International Journal of Scientific Research and Engineering Development-– Volume 3 - Issue 5, Sep - Oct 2020

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Structural Health Monitoring using Neural Networks in IoT and CPS paradigm- A Review

Partha S. Pal*, Sucharita Khuntia**

*(Department of Civil Engineering, CV Raman Global University, and Bhubaneswar, India

Email: partha371@yahoo.in)

** (Department of Computer Science and CV Raman Global University, and Bhubaneswar, India

Email : sucharitakhuntia1@gmail.com)

--************************----------------------------------

Abstract - Wireless based smart structural health monitoring is very essential for smart city applications. The huge civil structures are more vulnerable to public safety that needs efficient smart monitoring. In the past, an attempt has been made to go for an efficient way of monitoring by using wires connected to the sensors. But due to the vulnerability of wires in the physical environment wireless SHM has been the focal point of research. But certain limitations make wireless monitoring inefficient such as delay in latency and loss of data. In this paper exhaustive review has been done on wireless systems of SHM along with the usage of many emerging technologies such as the Internet of Things (IoT), Cyber-Physical System (CPS), along with the usage of Neural Networks (NN) in damage detection problems. Civil Engineers give more emphasis to the physics of damages in SHM rather than designing an optimal SHM concerning networking aspects. So, we take into consideration both mechanical as well as networking aspects in SHM. This paper helps both civil engineering and computer science and engineering researchers/engineers to understand and design Smart Wireless Structural Health Monitoring using eminent technologies such as IoT, CPS and NN based damage assessment. This paper strives to comprehend the works of major areas of both domains of engineering so that the subject SHM is looked upon comprehensively from all spheres and development takes place using new or better technologies taking it in the forum of interdisciplinary research and discussion.

Keywords—**Structural Health Monitoring, Finite Element Method, Wireless Sensor Network, Neural Network, Internet of Things, Cyber Physical System**

--************************----------------------------------

1. INTRODUCTION

The prosperity and development of a country are greatly influenced by infrastructure development which plays an important role in increasing economic status. The more the infrastructure the better the country develops. Big democracies like India is a very big economy and this flow of economy depends upon public infrastructures but after the construction of such infrastructure and putting the infrastructure into public service it is left unmonitored and unmaintained after the lapse of a certain time and this leads to the collapse of the structure and loss of human lives and various services which boost the economy get disrupted. Whenever a structure is put into service, with time the structure deteriorates until a point is reached when the structure can no longer be used in service. Every structure requires maintenance and for maintaining the structure periodically structural health monitoring [1, 2] becomes very essential because it helps us understand the defect and location of the defect. There are mainly three reasons why structures usually fail (i) error in the design of the structures, (ii) structural failures due to repeated and cyclic loads, cracks, etc and (iii) events such as road accidents, earthquakes, natural disasters, etc. Structural health monitoring involves periodic and continuous health assessments of structures when they are in service. It includes the detection of damage and characterization of structures. The structure is observed periodically over time using sensors, data installed in the structures, and with the help of the sensors data, required damage detection can be done and subsequent action can be taken by the authorities and stakeholders. SHM is not only done in civil engineering structures, but also it finds its use in damage detection in composite plates in aerospace industries [3, 4, 5, 6, 7, 8]. SHM is also performed in the conservation of heritage structures [25,79]. Many structures that are of cultural importance can be restored using health monitoring and are being extensively used either as wired networks or as wireless networks [9, 10, 11] Old structures should be continuously assessed for SHM for better maintenance of the structure and building a new structure if decommissioned or declared unsafe. There are many such incidents of bridges like the Majerhat bridge in Kolkata, India [Fig 1] and a 40 years old constructed bridge in Junagadh district of Gujarat [Fig 2] which collapsed killing and trapping many human lives due to the lack of proper health monitoring of such structures. Likewise, there have been many such incidents of the bridge and building collapse not only in India but also across the globe. As far as the National

Crime Records Bureau, in India more than 1200 people have lost their lives in 1161 building collapses in 2017. Hence, a Structural Health Monitoring system should be envisaged which can be cheap as well as efficient especially in developing countries like India where SHM is not given the utmost importance owing to the financial problems. Figure 1, 2, 3 and 4 shows the major structural failures that have occurred in different places in India which reveals the vulnerability of damage and collapse due to lack of proper health monitoring system for old structures. Fig 1 depicts a picture of the before and after collapse condition of the Majerhat bridge in Alipore Kolkata, India. The 50 years old bridge collapsed on 4th September 2018 at around 4.45 pm resulting in more than 25 people injured and 3 people dead. The Majerhat bridge was commissioned in 1964 and it was in service till it collapsed in 2018. The claims have arisen by the nearby residents and the commuters that the bridge was developing visible cracks. The vulnerability of the bridge was taken for granted and the structure was a Rail Over Bridge (ROB) which not only endangers the commuters of the bridge itself but also the train commuters passing below the bridge. Also, there is a construction site adjacent to the site of mishap where workers' lives were at risk. Fig 2 is a picture of a 60 feet long bridge collapsed in Junagadh district near in 2019. Due to the collapse of this 40 years old bridge, many got injured and two cars, three two-wheelers got stuck under the debris. Similarly, Fig. 3 shows a bridge in Goa which collapsed into Sanvordem River when nearby 50 people were standing and watching a man being rescued who had jumped to commit suicide. The collapse of this old bridge resulted in more than two deaths and several missings. 60 Fig. 4 is a painful picture showing 100 years old building collapse in Dongri, Mumbai in 2019. Some more than 15 families had been living in that building. It was reported more than 10 people died and many were trapped.

Fig. 1 The condition of the Majerhat bridge before and after the collapse in Kolkata

Fig. 2 The collapse of a bridge in Junagadh district in Gujarat.

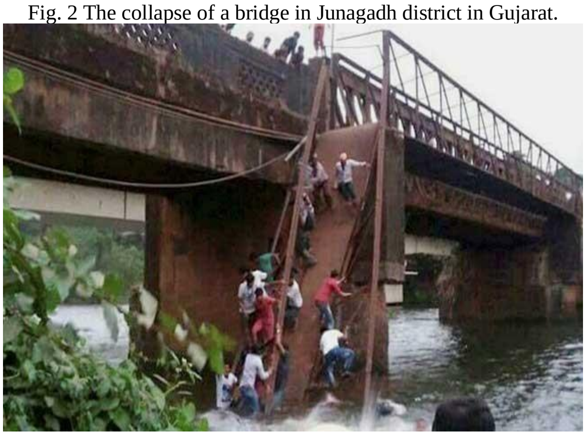

Fig. 3 The collapse of a bridge over Sanvordem River Bridge, Curchorem in Goa.

Fig. 4 The condition of an Old Building after the collapse in Mumbai

Due to poor construction practices, dilapidated buildings and lack of proper monitoring each year thousands of people lose their lives. Therefore, the failure of structures can directly or indirectly severely affect the lives of humans.

So, we know that SHM is very important in keeping an eye on the structure so that whenever there are abnormalities such as damages detected, the extent of damage and location if ascertained at an early stage, then this data can be used by the concerned authorities and stakeholders to take an impromptu action so that any such life-threatening incidents can be averted

A. Definitions in SHM

As stated earlier in the introduction that Structural Health Monitoring refers to the detection of damages periodically and continuously for a certain period. It involves the observation of a structural system with the help of data and sensors which are installed in the structure. Using sensors and computational algorithms and optimization techniques defects can be located, evaluated, and also predicted. The various aspects which are related to modern SHM methods have been defined below.

B. Damage

It is defined as the change in the characteristics such as geometry, boundary conditions, and properties of a material and the function of the entity under consideration which adversely changes the functionality of the structure.

C. Sensors

The sensors usually are devices used to catch signals such as acoustic waves from physical environments and convert to data which can be interpreted by any human or machine. There are various sensors available such as piezoelectric sensors, actuators, temperature sensors, humidity sensors, strain gauges, etc.

D. FEM

It is a numerical process of solving problems instead of partial differential equations. It involves discretization of elements into very small pieces and solving it using certain boundary conditions. FEM models are used in solid mechanics, thermodynamics, heat and mass transfer, computational fluid dynamics, and so on.

E. Optimization

An optimization is a methodology or an algorithm, which executes iteratively to solve quantitative problems by comparing it with different solutions until any satisfactory result comes. The study of optimization techniques develops the basis for various numerical techniques that involve building more advanced techniques most suitable for solving practical problems. There are many optimization techniques available such as many Numerical Methods of optimizations and many advanced optimization techniques are Ant Colony Optimization, Genetic Algorithms, Simulated Annealing, Hill Climbing, etc.

F. Acoustic waves

These are mechanical elastic waves that are generated from the physical system i.e. structure when there are cracks or any kind of defects. These waves, when generated by the structure, can be picked up from certain distances and the delays can be measured giving the knowledge of defects.

G. Mode shape

It is the pattern that the structure would show when a structure vibrates at its natural frequency. A structure may vibrate in a single mode or many modes. Mode shapes help in cross-relation of data and adjudging the defect.

H. Modal frequency/ Natural frequency

It is the frequency at which an element vibrates naturally after the element has been tapped and external load has been released. All objects have their own natural frequency at which they vibrate, which is called Natural frequency or Modal frequency.

I. Structural Event

Structural event can be defined as an event that takes place in the structure which adversely affects the performance of the structure. Such an event might lead to damage sometimes if the threshold of the energy absorbed by the structure is exceeded. There can be an event due to excessive loading, corrosion, cracks, fatigue, etc.

J. Internet of Things (IoT)

IoT describes the interconnection of physical things/devices that are capable of collecting data and transferring data over the internet without human intervention. The Internet of Things is making the world around us smarter, responsive, and has merged the digital with the physical universe. It gives more emphasis on connecting the physical devices and provides ubiquitous connectivity to the devices for smart computation.

K. Cyber-Physical System (CPS)

CPS which is similar to IoT ensures tight integration of computation, networking, and physical processes called the Cyber-Physical System. The computational elements coordinate and communicate with sensors. Sensors are used to get a deeper knowledge of the environment that enables more accurate actions and tasks and the physical processes are controlled and monitored by computer-based algorithms. Unlike IoT, CPS gives more attention to integration, computation, networking, and physical systems. Having a tight connection between the physical components, networking, and computational elements provides an automotive mechanism and better performances.

L. Artificial Neural Network (ANN)

These are computing systems that derive inspiration from a biological neural network of neurons present in the brain of humans. It is a part of Artificial Intelligence that functions like a human brain to develop algorithms, which is used to solve prediction problems and complex patterns. The processing units of ANN consist of inputs and outputs. It learns the inputs and produces desired outputs. Like human brains consist of million cells called neurons, these neurons consist of dendrites which receive the information and the neurons process the information and pass it on as output to the next neuron through axon. Similar way ANN works. The input signals received by the dendrites of neurons then the input processed inside the neuron cell by applying appropriate algorithms then produced the desired output that transmits to the next neuron through the axon received by the dendrites of the next neuron.

2. Damage Detection in structures

There are numerous Non-Destructive Tests to find out the damage in the structures which includes presence of damage, damage position and damage intensity. The detection of damage can be based upon acoustic emission[62,63], ultrasonic waves[64,65], vibration, radio-graph and strain[7]. The most common technique which is used for damage detection is vibration based technique[58,59,60,61] due to the ease in measurement and it has good strength of signals compared to noise. The damage is usually quantified using a damage index which depends upon the loss of stiffness in the structure. The greater the loss in stiffness, the more is the damage that has occurred in the structure. There are various domains of SHM are as follows: -

A. Time domain analysis

Time domain analysis is referred to as such scrutiny where functions of mathematics, physical signals or time series are used with respect to time for evaluation. A time series exhibits how signals change with respect to time. Therefore in SHM time- series models have been used for source characterization of sources [21]. Using the difference between the predicted model and true model the damage can be detected and the mathematical model gets updated [22].Jyrki[23] had used Bayesian Virtual sensing technique in the time domain under different environmental and operational situations. The signal to noise ratio was found more accurate when virtual sensors were used instead of hardware. M Anderson et al [24] used a novel time- domain technique for damage detection using a Savitzky-Golay filter by carrying a test in aluminium plate. Many linear time series models have been worked upon but the best alternative way is Auto-Regressive Models(AR) [21]. Using the Auto-Regressive Moving Average (ARMA) [21] and Support Vector Machines (SVM) [21], damage detection can be done. Sohn et al [116] demonstrated an AR approach of damage localization using vibration for lumped structures having eight degrees of freedom and three AR coefficients were taken to detect damages. Various types of models like the SVM model, hidden Markov model, and Gaussian matrix models have been used in conjunction with the Time series model to diagnose damage, classify damage, and extract other features. Using Eigenvalue and algorithm and comparing the modal vibrations from experiments the extent of damage can be calculated. Time-domain models are independent of physical models and make use of the principle of statistics for the representation of observations and complexities in computations are comparatively lesser than physical models. However, there are drawbacks in this method because the measured quantities have an indirect correlation to the actual mechanism underlying and thus may obstruct the detection of damage.

B. Frequency domain analysis

Frequency domain analysis is mainly used as a tool for signal processing applications. Frequency domain analysis, unlike time-domain analysis, exhibits the storage of signal energy on various ranges of frequencies. Using Transforms signals can be converted between time domain and frequency domains such as Fourier transforms. Any material vibrates at a natural frequency and with some mode number. Once the structure is set forth to vibration, the structure vibrates with a natural frequency or under forced vibration. The vibrations may cause resonance and the peak amplitudes are identified using modal shapes obtained at different locations. The waves that are generated due to damage are picked up by sensors and the cross-referencing of frequencies is done for getting mode shapes[21,25].

C. Time frequency-based Analysis

Time frequency-based analysis can be used for the retention of information on time and frequency information. Sengupta et al[26] explained that using Acoustic Emission(AE) technique for waveform analysis using frequency domain can be very advantageous due to the leverage of signal discrimination i.e signal to noise ratio. As per the literature, Suzuki et al [27] were the first to go for Wavelet Transform(WT) analysis using the AE technique and the study was performed in GFRP using tensile loading. They used Gabor wavelet-based Gaussian function. The frequency-domain uses Fourier Transform to get the modal properties. Hamstad [28, 29] and Prosser [121,122] also did the analysis using a FEM model for source localization using WT in plates.

D. *Statistical analysis*

Statistical analysis such as mean, variance, skewness, kurtosis is often done to detect damage in the structure. Kurtosis tells us about the shape of the probability distribution function. It describes the "tailedness" of a distribution function. When we normalize the third statistical moment, we get skewness and if we normalize the fourth statistical moment we get kurtosis. In skewness, positive says that in the right-hand side if the tail is longer, then distribution area is intensive below the average and while for negative skewness if the tail is longer in the left-hand side and the distribution area is above average. Ling Yu et al [30] has shown how the skewness and kurtosis varies when a structure is healthy and when the structure is subjected to damage.The paper has done a non-linear damage detection using statistical moments. A larger value of kurtosis indicated more cases far from mean. When the structure is healthy the skewness will be 0 and when the structure exhibits damage the skewness will be negative or positive. Kurtosis value will be 3 when no damage occurs and greater than 3 when damages occur.

$$S = \frac{E(x-\mu)^3}{\sigma^3} \qquad 1$$

and the kurtosis is given by

$$k = \frac{E(x-\mu)^4}{\sigma^4} \qquad 2$$

where E is Expectation operator, μ is the mean and Σ is the standard deviation. Sohn et al used the Damage sensitivity index where the ratio between the standard deviations of sample error and reference error respectively were taken and the value was almost 1 when no damages occurred and the value was more than 1 when damages occurred. Ling Yu et al used another ratio similar to what Sohn et al used. Ling Yu used the ratio in terms of skewness and kurtosis, they are:-

$$\gamma^{skewness} = \frac{S^{sample}}{S^{reference}};\ \gamma^{kurtosis} = \frac{K^{sample}}{K^{reference}} \qquad 3$$

Damage Index as given by Ling et al

$$\text{DamageIndex } DI_1 = \frac{(\gamma^{std} + \gamma^{skewness})}{2} \qquad 4$$

$$\text{DamageIndex } DI_2 = \frac{(\gamma^{std} + \gamma^{kurtosis})}{2} \qquad 5$$

$$\text{DamageIndex } DI_3 = \frac{(\gamma^{std} + \gamma^{skewness} + \gamma^{kurtosis})}{3} \qquad 6$$

$$\text{DamageIndex } DI_4 = \sqrt{\gamma^{std}.\gamma^{skewness}} \qquad 7$$

$$\text{DamageIndex } DI_5 = \sqrt{\gamma^{std}.\gamma^{kurtosis}} \qquad 8$$

$$\text{DamageIndex } DI_6 = \sqrt{\gamma^{std}.\gamma^{skewness}.\gamma^{kurtosis}} \qquad 9$$

Using Hotelling Multivariate T2 control chart which deals with multivariate observations that can be plotted in a single chart, Wang et al [31, 32, 33] monitored RC framed structures. Using some other charts like Statistics Process Chart (SPC) and control charts and spectral measurement charts damage detection was performed statistically.

E. *Using Artificial Neural Networks(ANN)*

ANN is a computing system designed in such a way human brains analyse and process the information. It has been proven that ANN have self learning capability that has capabilities to produce better results and can solve such problems that prove difficult to solve by humans or statistics. Artificial Neural Networks are like human brains made of neuron nodes connected with each other. Like any human brain, there are millions of cells that are called neurons responsible for processing the input information that has been carried from the environment that occurs inside the neuron and results in output. Similarly ANN have hundreds of artificial neurons named as processing units that are interconnected with each other through nodes. These processing units receive information from various structures on the basis of internal weighting systems[18] and the neural network makes an effort to learn the input information to produce output. ANNs follow a set of learning rules that is called "Backpropagation". It is a process to reduce backward propagation error to get desired output. Initial phase is the training phase where ANN goes through training to learn to recognise the patterns in a database, whether it would be visual, textual or acoustic data. During the supervised phase the network compares the produced/actual output with the desired output (that was meant to produce) and by using backpropagation[34]the difference between both the outputs can be adjusted. It is referred to as backpropagation because the network is working backward from output units to input units to adjust the differences between actual and desired output until it produces the lowest possible error. During the training and supervisioning phase ANN is trained to look at what it wants and what should be the output through yes/no questions using binary numbers. A schematic diagram of the Artificial Neural Network(ANN) has been given in Fig. 5

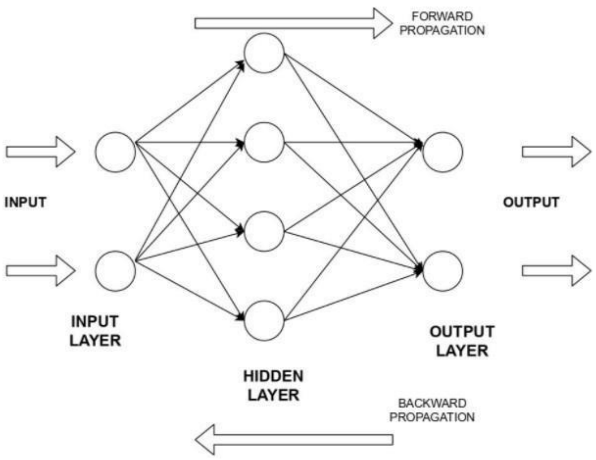

Fig. 5 Schematic diagram of Artificial Neural Network(ANN)

ANNs[35, 36] have been a revolutionary change in the field of smart civil infrastructures through structural health monitoring based on Artificial Intelligence(AI) using Neural Network[37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49]. Neural network models derive frequencies that are natural in nature and mode shapes from fit structures. These natural frequencies, mode shapes are used to derive structured simplified models to change the stiffness to construct different damage patterns[34].

3. From Wired Network SHM towards Wireless SHM

Before SHM had emerged into being, structures were monitored using visual inspection and walking around which is not sufficient. Routine maintenance team visits are done and this procedure is not only a costly affair but also time consuming, less frequent, and risky[50]. Moreover, this procedure involves less accurate or erroneous results. This led to the development of SHM. At present wired SHM is widely in practice all over due to its reliability and accuracy of results but owing to the requirements of wires, the process becomes costly as already mentioned, and is prone to damages. Wired SHM functions with the help of cables, optical fibers, piezoelectric sensors, etc. The sensors are installed on the structure and they catch the signals and the cables transfer the signals to a Data Acquisition Centre (DAC) where the results are obtained after running a FEM model algorithm. They are less flexible than WSN and are enormous and the cables are laid for large distances. Also, it takes a large amount of time for deployment i.e. almost a year. In the next section, a brief introduction of WSN is given.

Table 1: Differences between Wired SHM and Wireless SHM

Characteristics	Wired SHM	Wireless SHM
Cost effectiveness	Low	High
Sampling rate	Low	High
Accuracy	High	Low
Deployment/installation time	More	Less
Flexibility	Less	More
Design	Simple	Complex
Accessibility to adverse environmental or physical conditions	Less	More

3.1. Structural Health Monitoring System (SHM) using Wireless Sensors

Wireless sensors are measurement tools embedded with transmitters. The wireless sensors can be installed in such locations that are difficult to access because of some extreme conditions like high temperature, extremely low temperature. The wireless sensors sense data from the physical environment and the embedded transmitter converts the collected wireless signal to the desired output based on the application environment. The wireless sensors continuously monitor the environments that can be hazardous or normal and transmits the data to the operator in the monitoring system located at a far distance from the physical environment. Wireless monitoring is useful for remote monitoring of difficult to access locations. Wireless sensors can form networks that allow engineers to monitor many locations from one single station and can create web pages that can be accessed from anywhere. Fig. 6 depicts a schematic diagram of wireless sensor networks in structural health monitoring systems. The wireless sensors can reduce the monitoring cost by eliminating the use of wires, electrical conduit, and other accessories. There are a number of parameters that need to be considered while selecting a wireless sensor such as types of measurement, range, accuracy, and frequency.

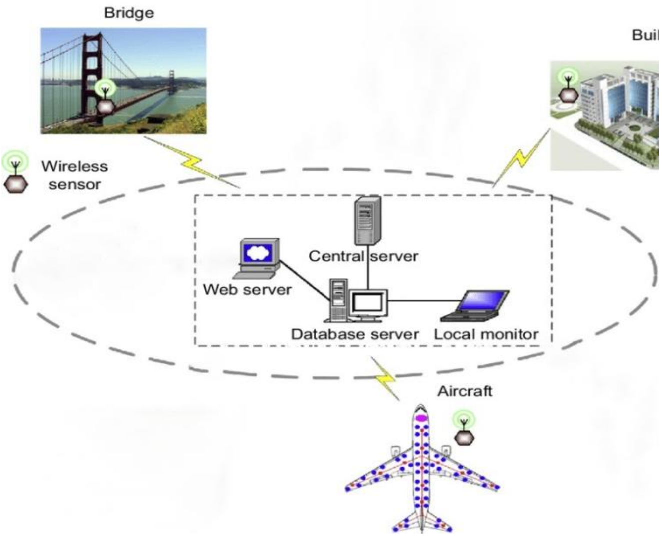

Fig. 6 Schematic Diagram of Wireless Sensor Networks in Structural Health Monitoring

As per the American Society for Civil Engineers one of the four national bridges are either functionally obsolete or structurally deficient. Deterioration of huge civil infrastructures are one of the major problems around the world. But these structures can not be monitored continuously due to the high cost of retrofitting wired sensors. Health Monitoring for large structures requires installation of a huge number of wireless sensors that are capable of sensing the structure and collecting data. The remote monitoring of such large structures gets easier through wireless sensors. In real time continuous remote monitoring of structures[51] increased public safety and damage detection at an early stage is able to reduce the cost and down-time associated for critical damage repair.

3.1.1. Usages of Wireless Sensor Networks(WSNs) in SHM:

Wireless sensors widely used for monitoring the health conditions of large infrastructures. J.P. Amezquita-Sancheza[52] have given a detailed description on the embedded chips associated with wireless sensors having processing capabilities which makes the sensors smart. Using Wireless Smart Sensors(WSS) for SHM have many advantages such as efficient data management, low expenses, high flexibility and increased potential for better understanding of structural response and behaviors. The authors have proposed an ideology of integrating wireless sensor technology with advanced machine learning technologies to make truly smart sensors and stated the next generation wireless smart sensors should have consumed less power can be integrated with more sensors that would have improved the immunity of the structural noises and can be work with huge data set without any loss of data over wireless communication. Rekha.K.Sa et al [53]aims to develop a real time embedded system, which can provide a flexibility robust mechanism for reconfiguration and remote monitoring of health of the structures and environment using wireless sensor networks. This proposed framework can also support two heterogeneous application deployment on the same wireless sensor network. Cem Ayyildiz et al [54]showed the measurements of PZT sensors could be done periodically by connecting the sensors to a system that keeps a log on data so that the fractures occur on the structures due to vertical loads, natural disasters and lack of durability can be easily monitored. PZT sensors can be attached to the existing concrete structures, masses structures and structures made up of bricks and this gives PZT advantage over strain gauge. According to Ayyildiz et al the forces applied on reinforced concrete columns trigger information about fractures PZT sensors through which impedance measurement can be taken and applied RMSD calculation from the data that is gathered. The result shows substantial contrast after clear fractures formed. Before they can be visible to human eyes the fractures formed initial cycles then developed to the following cycles those were detected in the experiment. Matteo Vagnoli[55] gave a review on most commonly used SHM methods by discussing the advantages and disadvantages of SHM based on model and non-model type. By considering various degradation mechanisms the behaviour of a bridge can be simulated through updating strategies of model based Finite Element(FE) model and also some good results found in few cases studies of non-model based methods but the accuracy depends on the data used in the training process. Matteo et al also proposed an optimal method for SHM by considering the need of robust, high speed and automatic fault detection of bridges. They said that the behaviour of the bridges should be monitored efficiently in real time through a system of measurement which is optimized with type of sensor, location of sensor and its cost. X.We.Ye et al [56] did review on usage of optical fibre sensing technology in composite structures. Optical fibre sensors have some advantages such as they are light in weight, small in size and immune to electromagnetic fields and corrosion therefore widely being used. Recently Christos Andreade et al[57] has proposed a non-linear ultrasonic method in SHM for localization of damage in Barely Visible Impact Damage (BVID) composite panels through a set of piezoelectric transducers. The algorithm used in this method does not depend upon the time the waves take to traverse the medium and baseline signals measurements. The damage can be spotted with the help of surface plot of amplitude obtained from nonlinear Acoustic Waves. Edward Sanzonov et al [58]with the help of Wireless Intelligent Sensor and Actuator Network (WISAN) with embedded fuzzy logic and Neural Networks, performed automated SHM which included the automation of modal identification due to vibrations occurring on the structure. It also included the automation of mode shapes that were obtained and the evaluation of the health of the structure. This automated SHM is based on modal strain energy.There are not many fully automated SHM in literature and therefore continuous monitoring is not possible as experts are sometimes required to interpret data for damage detection. As per Edward et al the power consumption for high-performance computing using Fast Fourier Transform on the nodes is more than use of WISAN. They proposed to use two-level cluster-tree architecture for SHM.

3.2. Internet of Things(IoT) and Cyber-physical System(CPS) platform for Realtime SHM

Although Wireless Sensor Networks(WSNs) are highly useful and make remote monitoring efficient enough due to its low installation and reduced expenses for maintenance. WSNs for structural health monitoring systems [54, 52, 59, 50, 60, 61, 62, 63, 64, 65, 66, 67, 68] for large structures allow dense deployment of sensors for measurement of data on the existing huge structures that avail fault tolerant and accurate damage detection techniques without having a wired infrastructure. For monitoring the health of the structures used wireless sensors have very limited storage capacity and dont have provisions for computation of the collected data. The SHM systems, which use WSNs suffer from increased energy consumption and long detection latency. Let's take the example of the golden gate bridge that takes 9 hours for a single round data collection from 64 sensors. The mentioned shortcomings are the reasons for shifting interest towards new emerging technologies such as the Internet of Things(IoT)[69]platform and Cyber Physical System(CPS)[70] paradigm for Structural Health Monitoring systems[71, 72]. Internet of Things is an interconnection of things that can be computing devices, machines, objects or people with unique identifiers and is able to transfer data over the internet through wifi module without any need of interaction from human to human or human to computer. To overcome this drawback, the IoT platform proves very efficient for real time SHM applications[73, 74, 75, 76, 77, 78]. IoT systems consist of smart devices which are web enabled such as sensors to sense the data from the environment, collect data, and act on that data to achieve tasks that are complex and need high intelligence. To fulfil this intelligence IoT platforms are embedded with sensors and actuators, which are devices used to interact with respective physical environments. After data is collected by sensors, data storing and processing is done intelligently to find useful information from it and actuators are used for showing an effect occuring from environmental change. The collected data storing and processing can also be done either on the network edge through Raspberry Pi or in the cloud remote server. If any prepossessing of data needed that can be processed at sensors also. Figure 7 showing schematic flow of a routine Structural Health Monitoring systems using IoT paradigm There are many challenges like data accuracy, efficient data collection and data handling in the IoT paradigm.

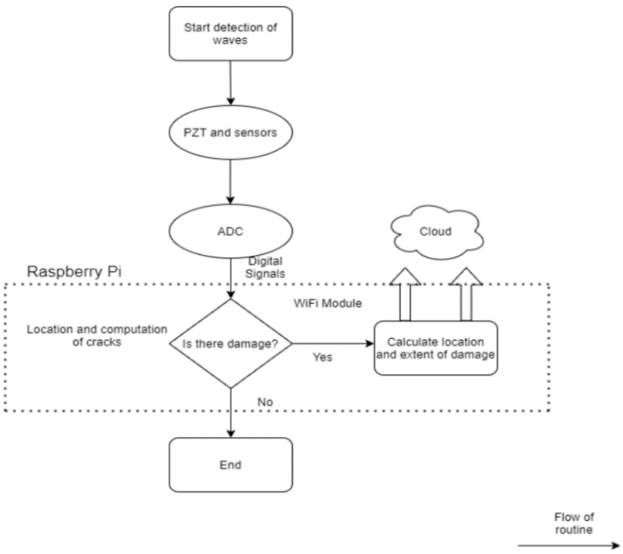

Fig. 7 Schematic flow of a routine SHM using IoT paradigm

The main challenge in IoT is an efficient communication between IoT devices and continuous communication between IoT devices in remote servers. The wireless devices mainly are installed at different geographical locations, the communication channels are unreliable and often face distortion at high rates. So, for a tight connection between different components of the paradigm there is another eminent technology that has been widely used for SHM applications for real time communications is Cyber Physical System(CPS). CPS is a tightly integrated physical environment, networking and computation. This mechanism is controlled and monitored through computer algorithms. CPS is similar to IoT sharing similar basic architecture but the former represents efficient coordination and high combination between physical processes and computational elements than the latter. The Cyber Physical System is diversified into many areas such as health care, civil infrastructure, aerospace, transportation etc. Cyber Physical System is used for monitoring of civil infrastructures as cyber infrastructure for monitoring the conditions of the structures continuously in real time. CPS is a three layer architecture consisting of physical Infrastructure, cyber layer and computational layer or cyber computing platform. The physical layer is the physical environment where the sensors are installed to sense the infrastructure that collect different structure responses dynamically. The cyber infrastructure has a network that communicate with physical infrastructures to collect data from the sensors and the computational platform is any remote server such as cloud involving tasks like data analytics, data management or provides web services for the support of SHM applications.Additionally CPS can provide a platform, which enables innovative data driven techniques for SHM. Fig. 8 showing a Cyber Physical System block diagram for bridge monitoring. In recent years a lot of applications have been seen in the area of Internet of Things(Iot) and Cyber physical systems(CPS) for real time SHM applications.

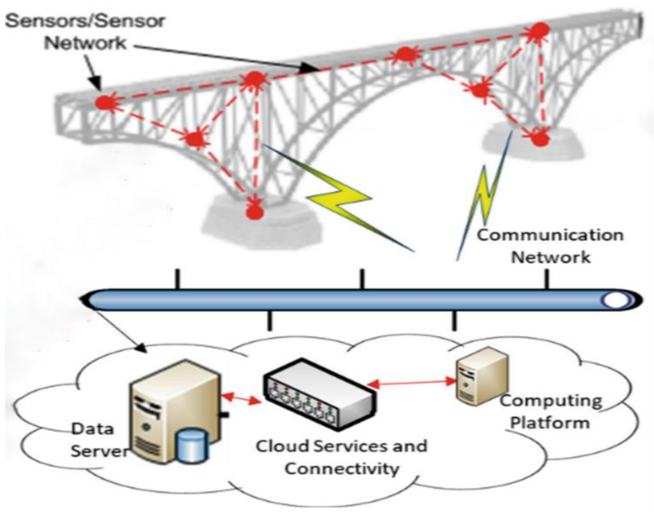

Fig. 8 The Cyber-Physical Bridge Monitoring System for SHM

3.2.1. Structural Health Monitoring using Internet of Things (IoT)

Md Anam Mahmud et al [9] has proposed a complete basic IoT platform for Structural Health Monitoring. They proposed using a Raspberry Pi, an analog to digital converter (ADC) MCP3008, and a Wi-Fi module for wireless communication. Piezoelectric (PZT) sensors were used to collect the data from the structures in real time SHM. The proposed system also used signal processing techniques for the analysis of collected data and two techniques have been used through Pitch-catch and Pulse-echo to detect the damages in the structure. Only one piezoelectric sensor and two nos. of PZTs were used for pulse-echo and pitch-catch techniques respectively. One technique was applied in this article to find location and the quantification of damage that is a comparison between the measured delay time of Lamb waves and signal coming from defects that was categorized as threshold time. If the time is less than threshold time, then the structure is considered as not defective. This paper has made use of Raspberry Pi for computation of the mathematical model in the form of algorithm, the result of which is then sent to the Cloud/Internet for due course of action.

Brinda Chanv et al [79] has given a monitoring system framework using Internet of Things and wireless technologies. In the proposed system various sensors such as vibration sensor(accelerometers), moisture sensor, strain sensor were deployed on the physical structures that collect data and the output was given to Arduino Uno which does the processing and sends to the visualization studio and transmits the data through Wifi Module to the cloud and the analysis of the results are done by algorithms in the cloud. The proposed system also used “Thing speak” Application Programming Interface (API) which provides simple communications among objects within an IoT environment. Also, this framework adopted a visualization technique to decipher and interpret the results. Although Brinda et al has proposed a good enough structural health monitoring system using IoT and wireless technologies, it would be more efficient and powerful by using Raspberry Pi instead of Arduino. Raspberry Pi is 40 times faster than Arduino. Operating Raspberry Pi is very user friendly, which needs no deep electronics background, with the Pi it is capable of doing multiple tasks at same time and the internet can easily run on Pi using Wifi dongles. Raspberry Pi has a built in Ethernet port that helps to directly connect to the network of the internet while connecting to the internet in Arduino. is very difficult because external hardwares must be connected and addressed using code to run a network using Arduino.

Cloud has been an important integral part of Structural Health Monitoring systems for efficient storage and processing of collected huge amounts of complex real time data from the large civil infrastructures. H. Chang et al[80] has given a real time SHM framework that is Inverted Movement Calculation Method in this process every timestamp is measured at every sensor node in the real world structure using an online 3D model that is capable of showing overall movement of the structures and its displacement in an 3 dimensional view in visual form. The output shows in the form of rotation and translation values in the local coordinate system in the 3D model. The sensors associated with microchips and accelerometers are installed in the structures. The visualization is obtained through web or mobile phones. To implement this visualization process client side web based technologies are used. MongoDB is used to store the data data based and the HTTP server performs computation on the database and through JavaScript Socket.io library and Node.js framework and the output is enforced into the web browser. Although in this proposed framework it is very much easier to monitor the structures in real time and can be easily detect the fractures on the structures through 3-D visualization but this system only gives warning of damages but not quantifying the damages. Chien Khong et al [81] has talked about the monitoring of the health of structures that can be efficiently done by using IoT nodes with organic pressure sensors. In this process to complete a flexible pressure sensor fabrication a thick 100Pm polyurethane film was sandwiched by top/bottom electrode. DAQ module is designed to collect data from sensors, then the sensed data transmitted through UMTS/3G to the cloud. The information collected in real time can also be displayed through a website. The proposed framework is a remote health monitoring system. The data of the SHM system can be accessed remotely from different geographic locations through an internet connection.

3.2.2. Advanced Technologies used in IoT for SHM

Many advanced technologies [82, 83, 84] such as Virtual Reality, Unmanned Aerial Vehicle can also be used in IoT platforms for efficient and continuous real time monitoring of ancient structures. Manlio Bacco et al[82]in the year 2020 has proposed an architecture based on Internet of Things(IoT) for remote monitoring that can be integrated through Unmanned Aerial Vehicles(UAVs) and virtual Reality(VR) paradigm for the three ancient buildings. A combination use of fixed sensor networks mobile sensors (i.e cameras, light detection etc) on board UAVs and VR technology make powerful capabilities for efficient and best monitoring in SHM. Even though the IoT model has brought good networking capabilities for the remote monitoring of the structures, the fixed installation of digital sensors used in the system are only concerned, temporary or definitive. Unmanned Aerial Vehicle (UAV) is changing the concept and provides the foundation of a great concept of monitoring remotely through flying UAVs over ancient structures. UAVs are known to be a mobile network of WSN that can be used on demand or in periodicity to monitor the patterns of the crack in the structure regularly. Through UVAs the part of the structures can be monitored where dedicated detection systems cannot be provided. The UAV is used in this proposed IoT framework to obtain a 3D reconstruction of a structure with the precise location of the deployed sensors, shows the exact location of the sensors with instantaneous records of the ancient structure and allows the operator to make a direct interaction with the sensors in a Virtual Reality environment. In this proposed system data is collected by the sensors and is transmitted to the remote server for storing and processing of data. The data collected from the sensors is pushed to a local gateway that ensures the proper working of the local network at each site and properly takes care of accurate data delivery at the remote server. The sensed data collected from the sensors can be envisaged in real time in order to get the status of health of structure. Using Artificial Intelligence techniques along with this method can automatically anomalies and generates alerts in the VR environment. The proposed system by the team of Manlio Bacco et al is referred as MOSCARDO system has taken three real case studies of three ancient buildings 1) The Mastio di Matilde is the large round tower considers as the Old Fortress in Leghorn. 2) The Voltone is the waterway situated below a large town square. 3) The Torre Grossa is the tallest of the historical towers in the city of San Gimignano. All the sites are located in Tuscany, Italy. In this model, the environmental data is acquired by the UAV through wireless sensors from the ancient buildings with images and context information. The drawback of this UAV technology is that it is not possible to fly UAV in every location and every time because this technology is driven by image processing that requires good quality images which may be difficult in adverse environments and the proposed procedure becomes costly augmented virtual reality due to the use of UAVs.

Woubishet Zewdu Taffesea et al [73] has been discussing the durability monitoring of reinforced concrete structures and its assessments through an Internet of Things based system. The convolutional methods of assessment of corrosion are not reliable due to the limitations during implementation. This traditional practise has been changed to low-power wireless communication technologies used in IoT platforms that has been discussed in this paper. Continuous monitoring of structures and long-time data collection can be achieved through IoT based corrosion monitoring. The main problems that created the corrosion are carbonation depth and permeability of structures. These problems can be ascertained by using Neural Networks and machine learning models through running algorithms on the collected data. The penetration of aggressive substances such as $CO2$ and chloride can be collected through IoT technology which is usually very difficult because of the complexity of chemical and physical processes and different transport mechanisms. For morden structural health monitoring Donato Abruzzese et al[74] has given a detailed study of realization of low cost devices and softwares for data management for health monitoring of buildings and CEIs with remotely controlled sensors installed in the structures to measure stresses together with accelerations. The system alerts the users and authorities of the constructions that are part of the proposed IoT system in case the safety of the structures is compromised. Yun Xiao et al[85] has proposed a new immune based theory of earthen sites health monitoring and risk evolutional model that uses IoT technology. This model had successfully applied the biological immune system in health monitoring and risk evaluation of earthen sites. The overall health risk and the health risk is caused by a single environment factor can be calculated by the proposed model accurately. So the macro environmental threats of earthen sites can be grasped by the conservation heritage workers and find which several factors or a single factor results in a high health risk to earthen sites. According to the important factor the environmental conditions can be adjusted to make the earthen sites for a good living environment. This work has been a new way to the earthen sites prevention conservation.

3.2.3. Structural Health Monitoring using Cyber Physical System (CPS)

Although the IoT platform for SHM does efficient monitoring of structures still there are few concerns over establishing a continual strong connection between the physical processes and computing elements for efficient results. Therefore, researchers started becoming more interested in the Cyber Physical System (CPS) based structural health monitoring [86, 87, 88, 89] that provides tight integration of different components of the system. Rosana E. Mart´ınez-Castroa et al [90] theoretically proposed a Structural Cyber Physical System (SCPS) by using the concept of CPS and using tuned dampers to control the structures effectively. This paper proposes usage of controller and EDM(Electronic Document Management) system for better control of structures and this paper also proved that hybrid system that is semi active control system gives better result in control than passive system but less power consumption happened in the active control. The author has proposed SCPS an efficient control system by using

EDM conjugation with controller for better Structural Health Monitoring from SHM data collected by EDM but the implementation of this proposed SCPS is not given. Gregory Hackmann[3]proposed a cyber physical co-design approach distributed approach for the monitoring health of the structures with wireless sensor networks.This method closely integrates flexibility based damage localization methods that is if any force applied on the structure as structure weakens, stiffness of the structure decreased then the flexibility of the structure slightly changes. A structure's flexibility changes over time and is able to identify and locate the damages. Flexibility approach which is used widely for solving structural engineering problems, but they usually face problems with selecting algorithms for recognition and localization of damages rather than efficiently using the methods in distributed WSN architecture. The proposed concept also has been executed on Intel Imote2 hardware platform that was developed by Illinois Structural Health Monitoring Project which provides the sub systems for data acquisitions to the sensors, reliable data transmission, time synchronization and remote procedure calls etc. Ekin Ozer et al [22] has stated a methodology of Cyber Physical System (CPS) and has proposed a framework based on that methodology. The proposed model generates a Finite Element Model (FEM) of a bridge integrated with vibrations measured by smartphone WSNs and centralized computational facilities then the structural reliability can be assessed based on updated FEMs. Modal frequencies of an existing bridge can be identified by processing the collected structural vibrations data by smartphones on the server. By using a secure CPS paradigm, the accelerometer sensors in the smartphones of the citizens are passed to the server. The full uncertainties FEM model is compared with the experimental data to find out the error and the error can be minimized by updating the FEM model in the MATLAB by using the opensee loop. The updated FEM model can be used to estimate seismic responses and structural reliability. Dmitrii Legatiuk et al [91] have stated a theoretical idea of the modeling and evaluation method of CPS in civil engineering. CPS can be used for efficient structured monitoring in civil engineering. For accurate assessment of a structure, the CPS is required to be modeled and evaluated. A methodology is necessary for assessing the quality of CPS for assuring the quality of individual components of CPS as well as of the complex coupling conditions between the components. For checking the quality assessment of CPS, the coupling between subsystems of CPS must be assessed but the existing methodologies do not address inter and intra coupling or access these couplings for better quality assessment of CPS. So, the proposed idea of developing a conceptual modeling methodology with sufficient power to describe such couplings is essential. A Multi-paradigm Modeling(MPM) of Cyber-physical system architecture has been proposed by Hans Vangheluwe et al[92]. In a socio-economic context, the Cyber-Physical System is considered with the networking of multiple physics such as mechanical, biochemical, hydraulics, and electrical with computational systems that are control systems, logical inferences, etc interact with uncertain environments frequently with human beings. The defined CPS model is reaching an earlier level of complexity, even though all individual engineering disciplines only capable of giving partial solutions but no systematic design methods nor unifying theory or tools exist for such Cyber-Physical Systems. The proposed MPM explicitly proposes to model every part and every aspect of such complex systems with the most appropriate level of abstraction using the most appropriate modeling format. To realize MPM model, modelling language engineering that includes model transformation of languages and study of semantics of these languages are used. MPM is an effective answer to designing CPS challenges. This paper also introduced some of the challenges for collaborative development of CPS along with possible MPM solutions such as co-simulation and inconsistent management.

3.2.4. Advanced CPS for Structural Health Monitoring

In the year of 2018 Gael Loubet et al[93] has proposed a new Wirelessly powered battery-free wireless sensor by a dedicated radiofrequency source via a far-field wireless power transmission system for SHM applications in a harsh environment in the CPS paradigm. In the harsh environment update and maintenance of the installed sensors is quite costly and inaccessible due to difficulty to reach out to the structures in harsh environments. So, for the long running of sensors for decades, the idea of making the sensors battery free has been proposed but this article is not considering any storing algorithms, routing protocols or data processing implementations through which the internet can serve. Jes´us El´ıas Miranda-Vegab et al [94] proposed an optical Cyber Physical System embedded on an FPGA for 3D measurement in structural health monitoring tasks. The system described the design of a soft sensing technique of virtual angle management based on information conservation of opto-electronic signal which is provided by a rotary scanning system through FPGA behaving as the controller of the sensors and actuators in the Cyber Physical System. In this process the coordination displacement of a specific indicator can be calculated over the structures under structural health monitoring. The sensor signals provided by rotary scanning systems can be processed through electronic devices and mathematical tools that are embedded in rotary scanning hardware for structural health monitoring and control. Rui Hou et al [95] talked about the fusion of the Weigh-in-Motion (WIM) System and bridge monitoring in CPS architecture. This architecture integrated bridge health monitoring, cameras and WIM in single CPS to collect and integrate together the data collected from bridge and truck. So that the huge collection of bridge data paired with weighted data from the vehicles can be collected at minimal cost and effort. To reflect the bridge's actual load carrying capacity and to produce accurate data driven rating factor the different loading conditions such as dynamic load allowance and unit influence lines can be calculated. Rui Houa et al[86] also proposed a CPS framework using Weigh in motion and computer vision for automatic tracking of truck loads to bridge response, here computer vision is used in connected highways. This framework shows integration of two vehicle induced responses of two highway bridges collected by wireless SHM corresponding to the vehicle weight that is measured by WIM station is located along the same highway corridor. The proposed system can perform better due to the ability to automatically identify the trucks and mapping their travel history and in response triggering the SHM data. Hailing Fua et al [96] talked about an energy efficient CPS model for wireless on board Aircraft SHM. The proposed cyber physical model is low powered using wireless sensors integrated with PZTs with an active 354 sensing mechanism is designed, implemented and validated experimentally for on board wireless SHM. Then the system 355 is designed with a holistic manner considering device dimensions, energy efficiency, monitoring 356 performance, crossing attenuation, the sensis coverage and the long-term performance.

Recently in the year 2020, Christos Andreade et al [97] gave focus on 5G technology in the automotive domain and the advantages of 5G technology in working in CPS paradigm. The study envisaged the future development of softwares that could be deployed coupled with physical devices with the integration of networking in CPS paradigm.

3.2.5. Usage of CPS in other Fields

Being a prominent technology Cyber Physical System (CPS) has been widely used in different sectors. Chao Liu et al [98] investigated CPS architecture in Shop Floor for intelligent manufacturing. The proposed architecture gives guidelines for designing CPS systems from interconnecting hardwares for data acquisition, processing, visualisation and final knowledge acquisition and learning. Congcong Sun et al [99] mentioned CPS architecture which provides reliable and efficient management of Urban water cycle (UWC) in real time integrated for drinking water systems. Except quality and quantity this architecture is also capable of reducing the pollutant than quality control.

Shafiq ur Rehman et al [100] discussed smart home security. The devices in the smart home are connected through a central hub LAN and all the devices can be collected by laptop or any devices through single touch. She has provided an idea of security of smart homes using Sicher Firewall by considering a few aspects of security such as confidentiality, authenticity, availability and integrity etc.

3.2.6. Security concerns in IoT and CPS paradigm

Security also becomes one of major concerns when talking about efficient and robust Structural Health Monitoring systems in the IoT and CPS platforms using remote servers. SHM uses a cloud central server to store and process the data collected by the wireless sensors. So, for a secure data collection for a cloud enabled SHM Md Zakirul Alam Bhuiyan et al [101] implemented a method using Kalman filter for efficient Structural Health Monitoring. When any system working over the internet there are chances of data being compromised by third party intruders. After collecting the signal data from the sensors and before transferring to the cloud server, there are possibilities that the signals can be compromised, hacked or false data would be injected. Once data reaches the cloud server it is difficult to identify the compromised or false signals. Therefore, to overcome such difficulties Md Zakirul et al applied a truth discovery algorithm to identify the compromised signals before the transfer to the cloud remote server. After identifying the hacked or false signals the true signals can be reconstructed through the extended kalman filter by using reconstruction algorithm. This paper also gives a comparison between voting, CRH, TPDC techniques. Jacob Wurm et al[102]also talked about security concerns in the modern Cyber Physical System from a cross layer perspective. This paper discusses the possible security vulnerabilities and the countermeasures coming in devices, systems and in hardware level. Also gave a detailed review on current challenges and the possible solutions and it is also mentioned that the existing solutions are not enough to give security to the CPS architecture are being widely used in national infrastructures along with being enlightened on the possible future research directions.

3.3. Usage of Neural Networks for smart wireless SHM

Technologies now used to produce structural components such as plates, low weight panels and other components. These materials are embedded with sensors, actuators and transducers are referred to as “smart structure” [100]. These smart structures are capable of sensing structural characteristics such as structural degradation or delamination. Smart wireless Structural Health Monitoring (SHM) systems monitor the damage locations and damage severity in the damaged structures by using Artificial Neural Network (ANN) techniques to find structural damages through analyzing continuous dynamic structural information.

Artificial Neural Networks (ANNs) are creating ways to develop new and innovative applications for use in almost all sectors to get maximum benefits with high efficiency. As discussed in section 2.5 through a neural network model the damage locations and severities can be identified. The ANN models are trained and built with structural modal properties and damage patterns. A lot of work has been done using neural network models for the health monitoring of huge civil infrastructures in SHM[37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49]. For multiple damage detection, ANN is used to assess the damage by using backpropagation algorithms such as Levenberg-Marquardt algorithm as done by Z X tan et al [16] using MATLAB R2015b. They performed damage detection in a steel beam experimentally and based on ANN using R as training set value for multiple damage scenarios and compared the target value by backpropagation. The input value was the damage index β [Stubbs and Kim] based on strain energy and the output was the percentage loss in stiffness of the beam. They found out that if the number of hidden neurons was increased to 10 then the R-value of the training set gave maximum correlation to target and output. For a single damage case, Vibration-Based Damage Detection could be used but not in case of multiple damages. The modal strain energy U of an Euler-Bernoulli beam is given by

$$U = \int \frac{EI}{2} \left(\frac{d^2 y}{dx^2}\right) \qquad 10$$

where EI is the flexural rigidity of the member, $\frac{d^2y}{dx^2}$ is the curvature the member attains, y is the vertical deflection and x is the distance along the beam. Jordan C et al [37]did a case study of Powder Mill bridge at Kansas and he proposed a bridge behavior model using ANN and peak strain data available were compared using Wilcoxon rank-sum test in which two groups of non-parametric data are studied.The ANN models are trained with bridge response data and through a bootstrapping scheme a probabilistic model of bridge behaviour can be generated. Jong Jae Lee et al[38]also did a similar study in multiple girder bridges i.e. Hannam Grand Bridge in Seoul where they used a Neural Network having multiple hidden layers where six damage scenarios were taken using three input quantities i.e. mode shape, mode shape differences before and after damage and mode shape ratio. They used 100 baseline FEM models for the effectiveness of these three input quantities and finally were successful in locating damages and estimating the damage with minimum error. Convolution Neural Network is one of the finest things that has come up which is inspired by biological neurons and networks in the nervous system in animals. It falls under the category of "deep learning" and it is stronger and more powerful than ANN. It has a very good, generalized classification and optimization and researchers are very much focused on CNN in the machine learning field. They are used in the classification of images or identification of language. Although few works have been done using CNN in SHM [103, 104, 105, 106, 107, 108] but researchers have given more focus to ANN for SHM and CNN has been the technique less explored. The CNN network consists of the following layers: -

Convolution layer.: Convolution layer forms the core of CNN. It connects the input using filters and the filters are trained for the detection of features in the image. If there are more no. of convolution layers, then the output of the previous layer will be the input for the next layer.

Pooling layer: It reduces the size of images such as height and width and thus reduces the parameter for computation.

Flatten layer: This layer changes the shape of the input by conversion into a 1D array. The flattening of output from convolution layers is done to obtain a single long vector.

Dropout layer: This layer ensures the reduction of overfitting cases by dropping out neurons in the network to realize a better generalization of CNN.

Densely connected layer: This layer consists of many networks densely connected. Each output neural network is connected to the neural networks in the input. A block diagram of Convolutional Neural Network (CNN) is shown in Fig. 9.

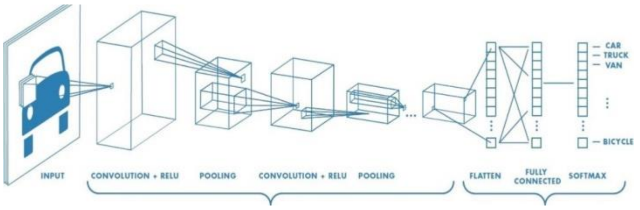

Fig. 9Block diagram of Convolutional Neural Network (CNN)

In CNN neurons in a layer are connected to small regions in the previous layer. Onur Avci et al [109] presented a novel technique i.e. 1D Convolutional Neural Network (CNN) for assessment of structural damage in real-time. CNNs are considered to fall in "deep learning" in the Neural Network field. CNNs can take images as inputs such as images of animals etc. They used three CNNs per joint which correspond to the three directions. They trained the CNNs by generating a number of damaged and undamaged acceleration signals at the joints. Though the technique they used gave good results and was inexpensive, this technique requires real damage data from real damage cases in order to train CNNs. The use of FEM models for training CNNs is still being investigated. In another study performed in a composite stiffened plate by Iuliana Tabian et al [104]using CNN where the input signals from piezoelectric sensors are taken as raw data in the form of the 2D image since the convolution layers in CNN resemble the human visual cortex.

Lian Zhang et al [8] did a similar study and classified the various types of cracks in bridges using IoT in conjunction with CNN and with the help of image preprocessing by dividing images into 3 samples. The modelling was done using MATLAB 2016a and they found out that the root mean square error was less than 0.1 therefore their method could be used in low fracture analysis and high-risk factors in fractures. Giorgio Vallonea et al [110] did monitoring of the tail end of helicopters whose components can get damaged due to harsh landing. They used Bayesian regularization for training of neurons using the Levenberg-Marqaurdt algorithm. They used stringers to do the study.

Different Soft Computing and Artificial Intelligence techniques such as Neural Networks, Genetics Engineering have been widely used in SHM due to its excellent pattern recognition capabilities in the process of Structural Health Monitoring. As considering these techniques Jong Jae Leea et al [111] has proposed a Neural Network(NN) based damage identification method using modal properties that is capable of considering effectively the modeling errors in the baseline Finite Element Model(FEM) from which the training patterns are generated. The difference between before and after damage of the mode shape components is used as input in the proposed neural network model because they are found less sensitive to modelling errors than mode shapes. The effectiveness of the proposed NN damage detection method is checked by applying two numerical examples on a simple beam and a multi girder bridge. The used simple beam model consist of 8 equal length i.e of 1.25 m beam elements and the original flexural rigidity is EI=7.75104 kNm2and the multi girder bridge consists of 5 girders, diaphragms,slabs, that are modeled using beam elements. The modeling errors of each structural member were assigned as random variables and by perturbing the bending rigidities of beam elements the effectiveness of the inputs to the NN under the modelling errors of the baseline FEM model was ascertained. The capability of the model confirmed with multiple girders by laboratory test on simple supported bridge and field test on old Hannam Grand Bridge over Han River in Seoul, Korea Chia-Ming Changa et al[103] proposed an artificial intelligence based Neural Network model for structural health monitoring. This model is developed according to a numerical model that is derived from the modal properties under ambient vibration. The initial process of this model involves generating mode shapes and natural frequencies of a healthy structure. These mode shapes and natural frequencies are used to derive the simplified model of the structure by allowing changing the stiffness terms to construct various damage patterns. This proposed model can be employed after a major critical event occurs like an earthquake to calculate the damage patterns as per stiffness reduction. To evaluate the performance of the proposed SHM strategy Chia-Ming et al carried out a numerical example by considering two damage scenarios on a twin-tower building by using shake table testing. The proposed implemented AI based framework is very effective to identify the damage if the modal properties that are identified are relatively accurate. Xiaobo et al [112] proposed a Neural Network (NN) based SHM using "Recall rate" evaluation matrix technique for classification problems. They used 8000 training examples for training the models and reaching optimal SHM. They did comparison of NN, SVM, Linear Regression (LR) and Decision Tree(DT) type of machine learning and found that NN gives the best result as the immunity against environmental noises is least in NN and NN performed better in training and testing period than other machine learning methods.

In monitoring of large civil infrastructure, ANN still suffers from imperfections of structural failures that lead to severe destructions. To address the defined problem Ch. Efstathiadesa et al [113] presented for monitoring structural health in curtain wall systems. This paper describes various respective health monitoring problems and proposed ANN to identify the possible solutions in a curtain wall system. This model developed a few Finite Element (FE) models of curtain wall system and carried out a parametric analysis for dealing with loss of rigidity in afore-mentioned connections. The data sets containing deflections of the columns of the curtain wall system were computed during the numerical investigation and obtained results were used to create a Patterns database that is used as input to the ANNs for the training phase. Because of the small number of training patterns, the regularization technique was applied to improve the network generalization. This paper shows that ANN can be an efficient method for identifying and localisation of damages imperfections in a curtain wall system.

Table 2: Summarized works on various types of wireless SHM

Type of Wireless SHM	Year	Instrument/interface used
IoT based using wireless sensors [9]	2017	Raspberry Pi, MCP3008, PZT
Using IoT and Wireless Technologies [5]	2017	Audrino, Thing speak, PZT
IoT and Cloud Computing [6]	2016	Mongo DB and Web
IoT Node with Organic Pressure Sensor [26]	2020	Polyurethane film, PZT
IoT using UAVs and Virtual Reality [25]	2020	UAV, Mobile network sensors
Cyber-Physical SHM [22]	2019	Smart phones, Opensee Loop
IoT using Convolutional Neural Network [127]	2018	CNN, MATLAB
Cloud Computing using Time series analysis [123]	2015	Hadoop and MapReduce
Cyber-Physical based distributed SHM [21]	2014	Intel Imote2 platform, ISHM
Optical cyber-physical system [28]	2018	Rotatory scanning system

CPS using Computer Vision [36]	2020		Highway bridges, WIM station

CONCLUSION

Therefore, from various literature there has been efforts to minimize the energy used for Structural Health Monitoring. The use of wired SHM is still prevalent worldwide owing to its accuracy in obtaining results.There are certain environmental conditions which can change the procedure of SHM and any inaccuracies can be fatal to human life and properties. Therefore, efforts are on to develop fool proof Wireless Sensor Networks in conjunction with better procedure and algorithm to obtain best results such as using ANN or CNN. Researchers are striving to get the best algorithm using various techniques to give solutions to real life problems. ANN and other Neural Networks are very helpful in giving better results inspired from nervous systems. As far as the networking part is concerned integrating wireless Sensor Networks with IoT and CPS infrastructure makes the Structural Monitoring System way smarter and more efficient. Though this area is hardly discussed in the Civil Engineering fraternity and mainly this area is dealt in Computer Science domain it becomes essential to look at the whole picture using interdisciplinary research. The usage of Neural Networks in conjunction with CPS can make the area of SHM really rewarding. Therefore, a comprehensive outlook to this area is required because if any of the domains fails to address the problems, the contribution of other domains goes in vain.

This paper tries to bring out the aspects of research going on both in the core field of modelling and monitoring that's being developed in the recent past and also the networks that have been developed to make the entire process of Structural Health Monitoring more robust. There is still future scope of improvement like development of better algorithms and more integration of Artificial Intelligence (AI) components which if developed can help accurate damage detection and as well as prediction of damages. Also using AI, the civil engineering structures can be controlled without the interference of human beings for controlling. Though there are few literature on structural control like damping using mass dampers for controlling deflection and vibrations using Neural Networks and modern IoT and CPS paradigm, we can only achieve that by gaining expertise in monitoring then we can go further for structural control.

ACKNOWLEDGMENT

None

REFERENCES

[1] W. K. Farrar CR, An introduction to structural health monitoring, Philos Trans R Soc A Math Phys Eng Sci 365 (2007) 303–15. doi:10.1098/ rsta.2006.1928.

[2] M. B. A Abrardo, L Balucanti, Health monitoring of architectural heritage: the case study of san gimignano, 2010 IEEE Workshop on Environmental Energy and Structural Monitoring Systems (EESMS) (2010) 98–102.

[3] G. Y. C. L. G. Hackmann, W. Guo, S. Dyke, Cyber-physical codesign of distributed structural health monitoring with wireless sensor networks, ICCPS.

[4] D. S. R, Fibre optic sensors for structural health monitoring of aircraft composite structures: Recent advances and applications, Sensors 15 (2015) 18666–18713.

[5] M. F. A. Hailing Fua, Zahra Sharif-Khodaeia, An energy-efficient cyber physical system for wireless on-board aircraft structural health monitoringdoi:https://doi.org/10.1016/j.ymssp.2 019.03.050.

[6] L. W. K. J. Ni YQ, Xia Y, Technology innovation in developing the structural health monitoring system for guangzhou new tv tower, Struct. Control Health Monit. 16 (2009) 73–98.

[7] S. Z. H. Boukabache, C. Escriba, J. Fourniols, Structural health monitoring on metallic aircraft using flexible and bulk pzt transducers: Case of corrosion detection and crack localization, Annual Conference of Prognostics and Health Management Society,.

[8] C.-H. K. Eschmann, C.-M. Kuo, C. Boller, Unmanned aircraft systems for remote building inspection and monitoring, 6th Eur. Workshop Struct. Health Monitor. 36 (2012) 13.

[9] H. Qarib, H. Adeli, Recent advances in health monitoring of civil structures, Sci. Iran. 21 (6) (2014) 1733–1742.

[10] S. S.-A. Sony, S.; Laventure, A literature review of next-generation smart sensing technology in structural health monitoring, Struct. Control Health Monit 26 (2019) e2321.

[11] L. R. D. S. L. H. N. Li, T. H. Yi, L. S. Huo, Reviews on innovations and applications in structural health monitoring for infrastructures, Structural Monitoring and Maintenance 1 (1) (2014) 1–45.

[12] G. C. Kru ger M, K. JH, Acoustic emission analysis techniques for wireless sensor networks used for structural health monitoring, 3rd international conference on bridge maintenance, safety and management–bridge maintenance, safety, management, life-cycle performance and cost, Porto (16-19) (2006) 873–874.

[13] VictorGiurgiutiu, Impact and acoustic emission monitoring for aerospace composites shm,structural health monitoring of aerospace composites (2016) 317–394doi:10.1016/0003-4916(63)90068-X.

[14] K.-Y. Jhang, Nonlinear ultrasonic techniques for nondestructive assessment of micro damage in material: A review, International Journal of Precision Engineering and Manufacturing volume 10 (2009) 123–135.

[15] Y. C. Zhenhua Chen, Wei Lu, C. Lu, Fatigue crack detection in aisi 304 austenitic stainless steel using nonlinear and linear ultrasonic testing methods, Journal of Materials Engineering and Performance 29.

[16] T. H. T. C. H. A. R. Z X Tan, D P Thambiratnam, Detecting damage in steel beams using modal strain energy based damage index and artificial neural network, Engineering Failure Analysis 79 (2017) 253–262.

[17] A. .Rytter, Vibrational based inspection of civil engineering structures, dept. of building technology and structural engineering., Ph.D. thesis, Dept. of Building Technology and Structural Engineering, Aalborg Univ.

[18] J. K. B. W. Y.Q. Ni, X.T. Zhou, Vibration-based damage localization in ting kau bridge using probabilistic neural network, Advances in Structural Dynamics II (2000) 1069–1076.

[19] P. M. Doebling SW, Farrar CR, Damage identification and health monitoring of structural and mechanical systems from changes in their vibrationcharacteristics:a literature review, Los Alamos National Laboratory report LA-13070-MS, Washington, DC: Los Alamos National Laboratory,.

[20] X. Y.-L. Brownjohn JMW, De Stafano A, Vibration-based monitoring of civi infrastructure: challenges and successes, J Civil Struct Health Monit 1 (3-4) (2011) 79–95. doi:https://doi.org/10.2172/249299.

[21] W. W. Justin Demetry, Review of structural health monitoring methods regarding a multi-sensor approach for damage assessment of metal and composite structures, Sensors 286. doi:10.3390/s20030826.

[22] E. Ozer, M. Q. Feng, Structural reliability estimation with participatory sensing and mobile cyber-physical structural health monitoring systems, Appl. Sci. 9 (2019) 2840. doi:10.3390/app9142840.

[23] JyrkiKullaa, Robust damage detection in the time domain using bayesian virtual sensing with noise reduction and environmental effect elimination capabilities, Journal of Sound and Vibration 473 (2020) 115232.

[24] V. L. j. D. J. I. M.Anderson De Oleveira, J.V. Filho, A novel time-domain technique for damage detection applied to shm using savitzky-golay filter.

[25] H. L. Y. Bao, J. Ou, Emerging data technology in structural health monitoring: compressive

sensing technology, Journal of Civil Structural Health Monitoring 4 (2014) 77–90.

[26] P. S.Sengupta, A.Datta, Structural damage localization by acoustic emission technique-a state of the art review, Latin American Journal of Solids and Structures 12.

[27] Y. H. M. T. Hiroaki Suzuki, Tetsuo Kinjo, K. Ono, Wavelet transform of acoustic emission signals, Journal of Acoustic Emission (1996) 14 (2).

[28] G. J. O. A. Hamstad, M.A., A. far-field acoustic emission waves by threedimensional finite element modeling of pencil breaks on a thick plate, Journal of Acoustic Emission 14 (2) (1996) 103–14.

[29] O. A. G. J. Hamstad, M.A., Modeling of buried monopole and dipole sources of acoustic emission with a finite element technique., Journal of Acoustic Emission 17 (3-4) (1999) 197–110.

[30] L. Yu, J.-H. Zhu, Nonlinear damage detection using higher statistical moments of structural responses, Structural Engineering and Mechanics 54 (2) (2015) 221–237.

[31] Z. Wang, K. Ong, Autoregressive coefficients based hotelling's t2 control chart for structural health monitoring, Computers and Structures 86 (19- 20) (2008) 1918–1935.

[32] Z. Wang, K. Ong, Multivariate statistical approach to structural damage detection, Journal of engineering mechanics 136 (1) (2009) 12–22.

[33] Z. Wang, K. Ong, Structural damage detection using autoregressivemodelingcorporating multivariate exponentially weighted moving average control chart, Engineering structures 31 (5) (2009) 1265–1275.

[34] C.-W. Chia-MingChang, Tzu-KangLin, Applications of neural network models for structural health monitoring based on derived modal properties, Measurement Volume 129 (2018) 457–470.

[35] B. IA, H. M, Artificial neural networks: fundamentals, computing, design, and application, J Microbiol Meth 43 (1) (2000) 3–31.

[36] M. H. Hassoun, Fundamentals of artificial neural networks, mit press.

[37] M. . . Jordan C. Weinstein1 ; Masoud Sanayei, F. Brian R. Brenner, Bridge damage identification using artificial neural networks, American Society of Civil Engineersdoi:10.1061/(ASCE)BE.1943-5592.0001302.

[38] J. H. Y. C. B. Y. H. Y. J. Jong Jae Lee, Jong Won Lee, Neural networksbased damage detection for bridges considering errors in baseline finite element models, Journal of Sound and Vibration 280 (3-1) (2005) 555– 578.

[39] J. I. Zhao, J., J. DeWolf, Structural damage detection using artificial neural networks, J. Infrastruct. Syst. 4 (3) (1963) 93–101. doi:https: //doi.org/10.1061/(ASCE)1076-0342(1998)4:3(93).

[40] M. Hadi, Neural networks applications in concrete structures, Comput. Struct. 81 (6) (2003) 373–381. doi:https://doi.org/10.1016/ S0045-7949(02)00451-0.

[41] N. K. H. M. Mehrjoo, M., A. Bahreininejad., Damage detection of truss bridge joints using artificial neural networks, Expert Syst. Appl. 35 (3) (1963) 1122–1131. doi:https://doi.org/10.1016/j.eswa.2007.08. 008.

[42] J. G. J. X. Wu, J. Ghaboussi, Use of neural networks in detection of structural damage, Computers and Structures 42 (4) (1992) 649–659.

[43] M. I. C. Zang, Structural damage detection using artificial neural networks and measured frf data reduced via principal component projection, Journal of Sound and Vibration 242 (5) (2001) 813–827

[44] J. K. Y.Q. Ni, B.S. Wang, Constructing input vectors to neural networks for structural damage

identification, Smart Materials and Structures 11 (2002) 825–833.

[45] G. I. Shu J, Zhang Z, The application of a damage detection method using artificial neural network and train-induced vibrations on a simplified railway bridge model, Eng Struct 52 (2013) 408–421.

[46] H. SJS, A. R. H., Structural damage detection of steel bridge girder using artificial neural networks and finite element models, Steel Compos Struct 14 (4) (2013) 367–377.

[47] S. K. D. I. O. Avci, O. Abdeljaber, Structural damage detection in real time: implementation of 1d convolutional neural networks for shm applications, C. Niezrecki (Ed.), Structural Health Monitoring and Damage Detection, Conference Proceedings of the Society for Experimental Mechanics Series 7 (2017) 49e54.

[48] Z. L. Waszczyszyn Z, Neural networks in the identification analysis of structural mechanics systems., Parameter Identification of Materials and Structures, CISM 469 (2005) 265–340.

[49] H. G. Ziemianski L, The use of neural networks for damage detection in eight storey frames, Advances in Structural Engineering 13 (1).

[50] J. Lynch, An overview of wireless structural health monitoring for civil structures., Philos. Trans. R. Soc. Lond. A Math. Phys. Eng. Sci. 365 (2007) 345–372.

[51] R. A. Keller E, Real-time health monitoring of mechanical structure, Struct Health Monit 2 (3) (2003) 257–67.

[52] H. A. J.P. Amezquita-Sanchez;, M. Valtierra-Rodriguez, Wireless smart sensors for monitoring the health condition of civil infrastructure, Transactions on Civil Engineering (A) 6 (2018) 2913–2925.

[53] D. Rekha.K.Sa, Dr.T.H.Sreenivasb, Remote monitoring and reconfiguration of environment and structural health using wireless sensor network, Annals of Physics 5 (2018) 1169–1175.

[54] T. D. O. D. T. K. F. A. V. C. G. Cem Ayyildiz, H. Emre Erdem, Structure health monitoring using wireless sensor networks on structural elements, Hd Hoc Networks 82 (2019) 68–76.

[55] R. R.-P. a. V. Matteo Vagnoli, Railway bridge structural health monitoring and fault detection: State-of-the-art methods and future challenges, Structural Health Monitoringdoi:https://doi.org/10.1177/1475921717721137.

[56] J. P. H. X. W. Ye, Y. H. Su, Structural health monitoring of civil infrastructure using optical fiber sensing technology:, The Scientific World Journal 2014.

[57] M. M. Christos Andreades, Gian Piero Malfense Fierro, A nonlinear ultrasonic shm method for impact damage localisation in composite panels using a sparse array of piezoelectric pzttransducersdoi:https://doi.org/10.1016/j.ultras.2020.106181.

[58] R. J. Edward Sazonov, Kerop Janoyan, Wireless intelligent sensor network for autonomous structural health monitoring, Smart Sensor Technology and Measurement Systems, Proceedings of SPIE 5384.

[59] F.-K. C. J.-B. Ihn, Pitch-catch active sensing methods in structural health monitoring for aircraft structures, Structural Health Monitoring 7 (2008) 5–19.

[60] A. B. T. E. M. A. M. S. A. Noel, A. Abdaoui, Structural health monitoring using wireless sensor networks: a comprehensive survey, IEEE Commun. Surv. Tutorialsdoi:https://doi.org/10.1109/COMST.2017.2691551.

[61] B. Spencer, T. Nagayama., Smart sensor technology: a new paradigm for structural health monitoring., In Asia-Pacific Work- shop on Structural health Monitoring.

[62] A. Z. R. Andrew Swartz, J. P. Lynch, Structural health monitoring system with the latest information technologies, 5th Infrastructure and Environmental Management Symposium.

[63] K. C. D. G. B. R. G. N. Xu, S. Rangwala, D. Estrin., A wireless sensor network for structural monitoring., In SenSys.

[64] G. A. D. T. M. Farrar, C.R.; Park, Sensor network paradigms for structural health monitoring., Struct. Control Health Monit. 13 (2006) 210–225.

[65] D. C. J. D. G. F. S. G. M. T. S. Kim, S. Pakzad, Wireless sensor networks for structural health monitoring, Struct Health Monitdoi:https://doi. Org/10.1145/1031495.1031498.

[66] D. I. D. Zhou, D.S. Ha, Ultra low-power active wireless sensor for structural health monitoring, Smart Struct. Syst.

[67] G. M. Whelan, M.J., K. Janoyan, Integrated smart wireless sensors for bridge structural health and homeland security monitoring, 3rd International Conference on Intelligent Infrastructure.

[68] T. E. M. H. A. A. B. M. S. S. A. B. Noel, A. Abdaoui, Structural health monitoring using wireless sensor net-works: A comprehensive survey, IEEE Commun. Surveys Tuts. 19 (3) (2017) 1403–1423.

[69] A. Abdelgawad, K. Yelamarthi, Internet of things (iot) platform for structure health monitoring, Wireless Communications and Mobile Computing.

[70] L. I. S. L. S. J. Rajkumar, R. (Raj), Cyber-physical systems: the next computing revolution, Proc. 47th Des. Autom. Conf. - DAC '10 731. doi: https://doi.org/10.1145/1837274.1837461.

[71] M. Kocakulak, I. Butun, An overview of wireless sensor networks towards internet of things, IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC) (2017) 1–6.

[72] T. Y.-C. Wu F-J, Kao Y-F, From wireless sensor networks towards cyber physical systems., Pervasive Mobile Computation 7 (3) (2011) 397–413. doi:10.1016/j.pmcj.2011.03.003.

[73] J. I. Woubishet Zewdu Taffese, Ethiopia Nigussie, Internet of things based durability monitoring and assessment of reinforced concrete structures, he 5th International Workshop on the Future of the Internet of Things (FIT 2019)doi:10.1016/j.procs.2019.08.096.

[74] A. T. M. C.-D. F. G. G. G. S. S. V. P. A. Donato Abruzzese, Andrea Micheletti, Iot sensors for modern structural health monitoring. a new frontier, 1st Virtual Conference on Structural Integrity - VCSI1doi: 10.1016/j.prostr.2020.04.04.

[75] T. A. M.A.Mahmud, K.Bates, K.Yelamarthi, A complete internet of things (iot) platform for structural, health monitoring (shm), IEEE 4th WF-IoT.

[76] K. S.Jeong, An iot platform for civil infrastructure monitoring, IEEE 42nd COMPSAC.

[77] A. A. K. Y. A. Myers, Md Anam Mahmud, Toward integrating structural health monitoring with internet of things (iot), IEEE Int. Conf. on Electro Information Technology (EIT).

[78] V. M. B. Chanv, S. Bakhru, Structural health monitoring system using iot and wireless technologies, Int. Conf. on Intelligent Communication and Computational Techniques (ICCT) 1 (2017) 151–157.

[79] S. B. Brinda Chanv, Structural health monitoring system using iot and wireless technologies, ICCT 2017 1 (2017) 151–157.

[80] T. L. H. Chang, Real-time structural health monitoring system using internet of things and

cloud computing, Eleventh U.S. National Conference on Earthquake Engineering.

[81] A. B. T. V.-P. H. L. Q. D. Chien Khong Duc, Toan Thanh Dao, An iot node with organic pressure sensor for structural health monitoring system, International Conference on Green and Human Information Technology (ICGHIT).

[82] P. C. D. G. A. G.-G. R. L. D. M. M. A. P. M. T. Manlio bacco, Paolo Barsocchi, Monitoring ancient buildings: Real deployment of an iot system enhanced by uavs and virtual reality, IEEE Acessdoi:10.1109/ACCESS. 2020.2980359.

[83] G. Rakha, T., A. review of unmanned aerial system (uas) applications in the built environment: Towards automated building inspection procedures using drones, Automation in Construction 93 (2018) 252–26.

[84] C. Kanellakis, G. Nikolakopoulos, Survey on computer vision for uavs: Current developments and trends, J. Intell. Robot. Syst. 87 (1) (2017) 141–168.

[85] X.-j. C. B.-y. L.-L. W. D.-y. F. Yun Xiao, Wei Li, An immune theory based health monitoring and risk evaluation of earthen sites with internet of things, IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber,Physical and Social Computingdoi:10.1109/GreenCom-iThings-CPSCom.2013.82.

[86] J. P. L. K. H. L. Rui Houa, Seongwoon Jeongb, Cyber-physical system architecture for automating the mapping of truck loads to bridge behavior using computer vision in connected highway corridors, Transport Research Part C:Emerging Technologies 111 (2020) 547–571. doi:https://doi. org/10.1016/j.trc.2019.11.024.

[87] T. T. G. C. L. C. G.-X. Huang, H.-M., S. Dyke, Cyber-physical systems for real-time hybrid structural testing: A case study, International Conference on Cyber-Physical Systems.Stockholm.

[88] E. L. J.C. Jensen, D.H. Chang, A model-based design methodology for cyber-physical systems, 7th International Wireless Communications and Mobile Computing Conference.

[89] S. W. Y. L. K. L. J. Hou, R.; Jeong, Camera-based triggering of bridge structural health monitoring systems using a cyber-physical system framework, Struct. Health Monit. 2 (2017) 3139–3146.

[90] R. E. Mart´ınez-Castro, S. Jang, Structural cyber-physical systems: A confluence of structural health monitoring and control technologies, CEE Articles.

[91] K. S. Dmitrii Legatiuk, Kosmas Dragos, Modeling and evaluation of cyberphysical systems in civil engineering, PAMM · Proc. Appl. Math. Mech. 17 (2017) 807 – 808. doi:10.1002/pamm.201710371.

[92] H. Vangheluwe, Multi-paradigm modelling of cyber-physical systems, 4th International Workshop on Softwar, Engineering for Smart Cyber-Physical Systems, IEEE.

[93] D. D. Gael Loubet, Alexandru Takacs, Implementation of a battery-free wireless sensor for cyber-physical systems dedicated to structural health monitoring applications, Special Section on CYBER-PHYSICAL SYSTEMS(IEEE Access) 7.

[94] O. S. M. R.-L. L. L. J. C. R.-Q. D. H.-B. Jes´usEl´ıas Miranda-Vegab, Wendy Flores-Fuentesa, Optical cyber-physical system embedded on an fpga for 3d measurement in structural health monitoring tasks, Elsevier B.V (0141-9331). doi:https://doi.org/10.1016/j.micpro.2017.11. 005.

[95] S. J. K. L. M. E. J. P. L. Rui Hou, Yash Amit Dedhia, Fusion of weighin-motion system and bridge monitoring data for bridge load rating, 9th International Conference on Structural Health Monitoring of Intelligent Infrastructure.

[96] M. F. A. Hailing Fua, Zahra Sharif-Khodaeia, An energy-efficient cyber physical system for wireless on-board aircraft structural health monitoring, Mechanical Systems and Signal Processing 128 (2019) 352–368.

[97] B. Stephen Curtis Jackson, Application of congestion notifications in a cyber-physical system, IEEE, 22nd Pacific Rim International Symposium on Dependable Computing.

[98] P. J. Chao Liu, A cyber-physical system architecture in shop floor for intelligent manufacturing, Procedia CIRP 56 (2016) 372–377.

[99] V. P. o. M. Congcong Sun, Gabriela Cembrano, Cyber-physical systems for real-time management in the urban water cycle, IEEE 1 (2018) 5–9.

[100] D. A. Sofge, Structural health monitoring using neural network based vibrational system identification, IEEEdoi:0-7803-2404-8/94/01994

[101] G. W. Md ZakirulAlam Bhuiyan, K.-K. R. Choo, Secured data collection for a cloud-enabled structural health monitoring system, 8th IEEE International Conference on Distributed Computing in Sensor Systemsdoi:10.1109/DCOSS.2012.38.

[102] Y. L. S. H. K. H. F. R. M. T. Jacob Wurm, YierJin, Introduction to cyber-physical system security: A cross-layer perspective, IEEE (2016) 2332–7766doi:10.1002/pamm.201710371.

[103] C.-W. C. Chia-Ming Changa, Tzu-Kang Linb, Applications of neural network models for structural health monitoring based on derived modal properties, Measurement 129 (2018) 457–470. doi:https://doi.org/ 10.1016/j.measurement.2018.07.051.

[104] Z. S. K. Iuliana Tabian, Hailing Fu, A convolutional neural network for impact detection and characterization of complex composite structures, Sensors 19 (2019) 4933. doi:doi:10.3390/s19224933.

[105] S. K. M. G. D. I. O. Abdeljaber, O. Avci, Real-time vibration-based structural damage detection using one-dimensional convolutional neural networks, Journal of Sound Vibration 388 (154e170).

[106] O. K. M. B. B. S. H. I. D. Abdeljaber, O.; Avci, 1-d cnns for structural damage detection: verification on a structural health monitoring benchmark data., Neurocomputing 275 (2018) 1308–1317.

[107] H. M. A. B. M. Mehrjoo, N. Khaji, Damage detection of truss bridge joints using artificial neural networks,, Expert Systems with Applications 35 (3) (2008) 1122–1131.

[108] J. S. L. K. L. J. Hou, R., Re identification of trucks in highway corridors using convolutional neural networks to link truck weights to bridge responses., SPIE 10970, Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems. International Society for Optics and Photonics (2019) 109700P.

[109] S. K. M. H. D. J. I. Onur Avci, Osama Abdeljaber, Wireless and real-time structural damage detection: A novel decentralized method for wireless sensor networks, Journal of Sound and Vibration 424 (2018) 158–172.

[110] A. M. Giorgio Vallonea, Claudio Sbarufatti, M. Giglio, Artificial neural networks for structural health monitoring of helicopter harsh landings, Applied Mechanics and Materials 390 (2013) 192–197.

[111] J. H. Y. C. B. Y. H. Y. J. Jong Jae Lee, Jong Won Lee, Neural networksbased damage detection for bridges considering errors in baseline finite element models, Journal of Sound and Vibration 280 (2004) 1555–578.

[112] H. Z. T. J. R. B. Xiaobo Xie, Junqi Guo*, Neural-network based structural health monitoring with wireless sensor networks, IEEEdoi: 978-1-4673-4714-3/13.

[113] P. N. L. Z. G. S. Ch. Efstathiades, C.C. Baniotopoulos, Application of neural networks for the structural health monitoring in curtain-wall systems, Engineering Structures 29 (12) (2007) 3475–3484. doi:http://dx.doi.org/10.1016/j.engstruct.2007.08.017.

[114] T. W. A. A. K. Y. Md Anam Mahmud, Kyle Bates, A complete internet of things (iot) platform for structural health monitoring (shm), IEEEdoi: 978-1-4673-9944-9/18.

[115] Y. H. H. L. Y. W. Liyan Zhang, Guanchen Zhou, Application of internet of things technology and convolutional neural network model in bridge crack detection, IEEE 6.