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Damage Prediction Techniques for Structural Health Monitoring in Bridge using sensors and ANN-Machine Learning Technique

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Abstract

In the last few decades, structural health monitoring(SHM) has been a major concern, and in the study of data collected from monitoring devices embedded in the networks, it gives engineers deep understanding about the failure of civilian infrastructure. Commonly named structural health monitoring is the method of applying a damage recognition for climate, civil and mechanical engineering facilities With both the growth of technologies sensor networks (SNs) a vast number of sensors is fitted with architectural or mechanical systems to receive real-time information on their wellbeing, suggesting that data handling in WSN-based SHM is of significant importance. Increased SHM innovation has been empowered with the development of intelligent sensors and real-time connectivity systems over wireless sensor networks (WSN). Recently, predictive time series simulations for structural damage detection due to the function coefficients resistance and unresolved structural damage mistakes have been commonly used. Machine Learning algorithms (ML) are progressively used to predict damage. The main approach is the tool used to estimate the degree of damaged brides via the sensors. In the second step artificial neural network (ANN) method enabling the detection level objectively describes the generalization error of each bride.

Keywords: *Machine learning Algorithms, Structural health monitoring, Damage detection, sensors, artificial neural network (ANN).*

1. Introduction

For structures including such bridge SHM is mostly necessary and buildings usually mean a network of constantly mounted sensors that track the structure's actions. It is often believed that SHM means online surveillance, but in general, it may be done if the structure is either in operation or is not in operation. Optical fibers, strain resistance tests or acoustic instruments are common sensors [1]. Nowadays the safest way to build efficient and trusted structural risk monitoring systems is without question to make use of ageing civil infrastructure structures such as bridges that go far past their original average lifespan. The degradation has already advanced well before considerable damage to the system is found, and the reparations needed are considerable and onerous. The building will rarely be dismantled and a fresh one should be built. This requires considerable investment which has detrimental environmental and traffic effects during substitution. The ability to track a structure in real time and diagnose failure as soon as possible helps smart repair methods and offers specific life observations. The requirement for such intelligent structural health monitoring systems (SHM) is currently strong for revealed purposes.

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WLAN is a collection of small equipment known as nodes. WLAN is the set of sensors [2]. These sensors are distributed dynamically across a region and operated by the batteries. These sensor nodes may be static or portable and they are used for researching occurrences in a certain area. There may be explosion, smoke, sun, moisture etc. This may be earthquake events.

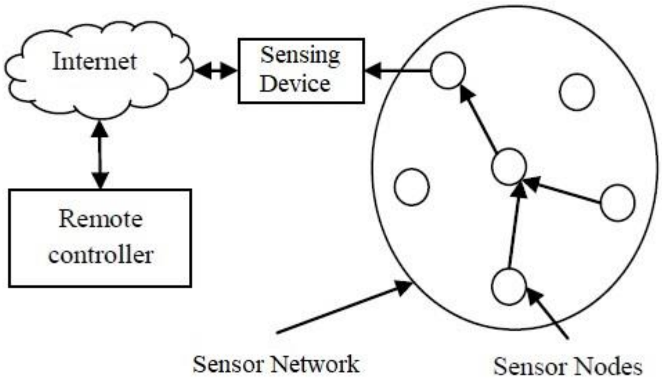

Figure 1. Structural design of Sensor Network

There are network protocols that have an on-board chip; original data are not transferred to other fusion-responsible nodes. The sensor nodes with their processing capability perform a basic computation for the data. Figure 1 demonstrates the generally known WSN structure. Three main components used in sensors are sensing subsystems, computing subsystems and Wireless communication subsystems [3]. A sensor device is used for the sensing of data from the node region. To access the raw data, a production subsystem has been used. For the transfer of data to a ground station, a wireless networking subsystem has been used.

In similar, there is an electricity supply that includes non-rechargeable cells, so decreased electricity consumption and the durability of network life are the key objective in developing networks based on WSN, The sensor node layout as shown in Figure 2.

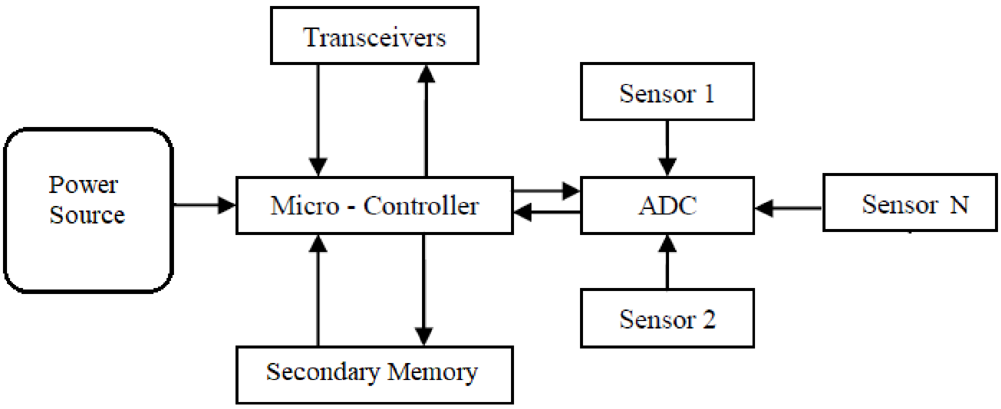

Figure 2: Sensor Node Design

WSN connectivity is raising requirement relative to other wireless networks. WSN routing protocols are listed according to four networking schemes, the coordination template strategies, the template schemes and the efficient routing scheme [4]. Communication network system is further grouped into two protocol groups First, plain protocols where every node in the network plays the very same part and secondly, hierarchical protocols under which protect the network of nodes is configured and the base station is based on different hypotheses.

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This essay provides an approach to damage detection focused on artificial neural networks, the data sets are extracted from a stable bridge situation and two risk possibilities. In fact, this information will be obtained straight from measurement taken on the current interest configuration without developing a complicated mathematical method. The proposed approach allows for the unsupervised training of sensors and artificial neural networks (ANN) [8] with data set consisting of acquired accelerations on the healthy bridge. The networks can help predict oscillations based on their value observed in preceding instants. Throughout the second phase, each network's statistical correlation coefficients support the selection of the cutoff for damage.

2. Sensor technology in SHM

Latest advances in sensor technologies have led to the production and deployment of Structural Health Monitoring (SHM) [31]systems in multiple structural components including bridges, houses, pipelines, power stations and reservoirs. Many sophisticated kinds of sensors are being equipped for the tracking of overall integrity regularly by real-time data gathering, from wire to wireless sensor nodes. Even then, by use of SHM sensors is still subject to a shocking amount of queries [10]. One of the crucial tasks for developing a SHM device is to detect an acceptable sensor type which can reach the sensing device's scopes adequately.

Structural health monitoring absolutely depends on the precise and large observations in actual environments of the structural aspect state, the coordination with the control system of this data and the alert warning needed should the uneven pattern ever be detected. Structural health monitoring sensors are built to promote the control activities and to allow maintenance technicians to use resources to make decisions that protect the security of the facilities and the community [13]. A standard health monitoring device consists of a sensor network that monitors various parameters, such as stress, friction, vibration, orientation, pressure and wind, associated with the current state of both the structure and its surroundings. Different forms of SHM sensors have become the latest innovations in sensor science study for structural health tracking. This provides the most commonly used SHM sensors for structural monitoring.

2.1. Sensors for Optical Fiber

In latest days, optical sensors have evolved quite successfully. These sensors could be used to calculate different factors in civil engineering. Examples usually involve pressures, physical motions, frequency of friction, motion, strain, moisture content. The structure monitoring may be regional or worldwide [12]. The regional method based on the component actions whereas the overall approach is linked to different structural control. For varied uses like strain control of the concrete components inside a bridge, fiber-optical sensors were tested shown in figure 3.

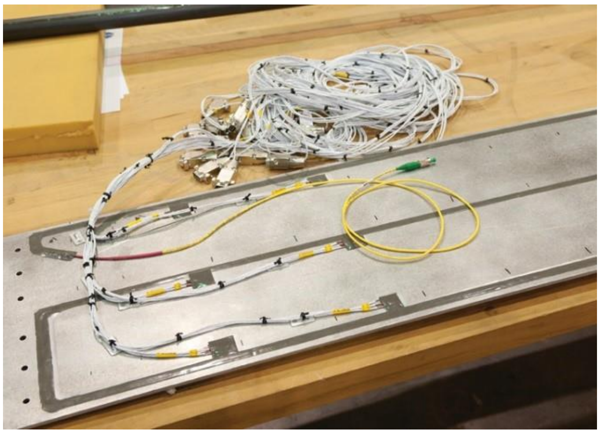

Figure 3. Sensors for Optical Fiber

2.2. SHM in Strain Gauges

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In structural health monitoring, strain gauges are by far the most common type of load cells used. A stress gauge is an instrument used for calculating stress regardless of the force applied to an object. The most popular type of pressure gauge consists of a lightweight, insulated support that supports a metallic sheet construction. A suitable sticky material binds the gauge to the piece. When the film is exposed to force, the strain gauge changes, and can be calculated. It is deformed. These sensors have been used most frequently for building structural systems to track tension.

Strain gauge Stripe shown in figure 4, it is a stress gauge is a type of strain gauge consisting of two or even more strain gauges, which are arranged similarly to measure strains in various directions [31]. The application of many strain gauges makes for a more detailed measurement of the stress on the continuous measurement.

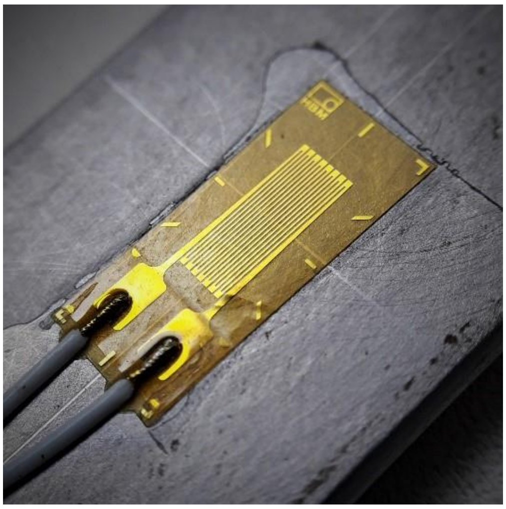

Figure 4. Strain Gauge Rosette

3. Category of ML methods for SHM

Machine learning method can be categorized as per their existence into three major areas: 1) supervised learning 2) unsupervised learning 3) semi-supervised learning [14]. The supervised learning framework offers "labeled data" learning structures, i.e. examples of defined outputs (pair of output data and input data). Regulations for classifying new data sources are generated with labeled data. In the data sets composed of 'unlabeled data,' meaning data sets with undefined outputs that are in line to the general rule and can thus be clustered together, non-supervised learning requires the identification of patterns. From both the point of view of the SHM, unattended learning can for example, be used for the identification of damage by the collection of systemic data analysis and supervised learning to detect form and magnitude of damage[15] could be used for benefit.

Semi-controlled learning, which is a mixture of both the above schemes, generally aims at obtaining a segmentation approach using labeled as well as unscheduled knowledge. In tandem with other surveillance methods, semi-supervised learning methods have been used to extract knowledge on modal bridge properties [17]. Since most SHM challenges need to provide a feature with labeled training knowledge (e.g. to evaluate data or forecast new data), supervised learning is an adequate way of addressing these problems. In supervised learning [18], the algorithms can be classified similar to as logical based algorithms (e.g. decision trees and rule-based classifiers), as concept-based or neural networks.

Supervised learning in which the input and anticipated output are provided to the machine. The device is meant to identify and make assumptions the complex patterns and interrelationships among them based on this training with the correct answers. Unsupervised, in

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which the device is educated to find the common characteristics in the information and provide a grouping institution. Almost all analytical techniques deal with some method of identity or sensors of damage..

The civil engineering areas are typically referred to as the Structural Health Monitoring or SHM as the relevant damage recognition field of study. One could argue that during its growth two dominant "competing" concepts were established for SHM, each from a different perspective [19]. The actual content is split into design SHM and information SHM. The first perspective is based in particular on the establishment, in its standard (and damaged) situation, of a simulation environment based on the law of the investment framework and when further data are collected they can be verified for model compliance and diagnosis can be made of any differences if the structure has been amended.

4. Techniques implemented in SHM

4.1. Wireless sensor networks (WSN)

WSN and ANN have structural similarity which allows the mapping of an ANN algorithm [16] into a WSN as a computing system for parallel and distributed systems. In reality, a single-to-one match occurs, as a sensor mote will reflect and execute neural network brain cell or node calculations, whereas wireless communications between the neurons/signals are similar to the cells in the brain. A WSN transceiver is a simple computer with an embedded microcontroller [21], a radio transceiver as a linking system for wireless communications as well as a range of sensors shown in figure 2. Calculation capacity associated with neuron dynamics is enough to execute several nodes in real time for most purposes. Therefore a WSN with sensors connected to each beam, it can measure damage in beam in bridges using parameters. The damage detecting process using sensors are given flow chart figure 5.

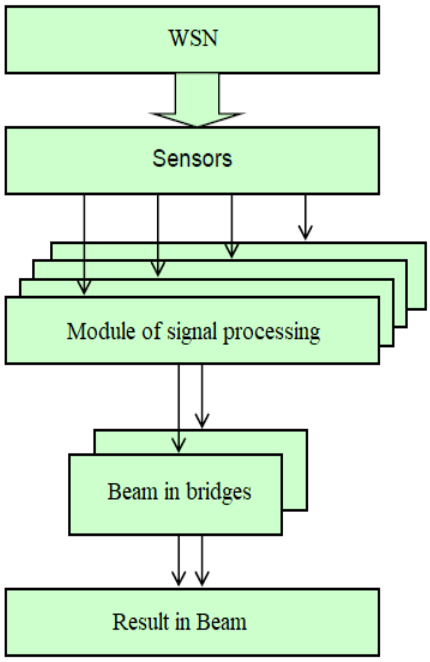

Figure 5. Damage detecting process using sensor

4.2. Artificial Neural Networks

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For the presented work, the ANNs were built and trained via the MATLAB Neural Network Toolbox. Before a training stage the structure of ANN should be built and mostly relies on the quantity of available data, which can be used to simulate bridge data [33]. In fact, the monitoring provides information is affected by different causes of error as well as several studies have examined the impact of organizational and environmental uncertainty on the harm detection mechanism [23] shown in figure 6.

This shows how the temperature and traffic mass usually will contribute to fluctuations in the bridge's modal characteristics within 5% to 10%. By learning the noise injection, the influence of input errors can be minimized. In addition to the unspoiled backgrounds of the FE model before the ANN was used, Gaussian noise was applied

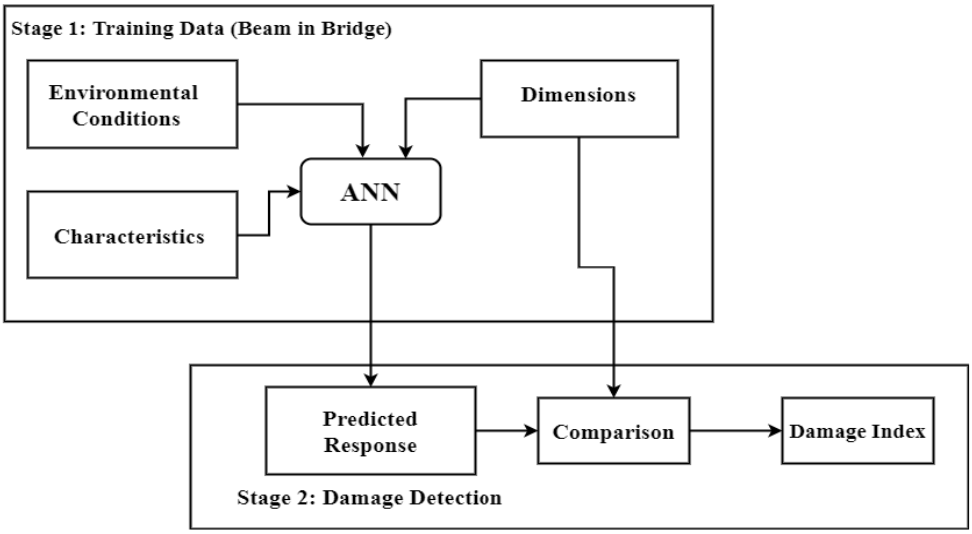

Figure 6. Using ANN to detect damage

There were 6 concrete beams with sizes 91×16×12 cm shown in the figure 7. In the experimental stage the cube strength property of 60 MPa on the concrete and a tensile fracturing power of 3.8 MPa on the scratch. The beam comes equipped with an optical fiber sensor; the frequency of signal was 1.30 Hz.

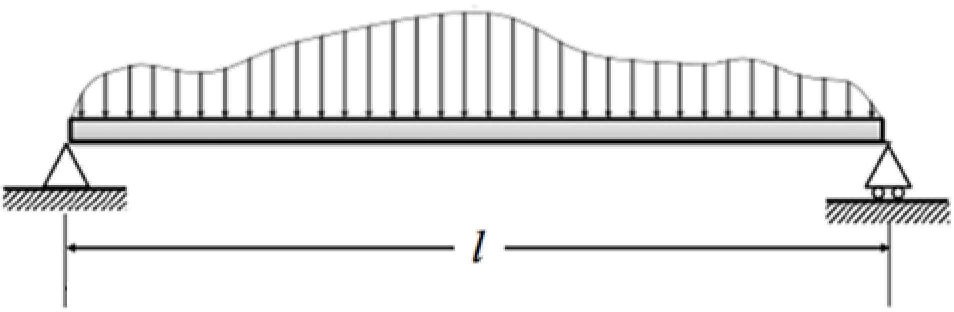

Figure 7. The sample 91cm supported beam

4.3. Damage Detection Algorithm

As stated before, HD optic fibers measure with an extremely high resolution. Herein, for a 91 cm beam we may end up with a dataset with more than 1100 features applying below algorithm find damage result in beams based on result generate the profile graph shown in figure 8. Although there might be applications where this kind of detail might be required, for the current

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(and most probably in any similar one) project, this abundance of information is unnecessary, and will increase the computational complexity for no concrete reason. Thus, a simple down sampling algorithm was implemented.

```
% Determine down sampling values
OD: Original data set
finD : Final data set
nstart : number of original features
nfinal : number of final features
rem = nstart − nfinal % nstart
div = int (nstart − nfinal / nstart )
% Down sampling algorithm
Dr = Dr(1 : end − rem)
Initialize finD
for i=1 : l ength (Dr)
Initialize helper array temp
for j=1 : nfinal
a = mean(Dr( i , div *( j )+1 : i , div *( j +1)))
end
Append an in finD
End
```

The following figures show the strain profiles acquired for all the experimental beams are presented, after being pre-filtered by the processing described above:

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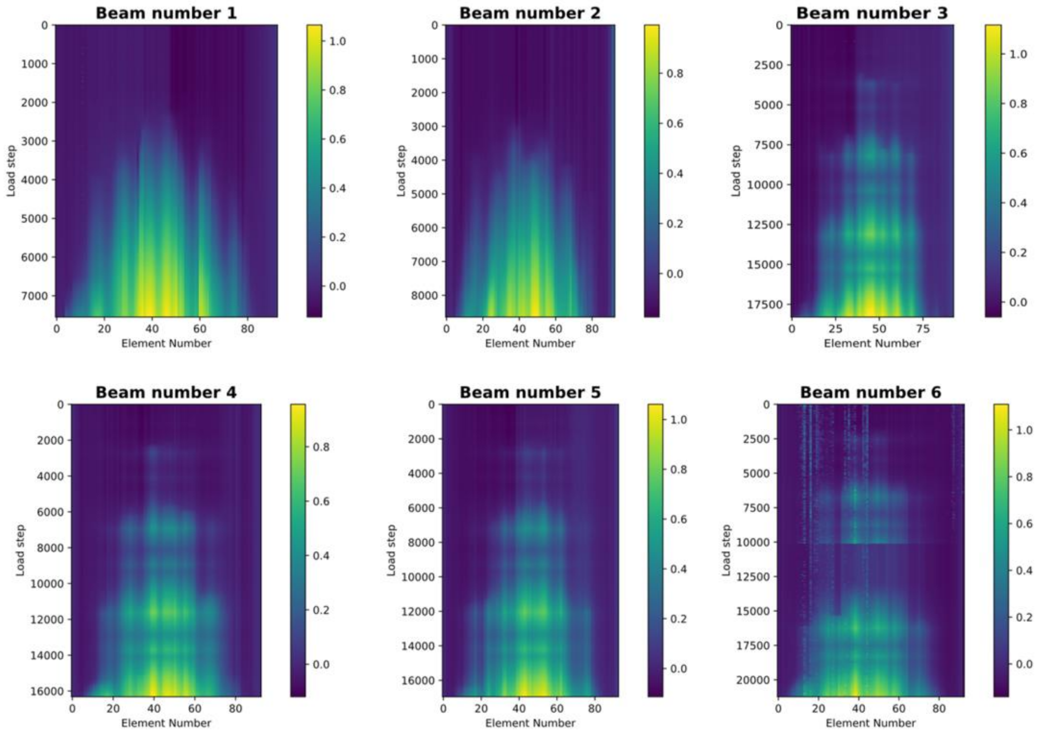

Figure 8. Strain profiles for all the real beams

The damage classification had some diversity, depending on both the loading pattern that was applied and also the levels of the signal noise. In particular, from the measured strain profiles, the ones that were considered to be the most problematic were the Beams 2 and 6. However, only Beam 2 detected the Hazardous level a little later than what it should have. For the rest of the beams, the hazardous damage was at approximately 45%-83% of the total beam capacity (Table 1), although the severe threshold of harm will enable an examination successfully and prevent the complete destruction of the concrete feature.

Table 1. Results obtained for all beams

	B1	B2	B3	B4	B5	B6
Training loss	0.00125	0.00109	0.00232	0.00060	0.00132	0.00272
CV loss	0.00114	0.00104	0.00236	0.00060	0.00134	0.00282
Small damage	12%	22%	12%	19%	15%	16%
Significant damage	38%	61%	33%	59%	38%	29%
Hazardous damage	52%	**90%**	**47%**	85%	56%	69%

As seen from the results, the detection system that was built was efficient and could detect damage in three different levels. In some cases (Beams 1 and 3) the classification might be more overprotective than what is should be, but that way the designer can be more confident that there will be no critical damage omission in the more noisy examples (Beam 2).

5. Conclusions

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The technique offers a technique for the damage diagnosis of weakened bridges that improves both protection and bridge cost mitigation. The approach provides an entry into an artificial neural network by using documented deck accelerations in the bridge. After correctly trained data, the next accelerations can be expected. The difference between the calculated value and the network value would serve as the key indicator of injury. The analysis involves a comparative estimation of the network's prediction errors by choosing the risk index threshold based on the threshold chosen and will measure the anticipated overall cost associated with the damage detection strategy. The optimum is the least expensive within the period of viable levels.

The results achieved allow some generalized drawing conclusions: the two sensors in the middle of the bridge seem the most powerful for distinguishing between healthy and damaged data clearly not taking into consideration where the damage happens in the bridge. This is because the response from the assisted bridge is illuminated in the half-way span. Eventually, the ANN was implemented and the fault was successfully found with the modal maximal amplitudes of the other three sensor nodes using artificial neural networks to increase the network's life cycle.

Future studies may require the creation, through the automatic implementation of the fault detection process, of a solid threshold that would distinguishes between faults and defective operations.

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