x_i - \bar{x}_i)^2 \sum_{i=1}^{S}(t_i - \bar{t}_i)^2\right]^{\frac{1}{2}}} \quad (3)$$

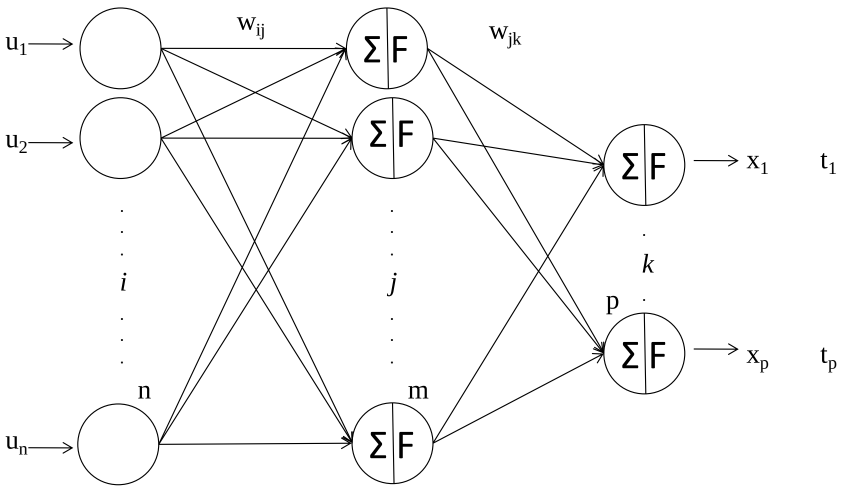


Fig. 1 Single Hidden Layer Feed Forward Neural Networks

2.2 Fuzzy Neural Networks (FNNs)

Fuzzy Neural Networks (FNNs) are neural networks that employ the fuzzy reasoning for calculations. Therefore, it has characteristics of both neural network and fuzzy reasoning that are learning ability of neural network and robustness of fuzzy reasoning (Dayhoff 1990, Wang and Mendel 1996). The structure of a fuzzy-neural network system is shown in Fig. 2.

This system uses a simplified fuzzy reasoning in which the consequent part is expressed in terms of crisp numbers. In Fig. 2, layers A and B correspond to antecedent parts, and layers C and D correspond to consequent parts. The weights of A to B and B to C are fixed to 1. The neurons of layer B express membership functions and they are expressed by Gaussian functions. Thus, the output of the neuron of layer B expresses the fitness of the each membership function. At layer C, the minimum value of the input signal of the neuron and its output are calculated. This value is the fitness of the fuzzy rule. Consequent parts are weighted from C to D. At layer D, the summation of the input values is calculated. The mean and width of the Gaussian function and weights of C to D are calculated using the following equations (Eqs. (4)-(6)) (Furuhashi and Hayashi 1996, Uchikawa 1995).

$$a_{ij}(t+1) = a_{ij}(t) + \beta(y^* - y)[\sum_{k=1}^{r} h_j(y_k - y)][2(x_i - a_{ij})/b_{ij}]/\sum_{m=1}^{n} h_m \tag{4}$$

$$b_{ij}(t+1) = b_{ij}(t) + \beta(y^* - y)[\sum_{k=1}^{r} h_j(y_k - y)][(x_i - a_{ij})^2/b_{ij}^2]/\sum_{m=1}^{n} h_m \tag{5}$$

$$y_i(t+1) = y_i(t) + \alpha(y^* - y) \tag{6}$$

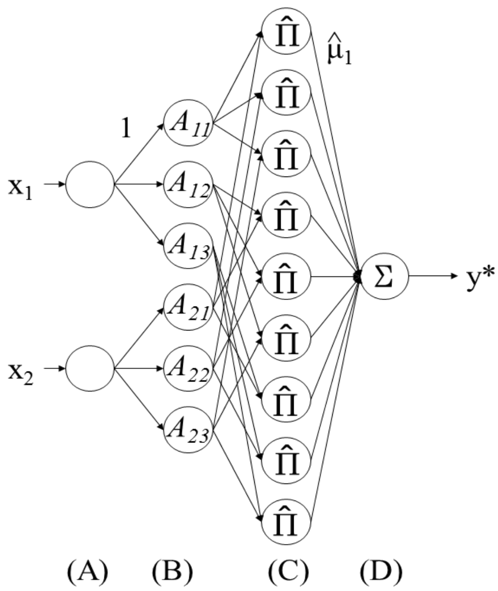


Fig. 2 Structure of a Fuzzy-Neural Network

where a_{ij} is mean of the Gaussian function, b_{ij} is width of the Gaussian function, h_i is the fitness of the rule i, y^* is output of the fuzzy neuron, y is training data, y_k is output of the rule k, x_i is input value, α and β are learning rates.

2.3 Use of ANNs for condition assessment

ANNs have motivated intensive studies for the purpose of structural damage assessment along with other methods such as Support Vector Machine and spectrum analysis. ANNs are selected for this study since their application for a long term monitoring study may be more practical. Once trained successfully; the network can be used to predict output values for new input data from the continuous monitoring of bridge components during the lifetime of the structure. In addition, since a large scale heavy movable structure is composed of many components each serving for different purpose, it is much easier to incorporate these components in ANNs. The reason is that ANNs have the ability of processing multi-input and multi-output problem for complicated scenarios such as the ones faced during the operation of a movable bridge. Moreover, some signals may not be easily recognized and interpreted by other methods, which is usually a more achievable task for ANNs. Finally, since it is not possible to collect perfect data and measurement uncertainties exist for every bridge operation, the ability of ANNs to handle noisy data becomes very critical.

Due to several advantages including the ones mentioned above, ANNs have been applied successfully in many diverse applications for vibration based damage identification of mechanical systems. Samanta and Al-Balushi (2003) developed an ANN-based procedure for fault diagnosis of rolling element bearings using features extracted directly from time-domain vibration signal segments through a pre-processing. The authors stated that the success rate for training was almost 100% and that of test was also quite high 98–100%. They indicated that the presented procedure could be used to classify the status of the machine in the form of normal or faulty bearings. Rafiee *et al*. (2007) presented a new procedure to recognize gear and bearing faults of a typical gearbox system using an MLP-NN. The authors developed the MLP network with a 100% perfect accuracy to identify gear failures and detect bearing defects. Castejon *et al*. (2010) developed an automatic fault classification technique based on multi-resolution analysis and neural networks. It was found that the MLP-NNs can be used to classify the bearing condition with a success rate of up to 80%.

Li *et al*. (2000) employed the neural networks to diagnose bearing defect types in motor-bearing systems by using frequency features of the rolling bearings as inputs. This study showed that neural networks could be effectively used in the diagnosis of various motor bearing faults through appropriate measurement and interpretation of motor bearing vibration signals. Kowalski and Kowalska (2003) used MLP-NNs and self-organizing Kohonen networks for diagnosis problems of the induction motors in the case of rotor, stator and rolling bearing faults. It was shown that ANNs could be effectively used for the recognition of stator, rotor and rolling bearings and supply asymmetry faults by appropriate measurements and interpretation of the current and vibration spectra. Rajakarunakaran *et al*. (2008) developed a fault detection model by using feed forward network with back propagation algorithm and binary adaptive resonance network (ART1) and former showed an overall detection rate of 99.3% and the latter showed about 100% accuracy. These studies show that ANNs can be successfully employed to identify the healthy and unhealthy condition of mechanical structures using vibrations data.

When ANN applications for bridges are considered, Barai and Pandey (1995) presented vibration signature analysis of steel bridge structures based on ANNs for the purpose of damage identification and the average percent error in the identification of stiffness of members was found to be less than 4%. Yeung and Smith (2005) developed a method for detecting the onset of damage in bridges using the dynamic response spectrum evaluated from continuous monitoring data, together with neural networks for pattern recognition. The authors showed that a reliable damage identification rate of about 70% could be achieved even with a moderate amount of noise added to the dynamic response signals. Fang *et al*. (2005) presented a structural damage detection method based on neural network with learning rate improvement. In that study, frequency response functions (FRFs) were used as input data to the back-propagation neural network to estimate the location and severity of damage as the outputs and the network gave a maximum error of 17.7%. Gonzalez and Zapico (2008) used neural networks for seismic damage identification intended for buildings with steel moment-frame structure using low natural frequencies and mode shapes. The study showed that the coefficient of variation of the errors should be less than 0.1% for natural frequencies and 0.02% for mode shapes to obtain absolute values of the damage prediction errors up to 0.05 with a 95% confidence.

As discussed above, there are examples of using ANNs for condition monitoring of mechanical components as well as bridges and other fixed structures. However, there are no studies conducted to identify long term performance of bascule type movable bridge machinery using ANNs. Moreover, most of the ANN applications rely on pre-processed data where modal parameters or features extracted in frequency domain are used. In the presented approach, minimum pre-processing is used since the ultimate aim is to develop a practical automated monitoring approach. Since the complex interaction between the structural and mechanical components make the movable bridges unique structures, the authors believe that this study will contribute to the body of knowledge by developing two different ANNs for condition monitoring of these structures and demonstrating them with long term monitoring data.

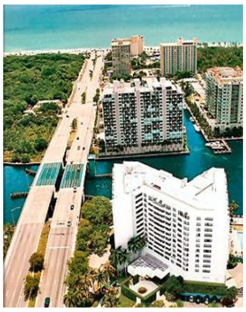
3. Structural Health Monitoring (SHM) of a Movable Bridge

Movable bridges are one of the most common types of heavy movable structures. Three main types of movable bridges are lift type, swing type and bascule type bridges. This study focuses on a bascule bridge, which is a drawbridge with a counterweight that continuously balances the span throughout the entire upward swing. The interior spans are also called “leaves” and a clear passage for marine traffic can be provided when these leaves rotate upward and away from the centerline of the waterway. The leaves rotate about the trunions and are counterweighted to reduce the power required for operation. The electrical motor provides the power to the gearbox, which rotates the shafts. These shafts are connected to rack assemblies and open gears, which are mounted to the main girders. Two-leaf bascule bridges have a locking device at the tips (span locks), and are arranged to act as cantilevers when closed, and sometimes as three-hinged arches. The span locks keep the ends of the leaves from bouncing as traffic crosses over the bridge (Koglin 2003).

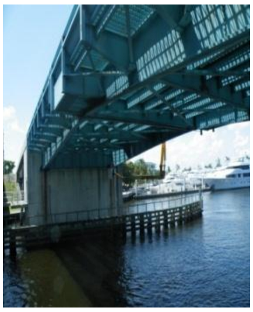
Movable components include all structural and mechanical parts as well as the machinery that operate for opening and closing of the bridge. The movable bridge also involves fixed components, such as reinforced concrete piers and approach spans. Proper functioning of all these components is critical for the bridge operation. Most common problems observed at the majority of the bridges are the mechanical system of the bridge, including the electrical motor, gearbox, span lock, open gear, racks, bearings, pinions, and the trunions. The drive motor components and the gears need continuous maintenance, lubrication and inspections. Still, the movable parts deteriorate very quickly due to fatigue and wear, and may fail unexpectedly. In addition, all mechanical components are subject to corrosion, due to high humidity and harsh conditions at the site. Also, movable bridges constantly suffer the wearing effect of opening/closing operations.

The authors investigated the most common issues associated with movable bridges and designed a comprehensive SHM plan and installed on a movable bridge over Florida Inter Coastal water way (Sunrise Bridge, Fig. 3). This bridge was constructed in 1989. It has double bascule leaves, each 22.50 m long approximately, and 16.15 m wide, carrying three traffic lanes and opening about 15 times a day. As a part of the research studies, main issues for the maintenance of electrical, mechanical and structural components of the movable bridge were identified. Based on these, an extensive sensor network was designed and implemented to monitor various parts of the bridge.

A total of 160 sensors (adding up to more than 200 channels) were deployed to the bridge for monitoring the electrical, mechanical and structural components as well as collecting environmental data. The electrical and mechanical components are monitored with accelerometers, strain rosettes, tiltmeters, microphones, infrared temperature sensors, ampmeters, video cameras, and pressure gages (Catbas *et al*. 2010). Structural components are mainly monitored with accelerometers, high speed strain gages and slow speed vibrating wire strain gages. A video camera detecting the traffic to correlate it with the other measurements is also installed. Finally, a weather station is installed to measure wind speed, wind direction, humidity, temperature, barometric pressure, and rain. Fig. 4 shows the schematics of the implemented monitoring system. The data acquisition system (DAQ) is controlled by two computers, which are synchronized by using a GPS and wireless Internet communication. Data collection and processing on each leaf are handled by two DAQs. All the dynamic sensors are connected to one of the two National Instruments SCXI 1001 chassis with its corresponding modules. The vibrating wire strain gages are controlled by one of two CR1000 units by Campbell Scientific.

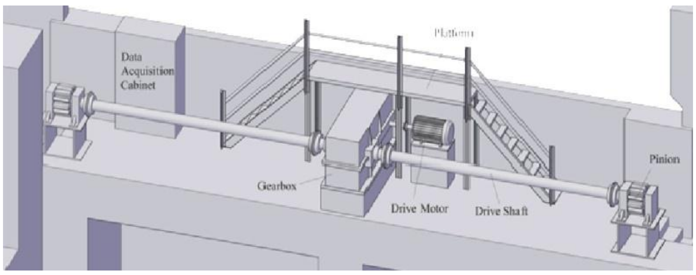


(a) Plan View



(b) Superstructure

(c) Bridge Opening



(d) Some of the Mechanical/Electrical System of Representative Movable Bridge

Fig. 3 Sunrise Bridge

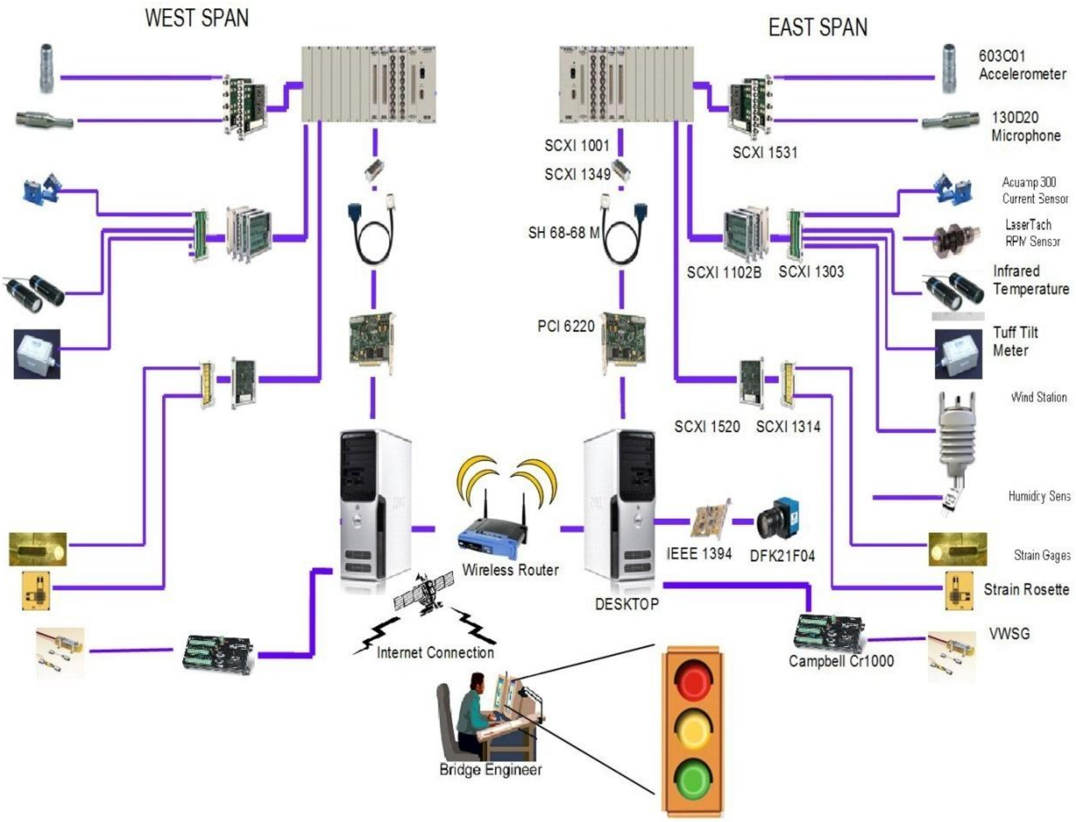
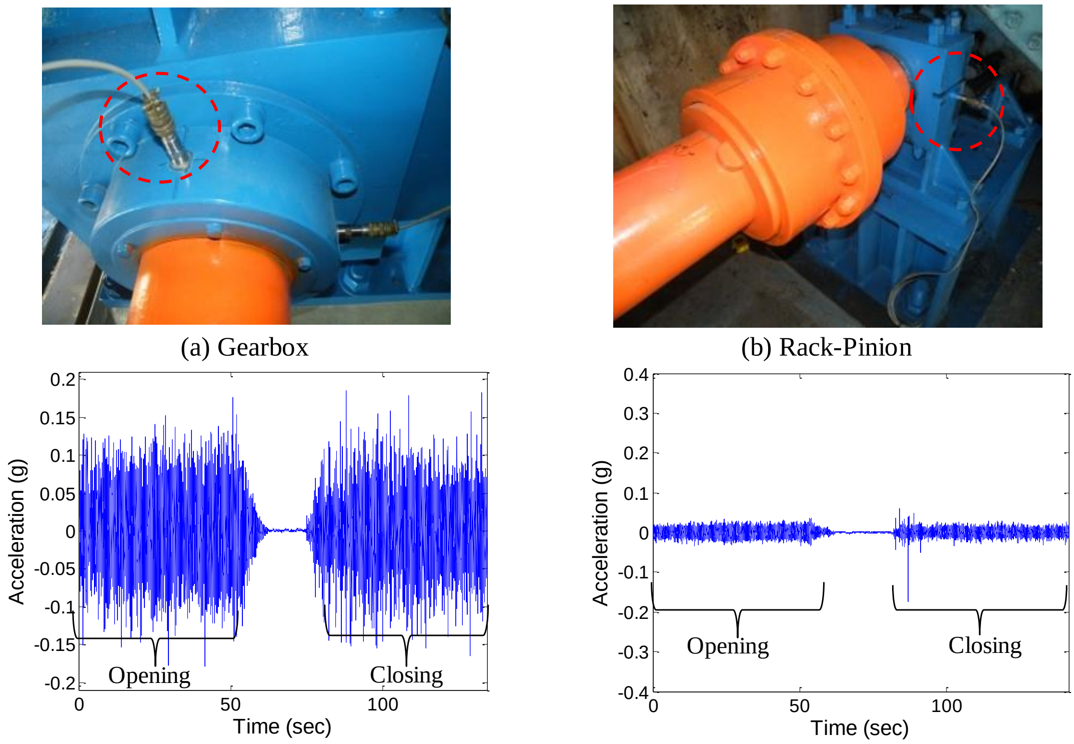


Fig. 4 Sensor network used in the movable bridge project

In this paper, the two critical mechanical parts of the bridge, gearbox and rack-pinnion/open gear assembly, are investigated by using the data from the accelerometers installed on these parts. The characteristics and distinct behavior change in dynamic response are tracked using the SHM system. Two types of damage identified for these two components are leakage from the gearbox and inadequate lubrication of the open gear. The early detection and diagnosis of damage in these parts are of great practical significance and paramount importance in the sense that it may help avoid performance degradation and major damage to the system. Therefore, these parts were monitored with accelerometers. The gearbox (Fig. 5(a)) is instrumented with six accelerometers at different locations in both horizontal and vertical directions. The rack and pinion/open gear assembly (Fig. 5(b)) is instrumented with horizontal accelerometer to monitor the open gear. Data is collected with a 250 Hz sampling rate. A large number of data sets from the components were collected (Figs. 5(c) and 5(d)).



(a) Gearbox (b) Rack-Pinion

(c) Gearbox health acceleration data (d) Rack-Pinion healthy acceleration data

Fig. 5 Sensors on gearbox and rack-pinion with corresponding sample acceleration data

The bridge owners provided a unique opportunity to artificially induce some of these possible issues as damage scenarios on the bridge. As a result, 25% of oil from the gearbox was removed to see the effect of leakage from the gearbox (Fig. 6(a)). In addition, to simulate inadequate lubrication of open gear, large portion of the grease on the open gear was removed (Fig. 6(b)). Under these damage conditions, the gearbox and the rack and pinion/open gear were monitored during the opening and closing of the leaves of the bridge. Using healthy (baseline, undamaged) and unhealthy (altered, damaged) data sets, an artificial neural network-based framework was developed for detecting the mechanical alterations at the gearbox and the rack and pinion/open gear. More than 170 data sets collected over a period of two months were employed for the analysis of the data.

3.1 Feature selection

The objective of this step is to extract features that are sensitive to the damage without a need of rigorous pre-processing. It is widely accepted that statistical parameters of the vibration signal may carry some information about the damage. For example, Samanta and Al-Balushi (2003) used some statistical parameters for detection of bearing and gear fault. Successful results were obtained where root mean square, variance, skewness, kurtosis and normalized sixth central moment were used from time-domain vibration signal as input to the network for fault diagnosis of rolling element bearings. In our study, several statistical parameters were tested initially for determining simple yet effective solutions. As a result, the characteristic features of the time-domain vibration signals were selected as maximum vibration (average of the ten largest to avoid outliers) and minimum vibration (average of the ten smallest values) of the signals from the opening part of the data sets along with the standard deviation. These features can be expressed as follows

$$Max = \frac{\sum_{i=1}^{10} Sort(opening\ data,'descend')(i)}{10} \tag{7}$$

$$Min = \frac{\sum_{i=1}^{10} Sort(opening\ data,'ascend')(i)}{10} \tag{8}$$

$$Stdev = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{9}$$

where N is the number of data points in opening parts.

When the data is collected during the opening and closing of the bridge, there are three distinct regions: bridge opening region, bridge open region (practically zero vibration) and bridge closing region. The preliminary analysis showed that the considered features extracted from opening region are more sensitive to the damage than the closing region. Therefore, only the opening region of the vibration signal is used in the analysis. Since the selected features show some differences between the healthy and damage condition, they are deemed appropriate for damage detection. The features of the time-domain vibration signals (six parameters: maximum, minimum and standard deviation of gearbox opening part and the same of the rack-pinion/open gear) with healthy and damaged condition were used as inputs to the ANNs. The output layer consisted of two binary nodes indicating the status of the components as healthy (0, i.e., no damage) or damaged (1, i.e., with damage).

(a) Removal of the oil from gearbox

(b) Grease removal from the open gear

Fig. 6 Changes in the condition of the mechanical components

3.2 Framework and training of the ANNs

ANNs learn from the existing patterns and then make predictions for the patterns that were not considered during learning. Therefore, the success of a network is measured by its generalization performance. If the difference between the actual and computed output by the ANN is within an acceptable level, the network can be used for prediction in a similar domain, which exhibits certain common characteristics with the existing patterns. As discussed earlier, the network parameters and topology play and important role in the prediction performance of a network. The best performance is generally achieved after extensive parametric studies on the different network using trial and error approach.

As mentioned before, a large number of data sets from the healthy condition and several data sets from the unhealthy condition of monitored parts were collected. Statistical parameters were used to identify the certain features of opening part of acceleration data. The analysis of these features was used to determine the current state of system health using neural networks.

One of the important considerations for training of the MLP-NN was to efficiently interpret the results from the ANNs. As a result, “0” was assigned to no damage (healthy condition) case whereas “1” was used for the damaged case as the output of the ANNs. A total of 172 input-output patterns (pairs) were generated and were divided into three sets as the training, the cross-validation and the test sets. The training set contained 125 patterns and was used to detect the relationship between the statistical parameters of the vibration signals and the damage. Out of 125 patterns, two patterns included damage due to removal of 25% of oil from the gearbox; three patterns included the damage due to the inadequate lubrication of the open gear. The remaining patterns represent the healthy condition of the components. The cross-validation set contained 40 patterns and was used to avoid the over-fitting (or memorizing) problem. The test set consisted of seven patterns that were not used in training phase and was used to evaluate the performance of the networks. Out of these seven patterns, one pattern was used to identify the removal of 25% of oil from the gearbox, three patterns were used to identify the damage due to the inadequate lubrication of open gear and the remaining three patterns were used to identify the no-damage case.

In this study, the Levenberg-Marquardt algorithm was used for the MLP-NN learning rule, and the sigmoid function was used for activation function. Since Levenberg-Marquardt algorithm usually converges faster than other learning rules and it performs more efficiently, it is more convenient and practical for trial of different networks (Rao and Kumar 2007). In addition, while almost all learning rules lead to somewhat satisfactory results, Levenberg-Marquardt algorithm based networks usually produce very good results (Hagan and Menhaj 1994, El-Bakhyr 2003, Cigizoglu 2004, Yetilmezsoy and Demirel 2008). The use of sigmoid function requires that the input and output data be scaled to the range [0-1]. In the present study, the input and output data were scaled to a narrower range between 0.2 and 0.8, resulting in a considerable improvement in learning speed due to increased sensitivity of the sigmoid function for this range. Based on the defined network parameters, the number of hidden layers and the number of processing elements in hidden layers were identified by testing several architectures. After completion of training of each network design, the performance of the network was tested using the test patterns that were not used during the training. The performance was measured by the average maximum error in the testing set and mean square error (MSE). This process was repeated for each network design. In this way, many networks, which were capable of generalization at different levels, were obtained and the best network is selected from these many network candidates.

As in the previous case, a total of 172 input-output pattern pairs were used for training of the

FNN. In the FNN case, these patterns were divided into two sets: the training set and the test set. The training set contained 165 patterns whereas the remaining seven patterns were used for testing the network. For this case, three out of 165 patterns are from the gearbox damage case (removal of 25% oil from the gearbox), six patterns are from the open gear damage case (inadequate lubrication of the open gear). Rest of the patterns are obtained from the healthy case of the structure. Seven patterns that were not used in the training phase are used in the test phase as was in the previous case. One of these test patterns was from the gearbox oil removal case, three patterns were from inadequate lubrication of open gear case and the remaining three patterns were from healthy case.

3.3 Development of the network models

Obtaining the best network is a lengthy process that requires trial of different network parameters in several architectures. After a number of trials, appropriate values of the MLP-NN parameters were set as shown in Table 1.

Several architectures were tested in conjunction with the network parameters shown in Table 1 to identify the one having the best prediction performance, e.g., the best generalization capability. A typical architecture is designated as "input nodes (*n*) - [hidden nodes per hidden layer (*m*)]-output nodes (*p*)". For example, the notation "6-(7-7)-2" indicates that the network architecture consists of an input layer of 6 nodes, an output layer of 2 nodes, and two hidden layers of 7 nodes each. Two cases were created and studied with respect to the choice of network architecture as well as the selection of network output. First case was 6-(m)-2 architecture (*m* varying from 1 to 15), which had one hidden layer with m nodes. Second case was 6-(*m*-*m*)-2 architecture (*m* varying from 1 to 15), which had two hidden layers both with m nodes. The network performance was associated with the maximum differences in the damage prediction of the network for all the testing patterns. If the maximum testing error appears to be below the tolerable level, then the performance of network was considered satisfactory.

Table 1 Summary of the MLP-NN Properties

Network Parameters	Values or Types
Number of training examples	125
Number of cross-validation examples	40
Number of test examples	7
Number of input layer neurons	6
Number of output layer neuron	2
Type of back-propagation	Levenberg-Marquardt
Activation function	Sigmoid function
Normalization range	[0.2, 0.8]
Learning rate	0.01
Training mode	Batch mode
Termination rule	Minimum cross validation error or maximum epoch

The impact of the number of hidden layer and hidden nodes on ANN performance in terms of MSE and prediction is shown in Figs. 7 and 8. The learning and prediction performances of the network vary depending on the number of hidden layers and the number of nodes in the hidden layers. It can be observed that the number of hidden layers and hidden nodes have a relatively significant effect on MSE and the predictive ability of the MLP-NN. Even if all of the networks considered here have adequate MSE, it does not guarantee the best prediction rate (generalization capability). However, all the trained networks are able to predict the existence and location of damage for all the testing patterns to some degree. Figs. 7 and 8 show that the MLP-NNs with two and three hidden layer nodes have the lowest MSE and lowest prediction difference. Hence, a single or two hidden layer with two or three number of neurons is sufficient for modeling of this problem with a good accuracy. The best MSE and prediction performance is achieved by a network architecture with two hidden layers and two nodes per layer which can be denoted as 6-(2-2)-2.

As in the ANN case, the best FNN structure was achieved after several trials. The details of the process which is very similar to the one described above is not presented here for the sake of brevity. The networkparameters for the FNN are chosen as summarized in Table 2.

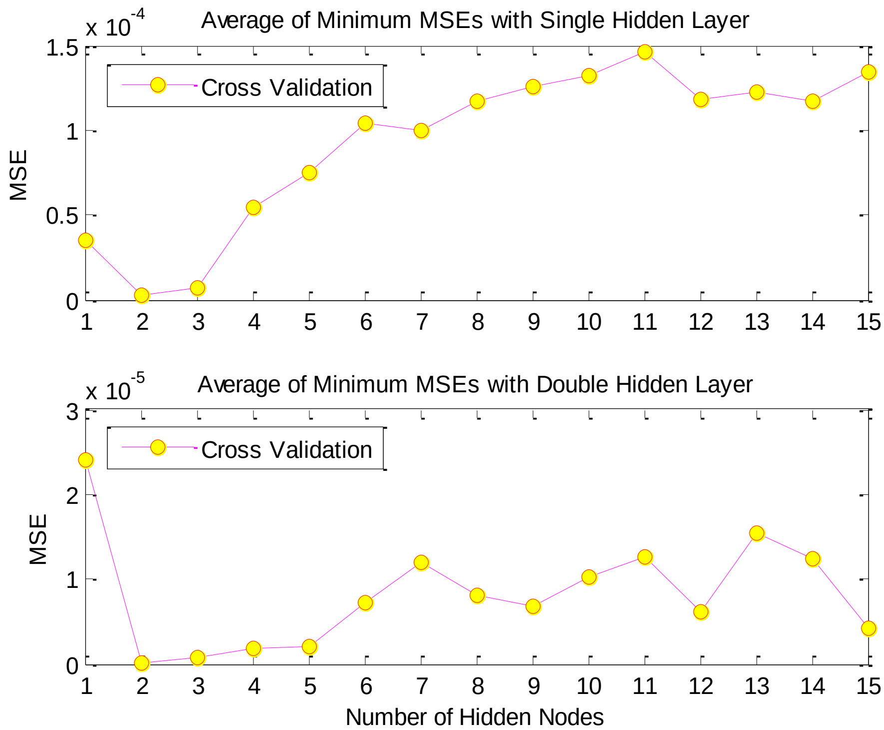


Fig. 7 Variation of Mean Square Error (MSE) of Network Architecture with Training Sets

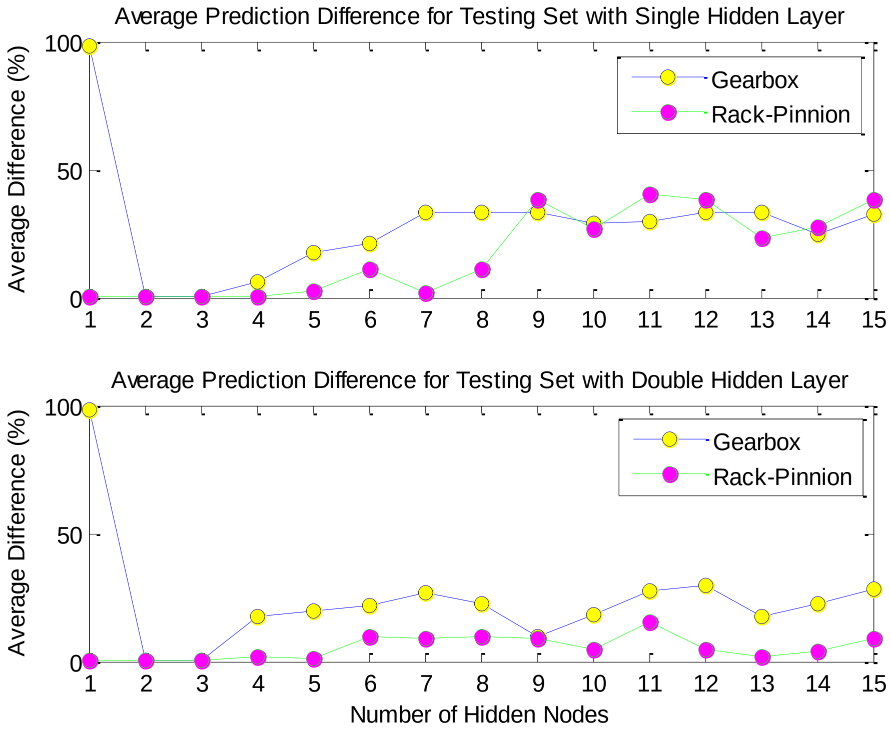


Fig. 8 Variation of Prediction Performance depending of the Network Architecture for Testing Set

Table 2 Summary of the FNN Properties

Network Parameters	Values or Types
Number of training patterns	165
Number of test patterns	7
Number of input layer neurons	6
Number of output layer neurons	2
Activation function	Gaussian function
Normalization range	[0.0, 1.0]
Learning rate	0.01
Number of the membership functions	5

4. Diagnostic of Bridge Gearbox and open gear damage

As mentioned in the previous section, the best performance of MLP-NN in predicting is achieved by using two hidden layers each having two nodes with the defined network parameters. In Fig. 9, the average MSE in training versus epochs is plotted for this model. The MSE drops drastically after 4 epochs and carries on running until minimum validation error which is reached at epoch 62 with an MSE of 6.44E-11.

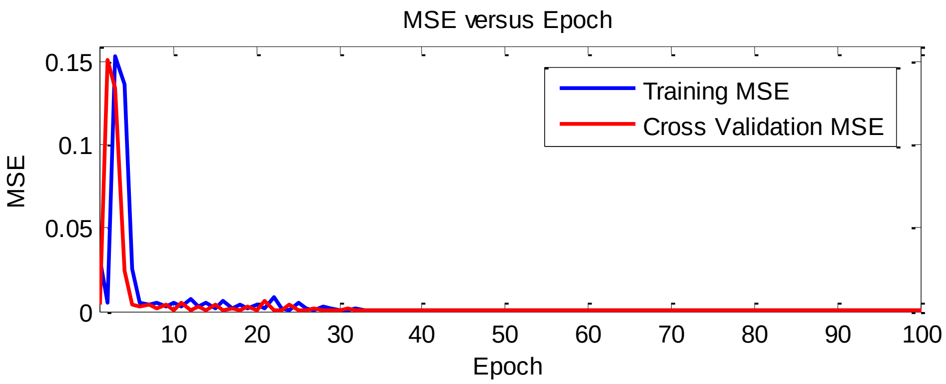


Fig. 9 Learning Curves for 6-(2-2)-2 Network

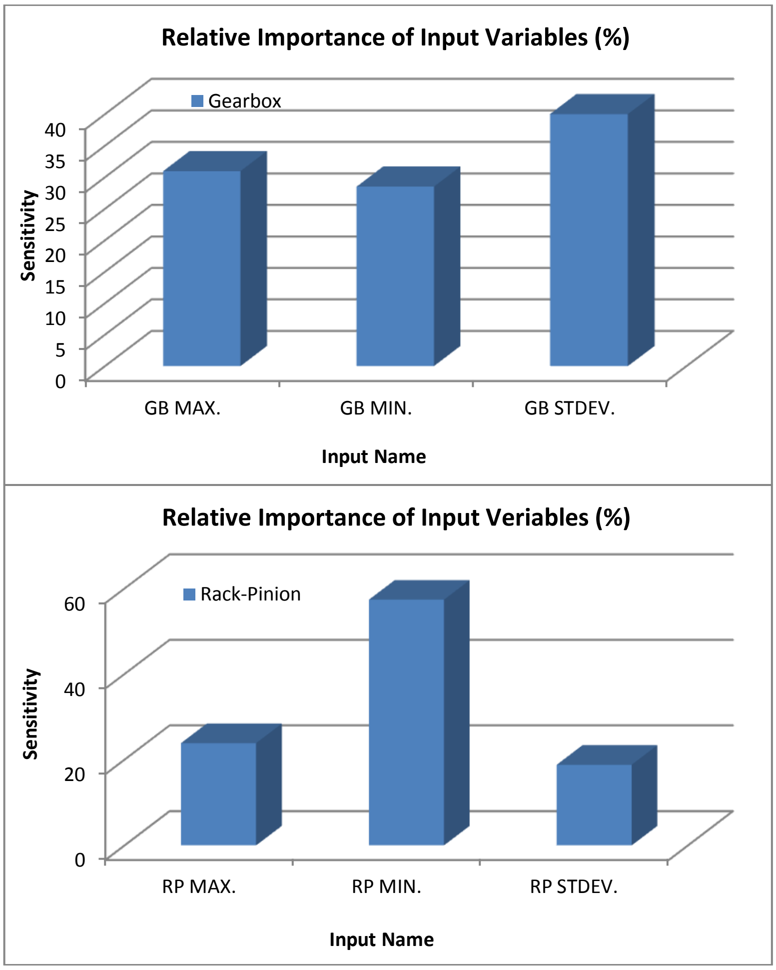


Fig. 10 Relative Importance of Input Variablesfor Gearbox and Rack-Pinion

The sensitivity analyses are carried out using the trained networks to extract the relationship between the inputs and outputs of the network. This testing process provides a measure of the relative importance among the inputs of the neural model and illustrates how the model output varies in response to variation of an input. The results of sensitivity study are shown in Fig. 10. It can be observed that standard deviation of gearbox data is the most sensitive input for the removal of oil from the gearbox with average relative importance equal to 40.6%, while the maximum and minimum of gearbox acceleration signal are with average relative importance equal to 31% and 28.4%, respectively. The sensitivity analysis also indicates that the most sensitive input to the inadequate lubrication of open gear is the minimum of rack-pinion acceleration signal with average relative importance equal to 57.4%, while the maximum and standard deviation of rack-pinion data are with average relative importance equal to 23.8% and 18.8%, respectively. These results verify that all parameters are sensitive to damage and should be considered in establishing a robust ANN model.

To ensure that the network training has been satisfactorily completed and the network is capable of generalization, a set of unseen patterns must be selected and the network should be tested using these patterns. For this purpose, a total of seven testing patterns were used to observe the prediction performance of all the architectures considered in the study. As discussed before, out of seven patterns, one pattern is from the removal of 25% of oil from the gearbox case, three patterns are from the inadequate lubrication of open gear case and the remaining three patterns are from the no damage case.

Table 3 shows the desired outputs and best MLP-NN and FNN outputs for all testing patterns. It is clear that the prediction of the best MLP-NN for seven unseen patterns is quite successful. For this network, the best network yields maximum difference of 0.007% for gearbox and yields maximum differences of 0.005% for rack-pinion/open gear under the defined network parameters. This indicates that the network was trained successfully to establish the relationship between the statistical parameters and damage and to interpolate this relationship for other unseen data with a great accuracy. In addition, the coefficient of correlation between actual and predicted outputs is 0.999 for gearbox and 1.000 for rack-pinion, indicating that generalization performance of the network is very good and it is able to generalize within the range of the data used for training.

The same testing patterns were also used to assess the prediction performance of all of the FNN architectures considered. As seen in the last two columns of Table 3, outputs of the best FNN can predict the damage. This indicates that the network is trained successfully to establish the relationship between the statistical parameters and damage and to interpolate this relationship for other unseen data with an acceptable accuracy. An important observation is that this prediction is less clear for some of the patterns compared to the MLP-NN case. So, it can be stated that using FNN did not improve the results obtained with the MLP-NN for this particular application although comparable results are obtained.

In this case, the structure of the FNN is more complicated than MLP-NN. Thus, the number of the weight values that are required for adjusting is significantly higher. For this reason, more data points for training could have increased the performance of the FNN and improved the recognition rate of test data. In addition, the number of the neurons used for the FNN may be high. In this case, the numbers of the membership function for each input value are 5. It was observed for this problem that the MLP-NN can obtain the rule by using few neurons like 6 [7 7] 2. This means that the problem could have been solved with a less complex FNN, which could have increased the prediction performance. However, since the two networks are created independently, the results of the MLP-NN network were not considered in creating the FNN or vice versa.

Table 3 Results obtained using the ANN and FNN for the test set

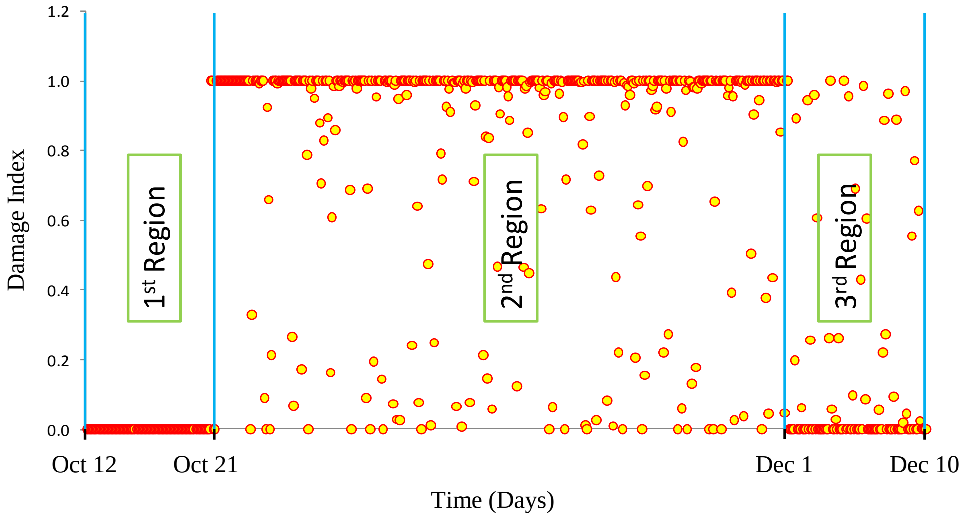
Inputs to the Networks						Actual Outputs		Outputs of the Networks			
GB			RP					MLP-NN		FNN	
Max	Min	Stdev	Max	Min	Stdev	GB	RP	GB	RP	GB	RP
0.1650	-0.1682	0.0495	0.0276	-0.0321	0.0093	1	0	1.000054	0.000053	2.228445	-0.071364
0.1332	-0.1398	0.0360	0.1585	-0.1442	0.0118	0	1	-0.000010	1.000018	-0.205481	0.844364
0.1392	-0.1348	0.0358	0.1299	-0.1863	0.0125	0	1	0.000038	1.000020	-0.254492	0.907844
0.1417	-0.1523	0.0364	0.1236	-0.1563	0.0114	0	1	0.000038	1.000020	-0.121016	0.695003
0.1437	-0.1524	0.0416	0.0337	-0.0286	0.0094	0	0	-0.000025	0.000016	0.125264	-0.065874
0.1481	-0.1484	0.0397	0.0313	-0.0295	0.0092	0	0	-0.000026	0.000016	-0.015898	-0.073897
0.1356	-0.1475	0.0404	0.0302	-0.0329	0.0092	0	0	-0.000025	0.000016	-0.003853	-0.074152

4.1 Condition evaluation with the MLP-NN and FNN models

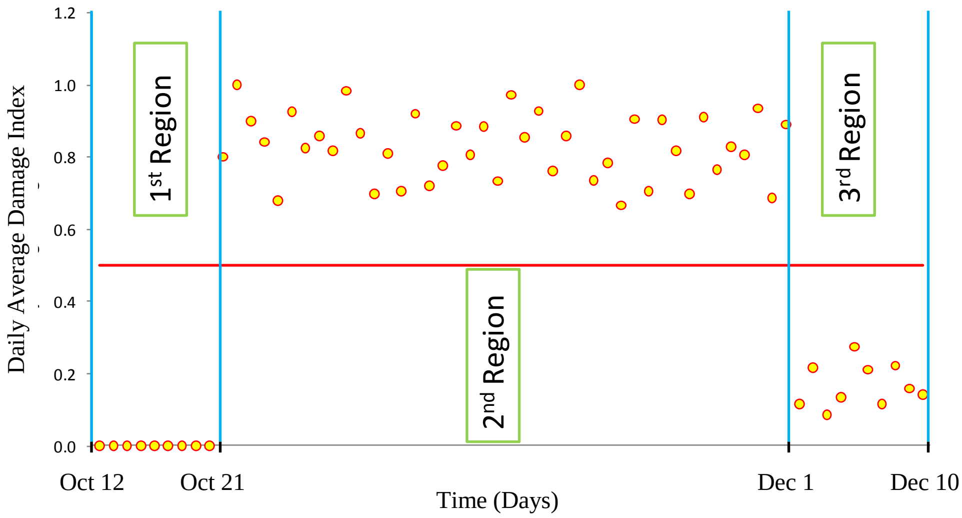
In this section, long term monitoring data (for approximately two months) from the movable bridge is analyzed by using the ANNs that were developed in the previous sections. After applying the controlled damage simulations, i.e., oil reduction in the gearbox and grease removal at the open gear, the grease at the open gear was not replaced to facilitate an opportunity for monitoring the bridge under this condition for a long term. The gearbox damage had to be repaired since there would be serious damage do the mechanical systems of the bridge if it was operated with reduced oil levels in the gearbox for a long time. Therefore, the results from the long term monitoring data for the lack of lubrication of the rack-pinion/open gear assembly will be presented in this section.

Once trained successfully, the networks can be used to predict the output values for the new unseen data. The condition of the components using new input data can be obtained (e.g., “1” or “0”) from the trained networks with a trivial computational time during the lifetime of the structure. Fig. 11(a) shows the prediction of the MLP-NN model for the rack-pinion/open gear assembly for a two-month period. This time period is composed of three important regions. First region shows the prediction of the ANN model before the damage (i.e., grease removal) was imposed on the open gear. Patterns in this region show the undamaged case used in the training of ANN. Predictions are quite satisfactory and all are around “0” which implies no damage as expected. Second region shows the period during, which the open gear is operated without proper lubrication. Predictions for this region are also as expected. Most of the predictions are around “1” indicating open gear is not properly lubricated. Third region shows the response of the ANN model after the open gear is lubricated again. Following the greasing of the open gear, the predictions mostly drop to “0” again indication the component has no damage anymore.

As can be seen from the Fig. 11(a), there are some predictions in the second region which are not around “1” and similarly there are some predictions in the third region which are not around “0”. These occasional inconsistent results are expected due to the random noise in the data and suggest that there needs to be a strategy to be defined to decrease the number of false positive or false negative alarms. One option for reducing the false alarms may be to look at the average of the daily values since it is not practically possible that the grease level of the open gear will decrease significantly each day. If such an average is calculated for all the opening-closings in one day, it may give a very good idea of the condition of the open gear with a reduced number of false alarms. Such approaches were also considered by different researchers in the literature to come up with more robust approaches to eliminate false positives and false negatives (Worden *et al*. 2000, Sohn *et al*. 2002). With this approach, if the daily average of the MLP-NN output is above 0.5, it can be considered damaged. Fig. 11(b) shows the results obtained by using the daily averaging approach and it is observed that the damage identification results are significantly improved.

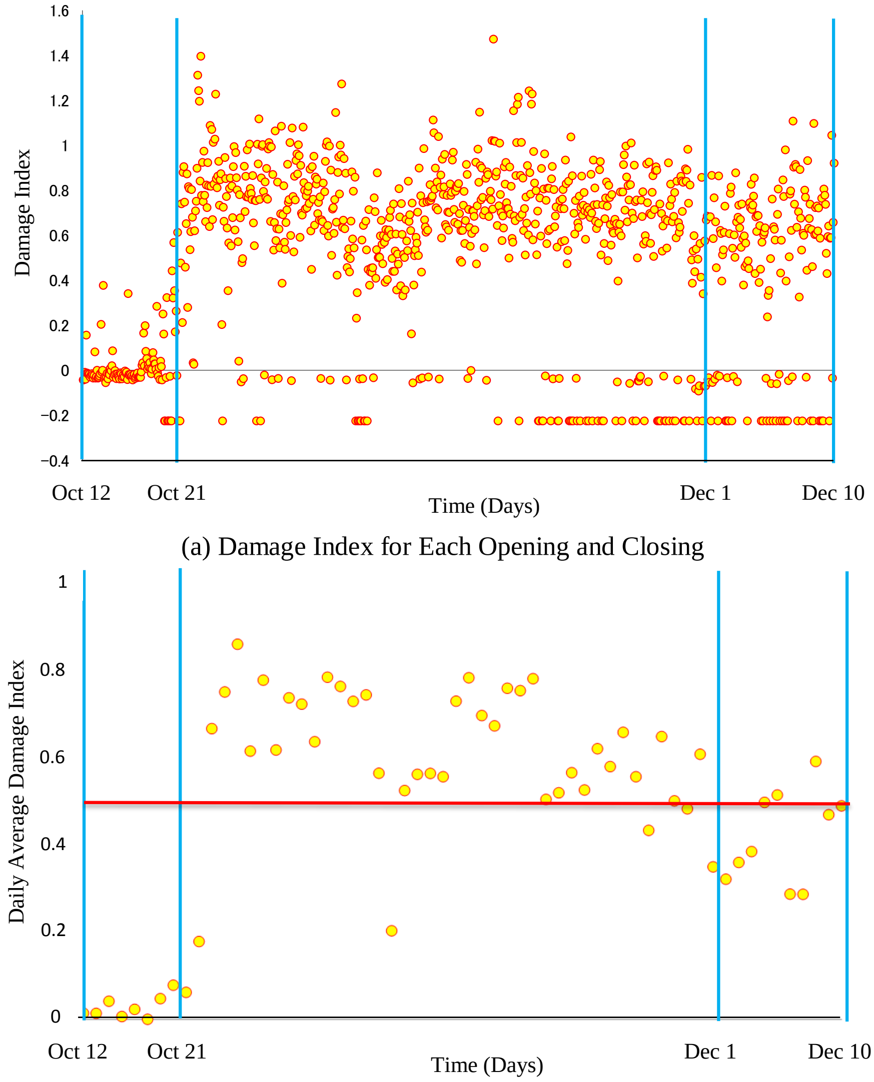


(a) Damage Index for Each Opening and Closing



(b) Daily Average Damage Index

Fig. 11 Monitoring of Rack-Pinion with MLP-NN Model for two Months including Damage (2nd Region) and Undamaged Periods (1st and 3rd Region)



(a) Damage Index for Each Opening and Closing

(b) Daily Average Damage Index

Fig. 12 Monitoring of Rack-Pinion with FNN Model for two Months including Damage (2nd Region) and Undamaged Periods (1st and 3rd Region)

Looking at the results obtained for the long term monitoring using FNN in Fig. 12(a), it is observed that the prediction accuracy is somewhat smaller compared to the results obtained with MLP-NN. In particular, it is noted that the damage indices do not drop significantly after the replacement of the open gear grease on Dec 1. As in the MLP-NN case, the number of the false alarms for FNN also decreases significantly when the daily average concept is implemented. The daily average damage index values are significantly lower than the threshold value for the undamaged regions whereas the values are higher than the threshold for the damage region with occasional outliers.

Generally speaking, the accuracy of the FNNs can be improved by increasing the number of the membership functions. However, if the network is too complex, the accuracy of predictions for the test data may decrease. As discussed previously, the performance of the FNN may improve by using a less complex network, which will be investigated by the authors in near future.

5. Conclusions

The objective of this paper is to present a unique Structural Health Monitoring (SHM) study carried out for the maintenance decision making about a real life movable bridge. While the mechanical components of movable bridges are maintained on a scheduled basis, it is desirable have monitoring technologies and data analysis methods for condition-based maintenance. The specific objective of the study presented in this paper is to track the operation of a gearbox and a rack-pinion/open gear assembly, which are critical parts of bascule type movable bridges. In this study, vibration data from mechanical components of a movable bridge is analyzed to predict their conditions using ANNs. The components under consideration are the gearbox and rack-pinion/open gear assembly, which are critical for the opening and closings of movable bridges. These components are monitored using accelerometers for healthy condition for a sufficiently long period of time. With the unique opportunity to artificially induce reversible damage on the gearbox (reduction of the oil) and rack-pinion/open gear (grease removal) in a controlled manner, these components are monitored to acquire data representing the unacceptable bridge mechanical condition. Damage-sensitive features based on statistical properties are extracted from the vibration data.

Then, these features are utilized to train two different ANNs, an MLP-NN and an FNN, to identify the patterns between the statistical parameters and damaged/undamaged cases. A database containing a total of 172 input-output patterns is used for model development and verification. The effect of using various network parameters on the results of for both MLP-NN and FNN is investigated. The results from the different network models are compared with each other to identify the one providing the most accurate solutions. A sensitivity analysis is also carried out to study the relative importance of the input parameters. Finally, the best models are used to evaluate the condition of the components for a certain period time.

The results indicate that both of the networks have the ability to identify the damage by using the correct network parameters with the right architectures. The best network for MLP-NN is found to be one having 6-(2-2)-2 network geometry with Levenberg-Marquardt learning algorithm. It yields maximum difference of 0.007% for gearbox (between actual and predictions) and yields maximum differences of 0.005% for rack-pinion/open gear assembly under the defined network parameters for testing set. The best network for the FNN is achieved by using a Gaussian activation function and seven membership functions.

Finally, long term monitoring data for two months was analyzed for investigating the prediction capabilities of the networks. For the long term monitoring, the gearbox was in healthy condition whereas the rack-pinion/open gear assembly was in damaged condition since the removed grease was not replaced for two months intentionally. The long term predictions of both of the networks were successful for identifying the damage although there were some false positives and false negatives observed. The prediction accuracy dramatically increased when a daily average damage index was introduced. It should be mentioned here that, the MLP-NN performed better than the FNN overall.

The results of this study indicate that ANNs perform successfully making them a powerful and practical tool for identification of damage in critical mechanical components of a movable bridge. This study can also be expanded such that not only the existence and location of damage but also the level of the damage can be determined by using the damage data at different damage level in training phase. In addition, the long term monitoring can be employed to explore environmental effects on mechanical component operation and performance.

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