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Impedance-based structural health monitoring incorporating neural network technique for identification of damage type and severity

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ABSTRACT

Impedance-based structural health monitoring (SHM) has come to the forefront in the SHM community because of its practical potential for real applications. In the impedance-based SHM technique, it is very important to select the optimal frequency range most sensitive to the expected structural damage, and more quantitative information on the structural damages might be needed compared to the conventional damage index. Therefore, this study proposes an innovative neural network (NN)-based pattern analysis tool (1) to identify damage-sensitive frequency ranges autonomously and (2) to provide detailed information such as the damage type and severity. The importance of selecting the optimal frequency range was first investigated experimentally using a simply-supported aluminum beam. The performance of the proposed NN-based approach was validated throughout damage identifications of loose bolts and notches on a bolt-jointed aluminum beam and a lab-scale pipe structure. Finally, the proposed NN-based algorithm was embedded into a wireless impedance sensor node to detect real damage in a full-scale bridge. Overall, the proposed approach incorporating a wireless impedance sensor node was used to evaluate the damage type and severity in multi-type and multiple structural damage cases.

1. Introduction

Most civil infrastructure, such as bridges, buildings, water supply lines, offshore platforms, nuclear power plants, and oil tanks, are assemblies of load carrying members capable of transferring a load to the foundations. They are sometimes exposed to severe environmental and service loading during their lifetime. In particular, extreme events including earthquakes, typhoons, blast loading, and overloaded traffic deteriorate the strength and serviceability of members, which is generally called 'damage'. Therefore, it is important to develop reliable online structural health monitoring (SHM) technologies and deploy the rational SHM systems for civil infrastructure. In particular, there has been increasing interest in local health monitoring for critical members of a host structure by utilizing smart sensors such as fiber optic sensors and piezoelectric sensors during the last decades. Among them, the electromechanical impedance-based SHM technique using piezoelectric sensors is a promising tool for host structures [1–14].

The impedance-based SHM technique utilizes small piezoelectric sensors, such as piezoceramic (lead (Pb)–zirconate (Zr)–titanate (Ti); PZT) and macro-fiber composite (MFC) patches, attached to a host structure as self-sensing actuators to excite the host structure with a high-frequency sweep and monitor any changes in the structural mechanical impedance [7]. An assessment regarding the structural integrity can be made by monitoring the change in electrical impedance of a piezoelectric sensor. Selection of the optimal frequency range in the impedance signature is closely related to the sensing capability of the impedance-based SHM technique in detecting structural damages [15]. On the other hand, few studies have examined the effect of the frequency range on impedance variations and it has been recommended that several frequency ranges containing 20–30 peaks be examined to select the most suitable range by a trial and error method [7,16].

To this end, an automated technique to select damage-sensitive frequency ranges and diagnose the damage quantitatively was proposed by using neural network (NN), which consists of an interconnected group of artificial neurons and processes information using a connectionist approach to its computation. Many studies have examined the NN approach for a damage estimation of a structure due to the versatility in dealing with various types of inputs and outputs and a quick diagnosis capability after training of the NN was completed. Chaudhry and Ganino [17] examined de-bonding on a composite/aluminum beam structure with the NN to identify the severity and presence of delamination. Okafor et al. [18] estimated the delamination of composite beams using piezoelectric devices using modal analysis and NN. Modal frequencies were used

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for multi-input and the size of the delamination was predicted. Lopes et al. [19] applied the back propagation NN technique with impedance measurements to identify the damage and estimate the severity and location of damage. Giurgiutiu et al. [3] proposed a damage metric quantification achieved with a features-based probabilistic neural network. Feature vectors consisted of resonance frequencies, resonance amplitudes, and damping factors. On the other hand, when the number of features was insufficient and frequency ranges for impedance measurements were varied, a misclassification occurred and thus more features were needed for correct classification. Min et al. [15] utilized the NN approach to select the optimal frequency range automatically in the impedance-based method. The process to determine governing frequency components for damage diagnosis was validated by observing the internal weights and biases in the NN. This study focused on an extension of this research to extract more information on the level of structural damage from impedance signatures.

In this study, the impedance-based technique was incorporated with NN features to select damage-sensitive frequency ranges and to estimate a range of damage information such as damage type and severity simultaneously. The theory behind the proposed technique was presented, and the importance of this approach is described with experimental results of an aluminum beam. A series of experimental applications were then carried out to validate the feasibility of the technique in detecting loose bolts, crack damages, and multi-type damages on a bolt-jointed aluminum beam, a lab-scale pipe structure, and a critical member of full-scale bridge.

2. Electromechanical impedance-based SHM technique

The impedance-based SHM technique employs small piezoelectric sensors that excite a host structure with a high-frequency band, and simultaneously monitor any changes in the impedance signature. In addition, the self-sensing property allows one piece of the piezoelectric sensor to obtain frequency response functions between the input voltage and output current. When a PZT patch is surface-bonded to a host structure, Liang et al. [20] first proposed a one-dimensional analytical model of this setup, and reported that the electrical admittance (inverse of the electrical impedance), $Y(\omega)$, of a PZT patch is associated with the mechanical impedance of the host structure, $Z_s(\omega)$, and that of a PZT patch, $Z_a(\omega)$, for the frequency range of interest in most applications as follows:

$$\begin{aligned} Y(\omega) &= \frac{I_o}{V_i} = G(\omega) + jB(\omega) \\ &= j\omega a\left(\bar{\varepsilon}_{33}^T - \frac{Z_s(\omega)}{Z_s(\omega)+Z_a(\omega)} d_{3x}^2 \hat{Y}_{xx}^E\right) \end{aligned} \tag{1}$$

where V_i is the input voltage to the PZT actuator; I_o is the output current from the PZT; a, $\bar{\varepsilon}_{33}^T$, d_{3x}, and Y_{xx}^E are the geometry constant, complex dielectric constant, piezoelectric coupling constant, and complex Young's modulus of the PZT at zero stress, respectively. Given that the mechanical impedance and material properties of the PZT remain constant, the equation shows that a change in the mechanical impedance of a structure results directly in a change in the electrical impedance measured by the PZT. It should be noted that the admittance function, $Y(\omega)$, is a complex number. Bhalla et al. [1] demonstrated that the real part of the measured admittance (the conductance) changes more sensitively due to the structural damage condition than the imaginary part (the susceptance). Park et al. [8] reported that the susceptance can be used more effectively for piezoelectric sensor self-diagnosis. It can be justified by the fact that the PZT is a capacitive device and its admittance is dominated by the imaginary part ($j\omega C$).

By observing changes in impedance signals acquired from the PZT attached on a host structure, assessments can be made regarding the integrity of the host structure [1–14]. Since an impedance change provides only a qualitative assessment for damage detection, a scalar damage metric has been used for a quantitative measure of the damage severity. Peairs et al. [12] compared several damage metrics but the root mean square deviation (RMSD) and cross-correlation coefficient (CC) were most commonly used for the impedance method. These metrics employ the difference in the impedance value at each frequency as follows:

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}\{\mathrm{Re}(Z_0(\omega_i) - \bar{Z}_0) - (\mathrm{Re}(Z_1(\omega_i)) - \bar{Z}_1)\}^2}{\sum_{i=1}^{n}\mathrm{Re}(Z_0(\omega_i) - \bar{Z}_0)^2}} \tag{2}$$

$$CC = \frac{1}{n}\sum_{i=1}^{n}\frac{\{\mathrm{Re}(Z_0(\omega_i)) - \bar{Z}_0\}\{\mathrm{Re}(Z_1(\omega_i)) - \bar{Z}_1\}}{\sigma_{Z_0}\sigma_{Z_1}} \tag{3}$$

where $Z_0(\omega)$ is the impedance of the PZT measured in the healthy condition (baseline); $Z_1(\omega)$ is the impedance in the concurrent condition; n is the number of frequency points; $\bar{Z}_0$ and $\bar{Z}_1$ are the mean values of impedance signals of $Z_0(\omega)$ and $Z_1(\omega)$; σ_{Z_0} and σ_{Z_1} are the standard deviations of the real parts (i.e., resistances). With the RMSD metric, the difference between the baseline reading and the subsequent reading increases with increasing numerical value of the metric, which indicates the clearer presence of structural damage. On the other hand, the difference between the baseline reading and the subsequent reading increases with decreasing value of the CC metric.

Recently, Koo et al. [21] proposed an effective frequency shift (EFS; $\tilde{\omega}$) method, in which a new damage metric was suggested to compensate for the temperature effect on the impedance method. The temperature effects due to the surrounding change should be considered with careful attention because it might result in significant impedance variations, particularly a frequency shift in the impedance, which may lead to erroneous diagnostic results on the real structure. This was based on the frequency shift giving the maximum correlation coefficient between the baseline impedance data, $Z_0(\omega)$, and the concurrent impedance data, $Z_1(\omega)$, as

$$CC = \max_{\tilde{\omega}}\left\{\frac{1}{n}\sum_{i=1}^{n}\frac{\{\mathrm{Re}(Z_0(\omega_i)) - \bar{Z}_0\}\{\mathrm{Re}(Z_1(\omega_i - \tilde{\omega})) - \bar{Z}_1\}}{\sigma_{Z_0}\sigma_{Z_1}}\right\} \tag{4}$$

The EFS method provided consistent CC values for impedance signatures under temperature changes, which cause considerable variations including both vertical and horizontal shifts under the same damage condition.

3. Neural network-based intelligent damage diagnosis

A neural network (NN) is constructed using a number of processing elements connected to form layers of neurons. It provides a map between the sets of inputs and outputs by optimally determining the synaptic weights based on available training patterns of inputs and outputs. A supervised multi-layer feed-forward NN with a back propagation algorithm is typically employed (Fig. 1). During the training stage, the network propagates inputs through each layer until an output is generated. The calculated error is transmitted backwards from the output layer and the weights are adjusted to minimize the error. The training stage is terminated once a preset error level is reached and the node weights are fixed at this point. During the testing stage, sets of input data that have not been used in the training stage are used to validate and generalize the trained NN. For specific information, the following studies can be referenced in [19,22–27].

Fig. 2 shows the proposed scheme for an intelligent damage diagnosis to determine the most sensitive frequency range and extract quantitative damage information. The procedure is as follows. First, the impedance signals are obtained over a wide fre-