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Damage Assessment in Hyperbolic Cooling Towers Using Mode Shape Curvature and Artificial Neural Networks

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Abstract

Hyperbolic cooling towers are large thin shell reinforced concrete structures that are used to remove the heat from wastewater and transfer it to the atmosphere using the process of evaporation. During its long service life, a cooling tower can experience damage due to the large temperature variations, environmental degradation, or random actions such as impacts or earthquakes. Such a damage can develop over time and result in the sudden collapse of the cooling tower. To ensure that a cooling tower operates safely and efficiently at all times, it is important to monitor its structural health. In this context, structural health monitoring based on the vibration characteristics of the structure, has emerged as a useful method to detect and locate damage in structures. Hyperbolic cooling towers, due to their particular shape, exhibit rather complex vibration characteristics that do not suit the traditional vibration-based damage detection techniques. This paper develops and applies a damage assessment method using the absolute changes in mode shape curvature (ACMSC) in conjunction with Artificial Neural Networks (ANNs) to detect, locate, and quantify damage in hyperbolic cooling towers. ANN is a machine learning technique that can predict behavioural patterns using a set of data samples and finds use in the damage quantification process. The proposed method for detecting and locating damage is experimentally validated and demonstrated its capability to accurately detect and locate damage. A feed-forward network having one hidden layer with Bayesian algorithm is used to train the artificial neural network. Damage indices calculated from noise polluted mode shape data are used to train the network. The trained network is then used to successfully assess the unknown damage severities in the cooling tower. The outcomes of this paper will enable early warning of damages in the cooling towers and will help towards their safe operation.

Keywords: Hyperbolic Cooling Tower; Vibration Characteristics; Structural Health Monitoring; Artificial Neural Network; Damage Quantification; Absolute Change in Mode Shape Curvature Method

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Nomenclature

The following symbols are used in this paper

ACMSC	Absolute change in mode shape curvature	SHM	Structural health monitoring
ANN	Artificial Neural Network	U_1	Radial component
DIs	Damage indices	U_3	Vertical component
FEM	Finite element model	VBDD	Vibration based damage detection
h	Length of the element	$\emptyset j, i$	Magnitude of the mode shape of i^{th} vibration mode at j^{th} location
MSE	Mean square error	γ_x^{φ}	Random number with mean of zero and variance of 1
R	Regression	ρ_x^{φ}	Random noise level

1. Introduction

Hyperbolic cooling towers are large, reinforced concrete structures which are constructed to have long service lives. Their fundamental task is to eliminate the waste heat from the water and transfer it to the atmosphere [1]. Hyperbolic cooling towers are doubly curved thin-walled shell structures that can better withstand external pressure (than straight towers) [2]. During the service life of a cooling tower, sudden damage or collapse can occur due to structural deterioration, random actions, and environmental effects. It is therefore beneficial to examine the structural health of all important and especially large structures on a regular basis to ensure that they operate safely. Since most of the hyperbolic cooling towers are very tall and large in diameter, visual inspection can be very difficult, especially in the interior of the towers. Today, most inspections and assessments are done using non-destructive tests to detect the onset of damage and carry out appropriate retrofits to prevent the structure from collapse. [3], [4]. In this context, structural health monitoring (SHM) based on vibration characteristics of the structure has emerged as a useful technique. The principle of this technique is that the damage in a structure causes a change in its vibration properties, and this change can be used to detect damages in the structure. Vibration-based damage detection (VBDD) techniques are categorized as global methods [5]. They are cost-effective and comparatively easy to apply. Over the last few decades, mode shapes [6] and mode shape derivatives [7] have been used as damage detection indicators. Mode shape curvature is the second derivative of mode shape, and it has a direct relationship with bending strains in beams, plates, and shells [8]. Absolute change in mode shape curvature (ACMSC) can hence be an effective tool for detecting and locating structural damage.

Dynamic behaviour of a structure depends on the structure type, and hence damage detection methods developed for one structure type are normally not be applicable to other structure types. Hyperbolic cooling towers due to their unique shape, have rather complex vibration characteristics. It is thus necessary to develop an appropriate vibration-based damage detection method to detect, locate, and quantify the damage in them. To address this a coupled method associated with ACMSC was developed to successfully detect and locate damage in hyperbolic cooling towers, as presented in [9]. Quantifying the damage or predicting damage severity is a more challenging task than that of detecting and locating the damage and it is usually not within the capability of vibration-based damage detection methods. Existing numerical methods used for damage quantification in beams [10] and trusses [11] have some drawbacks. They are not generic but are specific for a particular structure and may not be capable of quantifying the damages in complex structures. There are few references in the literature on damage quantification in bridge structures using the combination of vibration characteristics and ANN [12], [13]. This present paper develops and applies ANN techniques, in conjunction with ACMSC method to detect, locate and quantify damage in hyperbolic cooling towers and thus complete the task of damage assessment in these types of structures.

ANN, which imitates the mechanism of the human brain is introduced as a smart and efficient tool to assess (locate and quantify) damage in cooling towers. ANN comprises of a large number of neurons which are simple processing units [14]. It can capture complex relationships between input and output through the process of learning, self-organizing, and auto improving [15]. A properly trained network is capable of predicting the accurate output from unknown input data which are inconsistent, noise polluted, and uncertain [16]. The method proposed in this paper is verified for a full-scale hyperbolic cooling tower for a range of damage scenarios. Further, its capability of damage quantification under field conditions is tested by adding white Gaussian noise to the input data in the numerical simulations. Results confirm the accuracy of the proposed method to detect, locate and quantify method in hyperbolic cooling towers and the outcomes of this paper will enable the safer operation of these large structures.

2. Methodology

2.1 Vibration based damage detection method

Hyperbolic cooling towers have complicated vibration mode shapes due to their geometrical shape. Preliminary studies indicate that the radial (U1) and vertical (U3) components of mode shapes in general provide the greater contribution for damage detection in hyperbolic cooling towers [9]. Therefore, instead of the resultant modes, mode shape components corresponding to maximum effective mass values are chosen for the process of damage detection considering the first three global modes [9]. The finite element model (FEM) of the cooling tower structure has two modes with the same frequency and similar mode shape, due to its symmetry. Therefore, the first three global modes represent the 1st, 3rd, and 5th mode shapes in general.

According to the Pandey et al. 1991[17], the mode shape curvature method was used to locate damage in cantilever and simply supported beams. Mode shape curvature can be determined from displacement mode shapes as in Equation 1 using the central difference approximation.

$$\emptyset''_{j,i} = \frac{\emptyset_{j-1,i} - 2\emptyset_{j,i} + \emptyset_{j+1,i}}{h^2} \qquad (1)$$

where h is the distance between two nodes and $\emptyset_{j,i}$ is the mode shape of the jth element for ith mode. As observed previously [9], the highest peak in the absolute change in mode shape curvature (ACMSC) between damage and intact states as shown in Equation 2 indicates the location of the damage in the hyperbolic cooling tower.

$$\mathbf{DI} = \Delta\emptyset''_{j,i} = \left[\frac{\emptyset_{j-1,i} - 2\emptyset_{j,i} + \emptyset_{j+1,i}}{h^2}\right]^{d} - \left[\frac{\emptyset_{j-1,i} - 2\emptyset_{j,i} + \emptyset_{j+1,i}}{h^2}\right]^{u} \qquad (2)$$

In the above equation superscripts u and d denote the undamaged and damaged states, respectively.

The above procedure was validated experimentally, and details are provided in [9]. For the completeness of this paper, a brief description of the validation is presented below.

Feasibility of the proposed method was verified using the results from experimental testing of laboratory scale cooling tower models, shown in Fig.1. The cooling tower models were made from general steel. Free vibration tests were carried out on the intact and damaged models to obtain the natural frequencies and mode shapes and were used to validate the proposed method under laboratory conditions. In practical situations, mode shape data are not measured directly, but are obtained from measured acceleration data. Damage was introduced by cutting a small hole in the upper section of the cooling tower model, as shown in Fig.1.

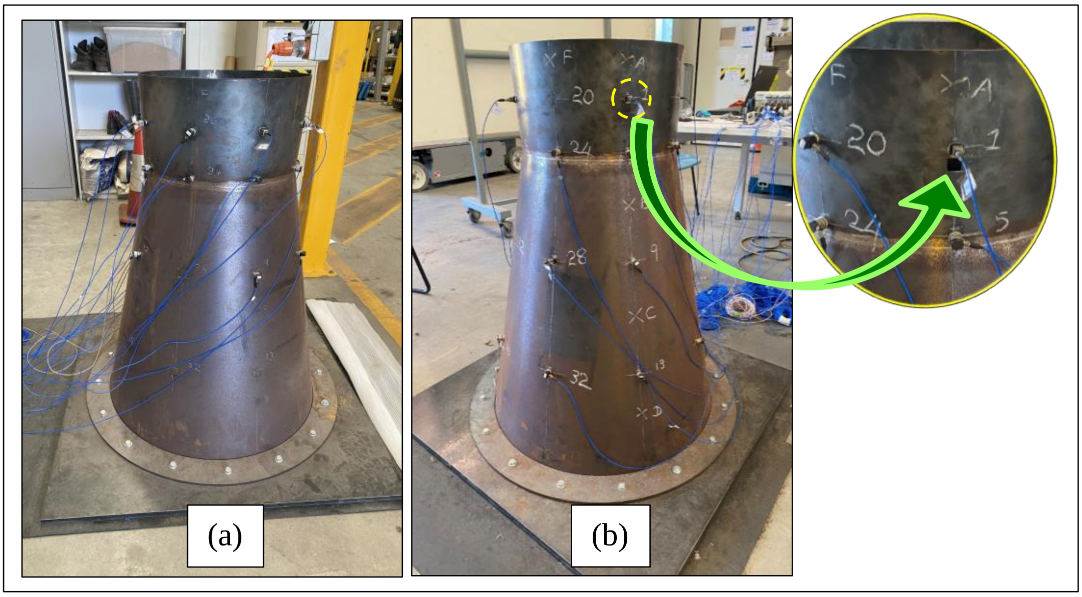

Fig.1. (a) Experimental cooling tower model with accelerometer arrangement (b) Damage at the upper section of the cooling tower model

A finite element model (FEM) of the experimental cooling tower was simulated in ABAQUS finite element modelling software package and validated by comparing the natural frequencies of the numerical and experimental models. Dominant effective mass values were extracted from the undamaged finite element model. Mode and mode shape components corresponding to maximum effective mass values were used to calculate Damage Indices (DIs), plot the DIs along a few vertical cross-sections to accurately determine the damage location. Lines A-B, C-D, E-F and G-H in Fig. 2 indicate the different vertical cross-sections of the cooling tower model considered in the damage detection process. Line G-H is very close to the damage location while the distance to the damage location gradually increases for lines E-F, C-D, and A-B. The two lines of "Damage Location" in legend of Fig. 3 indicate the starting point and ending point of the damage area. It can be seen from Fig. 3 that the damage around the upper section of the cooling tower model is precisely detected by the proposed procedure which can hence be considered as validated.

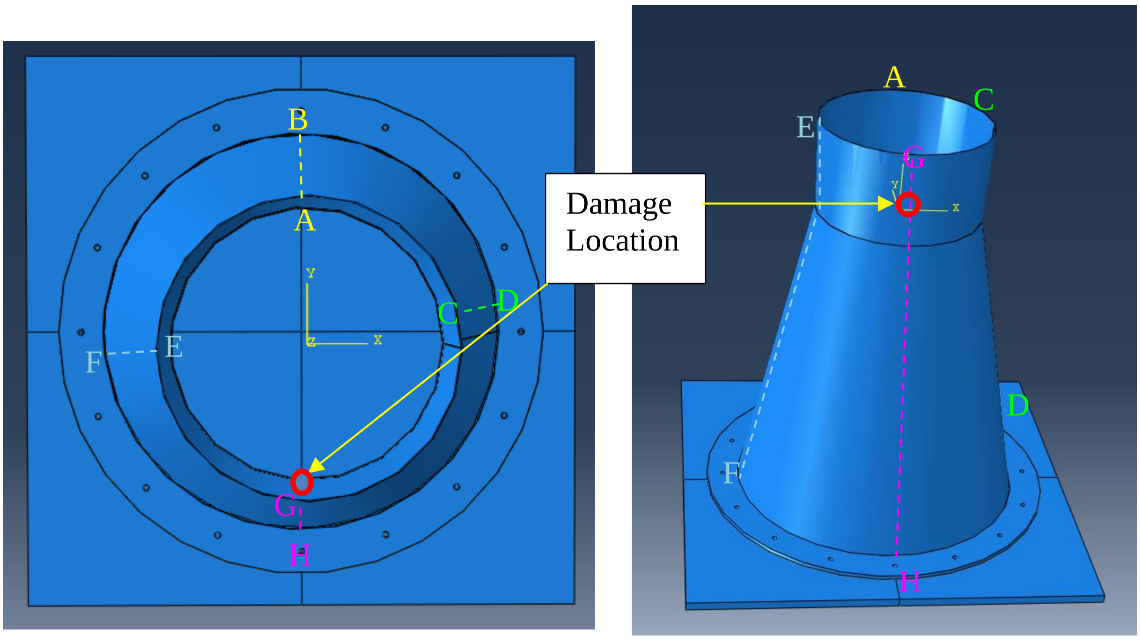

Fig.2. (a) Plan view (b) Front view of selected nodal paths

The applicability of the proposed damage detection method was illustrated using the full-scale Mülheim-Kärlich hyperbolic cooling tower in Germany [18]. A full-scale finite element model of this cooling tower was developed using ABAQUS finite element modelling software. The height of the

Mülheim-Kärlich cooling tower is 162 m. The throat, top and base diameters are 65.3 m, 68 m, and 117 m, respectively, while the thickness of the tower is 0.24 m. The throat is located 37 m above the base of the tower. As mentioned in the literature [19], unit weight, Poisson's ratio and Young's modulus of concrete were considered as 25kN/m^3, 0.2, and 39GPa, respectively.

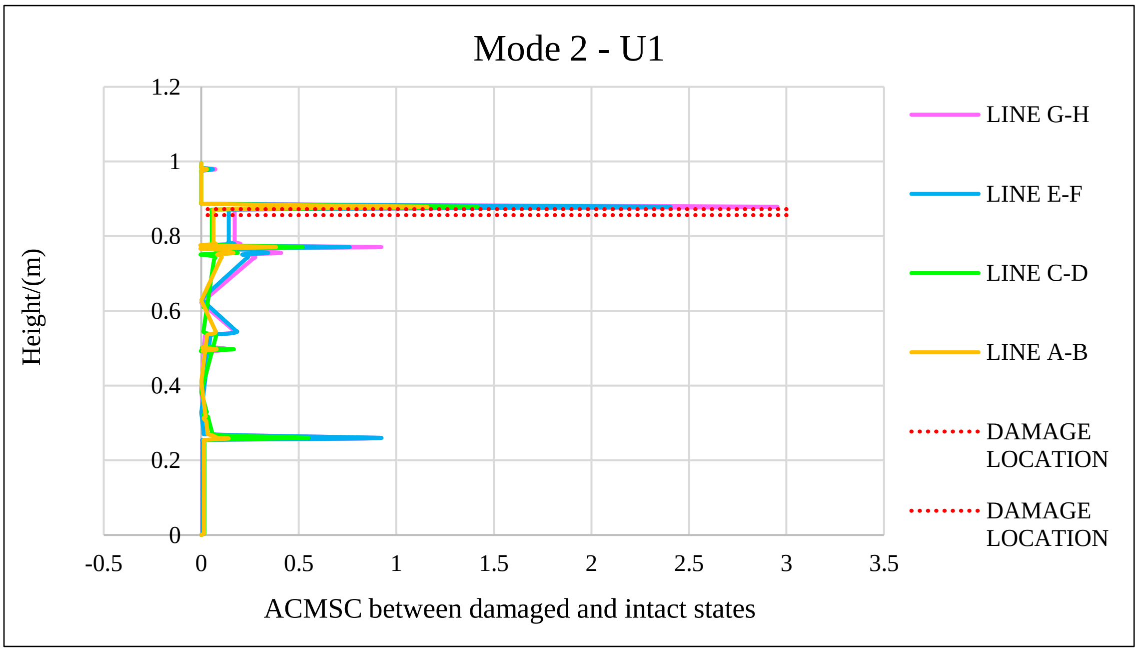

Fig.3. Locating damages at upper section of the cooling tower using dominant mode shape component (Mode 2 -U1)

Table 1. Selection of mode shape and mode shape component

Tower	Global Mode	Effective mass of U1 direction	Effective mass of U3 direction	Maximum effective mass	Selected mode shape and component
Mülheim-Kärlich	1	1.36E-12	1.68E-13		
	2	**5.41E-10**	1.47E-10	**5.41E-10**	Mode 2 – U1
	3	2.85E-10	5.32E-10		

Two damage cases, one at a time, were simulated by reducing the 10% of the Young's modulus at a small area in the upper section and the bottom section of the cooling tower, as shown in Fig. 4 to demonstrate the ability of proposed damage detection method. As described above, effective masses corresponding to first three global modes (1st, 3rd, and 5th mode shapes in general) are extracted from the intact finite model, as shown in Table 1. The mode and mode shape component (Mode 2 - U1) corresponding to maximum effective mass values is selected for the damage detection process. Figs.5 and 6 clearly show the significant increase of DIs at the damage locations in the upper and lower sections of the hyperbolic cooling tower.

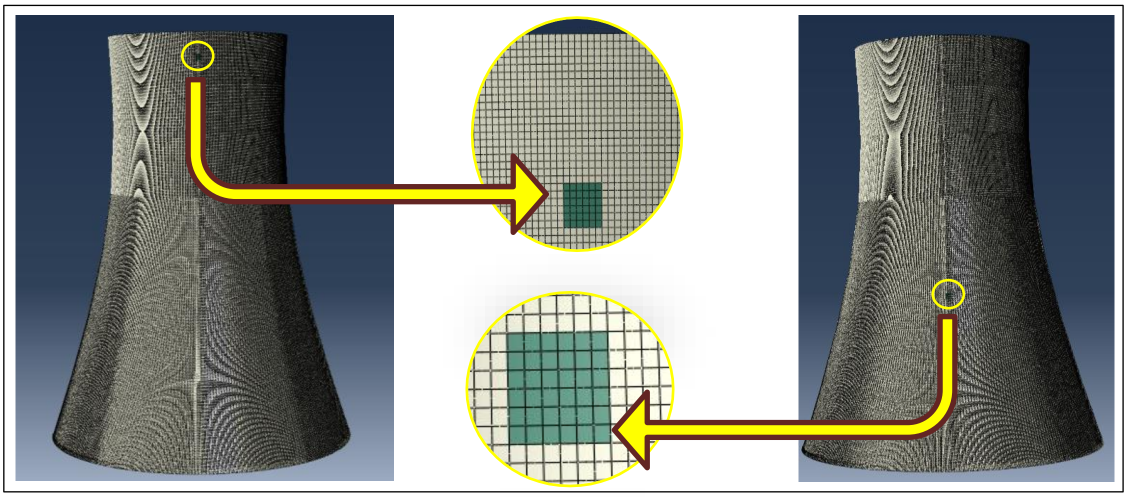

Fig.4. Two damage scenarios of hyperbolic cooling tower

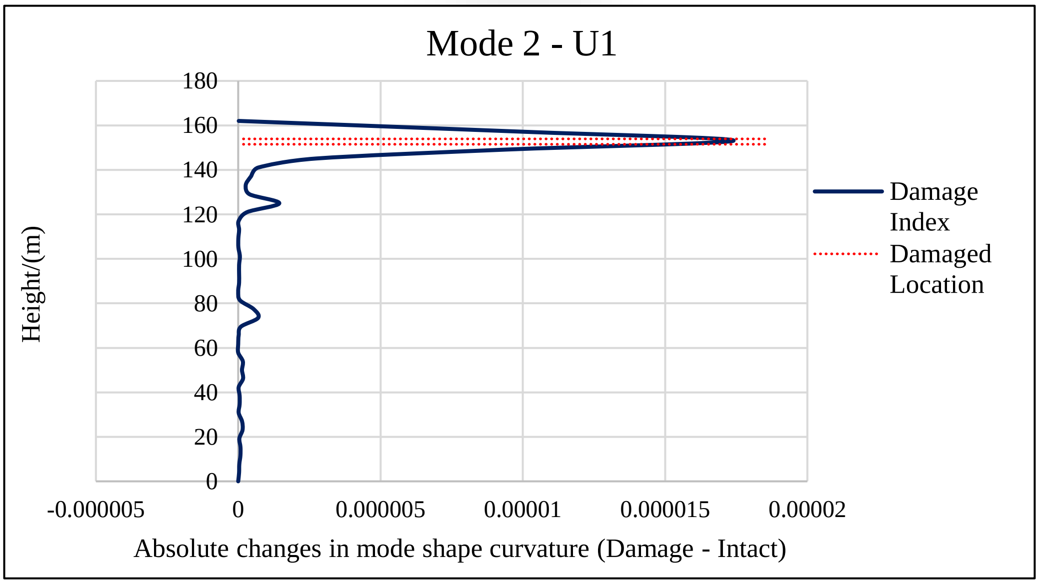

Fig. 5. Results of locating damage between the neck and the upper section of Mülheim-Kärlich cooling tower

These results demonstrate that the proposed method is able to detect and locate damage in hyperbolic cooling towers as shown in Figs 5 and 6. Figs. 7,8 and 9 show the plots of the damage index (ACMSC) at three different locations for different damage intensities. It is evident from these figures that the intensity of damage at a location is proportional to the peak of the damage index at that location. This paper therefore explores the use of regression analysis to quantify damage and then due to its limitation, it develops and applies Artificial Neural Networks (ANNs) to extend the damage assessment procedure to quantify (or predict damage severity) under field conditions and thereby complete damage assessment in hyperbolic cooling towers.

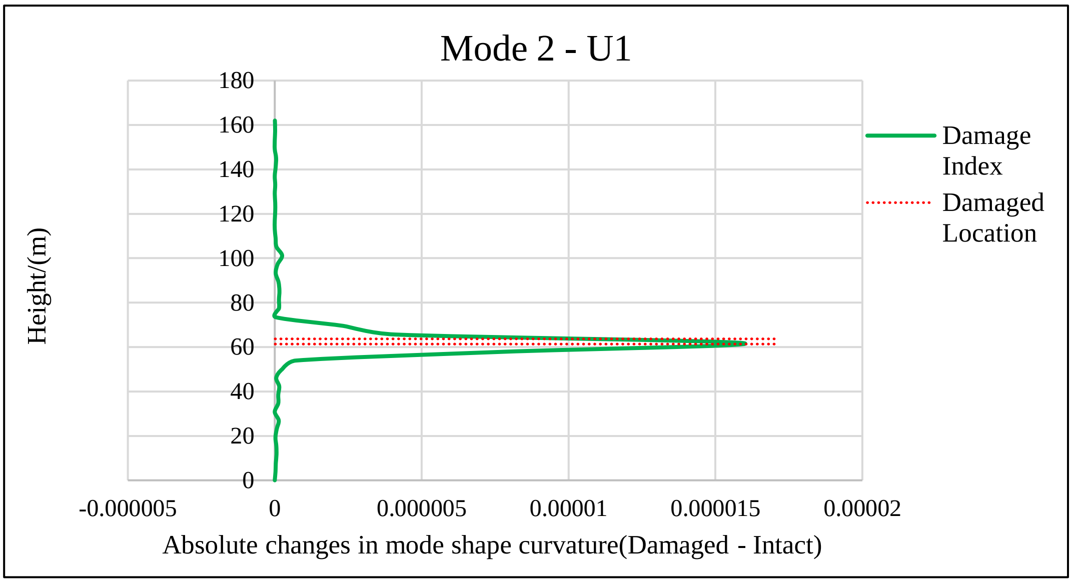

Fig. 6. Results of locating damage between the neck and the bottom section of Mülheim-Kärlich cooling tower

3. Damage quantification

3.1 Damage quantification in hyperbolic cooling towers using linear regression

The Mülheim-Kärlich cooling tower mentioned earlier was selected to test the proposed damage quantification method. As categorized by the Rytter [20], quantifying the severity of the damage is the third level of damage detection in a SHM system. Compared to detecting and locating damage, quantification of damage is quite a challenging task. Most of the procedures for damage quantification are not generic but treat specific simple structures such as beams [10] and trusses [11]. These techniques may not be pertinent for damage quantification in complex structures. To address this issue, this paper first tried using ACMSC based damage indices (DIs) to quantify damage in cooling towers.

As shown in the Figs. 7, 8 and 9, the ACMSC based DIs are plotted along the height of the cooling tower for different damage severities of 10%,15%,20%,25% and 30% (or stiffness reductions). The damage is represented by reducing the Young's modulus of elements in a small area at the particular damage location.

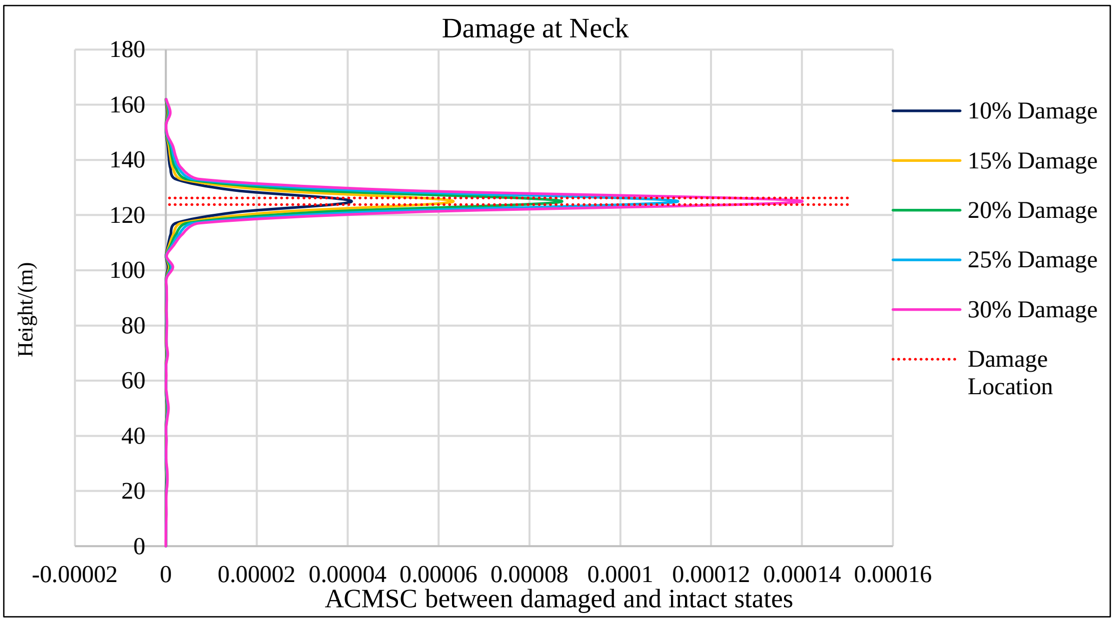

Fig. 7. Plots of DIs based on ACMSC for 10%, 15%, 20%, 25% and 30% damage (stiffness reduction) at the neck of the Mülheim-Kärlich cooling tower

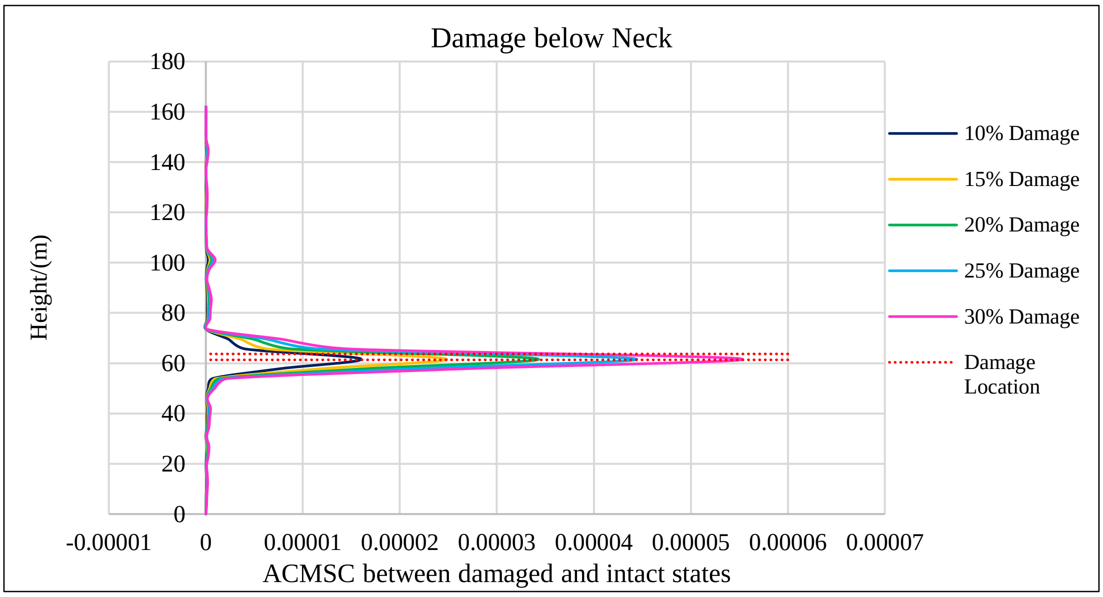

Fig. 8. Plots of DIs based on ACMSC for 10%, 15%, 20%, 25% and 30% damage (stiffness reduction) between the neck and base of the Mülheim-Kärlich cooling tower

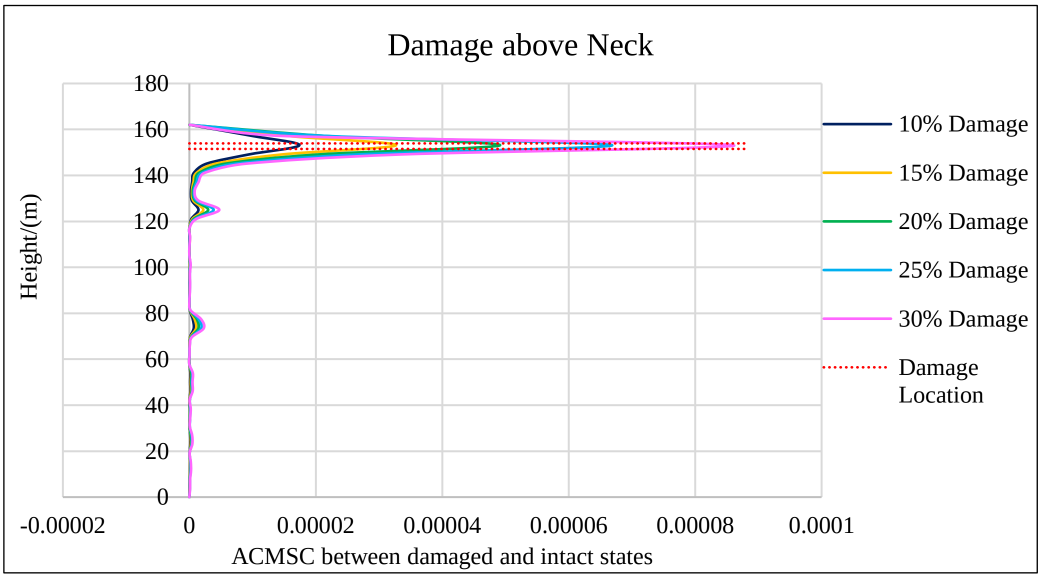

Fig. 9. Plots of DIs based on ACMSC for 10%, 15%, 20%, 25% and 30% damage between the neck and top of the Mülheim-Kärlich cooling tower

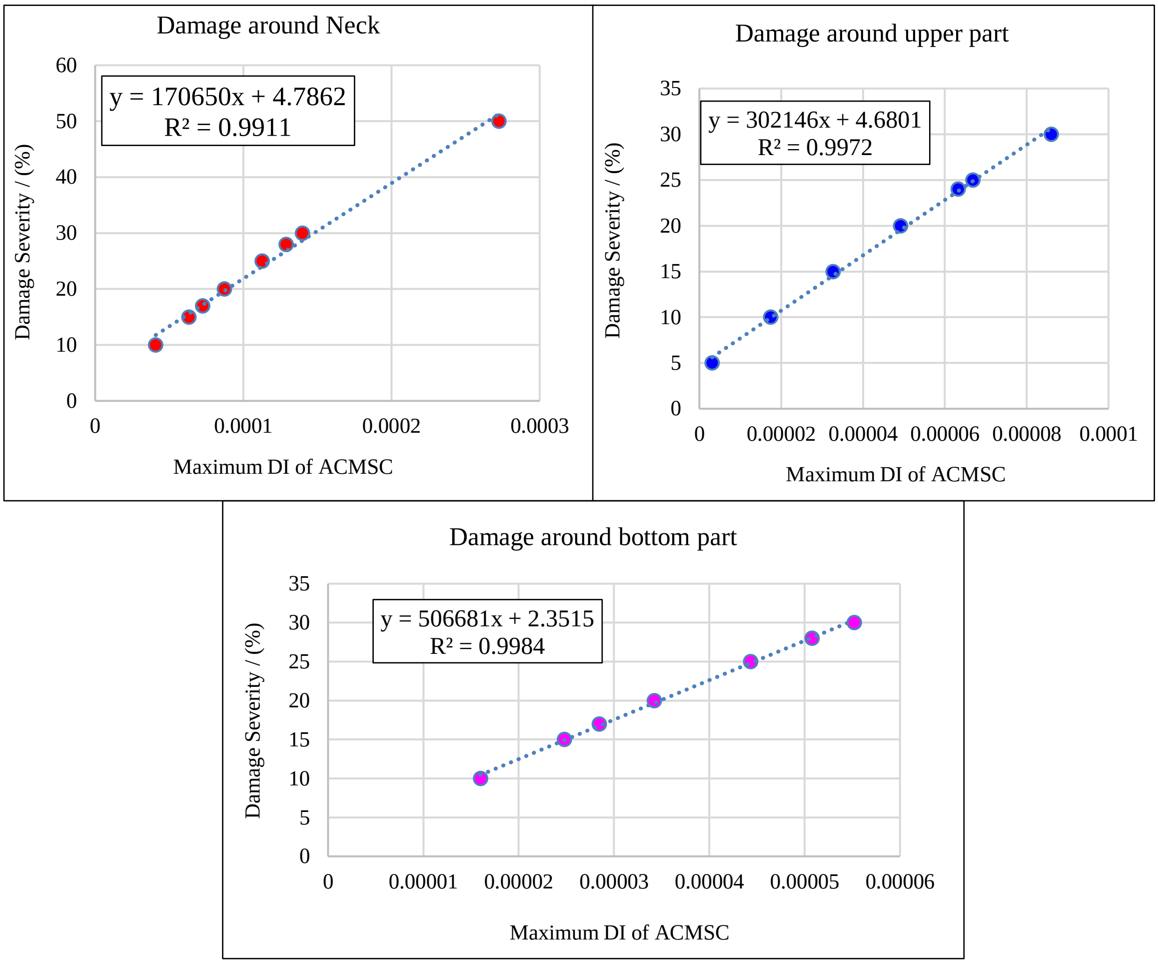

Fig. 10. Plot of maximum DI values of ACMSCs vs percentage stiffness reduction in (a) neck (b) upper part and (c) lower part of Mülheim-Kärlich cooling tower

As seen from these Figures the maximum values of the DIs, at a particular damage location seem to vary linearly with the severity of the damage. Linear regression analysis was therefore used to develop an the equation for damage quantification in hyperbolic cooling towers. A set of equations was developed for the three different locations, as shown in Figs. 10 (a),(b) and (c). In this process, the damaged location has to be determined first using ACMSC method and then maximum DI value of ACMSC in that nodal path can be applied to the relevant equation to calculate damage severity as shown in Table 2. These equations unfortunately are not capable of quantifying damage when DIs are calculated in the presence of noise.

Table 2. Calculation of damage severity using equations

Location	**Absolute damage severity**	**Results obtained from equations**	**Variation**
Damage around neck of the tower	12.5%	13.65%	-1.15%
	22.5%	21.80%	0.70%
	35%	33.70%	1.30%
Damage around neck and upper section of the tower	13%	12.67%	0.33%
	33%	34.39%	-1.39%
	40%	43.80%	-3.80%
Damage around neck and bottom section of the tower	12.5%	12.64%	-0.14%
	22.5%	22.21%	0.29%
	35%	36.28%	-1.28%

Table 2 compares the predicted damage severities at the 3 locations obtained from these equations with the actual damage severities at these locations. It is evident that the errors are quite small making the results quite acceptable.

Fig. 11 shows the plots of the ACMSC based DIs for 20 damage scenarios along the height of the Mülheim-Kärlich cooling tower for 10%,15%, 20%, 25% and 30% damage severities. As shown there, the peak value is location specific. The peak values of DIs curves can be different for two similar damage intensities at different locations. Therefore, these patterns can cause problems when the location and intensity of the damage are not known. To overcome this issue, most researchers have commonly used ANN, generic algorithm, and computational intelligence techniques to quantify the damage severities of the structure [21], [22]. To address the problems with using equations to quantify damage, this paper develops and applies ANNs. These ANNs are trained to detect, locate, and quantify damage in hyperbolic cooling towers using the vibration characteristics (mode shapes) of the cooling tower.

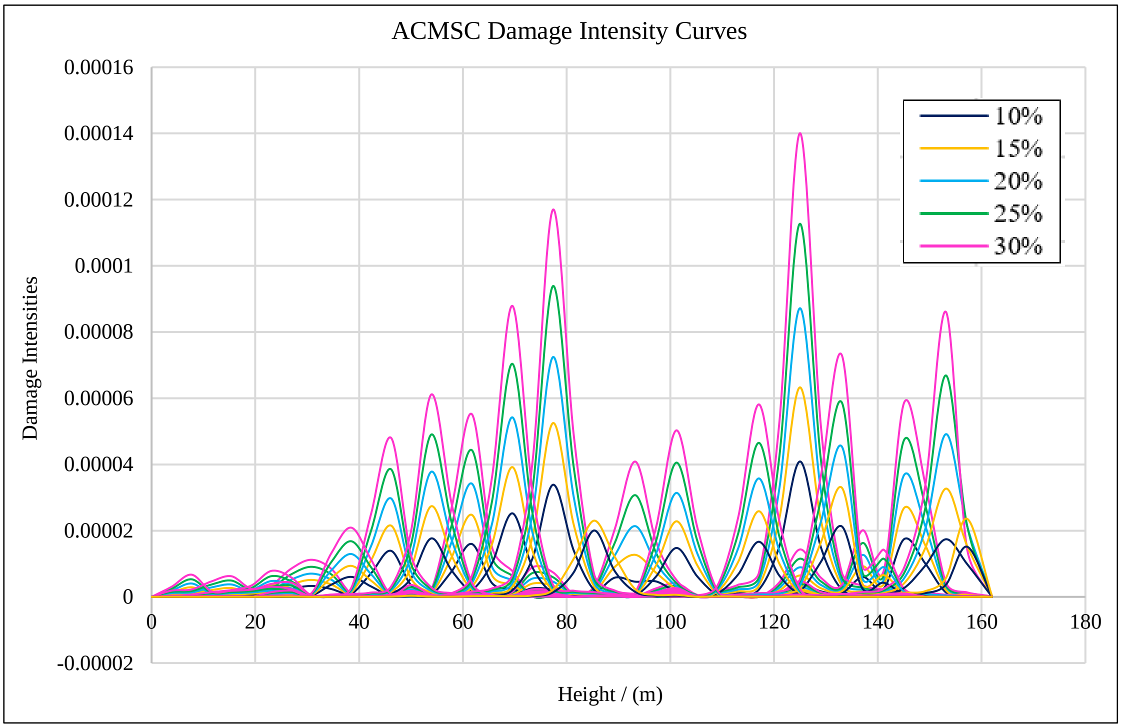

Fig. 11. Plots of DIs based on ACMSC for 10%, 15%, 20%, 25% and 30% damage at different locations in the Mülheim-Kärlich cooling tower

3.2 Damage quantification using Artificial Neural Network (ANN)

3.2.1 Background

Artificial Neural Network (ANN) is a smart and efficient technique that is used to recognise patterns, analyse data, and provide nonlinear control. It is capable of learning the solution to a problem from the set of examples and also it has a high processing speed. The mechanism of the neural network inspires from the biological nervous system. The neuron is the combination of body, axon, dendrites, and synapses. In the biological network, dendrites (input) transfer the signals to the neurons, while axon (output) carries away the signal from the neurons. Synapses are used to communicate between neurons. Each synapse has its own strength which is similar to the weight used in the neural network [23].

The concept of the neural network was introduced by McCulloh and Pitts in 1943 [24]. The structure of the ANN is the combination of three layers which are the input layer, the output layer and one or more hidden layers. Each layer has a number of processing units called neurons. All the inputs are fed to the network through the input layer (i), which is the first layer of ANN, as shown in Fig. 12, while the last layer, which is called the output layer (k), gives the outputs.

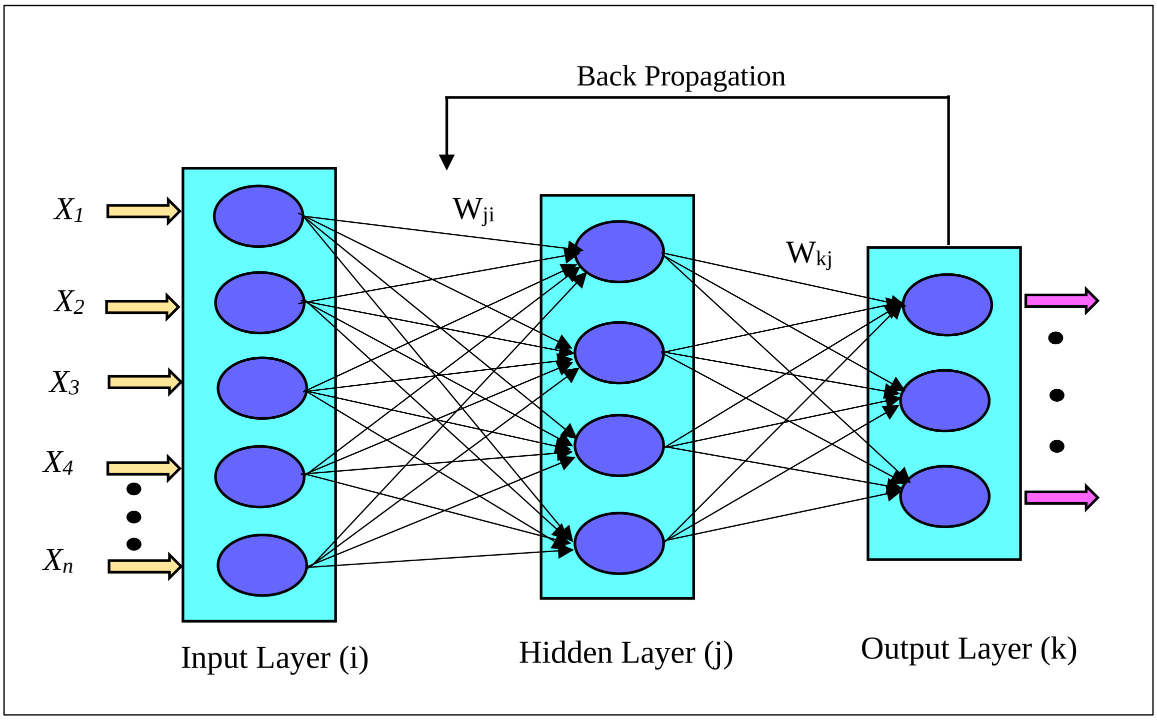

Fig. 12: Neural network architecture

A single neuron is a nonlinear function that transforms a set of input variables into output variables. The transformation process of the McCulloh and Pitts model can be presented, as shown in Equation 3. The input variables (x_i) are multiplied by the weights (w_{ji}) and then added to all the other weighted input variables to give a total input to a resultant unit. In Equation 3 w_{j0} is the bias which corresponds to the firing threshold in a biological neuron. The net input value in the hidden layer (z_i) is processed using linear or nonlinear activation function (g) as shown in Equation 4. The output from the hidden layer (z_j) is considered as the input of the output layer. The final output (z_k) can be written, as shown in Equation 5.

$$z_i(x) = \sum_{i=1}^{n} w_{ji} x_i + w_{j0} \tag{3}$$

$$z_j(x) = g\left(\sum_{i=1}^{n} w_{ji} x_i + w_{j0}\right) \tag{4}$$

$$z_k(x) = g\left(\sum_{j=1}^{m} w_{kj}\, g\left(\sum_{i=1}^{n} w_{ji} x_i + w_{j0}\right) + w_{k0}\right) \tag{5}$$

Neural network training is performed by changing the weights and bias parameters to obtain the predefined targets (t_k). The total error (E) can be calculated from the average squared difference between outputs and targets, as shown in Equation 6.

$$E = \frac{1}{2}\sum_{k=1}^{m} (t_k - z_k(x))^2 \tag{6}$$

A feed-forward neural network having one hidden layer with the backpropagation learning technique is used to train the network in the present study. This feed-forward network consists of three layers which include input, hidden and output layers. The network input is connected to the first layer and each subsequent layer is connected to the one before it. The final layer produces the output of the network. Feed-forward networks are the ones in which the information moves through layers in only one direction, i.e., from the input layer to the output layer through hidden layers. Backpropagation belongs to supervised learning, which used the known behaviour to train the network. The error term is backpropagated to alter the weights and the bias to obtain the optimum network, as shown in Fig. 12 [25]. It is necessary for a network to have adequate training.

In the present study, ANN was developed to predict the damage severity in a hyperbolic cooling tower. The absolute changes in mode shape curvature (ACMSC) based damage index was used as the input for the ANN network instead of mode shape values to avoid overfitting and reduce the computational effort. Also, lessor data can be used for input of the network to train the network.

The selection of ANN architecture is mainly based on trial and error because there is no theoretical procedure [26]. Neural network architecture consists of different key features such as type of neural network, number of hidden layers, number of hidden neurons, learning algorithms, transfer functions and convergence algorithm.

This paper used the multilayer feed forward network with backpropagation algorithm in MATLAB 2018a to learn the relationship between inputs and outputs. The number of hidden layers and the number of hidden neurons depend on the complexity of the problem and the amount of noise [27]. Insufficient selection of hidden layers will cause large training and generalisation errors. The selection of the convergence algorithm depends on the complexity, size of the training set and the number of input parameters in the neural network. Convergence algorithm has different performance speed, memory requirements and different efficiencies. In this paper, optimum convergence was achieved by using Bayesian Regularization (trainbr) as a training algorithm. This algorithm typically requires more time to train, but it gives good generalization for complicated, limited, or noisy data sets. Regularization method [28], early stopping method [29] and Pruning [30] are the few methods which can be used to minimise overfitting and increase the generalization capacity of the training network. The training function (trainbr) usually works well with the early stopping method and hence in this paper, the early stopping method [31], which is also easy to handle, is used to terminate the training process. The termination of the training process was done manually.

3.2.2 Data extraction from numerical model

Mülheim-Kärlich cooling tower in Germany mentioned earlier was studied for damage assessment using ANN. A validated FEM model of this cooling tower was used to create the input data for ANN. Capability of detecting and locating damage in the Mülheim-Kärlich cooling tower using the DIs based on ACMSC has been presented in section 2.1.

This time damage is simulated by reducing the Young's modulus in 20 different locations along the height of the cooling tower for a range of damage severities (5%, 10%, 15%, 17%, 20%, 24%, 25%, 28%, 30%, 50%). Mode shape data are extracted from the intact and damaged structures using the validated FE model. Mode shape data generated from the FEMs are free from noise. But in practice vibration responses of the structure are polluted with environmental and measurement noise. Therefore, field testing conditions are simulated by adding white Gaussian noise [32],[33] and with limited data points. Adding noise not only reduces the overfitting but can also be used for faster optimization. Adding artificial noise into the input data set is one way of improving the generalization error, and it also improves the robustness of the model [34]–[36]. Moreover, adding noise also expands the size of the data set, which is used for training. Equation 7 [33] was used to create noise-contaminated mode shape data by changing the random noise level ($\boldsymbol{\rho_x^{\varphi}}$) by 2%, 5%, 10%, 15% and 20%.

$$\overline{\emptyset_{xi}} = \emptyset_{xi}\left(\mathbf{1} + \boldsymbol{\gamma}_{\mathrm{x}}^{\boldsymbol{\varphi}}\boldsymbol{\rho}_{x}^{\boldsymbol{\varphi}}\left|\emptyset_{max,i}\right|\right) \tag{7}$$

In the above equation, $\overline{\emptyset_{xi}}$ and $\emptyset_{xi}$ denote the mode shape values with and without noise at the location of x in the ith mode. $\boldsymbol{\gamma}_{\mathrm{x}}^{\boldsymbol{\varphi}}$ is a random number with a variance equal to 1and mean equal to zero. |Ø_(max,i) | denotes the absolute maximum mode shape value.

3.2.3 ANN model architecture

All the extracted mode shape data are converted to DIs using Equation 2 to create the input data for the neural network. Damage severity and location are used as the target values for the neural network.

Altogether 612 data samples are used to train the network. A higher number of input data will increase the accuracy of the outcome. The number of input and output nodes depends on the number of variables in input and output data sets. A trial and error process was used to find the number of neurons in the hidden layer. After finding the best network configuration, few trials were carried out to acquire the best network with minimum error. This was been done because each network assigns different weights and sampling, which will create different networks. The input data is divided into three sets, namely training (75%), testing (20%) and validation (5%). Training data set is used during the training to adjust its error while the validation set is used to measure network generalization. Testing data set has no effects on training, but they are used to measure the performance of the network during and after training.

The neural network shown in Fig. 13 has one hidden layer which contains 24 hidden neurons. Letters ‘w’ and ‘b’ refer to the weight and bias, respectively. The training function of the network is Bayesian Regularization (trainbr), while the transfer function of the hidden layer is the hyperbolic tangent sigmoid function. Performance of the trained neural network can be evaluated using mean square error (MSE) and regression analysis. Regression plots of trained neural network are presented in Fig.14 in which the regression value (R) represents the correlation between output and targets. The value close to 1 means, it has a close relationship while 0 means random relationship. The overall values of R (0.99274) confirm that the network is properly trained. These graphs illustrate the variation of target values (FEM results) vs ANN outputs. As shown in Fig.14, the best fit line of the trained network overlaps with perfect fit line (Y=T). MSE is the average squared difference between outputs and targets. MSE value of this trained network is 0.0289. Moreover, the error histogram Fig. 15, shows the variation of error between targets and outputs for training and testing stages of NN. In most instances these are at zero line.

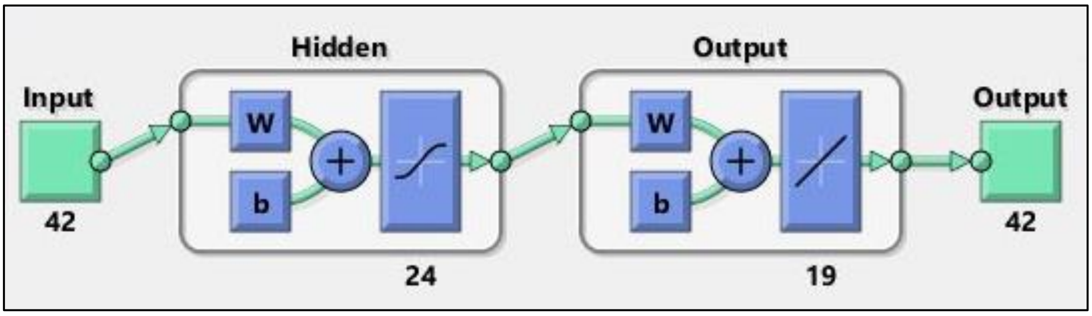

Fig. 13. Neural network configuration

Once the network is trained, it can be used to predict the location of damage and the severity of the damage in unknown scenarios.

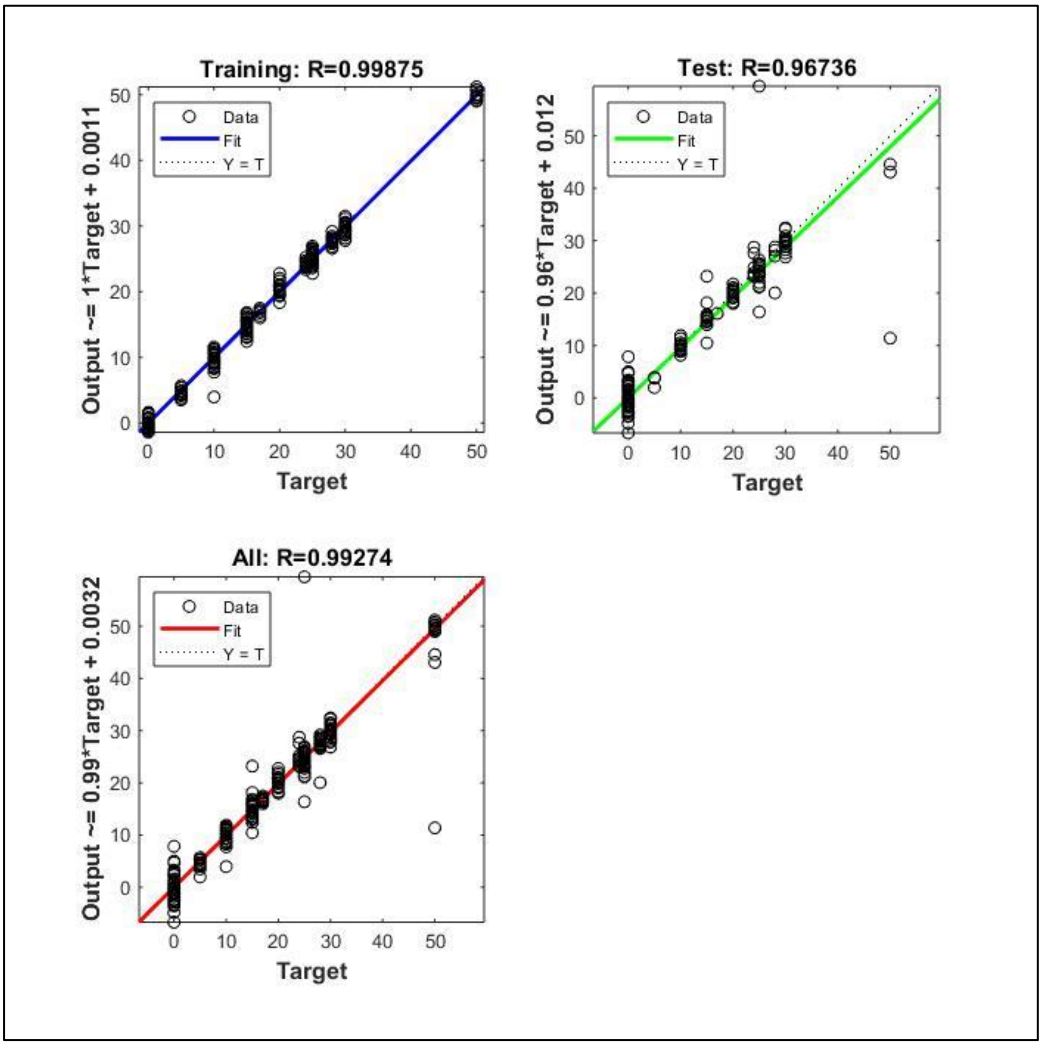

Fig. 14. Regression plots of trained Neural Network

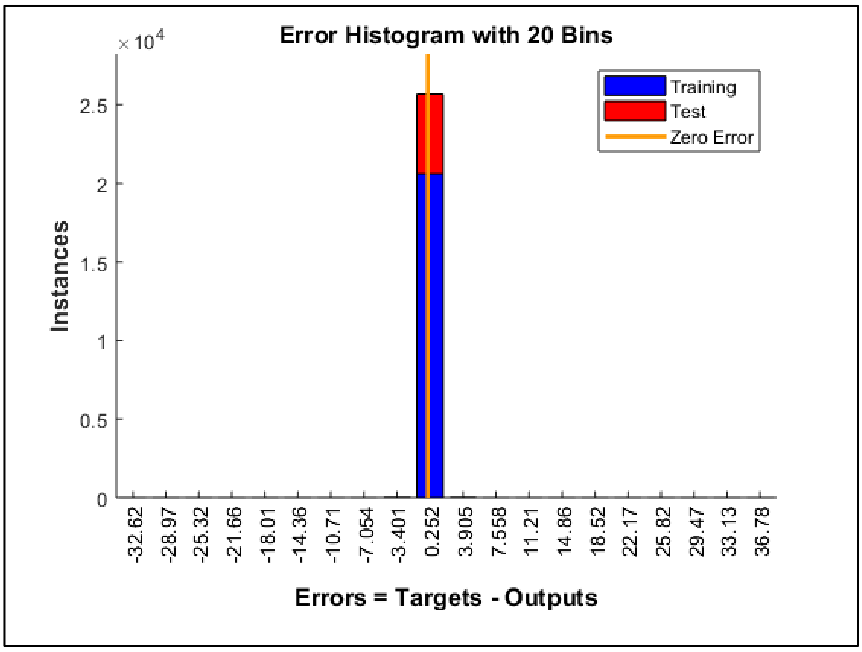

Fig. 15. Error histogram

4. Results and Discussion

4.1 Single Damage Scenarios

The developed ANN is used to predict the location and severity in unknown damage cases. Seventy-five damage cases corresponding to 12 locations, 12 severities and 10 noise levels are simulated in the FEM of Mülheim-Kärlich cooling tower and mode shape data corresponding to each damage case are extracted. As the next step, DI values of unknown damage cases are calculated using Equation 2. These DIs are fed into the trained neural network in order to test its ability to locate and quantify damage. The capability of the network is tested considering five types of unknown damage cases as follows.

(i) DIs calculated from different damage severities under different noise conditions

(ii) DIs calculated from different damage severities at different locations with respect to height and circumference at that height

(iii) DIs calculated from different damage severities with the same noise

(iv) DIs calculated for same damage severity, but with different noise conditions

(v) DIs calculated for zero damage severity

4.1.1 DIs calculated from different damage severities under different noise conditions

Each of these damage scenarios are different, and none of these damage severities and noise conditions were used to train the network. Table 3 shows the damage cases tested on the trained neural network with actual damage severities and neural network predictions. It can be seen that the variation between two actual and predicted severities (in columns 3 and 5) is less than 2.2%. This confirms that the trained neural network (NN) is capable of accurately predicted different damage severities even under different noise conditions. Figs 16 (a), (b), (c), and (d) show the graphical representation of few cases in Table 3. It can be seen that the actual and predicted damage severities match reasonably well.

Table 3. Neural network predictions for different damage severities with different noise conditions

Damage case	**Actual Damage**			**NN Prediction**		**Variation**
	Noise	Severity	Location	Severity	Location	
1	0%	13%	H_i=30.79 m	13.18%	H_i=30.79 m	-0.18%
2	0%	13%	H_i=133 m	12.92%	H_i=133 m	0.08%
3	0%	33%	H_i=153.2 m	32.88%	H_i=153.2 m	0.12%
4	0%	33%	H_i=93.27 m	33.37%	H_i=93.27 m	-0.37%
5	0%	40%	H_i=153.2 m	40.83%	H_i=153.2 m	-0.83%
6	0%	55%	H_i=125 m	54.39%	H_i=125 m	0.61%
7	3%	13%	H_i=30.79 m	13.73%	H_i=30.79 m	-0.73%
8	3%	13%	H_i=93.27 m	13.59%	H_i=93.27 m	-0.59%
9	3%	13%	H_i=153.2 m	13.66%	H_i=153.2 m	-0.66%
10	3%	40%	H_i=93.27 m	40.51%	H_i=93.27 m	-0.51%
11	4%	13%	H_i=30.79 m	14.27%	H_i=30.79 m	-1.27%
12	4%	33%	H_i=93.27 m	33.17%	H_i=93.27 m	-0.17%
13	4%	33%	Hi=133 m	32.53%	Hi=133 m	0.47%
14	7%	13%	H_i=93.27 m	12.52%	H_i=93.27 m	0.48%
15	7%	33%	H_i=30.79 m	33.18%	H_i=30.79 m	-0.18%
16	7%	40%	H_i=93.27 m	42.16%	H_i=93.27 m	-2.16%
17	12%	13%	H_i=30.79 m	13.01%	H_i=30.79 m	-0.01%
18	12%	13%	H_i=93.27 m	13.67%	H_i=93.27 m	-0.67%
19	12%	33%	H_i=30.79 m	32.78%	H_i=30.79 m	0.22%

20	12%	33%	H_i=93.27 m	33.34%	H_i=93.27 m	-0.34%
21	12%	40%	H_i=93.27 m	41.47%	H_i=93.27 m	-1.47%
22	12%	55%	H_i=125 m	56.58%	H_i=125 m	-1.58%

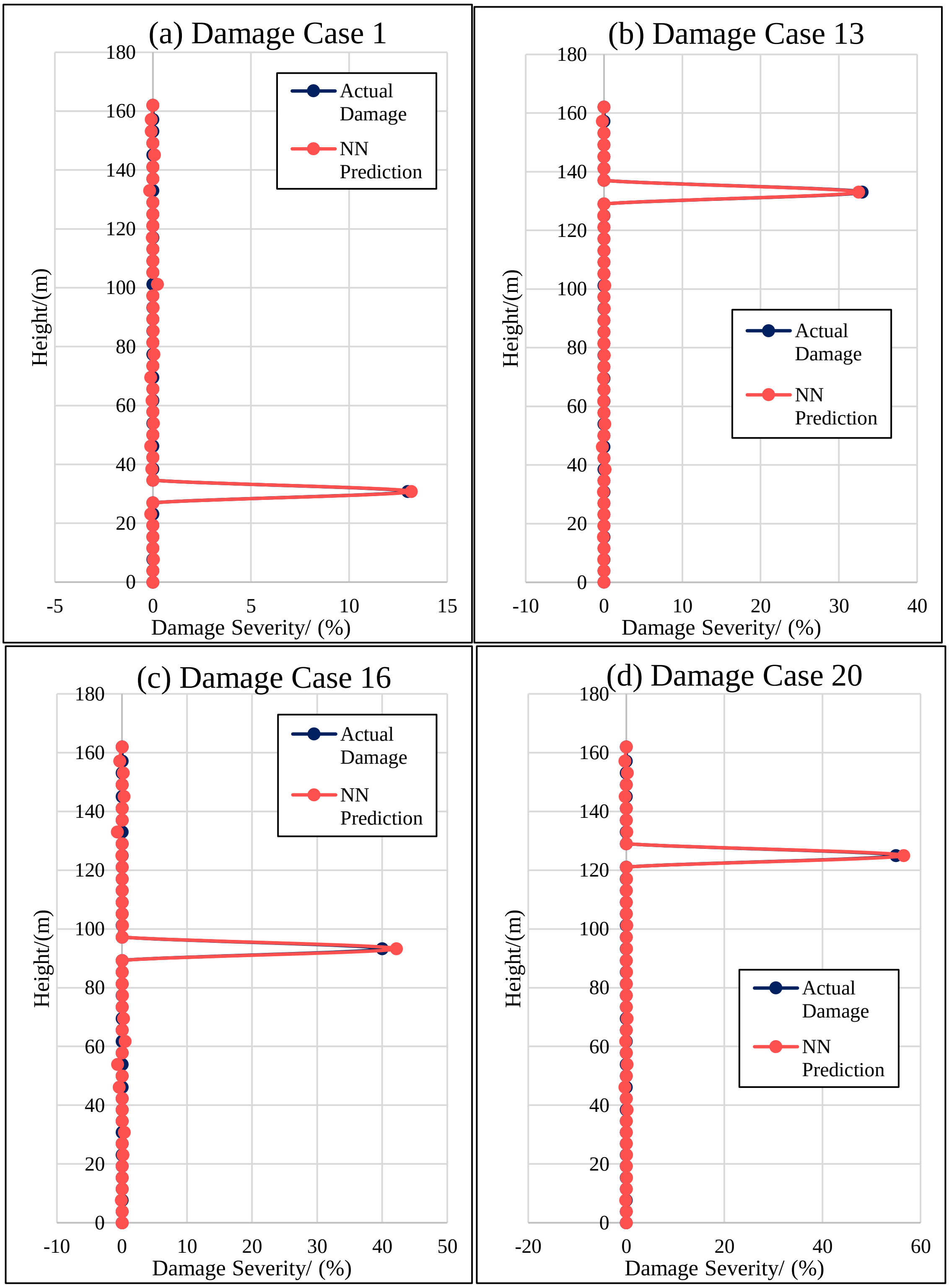

Fig. 16. Graphical representation of few damage cases in Table 3

4.1.2 *DIs calculated from different damage severities at different locations with respect to height and circumference at that height*

In order to test the ability of the trained neural network, unknown damage severity cases at different locations with respect to height and circumference at that height are considered, as shown in Table 4. These damage locations and severity cases are completely random. It can be seen that the variation between the actual and predicted severities (in columns 3 and 5) is less than 2.4 %. This verifies that the trained NN is capable of determining other damage severities and at other locations different from that used in the training.

Table 4. Neural network outcomes for different damage severity with different Locations

Damage case	**Absolute Damage**			**NN outcome**		**Variation**
	Noise	Severity	Location	Severity	Location	
1	0%	52%	Hi=92.8 m	54.4%	Hi=93.2 m	-2.4 %
2	0%	23%	Hi=69.55 m	23.8%	Hi=69.55 m	-0.8 %
3	0%	45%	Hi=125 m	45.8%	Hi=125 m	-0.8 %
4	3%	18%	Hi=46.8m	16.44%	Hi=46.2 m	1.56 %
5	3%	23%	Hi=69.55m	22.15%	Hi=69.55 m	0.85 %
6	4%	52%	Hi=92.8m	52.7%	Hi=93.2 m	-0.7 %
7	4%	23%	Hi=124.2m	20.7%	Hi=125 m	2.3 %
8	7%	18%	Hi=46.8m	18.6%	Hi=46. 2m	-0.6 %
9	7%	45%	Hi=125m	44.72%	Hi=125m	0.28 %
10	7%	23%	Hi=69.55m	23.17%	Hi=69.55m	-0.17%

4.1.3 *DIs calculated from different damage severities with same noise conditions*

In order to test the ability of the trained neural network, unknown damage severity cases with the same noise conditions are tested, as shown in Table 5. These damage severity cases are completely random. Same noise conditions which are used to train the network are used to train the network. It can be seen that the variation between the actual and predicted severities (in columns 3 and 5) is less than 2.2%. This verifies that the trained NN is capable of determining new damage severities even under the same noise conditions.

Table 5. Neural network outcomes for different damage severities with same noise conditions

Damage case	**Absolute Damage**			**NN outcome**		**Variation**
	Noise	Severity	Location	Severity	Location	
1	0%	12.5%	H_i=61.73 m	11.72%	H_i=61.73 m	0.78%
2	0%	12.5%	H_i=145.1 m	11.87%	H_i=145.1 m	0.63%
3	0%	22.5%	H_i=125 m	22.24%	H_i=125 m	0.26%
4	0%	35%	H_i=125 m	35.12%	H_i=125 m	-0.12%
5	2%	12.5%	H_i=61.73 m	12.40%	H_i=61.73 m	0.1%
6	2%	22.5%	H_i=145.1 m	22.2%	H_i=145.1 m	0.30%
7	2%	22.5%	H_i=61.73 m	22.18%	H_i=61.73 m	0.32%
8	2%	35%	H_i=125 m	34.24%	H_i=125 m	0.76%
9	5%	12.5%	H_i=145.1 m	12.57%	H_i=145.1 m	-0.07%
10	5%	22.5%	H_i=61.73 m	22.92%	H_i=61.73 m	-0.42%
11	5%	35%	H_i=125 m	36.20%	H_i=125 m	-1.20%
12	5%	35%	H_i=145.1 m	33.60%	H_i=145.1 m	1.40%
13	10%	12.5%	H_i=61.73 m	13.26%	H_i=61.73 m	-0.76%
14	10%	12.5%	H_i=125 m	14.67%	H_i=125 m	-2.17%
15	10%	22.5%	H_i=145.1 m	22.76%	H_i=145.1 m	-0.26%
16	10%	35%	H_i=145.1 m	35.87%	H_i=145.1 m	-0.87%
17	15%	12.5%	H_i=61.73 m	12.44%	H_i=61.73 m	0.06%
18	15%	12.5%	H_i=145.1 m	12.24%	H_i=145.1 m	0.26%
19	15%	22.5%	H_i=125 m	24.54%	H_i=125 m	-2.04%
20	15%	35%	H_i=145.1 m	35.65%	H_i=145.1 m	-0.65%
21	20%	12.5%	H_i=125 m	11.31%	H_i=125 m	1.19%
22	20%	12.5%	H_i=61.73 m	12.36%	H_i=61.73 m	0.16%
23	20%	22.5%	H_i=125 m	24.37%	H_i=125 m	-1.87%
24	20%	35%	H_i=145.1 m	33.36%	H_i=145.1 m	1.64%

4.1.4 DIs calculated from same damage severity, but with different noise conditions

The capability of locating and quantifying damages in the cooling tower is also tested for the same damage severity (which was used for training the network), but under different noise conditions. Results are shown in Table 6, where the variation in percentage severity between actual predicted values (in columns 3 and 5) is less than 1.75%. This trained neural network is therefore capable of detecting damage severity even in the presence of different noise conditions.

Table 6. Neural network outcomes for same damage severity, but with different noise conditions

Damage case	**Absolute Damage**			**NN outcome**		**Variation**
	Noise	Severity	Location	Severity	Location	
1	3%	5%	Hi=30.79 m	4.43%	Hi=30.79 m	0.56%
2	3%	5%	Hi= 153.2 m	4.99%	Hi= 153.2 m	0.01%
3	3%	24%	Hi=93.27 m	22.26%	Hi=93.27 m	1.74%
4	3%	24%	Hi=133 m	25.55%	Hi=133 m	-1.55%
5	4%	5%	Hi=30.79 m	4.37%	Hi=30.79 m	0.63%
6	4%	5%	Hi=93.27 m	5.23%	Hi=93.27 m	-0.23%
7	4%	24%	Hi=133 m	25.53%	Hi=133 m	-1.53%
8	4%	24%	Hi= 30.79 m	25.35%	Hi= 30.79 m	-1.35%
9	7%	5%	Hi=30.79 m	5.04%	Hi=30.79 m	-0.04%
10	7%	5%	Hi=93.27 m	5.01%	Hi=93.27 m	-0.01%
11	7%	24%	Hi=133 m	22.59%	Hi=133 m	1.41%
12	7%	24%	Hi= 153.2 m	23.25%	Hi= 153.2 m	0.75%
13	12%	5%	Hi=30.79 m	5.35%	Hi=30.79 m	-0.35%
14	12%	5%	Hi= 153.2 m	4.90%	Hi= 153.2 m	0.10%
15	12%	24%	Hi=93.27 m	24.68%	Hi=93.27 m	-0.68%
16	12%	24%	Hi= 133 m	24.92%	Hi= 133 m	-0.92%

4.1.5 DIs calculated from zero damage severity

The trained artificial neural network is tested using the DIs calculated from locations where the damage does not exist (zero damage severity). The results are presented in Table 7. The variation of percentage severity between actual and predicted values is less than 0.15%. This trained neural network therefore will not capture false alarms.

Table 7. Neural network outcome for zero damage severities

Damage case	Location	Actual Damage Severity	NN outcome	Variation
1	Hi=46.17 m	0%	0.11%	-0.11%
2	Hi=30.79 m	0%	-0.08%	0.08%
3	Hi=30.79 m	0%	0.15%	-0.15%

Conclusions

Hyperbolic cooling towers are large, reinforced concrete structures used to cool wastewater. Though they are designed to have long lives, damage can occur due to one of many reasons. Such damage must be detected and assessed at the outset to enable appropriate retrofitting and prevent the collapse of these large structures. Due to their unique shape, hyperbolic cooling towers have rather complex vibration characteristics. Traditional vibration-based methods are hence not applicable to detect, locate and quantify damage in them. This paper developed and presented a method incorporating artificial neural networks together with the absolute change in mode shape curvature-based DIs for locating and quantifying damages in hyperbolic cooling towers. The proposed method includes the input data using absolute mode shape curvature method, network architecture, network training and validation processes. The feasibility of the trained neural network was illustrated through its application to several damage scenarios, even in the presence of noise polluted data. Results confirm the accuracy of the proposed method. The outcome of this paper will help towards the safe efficient functioning of hyperbolic cooling towers.

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The raw data required to reproduce these findings cannot be shared at this moment as these data also forms a part of ongoing research

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