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Distributed network-based structural health monitoring expert system

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ABSTRACT
Structural Health Monitoring (SHM) is a process of detecting damages to engineering structures. The goal of SHM is to improve both the safety and reliability of infrastructures such as buildings, bridges, and highways. Several efforts have been made to develop improved SHM systems. However, most of these studies only considered vibration as a monitoring parameter without incorporating expert systems based on fuzzy inference. In this work, an expert system was incorporated into SHM for monitoring residential buildings based on building temperature and vibration measurements. The developed system used a Wireless Sensor Network (WSN) with a 2.4 GHz Radio Frequency (RF) band. Results of the system performance evaluation indicated a decrease in reliability from 99% to 50% within a decade of its deployment. In terms of energy conservation, results showed that the system was able to save 30% of energy, thereby increasing its lifetime. The fuzzy expert SHM system is able to detect building conditions with a good level of reliability, energy conservation capability and high accuracy of 94.4% and 100% as the least and best performance, respectively. Hence, direct integration of this system into building structures could aid early detection of building impairment.

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Wireless sensor network; expert system; fuzzy logic; SHM; smart city

Introduction

Structural health monitoring is a process of constantly watching over civil engineering structures to find an anomaly. The structural engineering community has found that structural health monitoring is a necessary activity to efficiently protect engineering structures (Badejo, 2009; Lynch et al., 2001). SHM systems are designed to efficiently test and monitor the health performance of engineering structures, employing sensors deployed at optimal positions where it can give measurement needed for determining the safety of structures (Bremera et al., 2016). An early SHM method was designed based on manual feedback in which anomaly was reported by means of warning sound, advisory, caution, and maintenance panels. To addressed its shortcoming, various research efforts have been made to develop an improved SHM system with the capability to detect structural defects and inform the owner or authorities (Bremer, et al., 2016; Lynch et al., 2001; Wang et al., 2014; Wang et al., 2017; Wang et al., 2019; Zhang et al., 2012). The goal is to create cities (smart cities) where all their critical infrastructures such as buildings, bridges, and so on can be monitored so that preventive maintenance activities can be planned.

SHM has the following components: sensors, a data transceiver, and a computational unit with processing ability. Recent systems have employed a wireless sensor network (WSN) to transmit measured parameters to the point of processing. WSN is a combination of several battery-powered sensor nodes deployed to acquire parameters for monitoring(Wang et al., 2014). Each node consists of different sensor types to monitor different parameters and transmit data wirelessly between one another to the sink (static or mobile) using existing routing protocols(Wang et al., 2017; Wang et al., 2019). When a mobile sink is employed, topology changes from time to time are managed with a topology management protocol (Zhang et al., 2012).

Damage can be considered as a modification of physical parameters such as mass, stiffness, and damping. A physical parameter can be modified by a motion attributed to a vibration within a building. Environmental factors such as temperature can also affect the status of a building. To increase the efficacy of a damage detection system, we propose the incorporation of an expert system into the SHM. Expert systems are systems that can intelligently make decisions based on available input and knowledge programmed in the input (Angeli, 2010). Expert systems are developed to be able to solve a

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problem with less intervention from human beings. They imitate human reasoning about a problem and use that reasoning to solve the problem. Expert systems are implemented using different methods, including Java Expert System Shell (JESS) and Fuzzy Logic.

The objective of this study was to develop a structural health monitoring system with an integrated fuzzy logic expert system using structural vibration and temperature measurements obtained with piezoelectric velocity and LM35 sensors. The performance of the developed expert system was validated using British Standards (BS: 13670) (CONSTRUCT, 2010). Standard temperatures of a building structure and experimental phase II of SHM benchmark problem data were obtained from the structure under different deformation conditions (Dyke et al., 2003). The system can analyse temperature and vibration as two aggregated parameters to determine the health status of a building. Contributions of this paper include the incorporation of an expert system (fuzzy associations or rules) for the detection of structural damage based on a combination of building vibration and temperature changes. Contrary to existing studies, this system was designed to predict structures deformity early using a combination of building temperature and vibration aberrations. This will enable a householder to take preventive measures beforehand. Moreover, comprehensive studies were conducted for the development of an energy-efficient SHM system. The proposed intelligent SHM system could effectively improve structural safety and reliability, thereby implying that the expert system could have practical applications for structural damage prediction in a smart city. It is important to note that much energy is saved while employing the proposed sleeping scheme configuration compared to an active mode method. This is an asset of an energy-efficient SHM system.

Review of related works

Many recent studies have employed vibration sensors to develop structural health monitoring systems to assess the health of a building. Some works can be found in (Anthony et al., 2015; Ashwear & Eriksson, 2017; Li et al., 2015; Lorenzoni et al., 2016). However, each of these works used a different approach for analysing vibration data. For instance, in the work of Anthony et al. (2015), modal parameter (vibration) non-destructive tests were used for assessing damages in reinforced concrete beams under static load and a static test was conducted to assess the degree of stiffness degradation. Meanwhile, the work of Nasseradeen and Anders was focused on sensor and excitation location, environmental effect, and effects of different scenarios on building structures (Ashwear & Eriksson, 2017). On the other hand, Lorenzoni et al. (2016) employed a certain number of accelerometers in a distributed fashion to acquire vibration data and displacement transducers integrated with a temperature sensor to monitor the behaviour of some significant cracks of a building. Bremera et al. (2016) have designed fibre-optic sensors to detect cracks and moisture ingress in concrete building structures. The fibre-optic sensor has long-term stability and reliability due to chemical and mechanical impact of a concrete environment. On the other hand, Cataldo et al. (2017) have employed a Time Domain Reflectometry (TDR) system incorporated with sensing elements embedded inside the walls of a building for monitoring its health. The monitoring was based on the relative dielectric permittivity of water to analyse the characteristics of moisture walls.

In another effort, IoT and wireless technology have been proposed for structural health monitoring (Chanv et al., 2017). The system comprises of a sensor unit (vibration sensor, strain sensor, moisture sensor) and a data acquisition and processing unit (Arduino Uno and Wi-Fi module) to process and transfer acquired data to the cloud. Users are alerted when emission beyond a tolerant level is detected. However, the system is not intelligent as it simply alerts the user once emission is high. Likewise, a platform consisting of Pro-Trinket microcontroller, Raspberry Pi, Wi-Fi module, and the piezoelectric sensor has been proposed to detect, localize, and quantify the damage of a structure (Abdelgawad & Yelamarthi, 2016). Pitch-catch and pulse-echo techniques are employed to analyse the health of the structure. Only 1% error and 9% error were recoded for damage location and width detection, respectively. However, the system could not predict the damage before it occurs to prevent loss. A complete version of the system has been presented in (Mahmud et al., 2018) with the addition of a Butterworth filter to remove noise. To aid early detection of risk factors and mitigate the resulting loss, a utility computing system has been suggested for structural monitoring. The proposed utility model used the number of occupants in a building and SHM sensor data to provide expert advice using machine learning. However, the system is most suitable for monitoring a cluster of structures such as those in university settings (Tariq et al., 2018).

IoT has also been employed to perform real-time collapsing probability of structures to facilitate preventive measures in order to avoid loss of lives and properties (Paul et al., 2018). The system is designed to measure inclined angles and analyse bends on metal structures, concrete beams, slaps, and so on. Data obtained from such analyses are sent to the cloud/smartphone app in real-time through Bluetooth. Whenever deformation occurs, an alarm and LED will notify occupants. However, the system cannot predict deformity before it occurs to take preventive measures beforehand. An integrated construction approach for correcting design and monitoring the technical condition of buildings and structures using Fibre-optic and string sensors has been proposed (Mashukova, 2017; Mashukova, 2018). The system can monitor the stress–strain state of load-bearing of structures in order to track the degree and speed at which the technical condition of the structure is changing to enable timely detection of negative changes. Deformation is obtained by comparing initial values of the structural design with periodic values recorded during the operation of the building. However, the system is expensive. Besides, it requires a skilled workforce to install it.

In this regard, numerous techniques have been proposed within the context of expert and intelligent systems for SHM (Chen & Zang, 2011; De Oliveira et al., 2018; Pawar & Ganguli, 2011; Salehi et al., 2019). Salehi et al. (2019) have proposed a data-driven approach for the SHM system. In that study, an expert system integrating image-based pattern recognition (PR) and machine learning using the support vector machine (SVM) approach is presented. An image-based (PR) method was employed to represent sensor nodes' response patterns, while the SVM algorithm was utilized to determine the presence of damage. A relevant study presented by Chen and Zang (2011) has hybridized artificial immune and fuzzy clustering methods for structural damage pattern recognition. De Oliveira et al. (2018) have also proposed a hybrid of fuzzy network and particle swarm optimization approach. The effectiveness of the proposed method was demonstrated for SHM of a composite structure. Its applicability was evaluated based on continuous time-history sensor data.

An improved system for structural fault detection based on the fuzzy logic approach has been proposed (Sawyer & Rao, 2000). In that study, continuum damage mechanics and fuzzy logic associations or rules were utilized to process and analyse uncertainties and complexities of damaged structures. Obtained results demonstrated that the fuzzy logic-based model had performance advantages for a monitoring system under uncertain conditions. In a compressive study presented by Pawar and Ganguli (2011), several structural health monitoring studies using fuzzy genetic systems were analysed and compared. However, the impact of energy consumptions on SHM systems was not considered in these aforementioned studies.

A summary of related works is presented in Table 1. Based on previous works, it is necessary to develop resilient expert systems that can stand the test of time. Thus, in this paper, we proposed an expert system based on fuzzy inference and decision-making process using temperature and vibration parameters to determine the health status of a building.

Background – fuzzy system

The Fuzzy logic system (also known as fuzzy system) is a computational intelligence approach that employs a collection of fuzzy membership functions and rules rather than Boolean logic to reason about the data. A fuzzy system is typically modelled on the basis of fuzzy rules which serve as the guiding force toward information processing implemented as a series of if-then statements. The application of a fuzzy system has been found in different areas of science and engineering, among which an expert system appears to be the most obvious beneficiary based on the fact that its domain is often inherently fuzzy. Some expert systems have a logic central to their controls, include elevator control (Khurana, 1991), control of smart locomotives (Sugeno, 1985), traffic control, control of decision-support systems (Adewale et al., 2018), power electronics – speed control of DC motor, and so on. A typical structure of a fuzzy system has four basic blocks: a fuzzifier, a fuzzy inference engine, a knowledge base, and a defuzzifier. A typical structure of a fuzzy system is illustrated in Figure 1.

Fuzzy system inputs can be a combination of linguistic values and numerical (crisp) data. The mapping of input-output variables is achieved using fuzzy inference mechanics using rules and fuzzy reference sets. However, in a circumstance where numerical data are required as the output of the fuzzy system, defuzzification techniques that assign representative script data to resultant output fuzzy sets are used. Fuzzy systems whose input-output mapping is determined by a collection of fuzzy if-then rules and the associated fuzzy mechanism are referred to as rule-based systems. Such a rule-based fuzzy system can be a fuzzy linguistic model, a fuzzy relational model, and a Takagi–Sugeno fuzzy model. Details of these models can be found in (Czabanski et al., 2017). The general form of fuzzy linguistic model rules is given by:

$$\text{IF } x \text{ is A then } y \text{ is } B \tag{1}$$

where the fuzzy preposition $xisA$ denoting the rule and preposition $yisB$ denoting the consequent.

Table 1. Summary of related works.

Related works	Sensors/input system	ML algorithm	Demerit
Structural Health Monitoring Installation Scheme using Utility Computing Model (Tariq et al., 2018).	Attendance system, Seismic Sensor	multi-objective Supervised Machine Learning Technique	For monitoring cluster of structures such as public building like schools
Internet of Things (IoT) Platform for Structural Health Monitoring (SHM) (Chanv et al., 2017; Mahmud et al., 2018).	piezoelectric	X	No prediction model to prevent damage before it occurs
An Internet of Things (IoT) Based System to Analyse Real-time Collapsing Probability of Structures (Paul et al., 2018).	Flex sensor	X	No prediction model to prevent damage before it occurs
Improvement of the Monitoring System of the Technical Condition of Buildings (Marita H Mashukova, 2017; M. H. Mashukova, 2018).	fiber optic sensor, string sensors	X	Expensive
Vibration Health Monitoring for Tensegrity Structures (Ashwear & Eriksson, 2017).	vibration	X	Limited to sensor placement
Structural Health Monitoring System Using IOT and Wireless Technologies (Chanv et al., 2017).	vibration sensor, strain sensor, moisture sensor	X	Not intelligent
TDR-based Monitoring of Rising Damp through the Embedding of Wire-like Sensing Elements in Building Structures (Cataldo et al., 2017).	Reflectometry	X	Limited to moisture monitoring
Fibre Optic Sensors for the Structural Health Monitoring of Building Structures(Bremera et al., 2016).	fiber optic sensor	X	No prediction model to prevent damage before it occurs
Uncertainty Quantification in Structure Health Monitoring: Applications on Cultural Heritage Buildings (Lorenzoni et al., 2016).	accelerometer	Cluster analysis, Autoregressive models	Limited to cultural heritage structures
Vibration-Based Structural Health Monitoring: Theoretical Foundation and Experimental Validation on Reinforced Concrete Beams (Anthony et al., 2015).	–	X	Not for real-time monitoring
Structural Health Monitoring of Building Structures (Li et al., 2015).	Accelerometer, linear magnetic encoder (LM15) position sensor	Support vector machine	No prediction model to prevent damage before it occurs
Expert and intelligent system for SHM (Chen & Zang, 2011; Salehi et al., 2019) .	Vibration sensor, piezo transducer	Fuzzy logic	Power management not taken into consideration

Note that x and y are linguistic parameters obtained from linguistic values. They are defined as sets on parameters space $X \subset \mathbb{R}^N$ and $y \subset \mathbb{R}^M$, respectively. Constant linguistic terms that convey information for given linguistic variables such as low vibration and high vibration are represented by A and B.

In many applications, inputs and outputs of fuzzy systems are defined as numerical values instead of fuzzy sets. To convert these data to an appropriate format, a conversion process known as fuzzification and defuzzification is required. Fuzzification is the process of mapping real input values, for example, $\mathbf{X}_0 = [x_{01}, x_{02}, \ldots\ldots\ldots x_{0N},]^{\mathbf{T}} \in \underline{\mathbb{X}} \subset \mathbb{R}^N$ to an $N-$ dimensional fuzzy set A' defined on$\underline{\mathbb{X}}$. Fuzzification can be symbolically expressed as a mapping of $N-$ dimension coordinate space into a multitude of fuzzy sets as follows (Czabanski et al., 2017):

$$\underline{\mathbb{X}} \Rightarrow g(\underline{\mathbb{X}}) \tag{2}$$

where $\underline{\mathbb{X}} = \mathbb{X}_1 \times \mathbb{X}_2 \times \ldots\ldots\ldots \times \mathbb{X}_n$ is the variable on the parameter space.

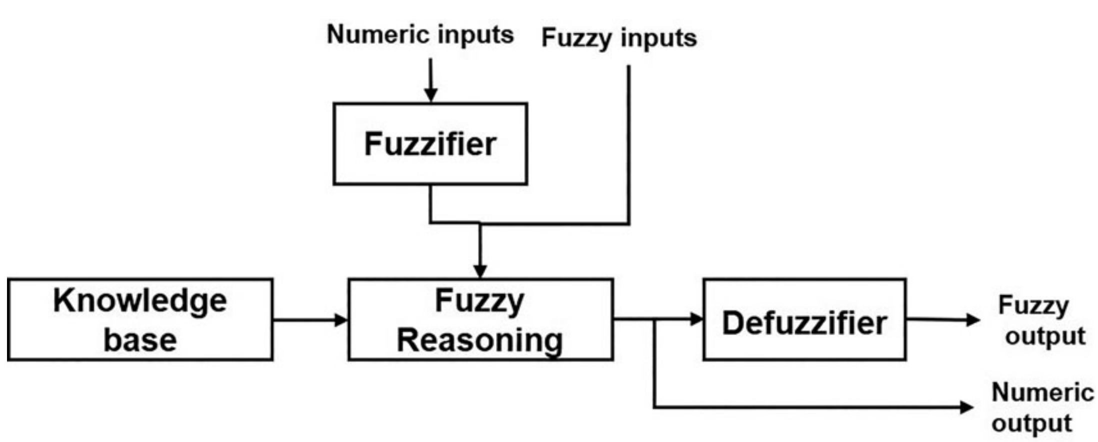

Figure 1. A typical structure of a fuzzy system.

By applying membership functions, Equation (2) can be written as:

$$\mathbb{X} \Rightarrow \{\mu A'(\mathbf{X})|\mathbf{X} \in \mathbb{X}, \mu A'(\mathbf{X}) \in [0, 1]\} \quad (3)$$

where $\mu A'(\mathbf{X})$ is the fuzzification operator. The possible choice of fuzzification operators is the Singleton fuzzifier that can be given by:

$$\mu A'(\mathbf{X}) = \delta_{\mathbf{X},\mathbf{X}_0} = \begin{cases} 1, \mathbf{X} = \mathbf{X}_0 \\ 0, \mathbf{X} \neq \mathbf{X}_0 \end{cases} \quad (4)$$

Defuzzification, on the other hand, is the process of computing numerical output $y_0 \in \mathbb{Y}$ from the fuzzy set outcome $B'(\mathbf{y})$ on $\mathbb{Y}$. Defuzzification can be symbolically expressed as a mapping of a multitude of fuzzy sets defined on the $\mathbb{Y}$ to a single crisp value from $\mathbb{Y}$ (Adewale et al., 2018):

$$g(\mathbb{Y}) \Rightarrow \mathbb{Y} \quad (5)$$

By applying membership functions, Equation (5) can be written as:

$$\{\mu B'(\mathbf{y})|\mathbf{y} \in \mathbb{X}, \mu B'(\mathbf{y}) \in [0, 1]\} \Rightarrow \mathbb{Y} \quad (6)$$

There are different defuzzification methods. Among them, the most popular ones are given as follows:

Centre of gravity (COG) method: The result stipulates as a centre of the area under the membership function $\mu B'(\mathbf{y})$ (Czabanski et al., 2017):

$$\mathbf{y}_0 = \frac{\int_{\mathbb{Y}} y\mu B'(\mathbf{y})dy}{\int_{\mathbb{Y}} \mu B'(\mathbf{y})dy}. \quad (7)$$

Mean of maxima (MOM) method: The defuzzified output $\mathbf{y}_0$ is given by:

$$\mathbf{y}_0 = \frac{\left[\sum_{j=1}^{m} y_j\right]}{m} \quad (8)$$

where $\mathbf{y}_j$ is the value corresponding to the j maximum of the membership function $\mu B'(\mathbf{y})$.

Methodology

The SHM system proposed in this study is designed to provide information about a building status in terms of its safety and reliability. For this purpose, the signed system is made up of hardware and software that together will monitor a building by measuring its temperature and vibration in a given condition. By analysing any variations in these properties, it determines if the building is about to show damage and possible damage levels. Details of the proposed methodology are presented in subsequent sections.

Physical model and experimental tests

The method applied for this paper is depicted in Figure 2. It provides information on the direction of data flow and interfaces between various components of the system. The system block diagram is comprised of three units: a data acquisition unit, a data conditioning and transmission unit, and a data reception and a processing unit. The flowchart shown in Figure 3 describes the process involved in data acquisition and

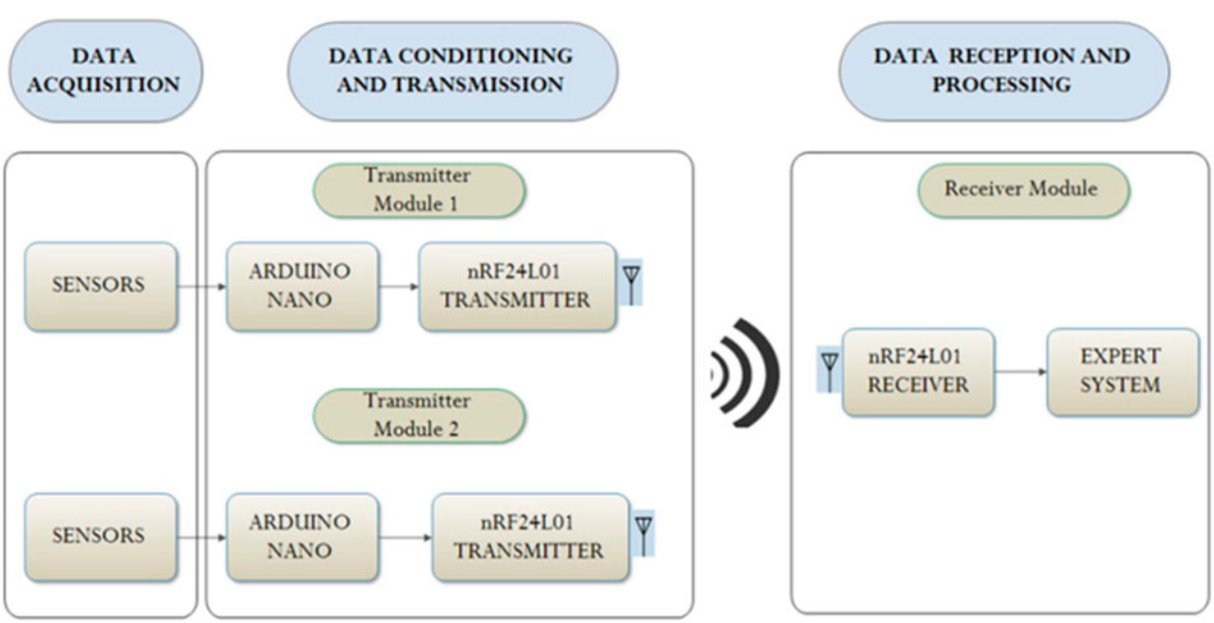

Figure 2. Block diagram of the system.

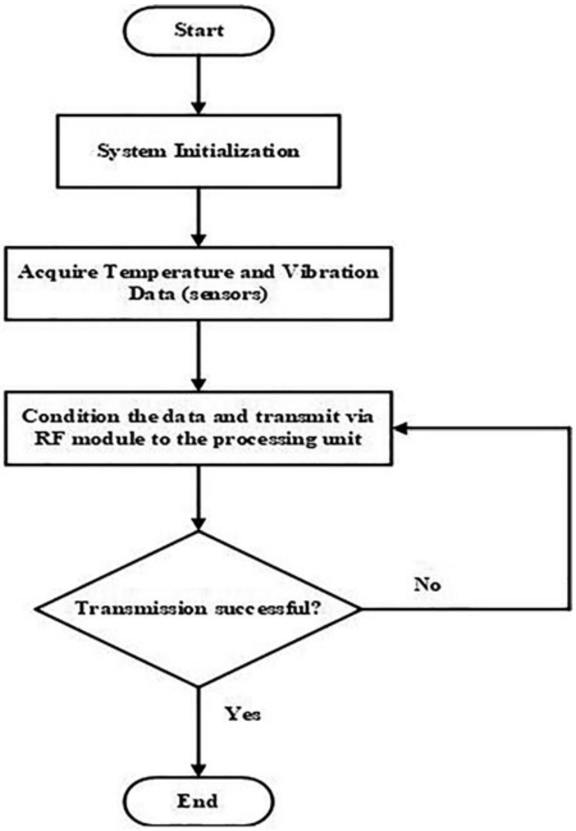

Figure 3. Flowchart of data acquisition and transmission.

transmission. Further explanation of components and interfaces in each unit is provided viz:

Data acquisition

Components of this unit are basically sensors (piezo vibration sensor and LM35 sensor) for vibration and temperature measurements of the structure. These sensors are interfaced with a controller (Arduino Nano) to which they can communicate their readings for conditioning and processing. Two modules are considered in a distributed fashion for accuracy.

Data conditioning and transmission

In this unit, data collected by sensors are processed by the controller. Processed data are displayed on a Liquid Crystal Display (LCD) to ensure the accuracy of data at both transmitting and receiving ends. Immediately after the processing is done, data are transmitted to the receiver module via a Radio Frequency (RF) transceiver (nRF24L01).

Data reception and processing

The component of this unit is majorly the Fuzzy expert system. Data received from the transmission module are processed using equations 9 and 10 to find average values. The average value is then passed to the expert system for decision-making. The expert system produces an output that explains the state of the building structure.

$$\text{Temp value} = \frac{t1 + t2}{2} \tag{9}$$

$$\text{Vibration value} = \frac{v1 + v2}{2} \tag{10}$$

where $t1$is the value of temperature sensor 1 and $t2$is the value of temperature sensor 2.

$v1$is the value of vibration sensor 1 and $v2$is the value of vibration sensor 2.

Expert system design for SHM

The developed SHM expert system is based on fuzzy logic, an Artificial Intelligence technique Capable of making a decision. In this study, fuzzy logic is used to predict consequent based on the antecedent. For simplicity, the antecedent, in this case, is referred to as building measure parameters (vibration and temperature). The consequent is a building condition (very safe, safe, and unsafe). The fuzzy model has associations expressed in the following forms:

$$\begin{aligned}
&\textit{If}\ \mathbf{X}\ \text{is}\ A_1\ \textit{and}\ \mathbf{Y}\ \text{is}\ B_1,\ \textit{then}\ \ \mathbf{Z}\ \textit{is}\ C_1\\
&\textit{If}\ \mathbf{X}\ \text{is}\ A_2\ \textit{and}\ \mathbf{Y}\ \text{is}\ B_2,\ \textit{then}\ \mathbf{Z}\ \textit{is}\ C_2\\
&\textit{If}\ \mathbf{X}\ \text{is}\ A_3\ \textit{and}\ \mathbf{Y}\ \text{is}\ B_3,\ \textit{then}\ \mathbf{Z}\ \textit{is}\ C_3
\end{aligned} \tag{11}$$

where A_i, B_i and C_i are fuzzy terms defined by fuzzy sets. **X** and **Y** are model inputs representing vibration and temperature, respectively. By evaluating rules using given input values (**X** and **Y**), the conclusion about the **Z** value is inferred. The correlation-maximum inference procedure is applied in this study to determine the overall degree of truth. In the association (Equation 11), two antecedents are connected with an **AND** operator. Therefore, the degree of truth is taken as a combination of these values. In this case, the degree of truth in Equation (11) for statement **X** is A_1 which is determined by the membership value of x (degree of temperature). Similarly, the degree of truth in the statement **Y** is B_1 which is determined by the membership value of y (degree of vibration). The structure of the SHM system proposed in this study is shown in Figure 4.

The fuzzy expert system was designed in MATrix LABoratory (MATLAB) environment, version R2015a. There are three important stages in the development of the fuzzy expert system. First, temperature and vibration inputs are fuzzified with triangular membership function. The inference engine then acts on these fuzzified inputs according to the set of fuzzy rules.

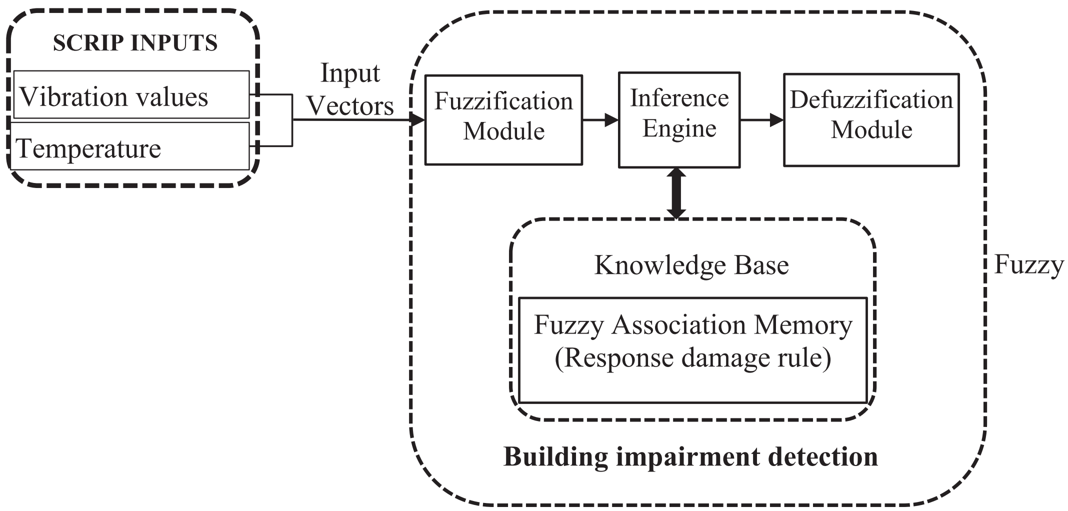

Figure 4. Schematic diagram of the SHM system based on fuzzy logic.

Finally, the output (status of the building) is defuzzified as shown in Figure 4. Building vibration and temperature conditions (inputs) are categorized using three linguistic variables. These categories are low, medium, and high. The linguistic variable "building condition" (output) could be "very safe", "safe", and "unsafe.

The inference system used in this work is a Mamdani-type inference as shown in Figure 5(a). The proposed SHM expert system with 2 inputs, 1 output, and 9 rules is presented in Figure 5(b). Nine fuzzy rules are formulated for the system as indicated in Figure 5 (c). The set of rules contains the description and knowledge of the expert system. The inference module provides a roadmap of the whole fuzzy process for which antecedent and consequent are represented. Finally, the surface output provides a three-dimensional curve that maps inputs (temperature, and vibration) to the status where the behaviour of the system response can be monitored.

The performance of the developed expert system was evaluated using experimental data of a Phase II benchmark problem of an SHM experiment described by Dyke et al. (2003) from a four-story steel frame structure (2-bay by 2-bay) investigated at the University of British Columbia. Data were generated as part of activities of the International Association for Structural Control (IASC) and Dynamic committee of the American Society of Civil Engineers (ASCE) SHM Task Group aiming to develop benchmark data to investigate the effectiveness of different structural monitoring methods. The test was conducted on a structure of 2.5 m x 2.5 m plain with a frame height of 3.6 m mounted on a concrete slab. Different slabs ware placed at various floor levels to enable the mass distribution practically realistic. More details on the structure designed can be found in (Dyke et al., 2003).

Excitation cases considered are ambient vibration and force excitation scenarios including impact hammer tests and electrodynamic shaker tests. Ambient vibration tests involve excitations generated from environmental conditions due to wind, traffic, and pedestrians. The impact hammer was experimented using a force transducer recorded during hammer tests. In each test conducted, two impact locations of the structure were chosen and a series of 3–5 hammer hits were recorded. The force excitation was applied to the structure in shaker tests using a Ling Dynamic System electrodynamic shaker placed on the top floor of the structure. Plots of representative data obtained on the 4th floor of the west side when the normal structure is tested with all braces in place for ambient vibration, hammer impact, and shaker tests are shown in Figure 6. Data were acquired using fifteen accelerometers positioned across frames of the structure throughout days. A total of nine structural damages cases were simulated on the benchmark frame.

Structure damage experimented included undamaged (case 1) and eight other damage cases comprising removal of diagonal braces across the structure (cases 2-7) and loosening of bolts connecting beams to columns (cases 8 and 9). Further information about these test cases can be found in (Dyke et al., 2003). Data engendered from these cases together with temperature randomly generated using BS: 13670 were employed as input for model validation. Normalization of these raw input data is important to make every datapoint have the same scale. In this regard, input data were normalized using the min–max normalization method.

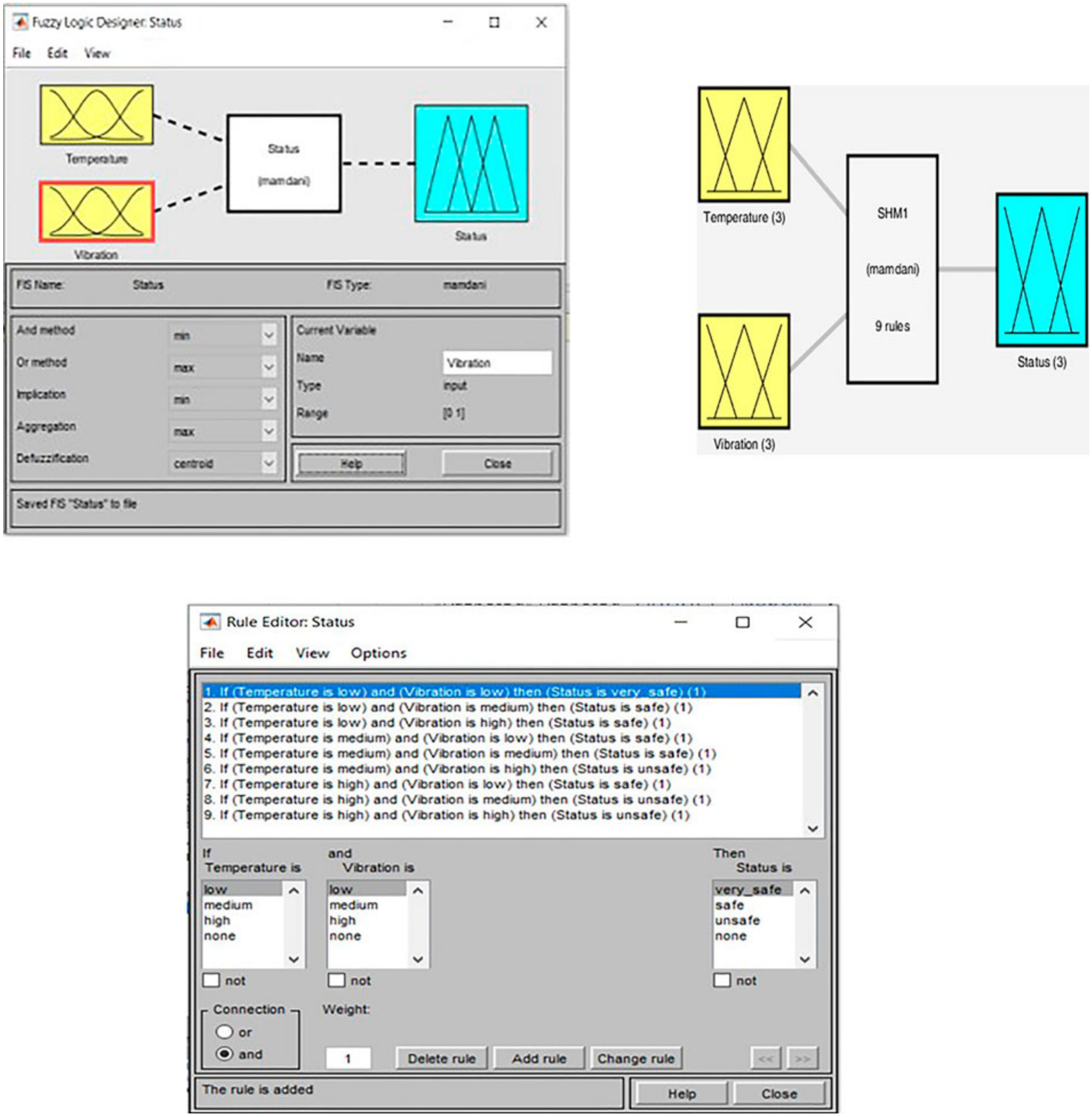

Figure 5. (a): Fuzzy logic interface Figure 5(b): System SHM: 2 inputs, 1 output, 9 rules. Figure 5(c) Fizzy Rules.

For every input value, the minimum value of data was transformed into a 0 and the maximum value of data was transformed into a 1. All other values were transformed into a decimal between 0 and 1. The min–max normalization formula is given as:

$$y = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (12)$$

where y is normalized output, X is raw input data, and X_{max} and X_{min} are maximum and minimum values of input data.

Results

Energy utilization result

SHM systems have witnessed technological improvements over a decade with major attention on modern sensing technology and robust anomaly detection algorithms. Despite significant improvement in WSN technology, the need for sufficient energy to power the sensor network for a long-term remains an important issue for SHM systems (Wang et al., 2017). To minimize energy cost, the system should be designed to ensure that it goes to sleep at intervals of five minutes in a loop process. A validation test was carried out between the following two conditions: (1) when the system

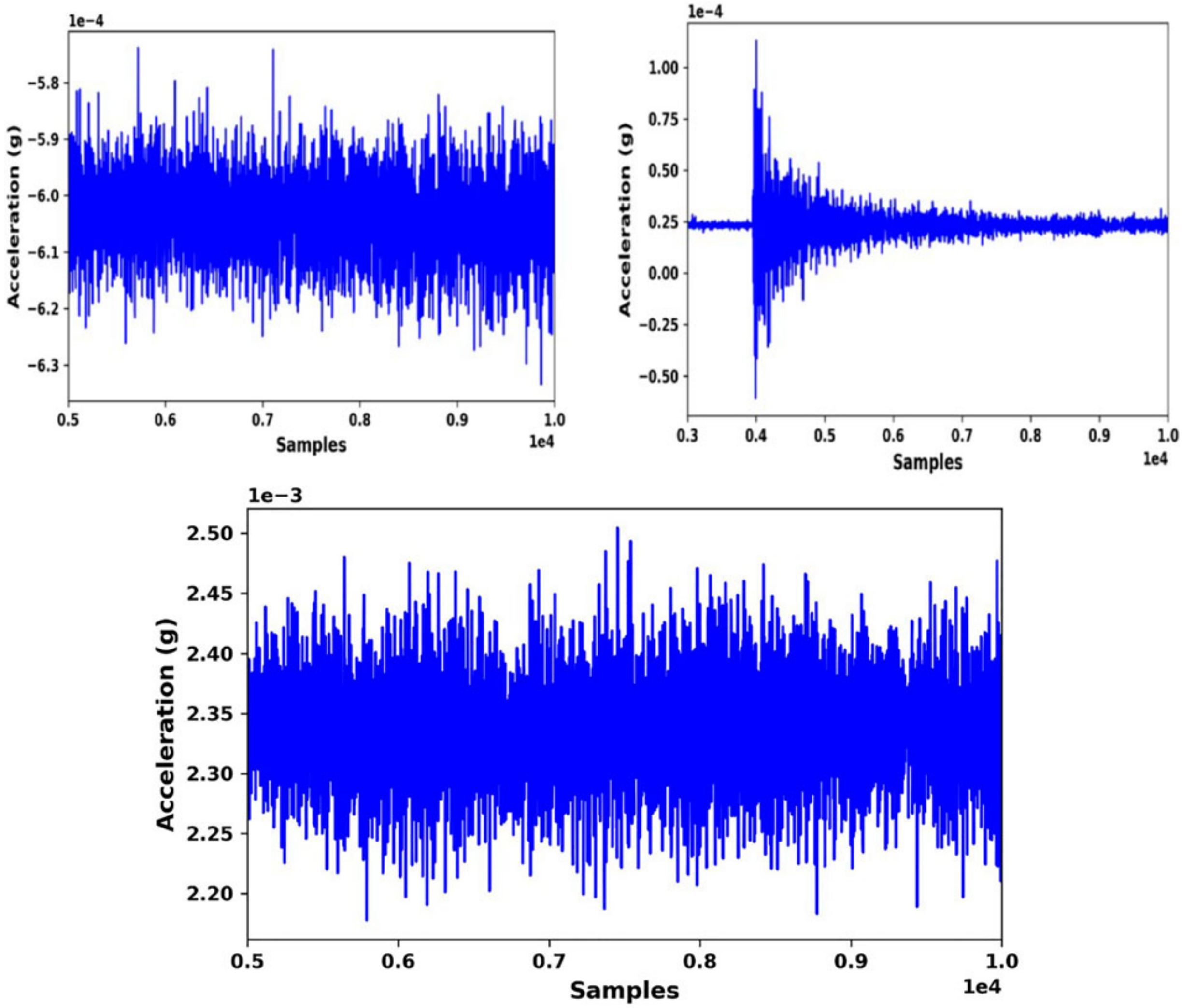

Figure 6. (a): Structure excitation cases for ambient vibration; b):Structure excitation cases for hammer impact; (c) shaker response.

works without sleeping, and (2) when the system works with sleeping schemes. In the power circuit unit, a 1.5Ω resistor was connected in series with a battery powering the system during the power consumption measurement. The voltage drop across the resistor was amplified using an AD620AN instrumentation amplifier. It was viewed and recorded through Sefram 5062DC oscilloscope. The amplifier has a gain of 106. The energy consumed by the system during each sensing cycle was computed using Equation (13).

The measurement was carried out at five minutes intervals for an hour. The results obtained are presented in Tables 2 and 3.

$$E(\text{joules}) = (V\ \text{scope} \div (106 \times 1.5)) \times 3 \times \Delta t \quad (13)$$

where 3 is the sum of voltage values of 2 A batteries powering each node, Δt is the time division setting of the oscilloscope, and Vscope is the voltage value of the oscilloscope.

The change in energy utilization by the system is calculated in percentage using Equation (14):

$$\%\Delta E_U = \frac{E_A - E_B}{E_A} \times 100 \quad (14)$$

where $\%\Delta E_U$ is the percentage change of energy utilization, E_A is energy utilized without a sleeping mechanism, and E_B is energy utilized with a sleeping mechanism.

Table 2 shows the results of the measurement of energy used by the system when configured to work without sleeping for an hour. Table 3 shows the results of the measurement of the energy consumed by the system when configured to work for 5 min and sleep for the next 5 min consistently within an hour. Using Equation (14) and results shown in Tables 2 and 3, the percentage change in the energy utilized by the SHM system was computed to be 30%.

Table 2. Results of energy utilized by the SHM system without sleeping scheme for one hour.

Time (mins)	Voltage (V)	Current (mA)	Power (W)	Energy (J)
5	4.78	132	0.63	0.0525
10	4.61	133	0.61	0.1017
15	4.81	135	0.65	0.1625
20	4.66	140	0.65	0.2167
25	4.80	142	0.68	0.2833
30	4.69	141	0.66	0.3300
35	4.80	141	0.68	0.3967
40	4.70	141	0.66	0.4400
45	4.82	139	0.67	0.5025
50	4.69	137	0.64	0.5333
55	4.84	137	0.66	0.6050
60	4.69	134	0.63	0.6300

Table 3. Results of energy cost of the system configured with a sleeping scheme.

Time (mins)	Voltage (V)	Current (mA)	Power (W)	Energy (J)
5	4.71	132	0.62	0.0517
10	4.61	49	0.23	0.0383
15	4.80	133	0.64	0.1600
20	4.61	52	0.24	0.0800
25	4.81	135	0.65	0.2708
30	4.59	56	0.26	0.1300
35	4.81	140	0.67	0.3908
40	4.62	67	0.31	0.2067
45	4.82	139	0.67	0.5025
50	4.61	61	0.28	0.2333
55	4.83	140	0.68	0.6233
60	4.64	64	0.30	0.3000

As shown in Table 3, when a sleeping scheme was activated, 30% of energy was saved compared to the first scenario without a sleeping scheme. This enables the system to have an extended lifetime. The energy versus time plot of the system configured without a sleeping scheme is shown in Figure 7. The energy consumed by the developed system increased exponentially with time.

The energy versus time plot of the system, when configured with a sleeping scheme, is shown in Figure 8. As is observed, energy usage is drastically reduced when the system is sleeping. An increase was observed immediately after the system awakened from sleep.

System reliability result

The reliability of the developed SHM system was calculated (forecasted) in months and decades using Equation (13). Forecasted results in months and its graph are shown in Table 4 and Figure 9, respectively. From the Table, the variation of the reliability of the system was small. At some points, the reliability of the system remained constant for two to three months. This shows that the system could retain its reliability over months after deployment.

$$\text{Reliability, } Rt = e^{-\lambda t} \tag{13}$$

where $\lambda$is failure rate and t is time.

Results from the reliability calculation in decades and the corresponding graph are shown in Table 5 and Figure 10, respectively. From the Table, it was noticed that there was a linear relationship. The reliability decreased in almost equal proportion every ten years. This followed the true curve of life of most products.

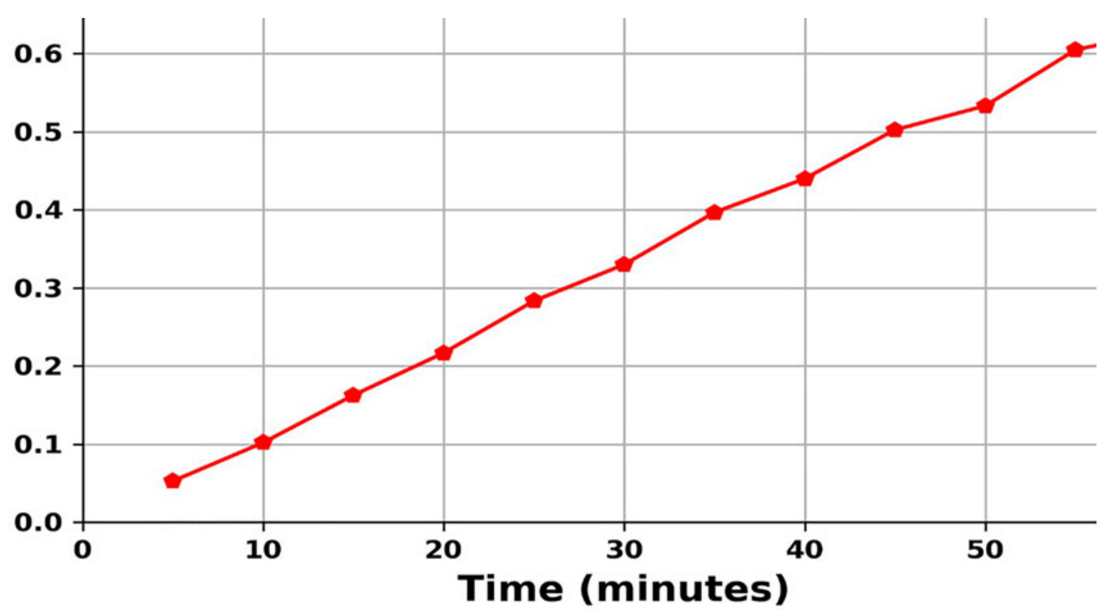

Figure 7. Energy Versus Time Plot of the System when Configured without a sleeping scheme.

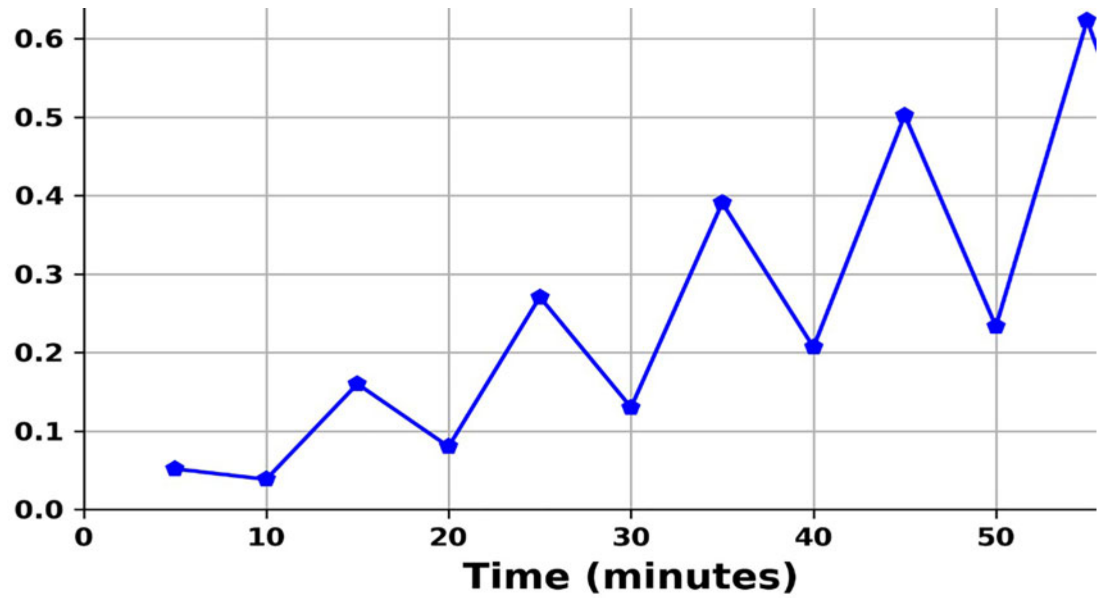

Figure 8. Energy Versus Time Plot of the System Configured with a Sleeping Scheme.

Table 4. Reliability of the system in months.

Time (Months)	Reliability, R_t
1	0.999
2	0.998
3	0.998
4	0.997
5	0.997
6	0.997
7	0.996
8	0.995
9	0.994
10	0.994
11	0.994
12	0.993

Performance evaluation of the expert system

The performance of the developed expert system was evaluated using experimental data found in the literature (see Figure 6). Three different structure conditions (very safe, safe, and unsafe) were studied using seven datasets for cases 1–7. Ambient, hammer, and shaker vibrations are considered as low, medium, and high, respectively. At the same time, the temperature was randomly chosen between −5°C and 100°C according to BS:13670 (CONSTRUCT, 2010). A temperature between −5°C and 17°C is considered as low

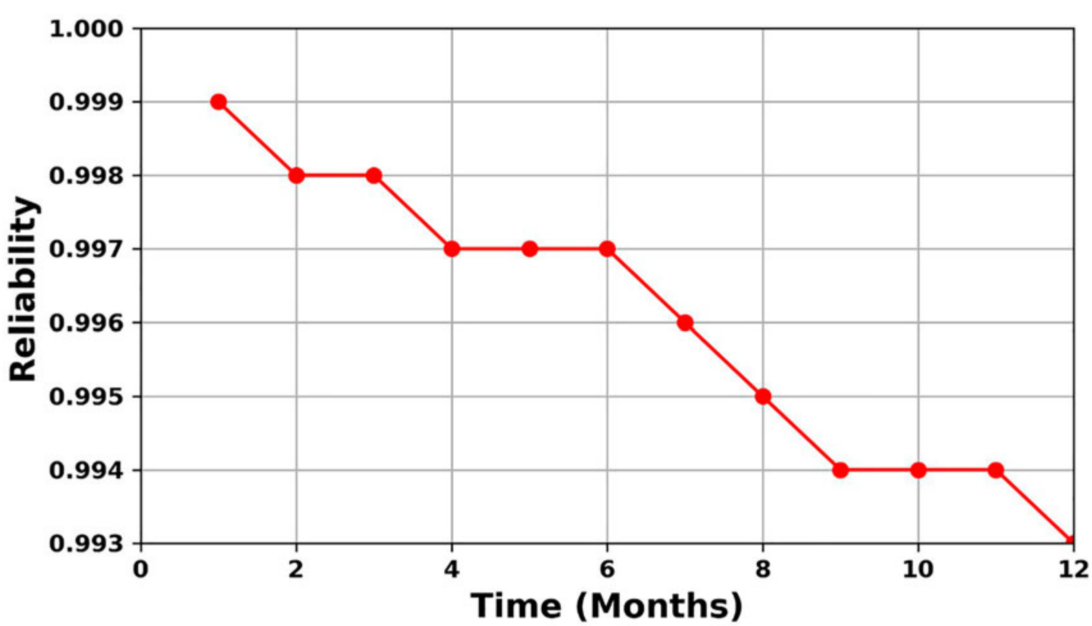

Figure 9. Reliability Versus Time Plot of the System in months.

Table 5. Reliability of the system in decades.

Time (years)	Reliability, R_t
10	0.93
20	0.87
30	0.81
40	0.76
50	0.71
60	0.66
70	0.62
80	0.58
90	0.54
100	0.50

temperature and temperatures between 17°C and 42°C and between 43°C and 100°C are considered as medium and high temperatures, respectively. Input parameters were applied to the fuzzy logic detection algorithm. The corresponding fuzzy rule viewer for the SHM system of case 1 is shown in Figure 11. Figure 11(a) illustrates the response of fuzzy detection with an output membership value of 0.344 for a safe condition of the building when the structure temperature is medium and the vibration is low. The result of fuzzy detection for the same temperature condition shown in Figure 11 (a) when the vibration is high is depicted in Figure 11 (b). The figure presents test results when the structure is in an unsafe condition with an output membership function of 0.73.

To evaluate the model detection accuracy for each case considered, the mean square error was calculated. A summary of correct detection for different cases of the employed dataset is shown in Table 6. The sensor location refers to the setting structure floor and position where the experiment is conducted. The model demonstrated good performance for all cases with a minimum accuracy of 97.1% for a very safe condition in case 5. The least performance of 94.4% and 96.7% was experienced in one case of unsafe and safe detection scenarios, respectively, as shown in Figure 12. Based on demonstrated results, it can be concluded that the proposed model can detect structure condition with high accuracy as can be seen in Table 6. This implies the feasibility of spotting a possible building failure at an early stage by monitoring building vibration and temperature using a fuzzy logic-based expert system. Therefore, the use of the proposed system for building failure detection is practicable. However, for systems to stand the test of time, the membership function must be defined for every structure monitoring from a target monitoring structure.

Discussion

We have developed an expert SHM system for the residential building conditions monitoring using building vibration and temperature measurements. Considering the combination of these two measurement parameters, the performance of the system is compelling, given the accuracy of prediction, and energy efficiency- In other words, our proposed system improves structural safety and reliability. This work improved on the existing studies in the following ways:

Firstly, it provides better efficiency by incorporating an expert system for structural damage detection using a combination of vibration and temperature measurements. From the summary of related works, it is evident that most of the existing works, considered vibration parameter alone for SHM, as can be seen in

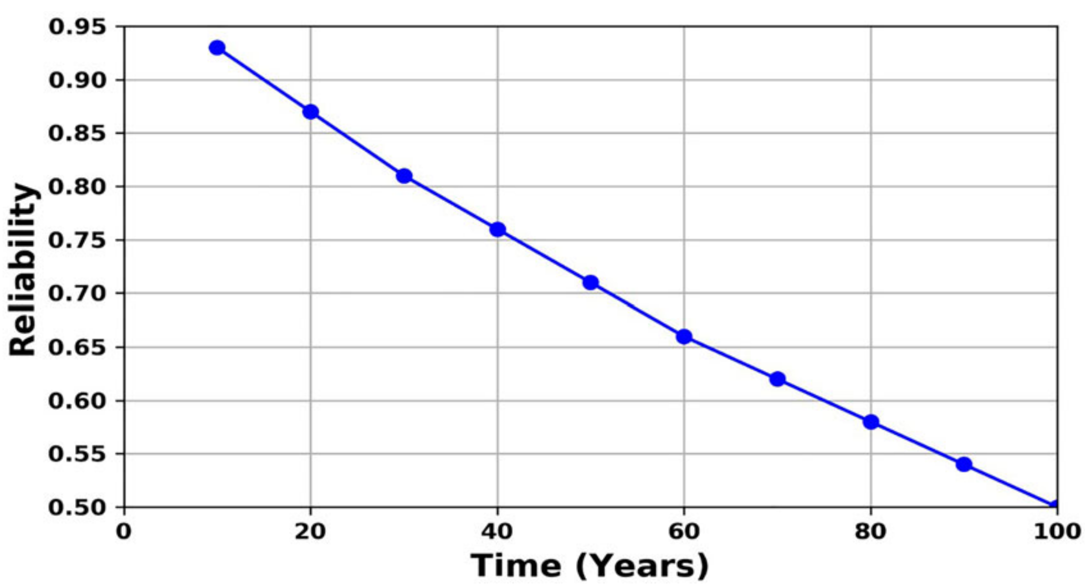

Figure 10. Reliability Time Plot of the system in decades.

Figure 11. (a): Test case 1 results for a safe condition of the building; (b)Test case 1 results for an unsafe condition of the building.

the works of Salehi et al. (2019), Tariq et al. (2018) and Paul et al. (2018) among others. Although vibration is a good parameter in detecting an earlier sign of structural failure, a system becomes more efficient, if it considers other parameters alongside vibration.

Secondly, it can perform timely structural damage detection while ensuring energy-efficiency. The study by Salehi et al. (2019) employed the use of data mining to reconstruct delays and missing signals to address the issue of energy availability, while we relied on the data-driven concept of sleeping mode to save energy. Their data mining technique is quite expensive as it requires a probabilistic approach to reconstruct the missing signal. Besides, the proposed methods by Li et al. (2015), Chanv et al. (2017), Mashukova (2017, 2018) and Mahmud et al. (2018) have no provision or strategy for energy efficiency which is required since the system is supposed to be operated for a longer time with less maintenance. While the system proposed by Tariq et al. (2018) offered the possibilities for data of various SHM deployed over several zones to be accessible to a specific authority, the power efficiency of the system was not considered. Without proper analysis of the power consumption, the system may not be adequate due to the need to change the batteries of the sensor nodes at regular intervals.

Table 6. Performance of the fuzzy expert SHM SHM model.

Structure locations	Sensor location	Sensor direction	Detection Accuracy (%)		
			Very safe	Safe	Unsafe
Case 1	1st Floor/Centre	E/W	100	99.1	99.4
	2nd Floor/East	N/S	100	98.4	99.1
	4th Floor/West	N/S	99.2	100	100
Case 2	1st Floor/East	N/E	99.7	97.5	97.3
	3rd Floor/East	N/E	100	100	100
	4th Floor/ Centre	E/W	100	96.7	94.4
Case 3	1st Floor/Centre	E/W	100	100	98.1
	2nd Floor/East	N/S	99.7	97.8	100
	4th Floor/West	N/S	100	100	100
Case 4	1st Floor/Centre	E/W	100	100	100
	3rd Floor/East	N/E	99.7	100	100
	4th Floor/ Centre	E/W	100	99.8	99.6
Case 5	1st Floor/East	N/E	99.3	100	100
	2nd Floor/East	N/E	97.1	98.8	99.8
	3th Floor/ East	N/E	100	100	100
Case 6	2nd Floor/West	N/E	100	99.6	100
	3rd Floor/East	N/S	100	100	100
	4th Floor/West	N/S	100	99.8	99.8
Case 7	1st Floor/Centre	E/W	99.2	100	100
	2nd Floor/East	N/S	100	99.8	100
	4th Floor/West	N/S	100	100	100

Thirdly, comprehensive performance analyses are performed using real data examples to illustrate the pertinence of the proposed model. For our work, the data was obtained from a benchmark prototype using a 4-story, 2-bay by 2-bay steel-frame scale-model of 2.5 m × 2.5 and 3.6 m plan, tall (Dyke et al., 2003). For instance, _ENREF_16 Li et al. (2015) used generated data from a shake table test. A smaller building prototype mounted on the shake-table. Likewise, Salehi et al. (2019) used a small cantilever plate of 890 mm by 508 mm for vibration testing. On other hand, Tariq et al. (2018) proposed a Structural Health Monitoring utility model that display building conditions virtually allowing safety decision to be reached by authorities. Therefore, our approach is better since it automatically makes a decision on the safety status of the building and reduced the cost of hiring personnel to continuously monitor the structure and interpret the result.

Although the fuzzy logic model recorded a good accuracy level in damage identification, it is important

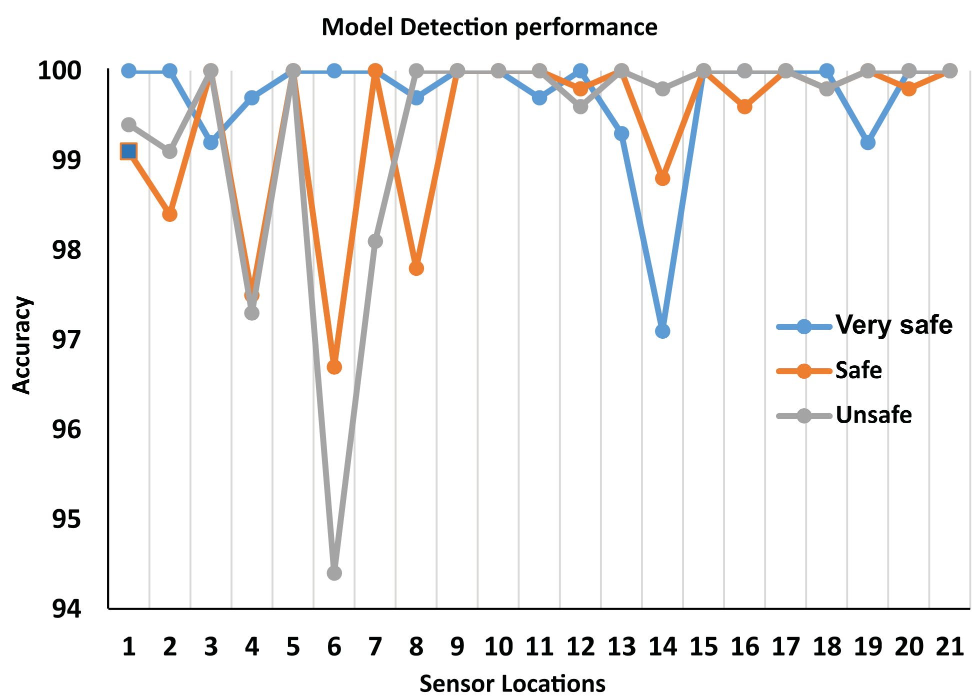

Figure 12. Model detection performance.

to note that the accuracy of the system largely depends on the number of sensors involved in the aggregation and the location of deployment as well as the rules defined in the expert system. Thus, some limitations must be considered when deploying the system:

- The system was tested with data points of temperature and vibration which were taken without regard to the location of data acquisition within the building (indoor or outdoor). For instance, if the temperature sensors are placed indoor or in a location where cooling and heating devices or environmental temperature can greatly temper with the actual reading of the structure's temperature, the expert system may give a false alert. There is a need to experiment on the effect of numbers of data acquisition points and locations that will yield high system accuracy before deployment in structures.
- In the case of the structural building material composition such as concrete structure, steel structure, etc and its relationship to safety considering temperature and vibration, proper attention is required for the deployment of the system in various structure with different material or composition, as the rules for safety in the expert system are determined accordingly. For this work, only steel material was considered.
- Since only British Standard (BS): 13670 – Evaluation and measurement for temperature in building and vibration aberration is considered for this work, there is need to consider the acceptable standard by the government in the geographical location of deployment. The rule in the expert system should therefore be adjusted to reflect the acceptable standard under consideration

Conclusion

The SHM system developed in this study is a prototype designed in the laboratory. We recommend an integration of the system to residential buildings to mitigate the increasing number of casualties resulting from building collapse around the globe especially in developing countries. As this paper is focused on the monitoring of residential structures in the current version, future work is needed to extend it to industrial structures. Also, improvement can be further made to enhance the lifespan of this SHM system by devising technologies such as low energy adaptive clustering hierarchy, in-network processing, and self-powered sensing technologies. Finally, our cities need to be recognized as a network of multiple systems that are closely connected to improve human living conditions. The integration of such SHM systems across cities will add value toward achieving a smart city.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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References

Abdelgawad, A., & Yelamarthi, K. (2016, October 16-19). Structural health monitoring: Internet of things application. *2016 IEEE 59th International Midwest Symposium on Circuits and Systems (MWSCAS)* (pp. 1–4). Abu Dhabi. doi:10.1109/MWSCAS.2016.7870118.

Adewale, A. L., Jumoke, A. F., Adegboye, M., & Ismail, A. (2018). An embedded fuzzy logic based application for density traffic control system. *International Journal of Artificial Intelligence Research*, *2*(1), 7–16. doi:10.29099/ijair.v2i1.44

Angeli, C. (2010). Diagnostic expert systems: From expert's knowledge to real-time systems. *Advanced Knowledge Based Systems: Model, Applications & Research*, *1*, 50–73.

Anthony, N. E., Ben, U. N., & Gideon, O. B. (2015). Vibration-Based structural health Monitoing: Theoretical Foundation and experimental validation on reinforced concrete beams. *The International Journal of Engineering and Science*, *22*(2), 1–12.

Ashwear, N., & Eriksson, A. (2017). Vibration health monitoring for tensegrity structures. *Mechanical Systems and Signal Processing*, *85*, 625–637. doi:10.1016/j.ymssp.2016.08.039

Badejo, E. (2009, 13th July). Engineers; Others Urge Multi-Disciplinary Approach to curb Building Collapse. *The Guardian Newspaper*, 15–17.

Bremer, K., Wollweber, M., Weigand, F., Rahlves, M., Kuhne, M., Helbig, R., & Roth, B. (2016). Fibre optic sensors for the structural health monitoring of building structures. *Procedia Technology*, *26*, 524–529, doi:10.1016/j.protcy.2016.08.065

Cataldo, A., De Benedetto, E., Cannazza, G., Monti, G., & Piuzzi, E. (2017). TDR-based monitoring of rising damp through the embedding of wire-like sensing elements in

building structures. *Measurement*, *98*, 355–360. doi:10.1016/j.measurement.2016.10.044
Chanv, B., Bakhru, S., & Mehta, V. (2017). *Structural health monitoring system using IOT and wireless technologies*. 2017 International Conference on Intelligent Communication and Computational Techniques (ICCT), Proceedings of a meeting held 22-23 December 2017, Jaipur, India pp. 151–157, doi:10.1109/INTELCCT.2017.8324036
Chen, B., & Zang, C. (2011). A hybrid immune model for unsupervised structural damage pattern recognition. *Expert Systems with Applications*, *38*(3), 1650–1658. doi:10.1016/j.eswa.2010.07.087
CONSTRUCT. (2010). National structural concrete specification for building construction. Fourth edtion complying with BS EN 13670:2009. A cement and concrete indutry publication.
Czabanski, R., Jezewski, M., & Leski J. (2017). Introduction to fuzzy systems. In P. Prokopowicz, J. Czerniak, D. Mikołajewski, L. Apiecionek, & D. Ślęzak (Eds.), *Theory and applications of ordered fuzzy numbers. Studies in fuzziness and soft computing*. Springer. doi:10.1007/978-3-319-59614-3_2
De Oliveira, M. A., Araujo, N. V., Inman, D. J., & Vieira Filho, J. (2018). Kappa-PSO-FAN based method for damage identification on composite structural health monitoring. *Expert Systems with Applications*, *95*, 1–13. doi:10.1016/j.eswa.2017.11.022
Dyke, S. J., Bernal, D., Beck, J., & Ventura, C. (2003). *Experimental phase II of the structural health monitoring benchmark problem*. Proceedings of the16th ASCE Engineering Mechanics Conference July 16–18, 2003. University of Washington, Seattle, USA.
Khurana, H. (1991). Fuzzy logic control—A Tutorial. *IETE Technical Review*, *8*(5), 280–288. doi:10.1080/02564602.1991.11438775
Li, X., Yu, W., & Villegas, S. (2015). Structural health monitoring of building structures with online data mining methods. *IEEE Systems Journal*, *10*(3), 1291–1300. doi:10.1109/JSYST.2015.2481380
Lorenzoni, F., Casarin, F., Caldon, M., Islami, K., & Modena, C. (2016). Uncertainty quantification in structural health monitoring: Applications on cultural heritage buildings. *Mechanical Systems and Signal Processing*, *66*, 268–281. doi:10.1016/j.ymssp.2015.04.032
Lynch, J. P., Law, K. H., Kiremidjian, A. S., Kenny, T. W., Carryer, E., & Partridge, A. (2001). The design of a wireless sensing unit for structural health monitoring. (Ed.),^(Eds.). Proceedings of the 3rd international workshop on structural health monitoring.
Mahmud, M. A., Bates, K., Wood, T., Abdelgawad, A., & Yelamarthi, K. (2018). A complete internet of things (IoT) platform for structural health monitoring (shm). (Ed.),^(Eds.). 2018 IEEE 4th World Forum on Internet of Things (WF-IoT).
Mashukova, M. H. (2017). Improvement of the monitoring system of the technical condition of buildings. (Ed.),^(Eds.). 2017 International Conference" Quality Management, Transport and Information Security, Information Technologies"(IT&QM&IS).
Mashukova, M. H. (2018). *Automated monitoring system for the technical condition of buildings*. 2018 IEEE International Conference "Quality Management, Transport and Information Security, Information Technologies" (IT&QM&IS), St. Petersburg, September 24–28, pp. 245–247. doi:10.1109/ITMQIS.2018.8525116
Paul, P., Dutta, N., Biswas, B. A., Das, M., Biswas, S., Khalid, Z., & Saha, H. N. (2018). *An internet of things (IoT) based system to analyze real-time collapsing probability of structures*. 2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, November 1–3, pp. 1070–1075. doi:10.1109/IEMCON.2018.8614743.
Pawar, P. M., & Ganguli, R. (2011). *Structural health monitoring using genetic fuzzy systems*. Springer Science & Business Media.
Salehi, H., Das, S., Biswas, S., & Burgueño, R. (2019). Data mining methodology employing artificial intelligence and a probabilistic approach for energy-efficient structural health monitoring with noisy and delayed signals. *Expert Systems with Applications*, *135*, 259–272. doi:10.1016/j.eswa.2019.05.051
Sawyer, J. P., & Rao, S. (2000). Structural damage detection and identification using fuzzy logic. *AIAA Journal*, *38*(12), 2328–2335. doi:10.2514/2.902
Sugeno, M. (1985). An introductory survey of fuzzy control. *Information Sciences*, *36*(1-2), 59–83. doi:10.1016/0020-0255(85)90026-X
Tariq, H., Al-Hitmi, M. A. E., Tahir, A., Crescini, D., Touati, F., & Manouer, A. B. (2018). Structural Health Monitoring Installation Scheme using Utility Computing Model. (Ed.), ^(Eds.). 2018 2nd European Conference on Electrical Engineering and Computer Science (EECS).
Wang, J., Cao, J., Ji, S., & Park, J. H. (2017). Energy-efficient cluster-based dynamic routes adjustment approach for wireless sensor networks with mobile sinks. *The Journal of Supercomputing*, *73*(7), 3277–3290. doi:10.1007/s11227-016-1947-9
Wang, J., Gao, Y., Liu, W., Sangaiah, A. K., & Kim, H.-J. (2019). An intelligent data gathering schema with data fusion supported for mobile sink in wireless sensor networks. *International Journal of Distributed Sensor Networks*. *15*(3), 1–9. doi:10.1177/1550147719839581
Wang, J., Zhang, Z., Li, B., Lee, S., & Sherratt, R. S. (2014). An enhanced fall detection system for elderly person monitoring using consumer home networks. *IEEE Transactions on Consumer Electronics*, *60*(1), 23–29. doi:10.1109/TCE.2014.6780921
Zhang, W., Xiong, N., Yang, L. T., Jia, G., & Zhang, J. (2012). BCHED-energy balanced sub-round local topology management for wireless sensor network. 網際網路技術學刊, *13*(3), 385–394. doi:10.6138%2fJIT.2012.13.3.02