Deep learning-based damage estimation in concrete structures using acoustic emission data

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Abstract

Conventional structural testing methods assess damaged condition of the structures and they generally base on subjective visual inspection. To take necessary precautions before/during a disaster, real-time monitoring of damage progression is very important especially for critical structures such as bridges, viaducts, tunnels, dams and nuclear power plants. Acoustic emission (AE) has been proved to be a successful method for this purpose and it is used to locate even invisible micro-level cracks in the structures. The most important feature that makes this technique advantageous over other non-destructive testing methods is that it continuously monitors damages in structures subjected to load by sensors converting the waves emitted from the damage into electrical signals. By analyzing the parameters of the recorded signals, critical information such as the type, location, origination-time, size and direction of the damage can be obtained.

In this study, it was aimed to estimate damage status of the concrete members exposed to loading by developing a deep learning-based damage detection model. The model was developed by monitoring AE activities of reinforced concrete subjected to loading. Afterwards, a relationship was established between the damage levels of the RC beam with features of the AE signals. The developed model was trained and tested for both raw and data-driven AE data obtained by continuously collected AE signals segmented into signals of one-second length. Estimation capability results of the model show that data-driven data is more successful than the raw data at estimating the damage level.

Keywords: Damage estimation, acoustic emission, artificial neural network, deep learning, concrete structures

1 Introduction

In recent years, the ability to design adaptive and data-driven structural health monitoring systems for reinforced concrete structures has become more popular due to technical improvements in sensors as well as data-driven methods using artificial intelligence-based deep learning approaches. With conventional structural testing methods, damage conditions of the structures are generally based on subjective visual inspection. To take necessary precautions before/during a disaster, real-time monitoring of damage progression is very important, especially for critical structures such as bridges, viaducts, tunnels, dams and nuclear power plants. Acoustic Emission (AE) is one of the most effective structural health monitoring methods for quantifying and locating micro and macro fracture events in concrete structures, as well as following the fracture process until it fails. The loss of integrity and adverse impact on mechanical characteristics in reinforced structures can be recognized as micro/macro damage levels under loading conditions [1]. These damage states must be identified by a reliable process to ensure structural safety. The most important feature that makes AE technique advantageous over other non-destructive testing methods is that it continuously monitors damages in structures subjected to load by sensors converting the waves emitted from the damage into electrical signals. The analysis of these AE waveforms helps for the identification of damage characteristics. Critical information such as the type, location, origination-time, size, and direction of the damage can be obtained by examining the
properties of the recorded signals. AE parameters such as amplitude, rise time, duration and energy have proven to be effective features in the classification of damage levels [2].

Aside from material design, the structural integrity of reinforced concrete structures is continuously monitored using AE, but one of the most potent approaches for identifying damage in reinforced concrete structures is using machine learning and deep learning. In the present era, deep learning has attracted a lot of interest among researchers since it was first introduced in civil engineering and researchers are focusing on developing automated monitoring techniques for structural responses [3]. Unlike the traditional parameter-based models, data-driven models offer bottom-up solutions that include the identification of damage/cracks and life estimation of structures [4]. In different fields, crack detection studies are carried out by using multiple modules related to deep learning [5],[6]. In AE, which is used for structural health monitoring in both infrastructure and superstructures is highly accurate in damage estimation and can be used with deep learning techniques [7],[3]. Although AE characteristic parameters can be used to identify damage modes in concrete structures utilizing a parameter-based approach, a data-driven approach shouldn't be ignored as well [2]. In this study, a deep learning-based model was developed to estimate damage level of a reinforced concrete beam subjected to bending. The model was trained with the relationship of damage levels identified from load-displacement curve with features of the AE signals. In addition, results of the raw and data-driven AE data obtained by continuously collecting AE signals into segmented signals of one-second length were compared for more effective damage estimation.

2 Method

2.1 Acoustic Emission (AE)

Acoustic emission (AE) is defined as the class of phenomena whereby transient stress/displacement waves are generated by the rapid release of energy from localized sources within a material, or the transient waves so generated [8]. In other words, AE is a non-destructive testing method used to monitor the structural state of different materials [9]. Physically, failure takes place due to the release of stored strain energy, nucleates cracks and generates elastic waves. These waves propagate inside a material and are detected by an AE sensor on the surface. AE has great importance for detecting and locating defects in real-time and it is different from other nondestructive testing methods in that it detects the flaws during their occurrence [10]. Many fracture behaviors can be identified using the AE parameters such as duration time, amplitude, AE energy, AE count and rise time shown in Figure 1. For instance, flaws can be classified by using AE parameters such as duration time, AE count, rise time and maximum amplitude [11].
Rise time is the time difference between the first threshold crossing and the peak signal. Duration time is the time interval between the first and last threshold crossings. AE energy is total elastic energy released by an acoustic emission event. AE count is the number of times within the duration, where one signal exceeds a present threshold. Threshold level is typically set on the positive side of the signal, just above the noise. Amplitude is a peak voltage in a waveform and is measured in decibels. In addition, some secondary features of the signals can be also used for different purposes. For instance, RA value (rise time/amplitude) and average frequency (count/duration) are useful for identifying damage type [11].

2.2 Deep Learning (DL)

Deep Learning (DL) is a subset or sub-branch of machine learning [12]. It employs machine learning algorithms and artificial neural networks with multiple layers and has proven to be very successful in dealing with large amounts of data in a variety of research domains e.g. speech, audio, video and image recognition etc. Deep learning models process the input data using multiple layers and generally contain three types of layers: input layer, hidden layer, and output layer. These layers are used for feature extraction/raw features as input, transformation, and pattern analysis respectively using supervised or unsupervised learning algorithms [13]. Based on the application and compatibility, there are multiple architectures that can be employed in deep learning. Some of them are Deep Neural Network (DNN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Deep Belief Network (DBN), Auto-encoders, and Generative Adversarial Networks (GANs), etc.[3]. In this study, concerning the classification of damage states, DNN based architecture using a multilayer perceptron (MLP) neural network was used to classify the damage states of the reinforced concrete beam which is discussed in section 4.

3 Experimental study

A 2350x250x150 mm reinforced concrete (RC) beam was produced as its geometric and reinforcement details are given in Figure 2. Mix design (W/C=0.66 and C25/30) of the concrete used for production of the specimen is presented in Table 1. The beam was designed for flexural failure containing four ø8 mm S420 longitudinal rebars in total.
The beam was tested under three-point-bending with clear span of 2300 mm. Monotonic load was applied with a rate of 30 N/s by a hydraulic pump. Eight AE sensors of 150 kHz were placed on the surface of the test specimen by silicon grease and an 8-channel DiSP AE system by MISTRAS was used to record AE activities to be trained to the artificial intelligence. AE waves were amplified with 40 dB gain by pre-amplifiers and threshold was set as 40 dB. Arrangement of the AE sensors are shown in Figure 2.

![Figure 2: Loading and AE setup of the test specimen](image)

### Table 1: Mix design of the concrete used for production of the RC beam (kg/m³)

<table>
<thead>
<tr>
<th>Cement</th>
<th>Aggregate 0-3 mm</th>
<th>Aggregate 5-15 mm</th>
<th>Aggregate 15-22 mm</th>
<th>Water</th>
<th>Fly ash</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEM I 42.5R</td>
<td>255</td>
<td>934</td>
<td>429</td>
<td>485</td>
<td>167</td>
</tr>
</tbody>
</table>

4 Analytical Modelling

Damage levels which were attributed to AE activities and used for training the model are shown as in Figure 3. As seen, load-displacement curve of the beam was divided into four damage stages based on main mechanical observations of the test. Damage level 1 (D1) starts from initial point to proportional limit, with no sign of cracks, damage level 2 (D2) is from proportional limit to yield limit, with micro-cracks, damage level 3 (D3) is from yield limit to ultimate limit, with major cracks and damage level 4 (D4) starts from ultimate point to fracture point, with macro cracks.
Since the aim of this study is to estimate these damage levels based on DNN, a multilayer perceptron (MLP) neural network using a pattern recognition approach was used to estimate the damage levels under loading conditions by considering observations of AE signals. MLPs are fully connected feed-forward neurons with one or more layers of nodes between the input and output nodes. Each layer is made up of one or more parallel artificial neurons. Because of its highly adaptable non-linear structure, a multilayer perceptron is an excellent tool for tackling a wide range of difficult pattern recognition tasks [14]. The methodology used in this study was broken down into three steps: AE data acquisition, feature extraction, and utilizing DNN for estimating damage levels. Significant AE parameters such as rise time, count, energy, duration, amplitude, average frequency, signal strength, absolute energy, central frequency, peak frequency, RA value (rise time/amplitude), and hit were extracted from the AE system and were used as input features to a typical architecture of an MLP neural network system as shown in Figure 4. The model includes hidden layers placed in between the input and output layers. The nodes of the first layer take input data as a group of vector weights with bias and use the activation function to transmit them to the next layer, while nodes of the last output layer give the result of targets.
The number of input nodes at the input layer was set as 12 according to the number of AE features with defined four damage levels as an output in the output layer. To build a pattern recognition network, the hidden layer size was set to 20, 40 and 20 nodes in each hidden layer respectively, and the “Trainscg” network training function was chosen, which updates weight and bias values using a scaled conjugate gradient method. Dataset which includes abovementioned AE parameters and referred damage levels was randomly divided into 70% for training, 15% for validation and 15% for testing purposes, and the hyperbolic tangent activation functions for the hidden layers and softmax activation function for the output layer were used by equation (1) and (2). Both the input and output nodes were normalized and the dataset was used to train the network with acceptable stopping criteria of network parameters such as learning rate, epochs, performance goal and validation failure.

\[
tanh = \frac{e^n - e^{-n}}{e^n + e^{-n}} \quad (1)
\]

\[
\sigma(\vec{x})_i = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_j}} \quad (2)
\]

To estimate the damages levels based on the raw AE dataset, the network was not found to be suitable for training the model within acceptable limits. Therefore, a data-driven approach was proposed and used to classify the damage levels acquired from AE activities. In the data-driven approach, a set of AE signals into segmented signals of one-second length were picked and all the input features of a single event were computed using their mean values. It was also
noted that the AE hit was also taken into consideration as an input feature in the data-driven approach. Both the models with raw dataset and mean dataset were trained using MLP network and their results were compared for damage estimation. To evaluate the performance of the models, all the testing results of the models were achieved in terms of cross-entropy loss, histogram error, confusion matrix, receiver operating characteristic (ROC) and feature importance based on accuracy.

5 Results & Discussion

For multiclass classifications, the performance of a model is measured in terms of cross-entropy loss or log loss whose output probability is 0 or 1. The aim is to get the model's log loss as close to 0 as possible. In Figure 5, both raw mean AE dataset models were trained throughout a single epoch. When an entire dataset is passed through the neural network once, it is referred to as an “epoch”. Because one epoch is too large to feed to the computer all at once, they were divided into smaller batches for training, followed by the validation set and testing datasets. The raw dataset was set to default of 1000 epochs however, the mean was set at 500 epochs. The number of epochs stops when the validation is optimized, and it was observed that the log loss is reduced from 0.3 to 0.124 when preferring the mean dataset over the raw AE dataset. The training was terminated at 843 and 285 epochs as the number of passes provided the best validation performance for the raw and mean AE datasets, respectively.

![Figure 5. Performance of the models trained with a) raw, b) mean AE dataset](image)

Figure 6. shows the error histogram or distribution of values indicating how predicted values are differing from the true values of the AE dataset in a neural network. The distribution of errors for training, testing and validation are centred on the zero error. The total error range was divided into 20 smaller bins on the x-axis and the y-axis represents the number of samples of the AE dataset lying in a particular bin. It was observed that in the raw dataset a lot of data samples have an irregular distribution of errors ranging from -0.4 to +0.85 whereas,
in the mean dataset, data fitting errors were found in normal distribution within a reasonably good range around zero error.

Figure 6. Error histograms of the models trained with a) raw, b) mean AE dataset

To check the performance of a model, a confusion matrix is used to identify observations of the model either properly categorized or not based on output class (true class) and target class (prediction class). The diagonal cells represent the observations where both the output class and target class match. In Figure 7, the overall confusion matrix of training, validation and testing shows the number of observations as well as the percentage of total observations of each cell for four damage levels using raw and mean AE dataset. In the graph, the last right columns and last rows of the graph represent the percentage of all true class and predicted class observations for each cell, respectively. Percentages in columns are referred to the criteria of true positive rates (TPR) and false negative rates (FNR), whereas percentages in rows are referred to positive predictive value and false discovery rate, respectively. Based on all these criteria’s, the overall accuracy of the network was drawn and it was observed that estimation accuracy of the model trained with raw AE data was 43.8%, which was not even within acceptable limits whereas when comparing it with mean AE data. The network performed certainly well with an accuracy of 84.2% in predicting the damage levels of the RC beam after being trained with mean AE dataset.
In Figure 8, the overall receiver operating characteristic (ROC) probability curves that are used to evaluate the performance of the classification models show the classifications of damage levels for both raw and mean AE data. These curves are based on true positive rates (TPR) and false positive rates (FPR) known as sensitivity and specificity, respectively at different classification thresholds. From these findings, it was observed that the performance of damage levels 3 and 4 outperforms damage level 1 and 2 in both cases this is because of the non-uniform distribution of AE data in damage levels 1 and 2. It was also observed that the performance of damage levels in the mean AE dataset are far better than the raw AE dataset.
In order to evaluate feature importance, Figure 9 was created which represents the performances of the model trained with mean dataset according to different AE parameters removed from the training. As clearly seen, accuracy of the model decreased to 77% while “hit” or “AE amount” was not used. This shows that the amount of AE hit for a certain amount of AE energy is the most effective parameter in scaling the activity and therefore determining the damage level. Because a large amount of AE hits with the same amount of total AE energy will define micro-scale activities (higher damage levels) while less AE hits will describe macro-scale activities (lower damage levels). Apart from this, absence of frequency parameters and RA value decreased the accuracy since they define the type of the damage, while the absence of count parameter increased it.

Figure 9. Feature importance of AE parameters based on accuracy

6 Conclusions

In this study, AE activities were attributed to four main damage levels aimed to develop a deep learning-based model trained with AE activities obtained from flexure failure of an RC beam to estimate the damage level. Accordingly, raw and new-developed data-driven AE data were used to train the model. Estimation capability results of the model show that data-driven AE data obtained by continuously collecting AE signals into segmented signals of one-second length is more successful (with an estimation accuracy of 84.2%) than the raw data (with an estimation accuracy of 43.8%) since it contains relations determining the scale of the activity with the parameter value depending on the hit amount. For this reason, on the other hand, AE hit was found as the most important feature because the prediction accuracy of the model decreased without it. Besides, frequency and RA value are the other significant features. In addition, performance of the higher damage levels (3 and 4) outperformed lower damage levels (1 and 2) due to the non-uniform distribution of AE data.
References


