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Research Article

A Damage Detection Approach in the Era of Industry 4.0 Using the Relationship between Circular Economy, Data Mining, and Artificial Intelligence

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Over the last decades, the emergence of new technologies has inspired a paradigm shift for the fourth industrial revolution. For example, circular economy, data mining, and artificial intelligence (AI), which are multidisciplinary topics, have recently attracted industrial and academic interests. Sustainable structural health monitoring (SHM) also concerns the continuous structural assessment of civil, mechanical, aerospace, and industrial structures to upgrade conventional SHM systems. A damage detection approach inspired by the principles of data mining with the adoption of circular-economic thinking is proposed in this study. In addition, vibration characteristics of a composite bridge deck structure are employed as inputs of AI algorithms. Likewise, an artificial neural network (ANN) integrated with a genetic algorithm (GA) was also developed for detecting the damage. GA was applied to define the initial weights of the neural network. To aid the aim, a range of damage scenarios was generated and the achieved outcomes confirm the feasibility of the developed method in the fault diagnosis procedure. Several data mining techniques were also employed to compare the performance of the developed model. It is concluded that the ANN integrated with GA presents a relatively fitting capacity in the detection of damage severity.

1. Introduction

Advanced, large, and expensive engineering assets such as high-rise buildings, long-span bridges, dams, oil platforms, hydraulic structures, wind turbines, offshore structures, railways, and ports were designed to last long [1–7]. However, many of them were more than halfway through their intended service life, and some of them have already reached the end of it [8]. Countries spend billions each year on the maintenance of these assets. For instance, according to ASCE 2021 infrastructure report card [9], there were more than 617,000 bridges across the United States. Currently, 42% of all bridges are at least 50 years old and 46,154 of the bridges are considered structurally deficient, meaning they are in "poor" condition and in need of repair that requires a $125 billion investment. In another example, road and rail infrastructures across Europe have been degrading because of too little maintenance due to the global economic crisis [10]. Therefore, the monitoring costs associated with the aging engineering assets have become an ongoing concern. Emerging technologies need to overcome such bottlenecks to act more cost-effectively and sustainably in the planning, control, and management of structures. Structural health monitoring (SHM) as a powerful tool was utilized to address the above concerns by changing timetabled maintenance with as-needed repairs [11].

SHM is the process of applying a damage detection approach to evaluate the health condition of mechanical, civil, and aerospace engineering assets [12]. Damage detection techniques can be considered in two categories due to their detection abilities which include local-based and global-based techniques [13]. Conventional approaches, e.g., visual inspections, ultrasonic, acoustic emissions, and radiography, are local-based damage detection methods with various drawbacks. For instance, the aforesaid costly techniques normally necessitate prior knowledge of the damage location which makes them laborious and inefficient, especially in big and complicated structures [14, 15]. In contrast, global-based methods, e.g., vibration-based techniques are based on global structural response and they have been developed to overcome the aforementioned drawbacks [16, 17]. From another perspective, emerging computer-based technologies require to be operated for achieving SHM data [18]. Hence, mathematical evolutions have upgraded the SHM schemes. For example, data mining methods [19, 20], cloud computing [21], and deep learning [22] have recently been employed in SHM. AI is also one of the developing scientific strategies in the 2020s [23, 24]. Over the past decade, ANN has provided broad solutions for structural system identification problems [25]. Moreover, according to [26], these days a lot of evolutionary techniques exist, e.g., GA [27], ant colony optimization [28], grey wolf optimization [29], particle swarm optimization [30], artificial immune algorithm [31], artificial bee colony algorithm [32], and firefly algorithm [33]. Among all metaheuristic techniques, the GA holds the highest standard aimed at resolving global optimization problems [34, 35].

The fourth industrial revolution, which is known as Industry 4.0, IR 4.0, or 4IR, includes various platforms, e.g., data mining, AI, and circular economy. Data mining has also several models to run [36–43]. Cross-industry standard process for data mining (CRISP-DM) is the most widespread paradigm [44]. This model has a hierarchical and cyclic process in six stages, i.e., business understanding, data understanding, data preparation, modeling, evaluation, and deployment. In the modeling phase of CRISP-DM, three types of techniques such as statistical, machine learning, and AI techniques can be used for different applications [45, 46]. Likewise, the circular economy has several frameworks [47, 48]. According to [49], the most comprehensive circular economy framework in six stages was proposed by Potting et al. [50]. Data mining and AI are considered as one of the main factors for an extensive adoption and enhanced modification to the circular economy.

Based on the literature review, it is felt to improve the smartification of global-based structural damage identification systems using Industry 4.0 technologies due to the demanding needs of developing the fault diagnosis of structures. Therefore, by taking advantage of the described relationship between circular economy, data mining, and AI, a generalized fault diagnosis workflow is proposed in this study. This is also associated with the fact that for the implementation of computational techniques in SHM, a systematic procedure along with relevant algorithms is essential. Consequently, in this article, a brief background of Industry 4.0, circular economy, and data mining are highlighted in Section 2. The architecture of the proposed circular model is presented in Section 3. Experimental modal analysis of a composite bridge deck structure is also detailed in this section. Here, a range of damage scenarios is introduced to generate the vibration characteristics of single-type and multiple-type damage cases as the input database for training the developed ANN integrated with the GA pattern. In Section 4, finite element modeling of the test structure is carried out to verify the experimental work. The outcomes of the introduced hybrid network are also presented in this section. Then, the performance of the pattern is compared with predeveloped ANN, support vector machine (SVM), and classification and regression trees (CART) using mean absolute error (MAE). Finally, Section 5 highlights the conclusions.

2. Fourth Industrial Revolution (Industry 4.0)

The term “industry” refers to the creation of products, services, and facilities within an economy. Our world has experienced four steps of industrialization. Table 1 presents the most important contributions of the fourth industrial revolution, adopted from [51–57]. Circular economy, data mining, and AI aligned with the fourth industrial revolution (Industry 4.0) promote smart tasks and diagnostics in research and analytics to industries and organizations in predictive policing. Data mining and AI platforms are also considered as one of the main factors for an extensive adoption and enhanced modification to the circular economy [58, 59].

The linear economy operates as if there are infinite resources in the world. In the same line, linear thinking as a traditional value chain has been started after the third industrial revolution [60]. A linear economy is based on a “Take, Make, and Dispose” model [61]. In the beginning, the implementation of this model was successful. However, it misused the resources in an unsustainable way. For example, the United Nations has estimated that by 2030, the world will need to double the existing resources to become equal with the rate of global production, consumption, and population growth [62]. Therefore, to become more sustainable, it is required to move to a circular system that is based on a closed-loop “Make, Use, and Return” model [63, 64]. In other words, the idea of a circular economy has been established from different aspects, i.e., finite resource stabilization, cost efficiency, pollution reduction, risk management, adoption of better retrofit practices, sharing economy, reusability, and recyclability of materials [65]. Therefore, this technology-focused system can be defined as a condition for sustainability. This is due to the fact that its concept moves towards the final aim of sustainability [66, 67].

With the rapid growth of database technology, more data were collected. Obviously, there is a lot of hidden important information behind the collected data. In this context, one of the popular strategies for knowledge discovery is the typical data processing approach. However, its assumption is difficult to converge with the actual work [68]. In addition, whenever there is a huge data collected, further drawbacks can appear. As a result, conventional strategies, i.e., classical

Table 1: Industry 4.0 contributions.

Key contributions of IR 4.0	(i) Internet of things (IoT) (ii) Smart factories/smart manufacturing/robotics (iii) Circular economy/product-lifecycle-management (PLM) (iv) Data mining/big data analytics/deep learning (v) AI/machine learning (vi) Smart sensors/remote sensing/wireless sensor network/online monitoring (vii) Cloud computing/cognitive computing/mobile computing (viii) Cybersecurity/blockchain (x) Digital twin/smart tasks and diagnostics/smartification (xi) Virtual reality/augmented reality/building information modeling (BIM) (xii) Unmanned aerial vehicles (UAVs)/internet of drone/smart cities (xiii) Smart environment/sustainable development/renewable energy

mathematical techniques perform rather inefficiently. Therefore, the analysis of information should be performed at a better level to better make use of the databases [69]. To overcome the mentioned drawbacks, sophisticated computing tools such as data mining can play a significant role in the extraction of valuable information from different databases [70, 71]. Data mining is an emerging procedure that is used to obtain knowledge from raw data. In fact, it can handle the qualitative analysis of complex and time-consuming real-world problems that cannot be solved with typical statistical techniques [72].

3. Methodology

By taking advantage of the described relationship between circular economy, data mining, and AI, a generalized fault diagnosis workflow is proposed in this study, as shown in Figure 1. This systematic model is based on the combination of CRISP-DM and circular economy closed-loop concepts for the health monitoring of engineering assets using inverse analysis. As can be observed from Figure 1, assessing the damage level is the initial part of the circular fault diagnosis model to collect data. The subsequent phase is focusing on data processing through a number of duties, i.e., data cleaning, data integration, data construction, and data transformation. Generally speaking, the data preparation step is one of the most problematic parts of the procedure. It is because several problems such as incomplete data, missing values, out-of-range records, wrong data type, and unavailable details should be solved in this step to construct a database. Then, the processed data are considered as inputs for the next step. In the modeling step, applicable algorithms such as ANN, fuzzy, support vector machine (SVM), principle component analysis (PCA), GA, ant colony optimization (ACO), Bayesian, and particle swarm optimization (PSO) can be applied for different purposes, i.e., classification, optimization, or perdition. The accomplished results are utilized for damage assessment of structural elements. Once the models are assessed, the deployment of the proposed circular model can be performed through the implementation of strengthening and retrofitting actions to expand the health state of structures. In this regard, the reliability of structures can be also estimated through a number of suggested treatments, e.g., repairing or upgrading the structural members, major/minor maintenance, or replacement of the damaged components, as indicated in Figure 1.

3.1. Experimental Modal Analysis. Modal parameter estimation relies on methods of excitation as well as the accuracy of data acquisition tools. Mode identification methods can be divided into operational and experimental modal analysis. Operational modal analysis regularly refers to output-only measurements whereas experimental modal analysis uses input excitation and output response measurements to estimate the modal parameters [73–76]. In this study, a series of experimental modal analysis of a bridge deck structure were conducted to generate the data. The common span length, as well as girder spacing of a common composite girder bridge, is 25 m to 30 m and 3.5 m to 4 m, respectively. A 1 : 10-scaled form of this girder deck was cast and tested in the heavy structure laboratory of the Department of Civil Engineering, University of Malaya. The model consists of three universal steel beams joined to a concrete slab using shear stud connectors (see Figure 2). The length of the tested model is 3200 mm including 100 mm at both support ends. The materials used in this work were cement, fine aggregates, silica fume, water, and superplasticizer. The reinforcement of the concrete slab is welded wire mesh. Its diameter is 5 mm with 100 mm by 100 mm spacing. The concrete cover for the mesh is 30 mm. According to [77], mechanical connectors (e.g., shear studs) are needed to succeed the composite action. Therefore, full composite action between the concrete slab and steel I-beams is modeled using sixteen shear stud connectors which are installed on each I-beam. To do so, the nuts are welded on top of the beam flange. Then, the bolts are firmly tightened to the nuts. The schematic view, physical preparation, and experimental setup of the specimen are presented in Figures 2 and 3.

Figure 4 presents the schematic illustration of the conducted experimental modal analysis. In the first step, the composite bridge deck structure was tested in its intact condition to obtain the vibration features of the model as the reference or benchmark model. To aid the aim, the specimen

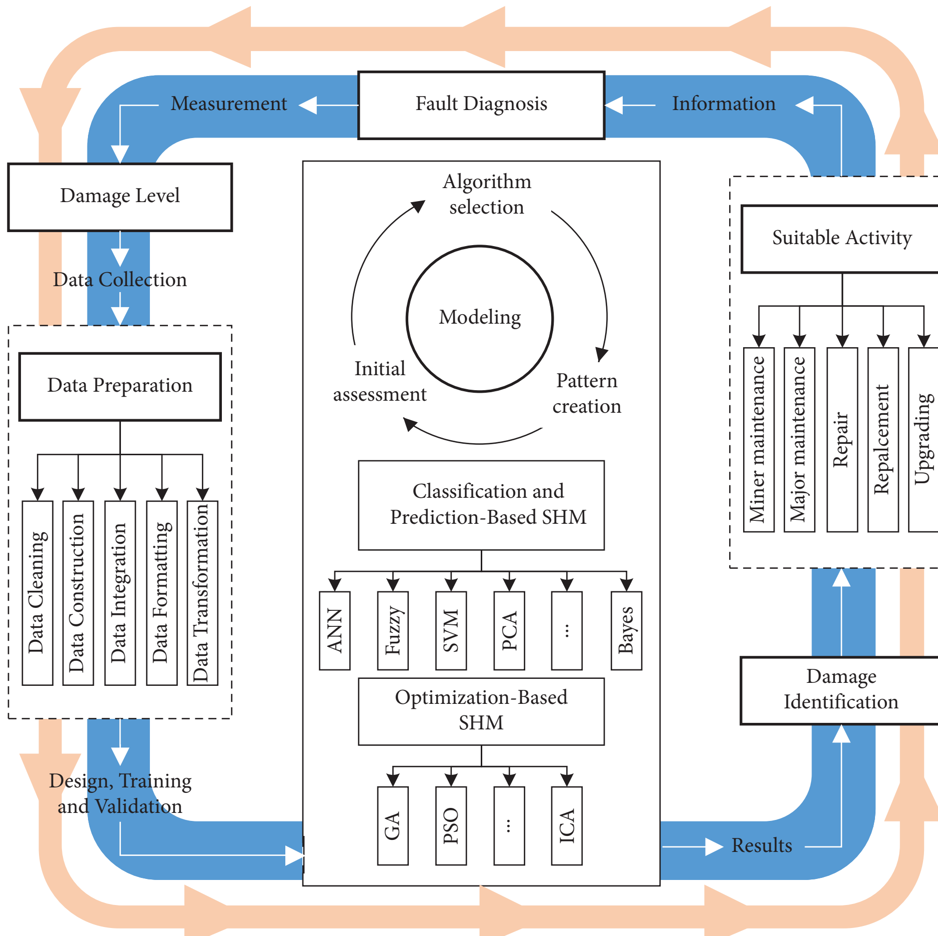


Figure 1: The proposed closed-loop model inspired by circular economy.

was excited using analogue signals of Wilcoxon accelerometers with the sensitivity of 100 mV/g through IMV VE-50 electrodynamic shaker which were amplified by VA-ST-03 power amplifier. Sixteen accelerometers were employed in each beam to record the time-domain responses of the model. OROS analyzer along with its platform, NVGate, recorded the measurements [78]. This signal analyzer transformed the input analogue signals to digital format with the sampling rate of 5.12 kS/s and the frequency bandwidth and resolution of 2500 Hz and 0.39 Hz, respectively. To do so, NVGate converted the time-domain data to the frequency domain utilizing fast Fourier transform. In the next step, the academic license of ICATS, which is the modal analyzer software, was used to extract the structural dynamic parameters, i.e., the first four flexural modes from measured modal test data [79].

Several damage cases (i.e., single and multiple) were induced to the test specimen through notching different locations in several members by saw cuts as well as a disk grinder. To aid the aim, twenty-five magnitudes of controlled damage from 3 mm to 75 mm depth with the increment of 3 mm and correspondingly the prescribed locations were generated for each damage case, as shown in Figure 5. The modal testing was carried out for each case, individually. As it can be seen from Figures 5(b) and 5(c), the mid-span of beam 1 was considered as the location of damage for a single-type damage scenario, though the one-quarter span of beam 1 and three-quarter span of beam 3 were selected as damage location for the multiple-type damage scenario. It should be noted that in this study, different parts of the undamaged structure were incised to generate the damaged state. Then, the loss of stiffness was recovered by welding back the members to create another undamaged state. In this regard, the process of controlled cutting and welding was repeated in different damage scenarios. Then, the findings of the experimental modal analysis were employed in the role of inputs for the circular data mining-based process.

Vibration characteristics of the first four flexural modes, i.e., F_i, $i = 1, 2, 3, 4$ in healthy and damaged cases for single- and multiple-type scenarios were obtained, as shown in Figure 6. The horizontal axis of each figure signifies the twenty-six damage cases including the intact state in addition to twenty-five damaged states. The vertical axis of each figure indicates the natural frequency measurements. As it can be seen from the figure, in general, the trend of modal parameters in both scenarios reduced with damage expansions. However, several damaged states experienced slight fluctuations in particular modes. For example, the maximum reductions of natural frequency values were 3.71% in F_2-multiple damage state, 3.68% in F_3-single

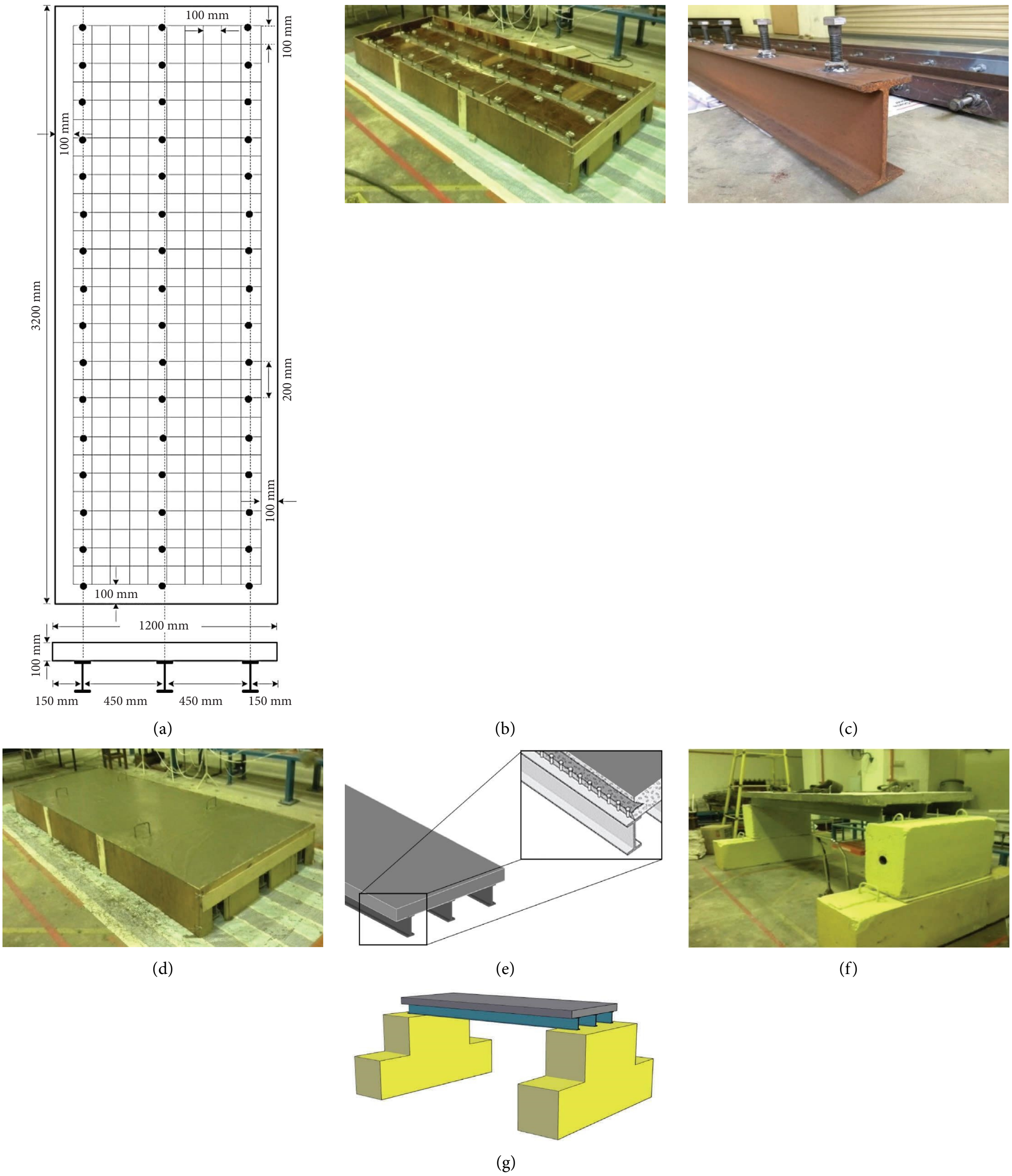


Figure 2: (a) Layout plan and dimensions, (b) construction of the specimen, (c) shear stud connectors, (d) casted model, (e) schematic view, (f) laboratory test setup, and (g) schematic setup of the specimen.

damage state, and 4.16% in F_3-multiple damage state. Conversely, the minimum reductions of natural frequencies belonged to mode 4 with 1.17% and 0.95% in single and multiple damage states, respectively. This is due to the node points aimed at certain mode shapes (see Figure 7). In addition, the results indicated that minor fluctuations of the natural frequencies affected by environmental uncertainties and noise were detected in some damage states, e.g., 36 mm damage state in modes 2 and 4 of single- and multiple-damage scenarios.

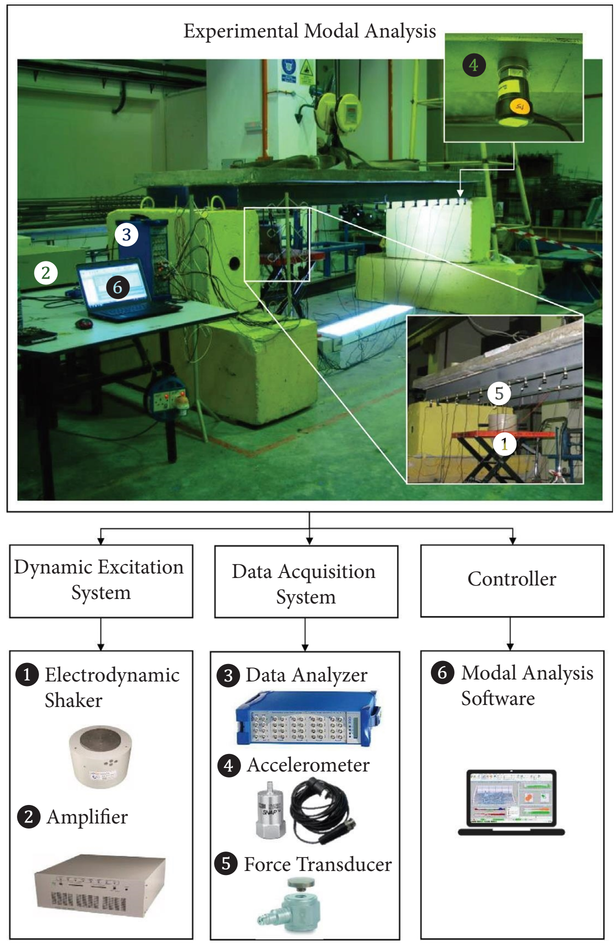


Figure 3: Experiment setup of the tested structure.

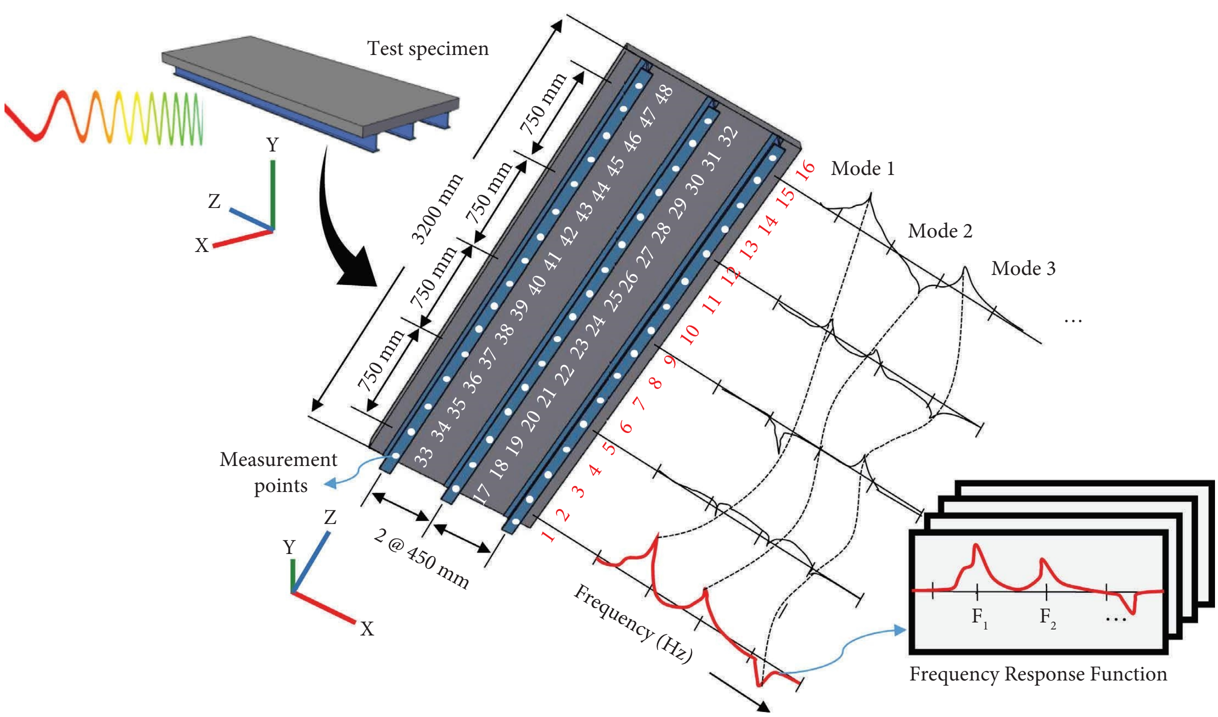


Figure 4: Schematic illustration of the conducted experimental modal analysis.

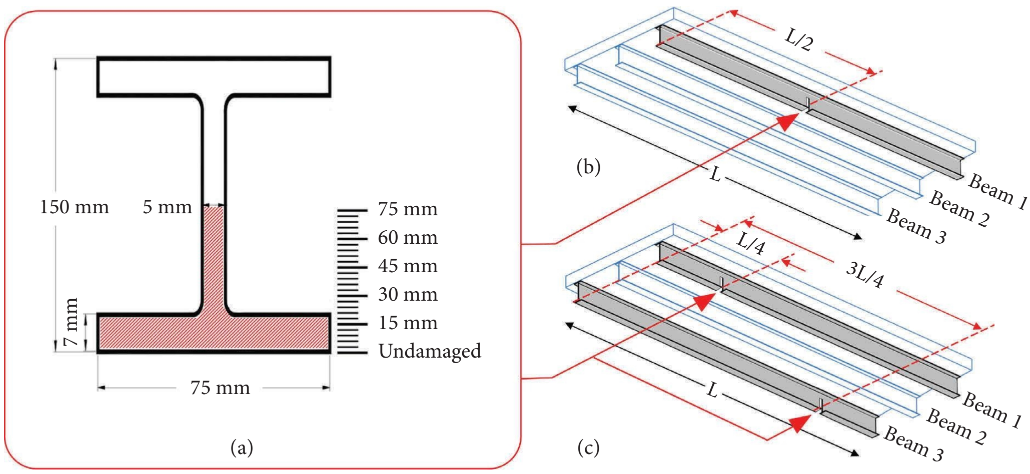
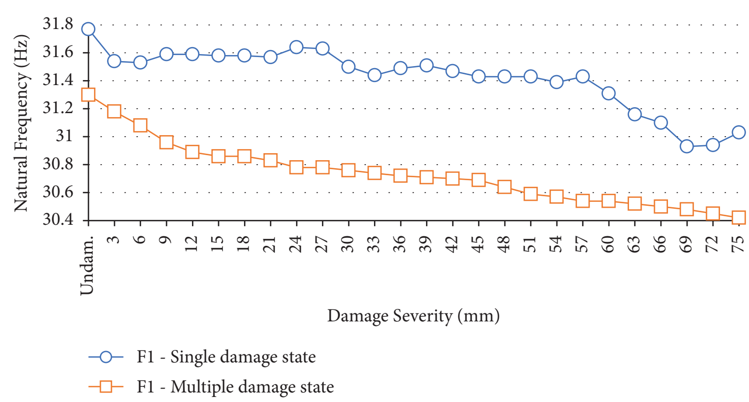
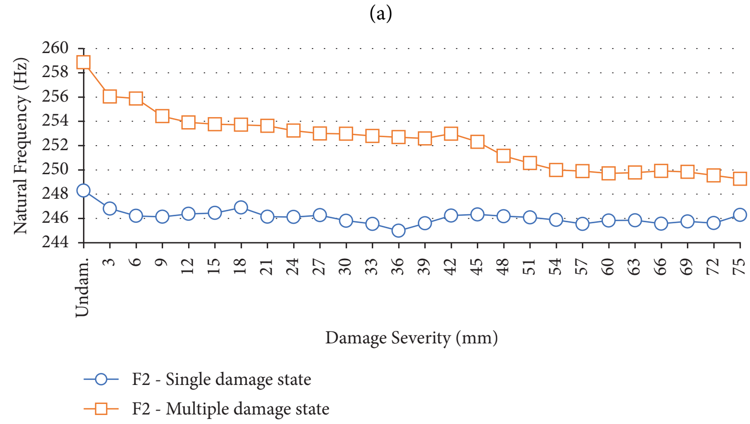


Figure 5: Damage simulation in the test specimen: (a) induced damage levels, (b) single-type damage location, and (c) multiple-type damage location.

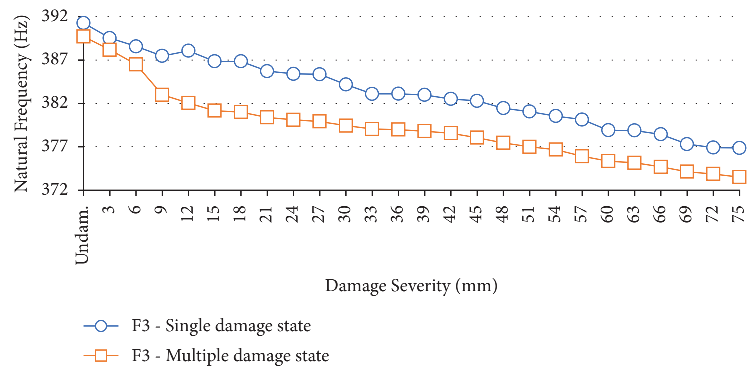


(a)



(b)

Figure 6: Continued.



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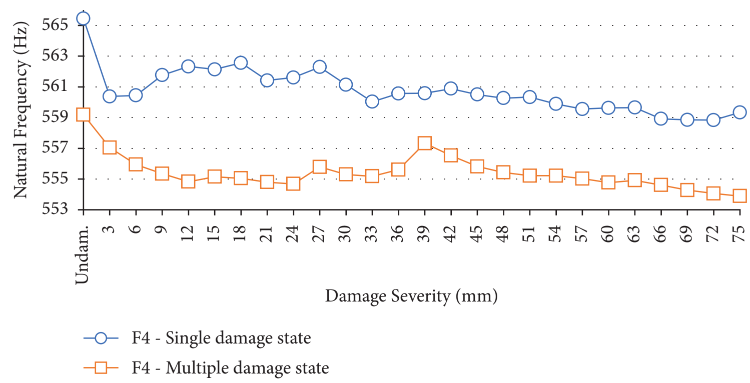


(d)

Figure 6: The experimental outputs of single- and multiple-type undamaged and damaged states. (a) Mode 1. (b) Mode 2. (c) Mode 3. (d) Mode 4.

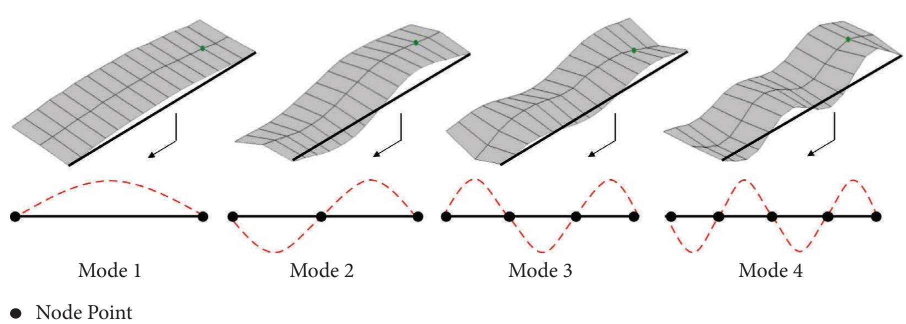
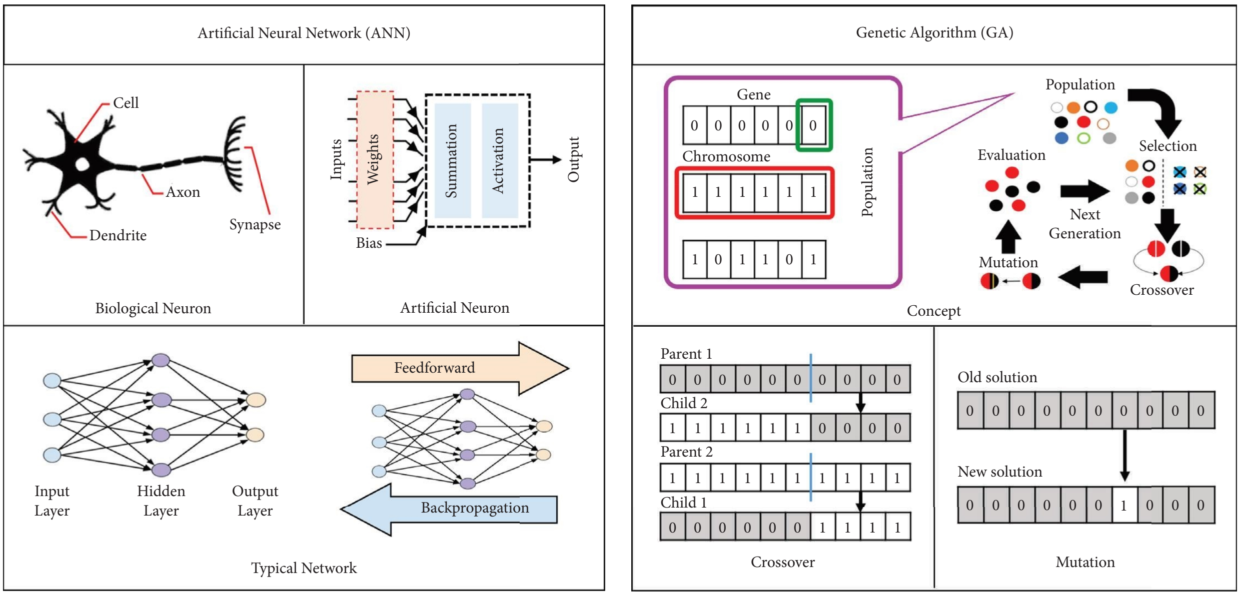


Figure 7: Node points of fluctuation modes.

3.2. Artificial Neural Network (ANN) Integrated with Genetic Algorithm (GA). ANN is one of the greatest powerful AI algorithms inspired by biological neurons [80]. ANNs are categorized using their topology. For instance, a neural network can be feedback or feed-forward. In recent years, ANNs have been employed for solving civil engineering problems encountered in different structures from basic structural members (e.g., truss structures [81], reinforced concrete beams [82], and steel plates [83]) to complex systems (e.g., dams [84], buildings [85–87], and bridges [88, 89]). In spite of this, according to [90, 91], ANNs are affected by a lack of reliance on allocating the weights to networks between layers. As a result, it can increase the error in the results of the network. In order to prevent such problems, an optimization-based algorithm can be applied in the training procedure of the network. GA holds the highest standard aimed at resolving global optimization problems [92]. This algorithm can enhance the generalization performance of artificial models. In addition, the technical advantages of GA are high parallelism, initial values independence, and outstanding robustness in the calculation of extreme values [93]. Figures 8 and 9 show the fundamental concepts and structures of ANN and GA, respectively. Based on the mentioned description, an ANN integrated with a genetic algorithm (GA) is developed in this study.



(a) (b)

Figure 8: (a) ANN and (b) GA overview.

(a)

1. Apply a sample and initialize weights

Repeat

2. Calculate the output of neurons:
   - 2.1. Summation and Activation
   - 2.2. Backpropagation of errors
   - 2.3. Update weights and biases

End

Until termination criteria are satisfied.

(b)

1. Generate the initial population

Repeat

2. Produce next generation
   - 2.1. Evaluate each individual
   - 2.2. Select parents based on fitness
   - 2.3. Apply search operators

End

Until termination criteria are satisfied.

Figure 9: The general structure of ANN and GA. (a) Framework of backpropagation ANN. (b) Framework of GA.

4. Results and Discussion

Finite element modeling of the test structure was carried out using ABAQUS to verify the laboratory outcomes using modal frequencies. The element type for the numerical model of the I-beam was Shell homogeneous S4R, which was a 4-node doubly curved thin or thick shell, reduced integration, hourglass control, and finite membrane strains. The element type for the finite element model of the girder deck was Solid homogeneous C3D8R, which was an 8-node linear brick, reduced integration, and hourglass control. The finite element model of the I-beam and girder deck consisted of 432 and 7533 nodes and 371 and 4800 elements, respectively. After a variety of trials, the boundary condition of the model on both sides was considered as simply supported, pinned-roller with spring elements. For pinned support, rotations along the X, Y, and Z directions and translation of the Y-axis were zero. For roller support, rotation along the X and Y directions and translation of the Y-axis were zero. To associate the rigidity of the beam and supports, two springs have been modeled at the locality of the top flange of the I-beam in the horizontal direction at roller supported side with a stiffness of 0.08 GN/m and in both supports in the vertical direction with a stiffness of 0.06 GN/m. For better understanding, the first four mode shapes in multiple-type damage scenario with 75 mm damage depth are detailed in Figure 10.

Figure 11 demonstrates the correlation between the numerical and experimental works based on finding their results. In this line, the difference between the numerical and experimental modal frequencies was around 5% in modes 1 and 2 and 2% in modes 3 and 4. Therefore, the outcomes of experimental and numerical analysis approved the validity of the findings.

As mentioned before, the ANN integrated with GA was trained using the first four experimental natural frequencies of undamaged and damaged states, i.e., F_i, $i = 1, 2, 3, 4$ as inputs and the acquired damage severities as outputs of the network. It should be noted that the database was separated into two partitions, comprising 80% for the training and 20% for the testing groups. This step was conducted by the modeling of two feed-forward neural networks for single-

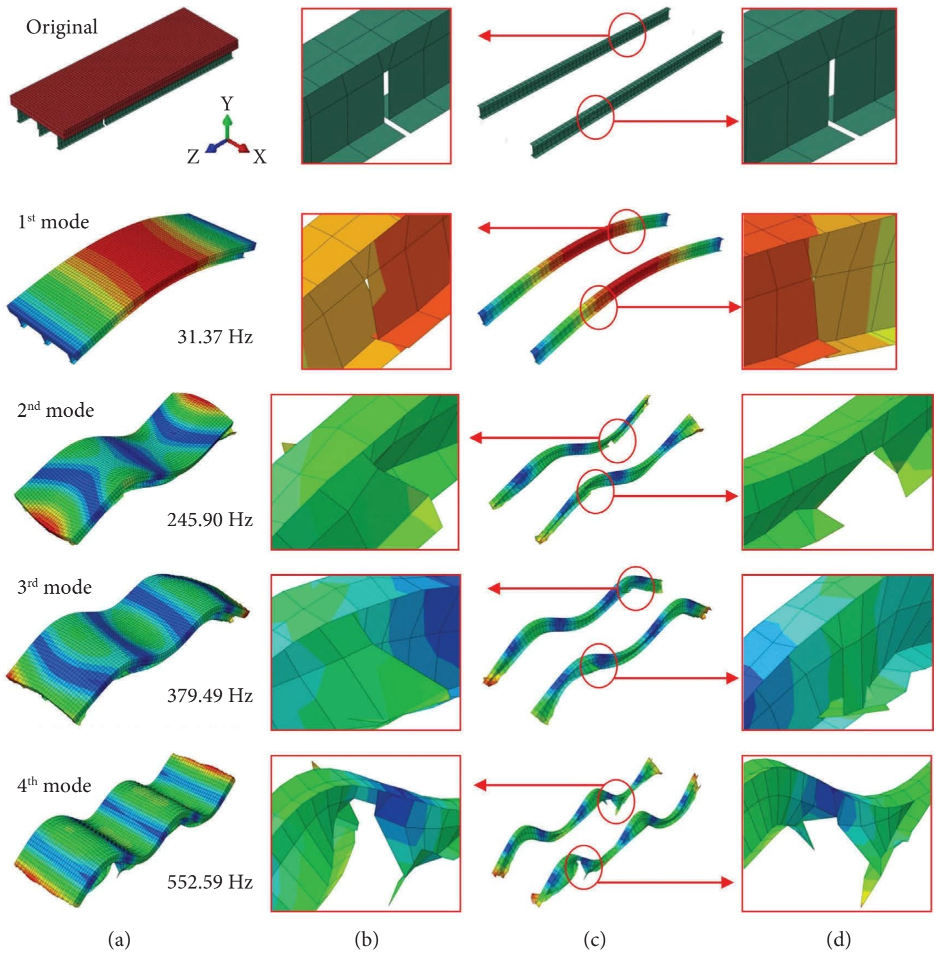


FIGURE 10: Numerical modeling of the test structure for 75 mm damage in multiple-type damage scenario. (a). Numerical model, (b) beam 1 (zoom-in), (c) beams 1 and 3, and (d) beam 3 (zoom-in).

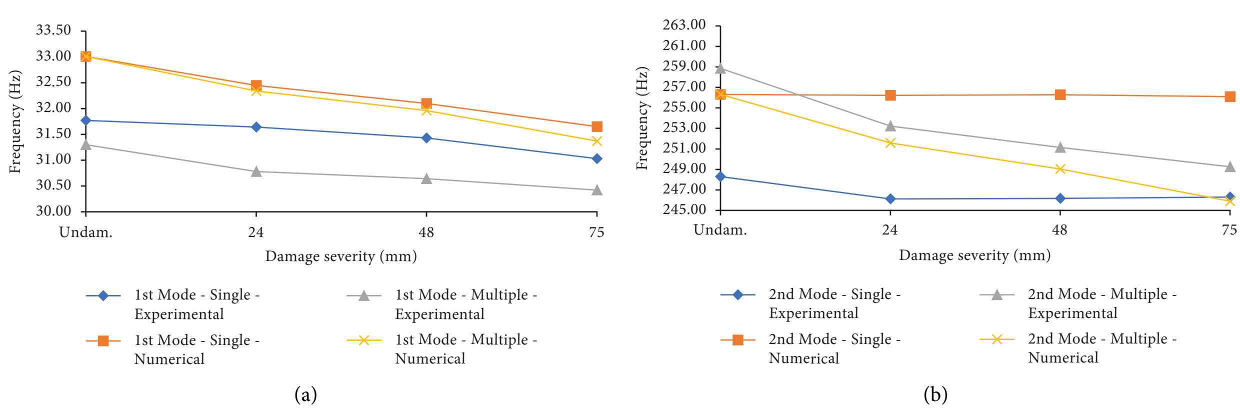
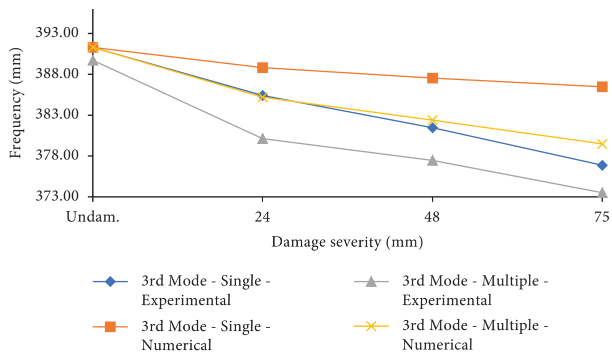


FIGURE 11: Continued.



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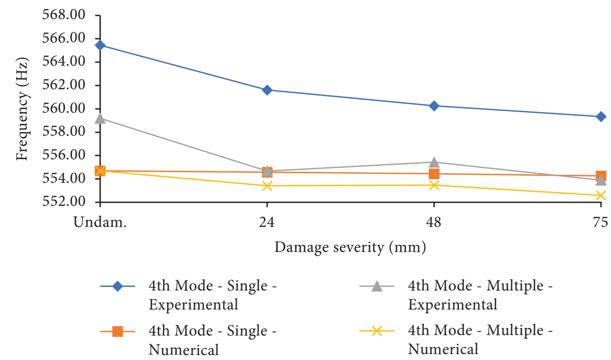
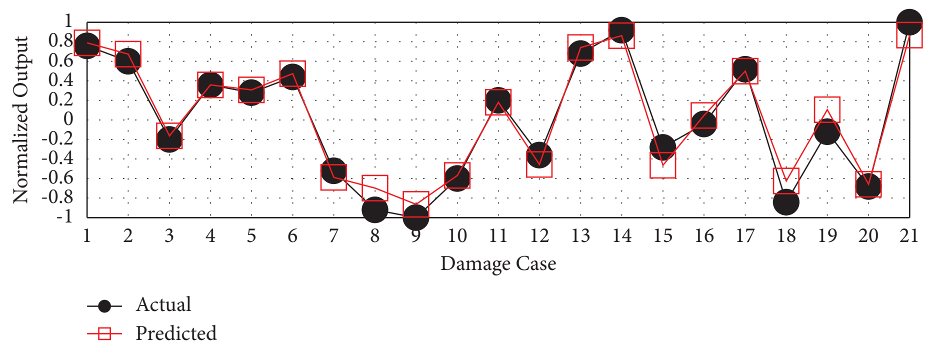
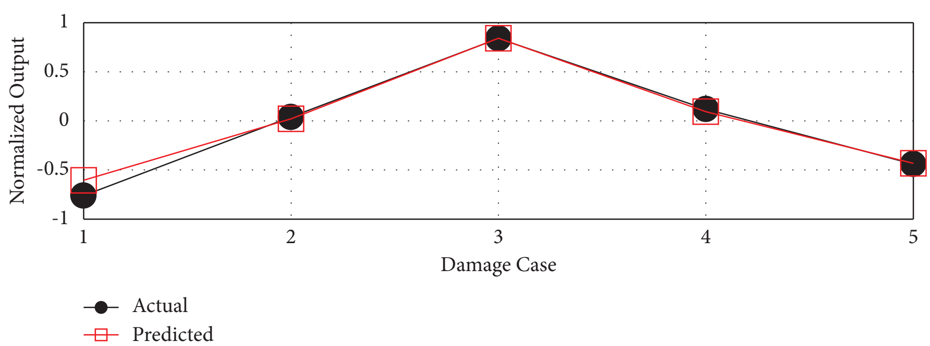


(d)

FIGURE 11: The difference between simulation analysis and laboratory work. (a) 1st mode. (b) 2nd mode. (c) 3rd mode. (d) 4th mode.



(a)



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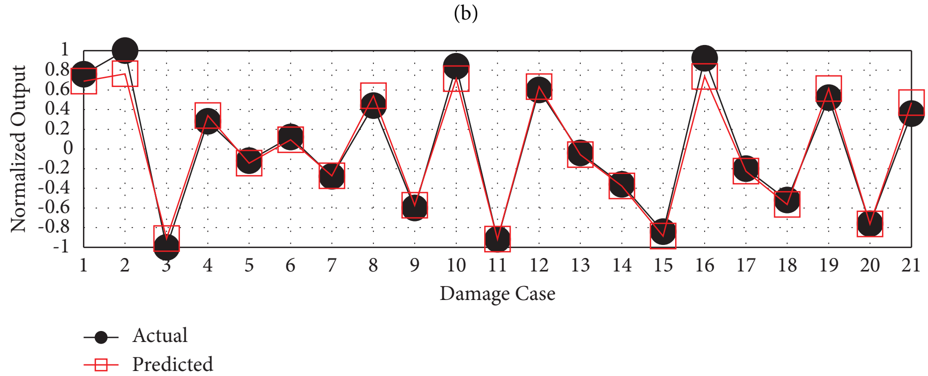

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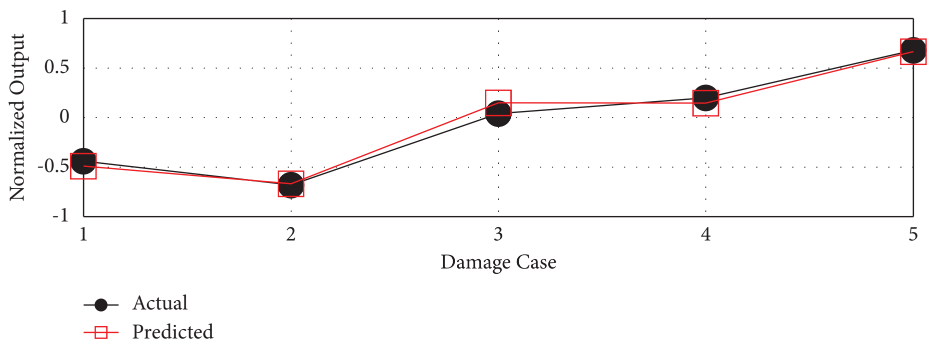
FIGURE 12: Continued.

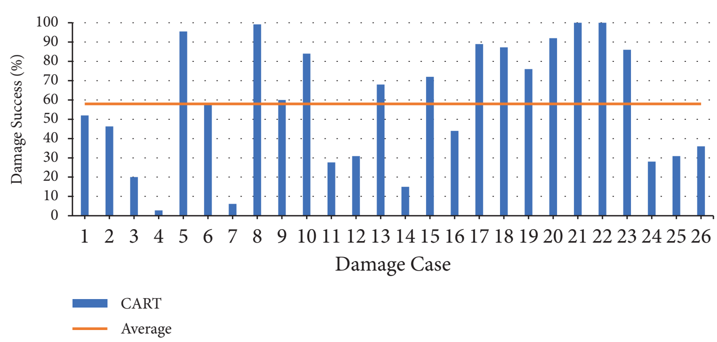


(d)

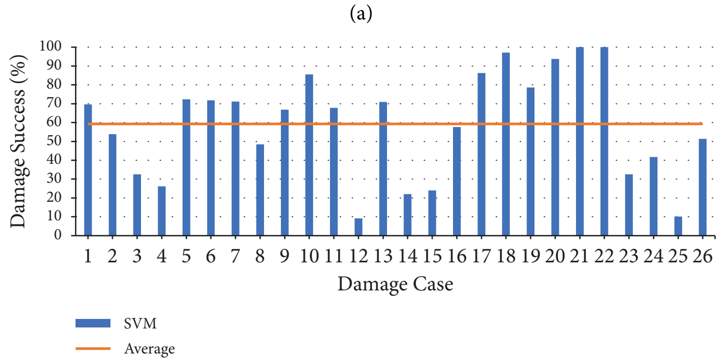
Figure 12: Comparison of results: (a) training section of single-type damage state, (b) testing section of single-type damage state, (c) training section of multiple damage state, and (d) testing section of multiple damage state.

Table 2: Comparison between the performance of patterns.

Model	Mean absolute error (MAE)	
	Training	Testing
CART	4.706	7.200
SVM	5.056	4.925
Predeveloped ANN	1.355	2.097
ANN-GA	0.070	0.084
ANN-ICA	0.057	0.075



(a)



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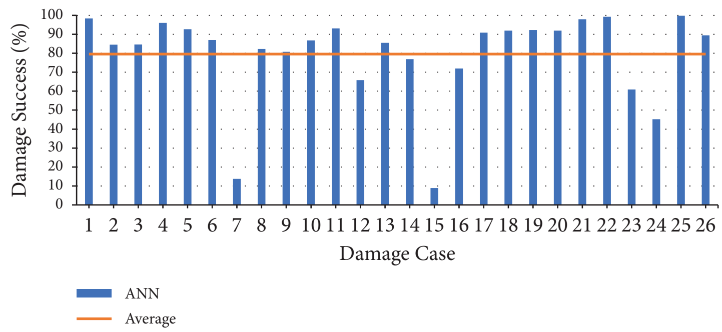

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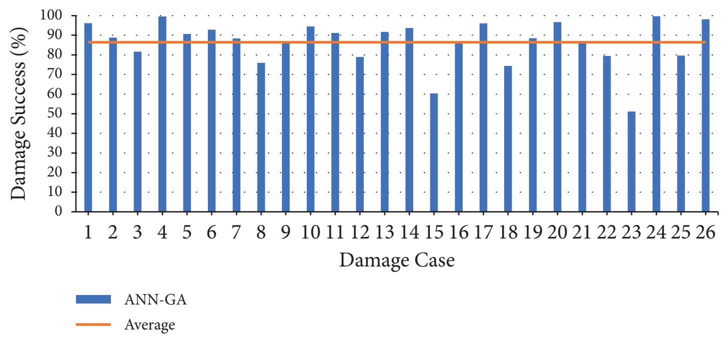

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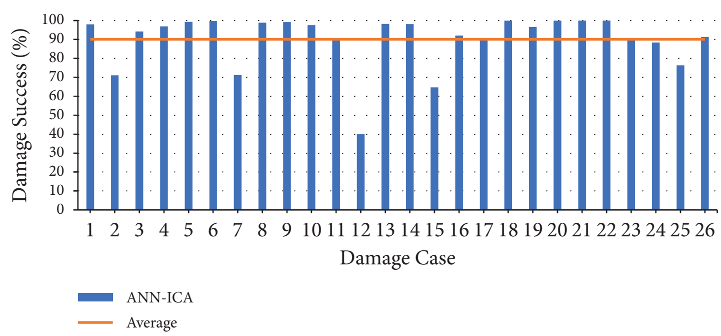

(e)

Figure 13: Accuracy of outputs in (a) CART, (b) SVM, (c) ANN, (d) ANN-GA, and (e) ANN-ICA.

type and multiple-type damage cases. Then, GA has been applied in the training procedure of the networks in order to reduce the cost function and improve the weights of the networks using its setting factors, i.e., population size = 150, mutation = 0.35, crossover = 0.5, and maximum generations = 50. Figures 12(a)–12(d) present the results of the developed hybrid network for single-type and multiple-type damage cases in training and testing segments, respectively. As shown in the figure, the normalized predicted damage severities were closely fitted to the actual measurements. However, the capability of individual models was not the same. For example, in the training segment of the multiple-type damage state, the calculated outcomes fitted to the actual recorded data with the matching pattern. In spite of this, the training segment of the single-type damage state gave lower fitness between forecasted and real data.

Recently, the performance of artificial intelligence, machine learning, and statistical algorithms aimed at the damage detection of the composite bridge deck structure has been reported through predeveloped ANN [94], support vector machine (SVM) [95], classification and regression trees (CART) [96], and hybrid ANN-imperial competitive algorithm (ICA) [97]. In the current work, a comparison between the aforesaid algorithms and the proposed model was made to show the performance of the developed algorithm, as shown in Table 2. Although the most appropriate robustness was succeeded by hybrid algorithms due to enhancing the learning procedure of the ANN utilizing metaheuristic algorithms, after ANN-ICA, the best MAE rates still belonged to the developed ANN integrated with GA, which were 0.070 and 0.084 for the training and testing, respectively. As shown in Table 2, the efficiency of other methods, from best to worst succeeded by the predeveloped ANN, SVM, and CART, respectively. It is mainly attributed to the fact that the ability and complexity of artificial intelligence techniques are beyond the capacity of statistical methods.

It is also required to investigate the damage success of the patterns. In this regard, Figure 13 illustrates the accuracy of all patterns. The detection success percentage is the ratio of predicted to the actual values. According to the figure, the average percentage success is 57.95%, 59.29%, 79.58%, 86.44%, and 90.11% for CART, SVM, predeveloped ANN, ANN-GA, and ANN-ICA, respectively.

5. Conclusions

Conventional approaches in SHM and nondestructive damage detection methods are common tools for the damage assessment of civil structures. However, they are mostly time-consuming, expensive, require damage location baseline data, and limited in capacity to assess the health condition of structures, particularly for deep unobservable damages as well as large and complex structures. However, they are not beneficial to continuous monitoring, real-time, and online assessment for solving real-world problems. To overcome the mentioned drawbacks, advanced vibration-based techniques using Industry 4.0 technologies can be developed to upgrade conventional SHM, achieve sustainable-based SHM, and implement reliable and economical SHM systems. Similarly, the concept of circular economy is a strategy to promote sustainable development. By taking advantage of the relationship between circular economy, data mining, and AI, a generalized systematic fault diagnosis approach has been proposed in this study using ANN-GA. After model creation, its performance was evaluated by comparing the MAE of different computing algorithms, i.e., CART, SVM, ANN, and ANN-ICA. The results confirmed the feasibility of the proposed damage detection approach for sustainable-based damage detection of composite bridges aimed at enhancing their smartification. The damage identification is not the last phase of the proposed circular model. After pattern assessment, the implementation of strengthening and retrofitting plans is required to ensure the reliability of the structure.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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