International Journal of GEOMATE, June., 2021, Vol.20, Issue 82, pp.46-52
ISSN: 2186-2982 (P), 2186-2990 (O), Japan, DOI: https://doi.org/10.21660/2021.82.Gx293
Geotechnique, Construction Materials and Environment

DAMAGE PREDICTION OF THE STEEL ARCH BRIDGE MODEL BASED ON ARTIFICIAL NEURAL NETWORK METHOD

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*Corresponding Author, Received: 30 Nov. 2020, Revised: 12 Jan. 2021, Accepted: 07 Mar. 2021

ABSTRACT: Failure in the advance prediction of bridge structure collapse requires an enormous cost of rehabilitation. In most cases, the projection of decreases or damage to the structure due to difficulty in the testing condition. Therefore, this study analyses the damage and identification of the critical structural components' severity on the steel girder arch bridge. Using the Artificial Neural Networks (ANNs), this research has tested a parametric steel girder arch bridge. The numerical model of the 146 supported girder has analysed by epoch 500 values of ANNSs's parameter. The stiffness of 10th element is assumed to drop 10%, 20%, 30%, and 40% of whole the tested. The architecture model of ANNs was three neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer. The simulation of the data set were 90:10, 80:20, 70:30, and 50:50. ANNs shows the damage' severity in this the stiffness reduction tested by applying the damage index methods. In this research, the ANNs' simulation has been reliable to predict 98% for identifying structural damage. Thus, the results confirm the feasibility of the technique and its application in predicting structural failure.

Keywords: Artificial Neural Network, Damage Assessment, Damage Index, Reduction Stiffness

1. INTRODUCTION

Deterioration of the bridge structure during service will cause damage and even collapse because of vehicle load overloading, fatigue on these structural elements, earthquake occurrences outside of planned predictions, and large wind loads[1]. In Riau province, several bridges have deteriorated. Based on the assessment carried out by the Bridge Management System (BMS) method on several bridges that have critical values, the Merangin Bridge, S. Jangkang Bridge, Parak Suak Buaya Bridge, and the Darauf Parit Bridge are most vital in the upper structure. Meanwhile, the Siak II Bridge condition is severely damaged, consisting of severely damaged buildings, a heavily damaged floor, a slightly damaged lower part of the building, and a little damaged watershed. Of the 114 bridges that exist, this bridge requires handling in the form of rehabilitation and repair [2].

The bridge must prevent Deterioration. A method of monitoring a bridge is needed to predict at any time so that maintenance can be done early and prevent sudden collapse. Bridge condition assessments developed Several techniques, such as BMS and Fracture Critical Member (FCM)[3,4]. However, the method has not shown satisfactory results because people cannot monitor the real conditions of bridge structure behaviour in detail. In recent times, the Artificial Neural Network (ANN) method is one way that has ascertained to be able to monitor bridge behaviour directly.

ANN is an excellent tool for recognizing patterns in data [5]. This method can predict and evaluate the condition of the bridge structure due to various factors. Damage can be expressed by several parameters and by several aspects such as tenacity, lost hysteretic energy, stiffness [4].

Research shows good results where neural networks with one hidden layer can help predict stability and health conditions at particular times [6-8]. Research on the application of ANN on the box girder concrete bridge has been carried out [9]. The various bridge models success above requires developing this ANN method on other bridges, such as the type of curved steel frame in this study. The proposed health monitoring of curved steel structure bridges in a disaster early warning system reduces casualties.

In this research, the case study used the Siak III bridge with a steel arch bridge type. The arch bridge is a bridge with a high level of difficulty of implementation. Based on field testing and visual observation. The Siak III Bridge camber has been negatively in the centre position. The position of the camber significantly affects the deflection value of the bridge structure. The camber should be positive (convex). But the negative camber (concave) looks. Deflection is an essential factor calculated to determine the bridge's level of use (serviceability) and predict [10]. A deflection is analyzing with a neural network system. Health monitoring of arch steel structure bridges with ANN will be carried out in this study so that the proposal in the disaster early warning system sought to reduce casualties.

This study also develops a damage index procedure to predict the location and severity of steel beams. The implementation is not as visual as the bridge scoring system because of inaccuracy due to improper testing or tools. However, the procedure conforms to experimental, observational conditions in the laboratory by creating failure scenarios created at several points along the block. The maximum degradation scenario can fully reflect, in this study, stiffness reduction, displacement, and location were considered the most influential parameters. Therefore, ANN can represent the value of the beam condition. The steel arch bridge structure compared to visual monitoring which has weaknesses.

2. LITERATURE REVIEW

2.1 Damage Detection Using Finite Element and Experimental Testing

The displacement, accelerometer, velocity, and location damage apply as inputs of the ANN. Numerical modelling performed using an undamaged bridge. The designed buildings subject to nonlinear pushover analysis followed by NLTHA. To get the structural response due to loading from the accelerograms to cannot finish. Direct numerical integration for the structure as a couple of equations is the basis of Time History analysis, where the general integration method used is the Newmark method. The SNI 1726: 2012 earthquake requires that at least three suitable ground motions must operate in the analysis. The location conditions, geology, topography, and seismotectonic are selected according to the location. Where the building structure under review locates, this is to reduce uncertainty regarding site conditions. So at least three accelerograms from 3 different earthquakes must be reviewed.

The earthquake load used is a record of the Pekanbaru data Modified with the Kobe earthquake response from Seismosoft Earthquake Engineering Software[11]. SAP 2000 is a structural computer program that can predict damage severity on non periodically [9]. In the first stage, numerical modelling performs using an undamaged bridge to obtain the displacements, accelerometer, velocity, and location damage. Damage index of structure based on structural performance levels in FEMA 356.

Each group has a wide range, which can be defined by individual structure owners. In the system, IO, LS, and CP are denoted by indexes 1, 2, and 3 [5]. On the other, the methods to predict damage indexed using Park Ang Methods can indicate the level of damage structures [12].

Experimental testing is needed to determine the behaviour of the bridge girder. Damage to steel beam is the percentage reduction in stiffness compared to the first result of steel beam stiffness. The stiffness reduction in the first yield, determine from the data obtained through experimental testing. The value takes the maximum amount of damage to the steel beam [13].

Later, numerous damage scenarios create by introducing different severity of damage at various locations along the bridge girder. The numerical modal analysis will then use as training data for the ANN algorithm [14].

2.2 Damage Index Using Park Ang Methods

Many researchers propose various Damage Index (DI) methods. Researchers have used many Damage Index methods. Based on the available literature. It found that the global damage index method uses multiple response parameters that are suitable for overall evaluation [13]. The type of damage depends on various factors, including tension strength, reduction of stiffness reduction—however, damage assessment with multiples factor, associates with the estimation of reliable wear. The type of damage depends on different factors such as displacement, tensile stress. In this study, the expression of damage has been proposed by considering, namely displacement.

Structural damage reduces stiffness and alters the structure's modal strain energy[12]. The damage index βji for the ‘j’th element and ‘i’th mode of the beam provided in Eq. (1):

$$\beta_{ji} == \frac{\left(\int_j \left[\phi_i^{''*}(x)\right]^2 dx + \int_0^L \left[\phi_i^{''*}(x)\right]^2 dx\right) \int_0^L \left[\phi_i^{''}(x)\right]^2 dx}{\left(\int_j \left[\phi_i^{''}(x)\right]^2 dx + \int_0^L \left[\phi_i^{''}(x)\right]^2 dx\right) \int_0^L \left[\phi_i^{''*}(x)\right]^2 dx} \qquad (1)$$

Or can be written as eq (2):

$$\beta_{ji} = \frac{\left[\left(\phi_{ji}^{''*}\right)^2 + \Sigma\left(\phi_{ji}^{''*}\right)^2\right]\left[\Sigma\left(\phi_{ji}^{''}\right)\right]^2}{\left[\left(\phi_{ji}^{''}\right)^2 + \Sigma\left(\phi_{ji}^{''}\right)^2\right]\left[\Sigma\left(\phi_{ji}^{''*}\right)\right]^2} \qquad (2)$$

where ϕ'' is the mode shape curvature, superscript * refers to the damaged state, and L is the beam length.

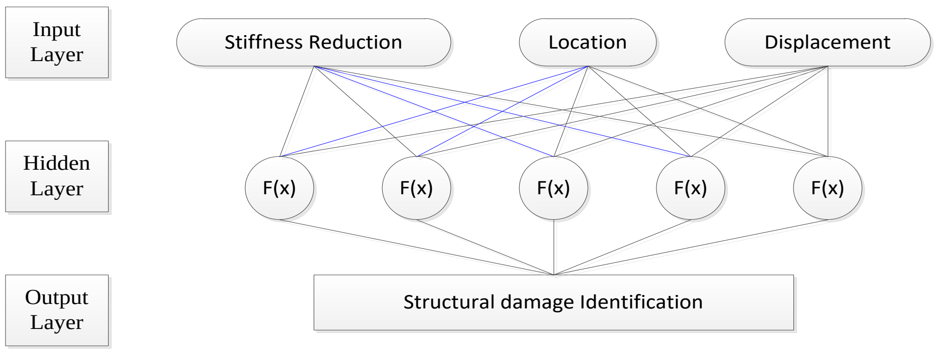


Fig. 1 Architectural Layer of Artificial Neural Network

2.3 Damage Detection Using Artificial Neural Network

Artificial neural networks (ANN) are derivatives of the biological nervous system. This method has reliability if used to complement the Structural Health Monitoring System (SHMS)[15]. ANN predicted the structural health conditions quickly. Because in the process ANN the workings of the human brain. The image in Fig. 1 shows a typical network of 3 perceptron layers.

The output parameter of the ANN is the damage index (DI), representing the severity of the damage. The architectural neural network layer uses many layers with backpropagation type. Information processing consists of interconnected elements (neurons) that work simultaneously (Fig. 1). These neurons consist of input layers, hidden layers, output layers. The pattern of neo-neurons in the network, connecting weights such as training algorithms and activation functions, is a determinant of an ANN reliability of [16].

The training process improves memorization and generalization capabilities, namely the ability of an ANN architecture design to absorb the input data amount and take the learned patterns. In contrast, the ability to generalize is the ability of ANN to make similar patterns learned.

A good model of artificial neural networks shown by the results of a small error rate. The accuracy of damage predictions uses the Mean Square Error (MSE), which offers a value close to zero is an accurate prediction. MSE can calculate to Eq. (3) [17]:

$$RMSE = \sqrt{\frac{\sum(X-Y)^2}{n}} \qquad (3)$$

With:

N = Amount of data
X = Observation Value
Y = Prediction Value

Correlation Coefficient (R) is a comparison of actual values with predictive values. The value of R can calculate to Eq. (4) [17]:

$$R = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \qquad (4)$$

By:
X = X-X '
Y = Y-Y '
X = Value of observation
Y = Prediction Value
X '= Average X value
Y '= Average Y value

3. METHODS

This research consists of the stages of diagnosis, analysis, and verification. The diagnosis and analysis phase have done by entering input data (modelling of structure) into the finite element program to be then used as input data on artificial neural networks with the help of a computer program MATLAB and LUSAS. The model used is the Siak III bridge in Pekanbaru, Indonesia steel arch bridge with 168 m. Bridge structure elements consist of arch rib frame (1200x800mm, tw : 24mm), hanger (100 mm, fy = 490MPa), tie beam (600x600 mm, tw = 24mm), floor beam (400x400 mm, concrete).

The design carries out utilizing the analytical method (NLTHA) carried out in SAP2000. The data is then propagated forward towards the training target through an artificial neural network architecture previously design.

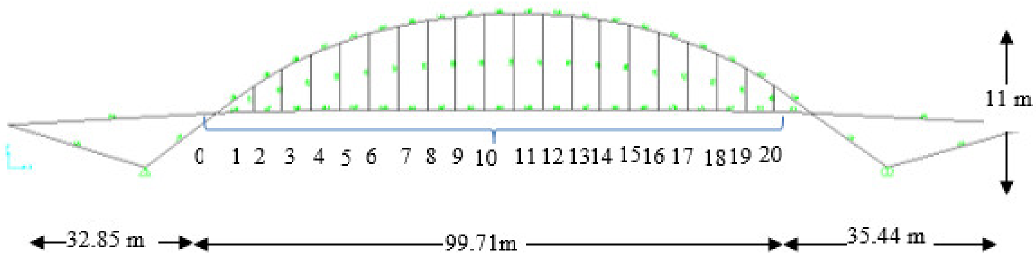


Fig. 2 Longitudinal Cross Section of the Bridge

The earthquake load used is a record of the Pekanbaru data Modified with Kobe, Loma Prieta, and Imperial Valley earthquake response from Seismosoft Earthquake Engineering Software[11]. The design uses the mechanical properties of the steel girder arch bridge (Table 1).

Table 1. Mechanical properties of the Steel Girder Arch Bridge

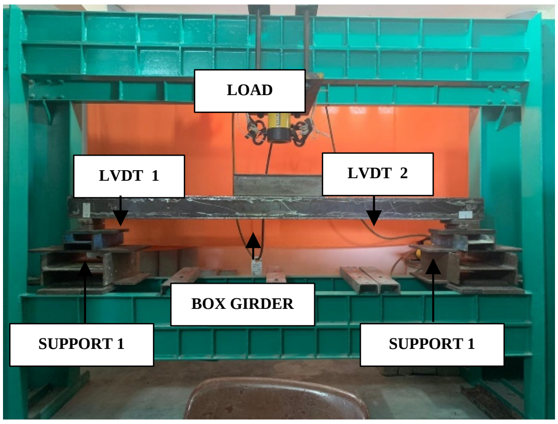
Type of structural	JIS G 3106 SM YB
Stress yield (fy)	295 MPa
Ultimate strength (fu)	490 MPa
Modulus of elasticity (existing condition)	200,000 MPa
Specific gravity	78.5 kN/m3

Experimental testing is needed to determine the behaviour of the bridge girder. The girder load model a simple supported I beam mini scaled with a 1: 5—span length of 1100 mm, depth of 150 mm. The yield load of the steel beam record at 60 kN in the experimental testing form. The experimental model is used to estimate lateral force-displacement relationships (stiffness) at different loads using the LVDT tool. The girder subjected to pushover loads based on FEMA 356. Tests of experimental work at the Structure Laboratory in Riau. The load is applied through the loading plate as pressure on the beam, as shown in Fig 3.

Girder's behavior analyzed through LUSAS is based on the theory of similitude laws. This finite element model simulation is useful for determining load tests. The type of element used is C3D8R (8-node linear brick, reduced integration)—the value of stiffness reduction, which is the limit in analyzing the collapse with ANN.

Damage Index methods in this study to predict the location and severity of steel beams. The expression proposed by considering the top parameters in the bridge structure, namely displacement. In this study, stiffness reduction, displacement and location were considered the most influential parameters.

The procedure for detecting damage in steel beams entails considering stiffness reduction every 10% of stiffness deficiency to yielding limits. The damage scenario by simulating a proportional stiffness reduction. The stiffness reduction of up to 40% in results and as shown in Table 3. The ANNs parameters used are epoch 500 values. Learning rate value 0.01-0.09, architecture three neuron input layer, five hidden layer neurons, and one output.



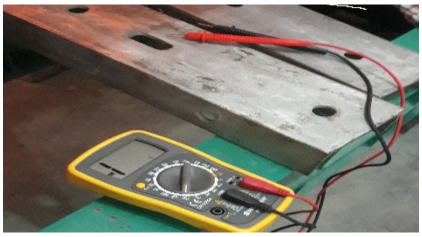


Fig. 3 (a) Schematic diagram of the laboratory girder of arch bridge model, (b) LVDT tool.

Simulation of the amount of training data and test data used are 90:10, 80:20, 70:30, and 50:50. Greater damage (or more significant stiffness reduction) will provide greater structural deformation. Validated FE models from simple beams used and 21 partitions. They simulate the beams at a distance of 4.73 m apart, not including support. Damage locations were 4.72 m, 9.45 m, 14.18 m, 18.91 m, 23, 64 m, 28.37 m, 33.1 m, 37.83 m, 42.56 47.29 m, which coincide with the centre of the 11 mm partition. Because the beams are symmetrical, four different damage severities (10%, 20%, 30%, and 40%) are introduced in the 21 left partitions to produce a single damage scenario. Only the smallest damage severity (10%) and the greatest damage severity (40%) introduce at two locations.

4. RESULT AND DISCUSSION

4.1 FE Displacements and Experimentally Measured Deflection.

Load variations compared to the displacement results with finite element analysis and experimentally shown in table 1. During the middle span testing, point 11 damage at 39 kN load, and the experimental results stated a more excellent value than FEM, as shown in table 2.

Table 2 Comparison of FE Displacements and experimentally measured deflection.

Load (kN)	Displacement 0,25 L(mm) (LVDT 1)		Displacement 0,25 L(mm) (LVDT 2)		Difference
	LUSAS (FEM), mm	Measured, mm	LUSAS (FEM), mm	Measured, mm	
10	1,015	1,780	1,528	2,260	-0,377
20	2,031	3,320	3,056	4,300	-0,339
30	3,046	4,820	4,585	6,460	-0,329
40	4,061	6,480	6,113	8,880	-0,342
50	5,076	8,480	7,642	11,920	-0,380
60	6,493	11,56	9,913	16,660	- 0,40

As shown in the table above, the models made in LUSAS show the same behaviour as the experimental results of the model, with a different maximum is 0.365%. During the test, the beam was damaged in the middle span when the load was 11.92 kN, and the resulting experimental test value was higher than the FEM results, as shown in the table above. Loads range from 10 to 60 kN. The load value is 40 kN; the percentage difference changes to + 0,400%. The results show that at 40 kN, the beam has already been yield.

When the beam is load in the range of 10 kN to 60 kN, the average percentage difference between the experimentally measured deflection and the deflection produced by FEM is 0.365%. Observation of stiffness reduction based on testing was the first time it yields when it is lower by 40%. The other damage scenarios are simulated with proportional stiffness reductions to the 40% stiffness reduction at yield and shown in Table 3.

Table 3 Damage scenarios of steel Hollow Beam

Damage Case	Stiffness reduction, SR (%)	Young Modulus (MPa)
1	10	180000
2	20	160000
3	30	140000
4	40	120000

Damage expression in the form of displacement, velocity, and acceleration obtained at each planned damage point. The study using the Park Ang equation, the damage index value of the simulated damage point shown in Fig 4.

Fig. 4 shows the level of damage index (β) along the block for the 21 locations of the gusset bridge girder points. The highest level (β) indicates the area that experienced the most significant failure found at point 20 for all severity reduction (SR).

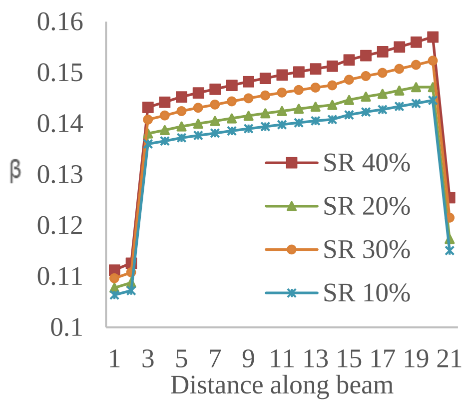


Fig. 4 The plot of β vs. distance along the beam

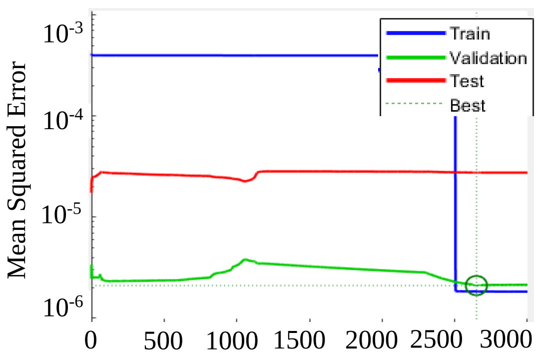


Fig. 5 Error value: Best Validation Performance vs. Mean Square Error (MSE).

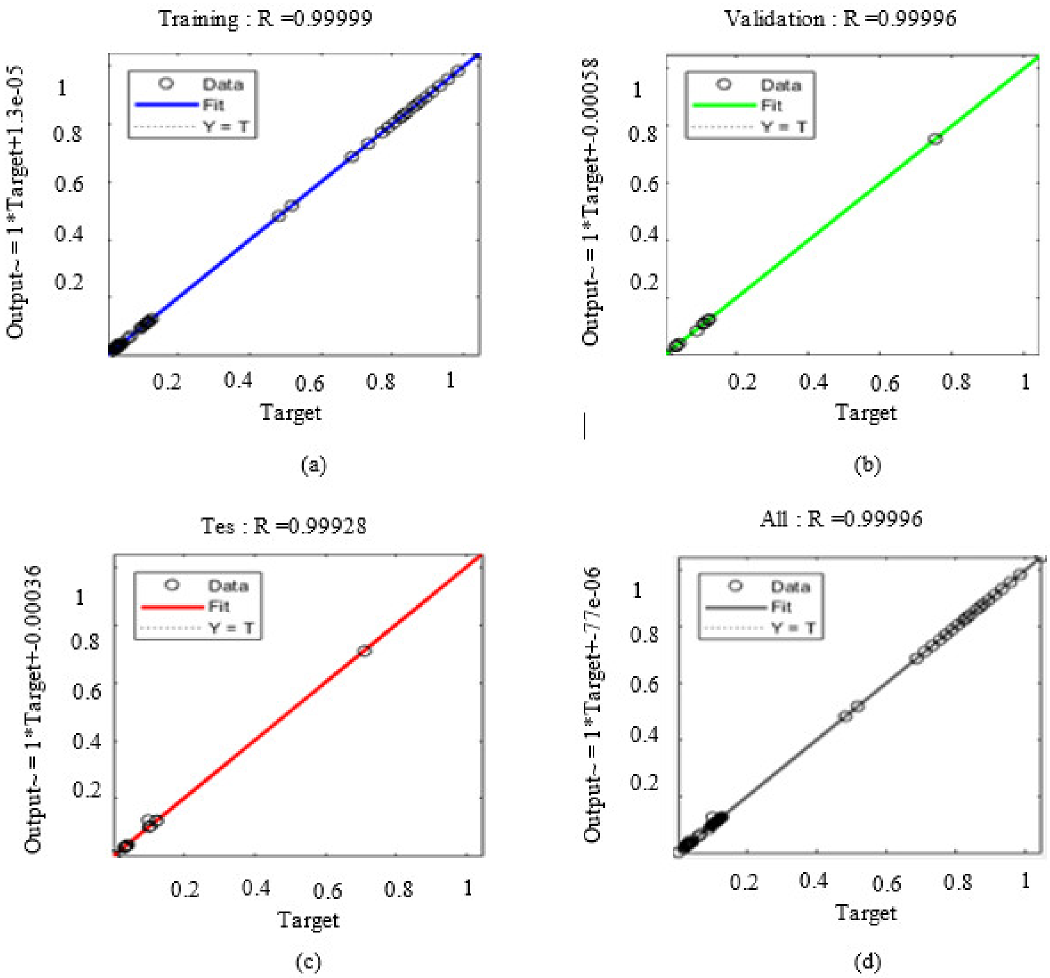


Fig. 6 Training process in matlab to predict the severity of damage on (a) training, (b) validation, (c) tes, and (d) All Regresion

After the damage location, the first determined from the plot β versus the beam's distance (Fig 4). Suppose several damage scenarios observe from the β plot. In that case, the β values calculated along the beam can be input to trained ANNs to obtain the severity of the damage to reduce stiffness at different damage locations along the beams. The layer and the curve obtained from MATLAB R2015. The input layer consists of β at 21 locations (excluding supports)—a total of 105 samples fed into the input layer. The target layer consists of stiffness reduction. During the training of ANN, each input vector would generate an output vector. The difference between the target vector and the output vector is an error and will propagate through the network backwards. In this way, the mean square error (MSE) can reduce so that the output vector can be as close as possible to the target vector. Simulation of the amount of training data and test data used are 90:10, 80:20, 70:30; and 50:50.

Fig 5 shows that the results of training and testing data using ANN have produced the best error value (Mean Squared Error, MSE) of 2.1043×10^{-6}. ANN will be of good value if the MSE value is close to 1. Fig 6 shows the number of neurons used in the hidden layer Aff MSE and the R-value, where the R-value measures the correlation between output and target. This R-value varies from 0, which means random relationship, to 1, which means a close relationship. Neurons were used in the hidden layer for this study because they gave high R values, as shown in Fig 6. Trained ANNs predict the severity of damage in terms of stiffness reduction with shallow errors of 2×10^{-6} for training sets, 9.05×10^{-6} for validation sets, and 3.85×10^{-5} for testing sets.

5. CONCLUSION

This paper has presented techniques for predicting damage to steel beams. This technique uses damage capital based on the damage index β, and Artificial Neural Network (ANN) Variable β used to measure the severity of the damage. The highest level (β) indicates the location that experienced the most significant failure found at point 20 for all severity reduction (SR). The procedure for using ANN is practical. The first bending mode's mode shape is required, and this can obtain from measurements. ANN has produced the best error value (Mean Squared Error, MSE) of 2.1043×10^{-6}. Therefore, the results show that ANNs are training to have a reliable potential of 98% for structural damage identification. Trained ANNs predict the severity of damage in terms of stiffness reduction with shallow errors. The results confirm the feasibility of the method and its application in preventing structural failure. This research only discusses the static load, while the bridge's natural dynamic response with the placement of the bridge testing equipment has not examined, so it is a future work that can be studied.

6. ACKNOWLEDGMENTS

Gratitude to the Ministry of Research, Technology and Higher Education of Indonesia Grant for Higher Education Cooperation Year 2019–2020, Ministry of Public Works and Public Housing Indonesia and Civil Engineering Study Program at Lancang Kuning University.

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