

Retraction

Retracted: Application of Distributed Network in Bridge Structure Safety Inspection

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] H. Xu and Y. Li, "Application of Distributed Network in Bridge Structure Safety Inspection," *Security and Communication Networks*, vol. 2022, Article ID 5430755, 6 pages, 2022.

Research Article

Application of Distributed Network in Bridge Structure Safety Inspection

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In order to solve the problems of the monitoring and health assessment of the main structure of bridges, and to provide technical support for the bridge from the regular inspection to the predictive maintenance mode, a distributed network is proposed for the safety inspection of bridge structures. Through the numerical simulation of the bridge, the finite element model is established and the modal analysis is carried out to obtain the modal data before and after the damage. The damage index of the bridge structure is taken as the input and output variables after the curvature of the modal data, and the nonlinear mapping relationship between the input variables and output variables is established. A large amount of damage modal data is randomly formed into the training set and the test set, and the training set is used to train the neural network. The training accuracy is set to 10^{-3} , and the learning rate is set to 0.01. The test set data is used to identify the damage to the neural network after the training. The experimental results show that the developed program is more accurate in identifying the damage position of the simply supported beam and the continuous beam, and the fitting degree between the predicted value and the real value of the damage degree of the structure can reach 0.97. It is concluded that the damage identification program can intelligently identify and predict two common types of bridge structural damage, namely, the simply supported beam and the continuous beam. And the identification effect is good and has certain feasibility.

1. Introduction

With the development of the transportation industry in all countries around the world, the proportion of bridge construction in infrastructure construction is also increasing [1]. In the process of the construction and operation of the bridge, because of the influence of the subjective and objective factors, the internal stress state of the bridge is complex and the regular inspection structure information is isolated and not complete, so it is difficult to find the hidden problems. Long-term real-time monitoring, forecasting, and evaluation of bridge structures is an important issue that needs to be solved urgently in our country and even all countries in the world. Distributed network bridge structure safety monitoring system is proposed for long-term real-time online monitoring of bridge construction and

operation status [2]. It is a bridge monitoring system integrating state monitoring, real-time analysis, and processing of structural information and response control, which is the basis of intelligent bridge health monitoring.

With the rapid development of national transportation, a large number of bridges are built and used, with huge loads. However, under the influence of the external environment, the bridge structure may be damaged, affecting the operation and use of bridges [3]. Therefore, how to effectively pre-evaluate the safety of bridge structures is an urgent problem to be solved at present, and also a prerequisite to control and ensure the operation safety of bridges. At present, the bridge safety state evaluation mainly adopts qualitative evaluation methods, such as the analytic hierarchy process (AHP), the fuzzy comprehensive evaluation method, the fault tree method, and so on. These methods lack objectivity, mainly

depending on the expert knowledge and experience scores. In determining the index weight, it has very strong subjectivity, which cannot reflect the risk level [4]. In fact, the safety of bridge structure is a huge uncertainty system, which is mainly manifested in the uncertainty of evaluation factors and the fuzziness and randomness of factor data [5]. Therefore, it is necessary to combine qualitative and quantitative evaluation, further integrate monitoring data of evaluation indicators and expert knowledge, and achieve an objective and accurate evaluation of bridge structure safety, so as to provide decision-making and guidance suggestions for managers [6]. Bridge structure safety assessment is a very complicated subject. Sensors and drive components have different types, which determines their information processing difficulty. At the same time, it is difficult to model the relationship between the structural health state and the test values of numerous sensors. At present, the research in this field at home and abroad is still in an exploratory stage [7]. There are many ways to implement the expert system, such as an expert system based on rules, framework structure, semantic network, and so on. Considering that a lot of knowledge about bridge structure diagnosis is empirical knowledge, there is not enough theoretical basis at present. In the system, a knowledge base based on production rules is used.

Under the combined effects of the long-term effect of external load, fatigue effect of vehicle load, erosion effect of the external environment, the aging effect of internal materials, and mutation effect of accidental disasters, various structural damage problems will inevitably occur in the design service life of bridge structure [8]. Especially in recent years, with the rapid development of China's transportation industry and the increasingly prominent characteristics of heavy load and heavy traffic, the load standard of some domestic bridge structures has far exceeded the original design value, and there is the risk of structural damage accumulation damage, resulting in major economic and safety accidents, as shown in Figure 1.

2. Literature Review

In recent years, the collapse of old bridges has occurred frequently in China, which has brought a great loss of personnel and property to society. Therefore, the safety of bridges in their whole life cycle has attracted more and more attention [9]. In order to avoid the occurrence of such accidents, how to accurately understand the state of the bridge structure and evaluating its safety is the core task of bridge management departments. A bridge health monitoring system can meet the needs of bridge management. However, restricted by factors initially such as sensor accuracy, environment, and stability, it was not widely used. With the rapid development of sensor technology, the precision and accuracy of bridge health monitoring have been greatly improved, and more and more bridges are equipped with bridge health monitoring systems [10]. The widening of the application range of bridge health monitoring systems makes bridge health monitoring become an important research field in civil engineering. The operation of the bridge

is accompanied by various loads and environmental effects, which will bring different degrees of damage to the structure.

When structural damage occurs, it is usually accompanied by cross-section damage and even degradation of the elastic modulus of a material. Therefore, it is very important to capture effective damage indicators from a large amount of data generated by the bridge health monitoring system [11]. Frequency and damping ratio are often used as indicators to judge whether structural damage occurs. However, after analyzing the dynamic load test results of a large number of bridges, it is found that when the structural damage does not occur to a certain degree, the frequency and damping ratio do not change significantly, and the identification effect is not obvious [12]. Compared with frequency and damping ratio, damage identification based on dynamic characteristics of structures, such as vibration mode, curvature mode, and strain mode, has better sensitivity.

In the process of the health monitoring of bridge structures, a large amount of data is often collected, and it is of great significance to quickly analyze the results in a large amount of data for rapid loss determination of practical engineering [13]. As an information processing system based on bionics theory, the artificial neural network can imitate the human brain to process external information. Due to its advantages in information processing such as parallelism, self-learning, self-organizing, and robustness, the artificial neural network has been widely used in civil engineering and other related fields in recent years. Using a large number of test data to train the neural network can replace the manual operation, so as to quickly identify the location and degree of damage. Shi et al. monitored and identified pick wear degree types through BP neural network system accurately [14]. Barkoula et al. verified the structural damage by using natural frequency and neural networks, and the ideal results are obtained [15].

The so-called distributed system refers to that according to the installation and layout of field sensors, the data collectors for collecting the status information of various devices are distributed locally not only in terms of data collection function but also in terms of geographical location, so that various data collectors can be conveniently configured and combined according to different monitoring objects [16]. The concept of a networked system refers to the condition monitoring and fault diagnosis system. The design of the network is adopted from the overall structure and system configuration. All kinds of data collected in the data collection station are sent into a web server database in order to realize the data sharing. The data related to the network server can be shared by the client program in each workstation. At the same time, it can also be sent to the same-level network or to a higher-level diagnosis center through a network server, thereby forming a condition monitoring and fault diagnosis network composed of several levels of networks [17]. The whole networked monitoring and diagnosis system consists of a three-level network. The first level is the state detection data collection network. Through the control of the data collector, the equipment status data collection and management are realized. The second level is the state monitoring local area network, which realizes the sharing



BIM based bridge safety monitoring and early warning system

- Field sensing element
- BIM bridge 3d simulation system
- Midas bridge finite element safety calculation system
- Remote data acquisition system

FIGURE 1: Distributed network in bridge structure.

and management of all the state monitoring data, and realizes the real-time monitoring and diagnosis of the bridge state in each functional department. The last level is the remote diagnosis network, which realizes remote data management and fault diagnosis without networking [18].

Based on this, professional programming software programming is used to directly interface with the finite element numerical simulation data. The BP neural network is trained using the modal data curvature dataset. Then, the structural damage is predicted through the trained BP neural network. Finally, the program is verified by combining the two most common bridge types [19]. The research shows that the program developed in this paper can identify and predict the damage to bridges well, and can output intelligently.

3. Methods

3.1. Basic Theories and Assumptions

3.1.1. Modal Curvature Theory. In the bridge structure, as the main stress member, the main beam is generally the bending member, mainly bending deformation. Other deformations such as shear deformation can be ignored. Therefore, by simplifying the virtual work principle, the deflection (1) is as follows:

$$y = \frac{1}{EI} \int M_i(x) n M_i(x) n ds. \quad (1)$$

According to the bridge deflection line, θ is the rotation angle, y_i is the deflection, and the curve curvature formula is as follows:

$$\frac{1}{\rho(x)} = \pm \frac{y''}{[1 + (y')^2]^{3/2}}. \quad (2)$$

In (2), $\rho(x)$ is the radius of curvature.

Eq. (2) can be transformed into

$$\frac{1}{\rho(x)} = y''. \quad (3)$$

The relationship between bending moment and deflection at the internal section of the beam is shown in (4) as follows:

$$\frac{EI}{\rho(x)} = -M(x). \quad (4)$$

Eq. (5) can be obtained by combining (3) and (4).

$$y'' = \frac{1}{\rho(x)} = \frac{M(x)}{EI}. \quad (5)$$

It can be seen from (5) that the curvature of a point on the main beam is inversely proportional to its corresponding stiffness, so once the stiffness of the structure changes, it can be reflected through the curvature.

In a practical engineering structure, all kinds of sensors are usually installed in the main girder, such as GPS sensors, the big dipper sensor, or other displacement sensors to cooperate structural vibration acquisition system for real-time acquisition. It acquires the bridge station displacement $\delta(x_i)$ at some point. After calculating, the displacement of the structure of the whole formation δ can be obtained, it is shown in (6) as follows:

$$\delta = [\delta(x_1)\delta(x_2) \cdots \delta(x_i) \cdots \delta(x_{n-1})\delta(x_n)]. \quad (6)$$

In (6), i is the number of sensors deployed.

Curvature mode $\rho(x_i)$ can be obtained by the displacement formation center difference method, and its calculation (7) is as follows:

$$\rho(x_i) = \frac{\delta(x_{i-1}) - 2\delta(x_i) + \delta(x_{i+1}))}{l_{i-1,i}l_{i,i+1}}. \quad (7)$$

In (7), $l_{i-1,i}$ is the distance from the sensor $i-1$ to sensor i ; $l_{i,i+1}$ is the distance from the sensor i to sensor $i+1$.

In practical calculation, the curvature modal data is usually normalized to make the damage index more sensitive.

3.1.2. BP Neural Network. BP neural network builds a multilayer perception model by imitating the response of neurons in the human brain to external stimuli. By transmitting the signal in the positive direction, the error is obtained and then adjusted in the reverse direction, and the iterative trial-and-error learning is carried out continuously. Finally, an intelligent network model that can process nonlinear information is formed as follows:

$$y_k = \sum_{j=1}^{n_1} \omega_{hj}^2 f \left(\sum_{i=1}^{n_2} \omega_{ji}^1 x_i + b_j \right). \quad (8)$$

In (8), x_k is the k th input; y_k is the k th output; ω_{kjj}^2 is the weight of neuron NO. j from the second layer (hidden layer)

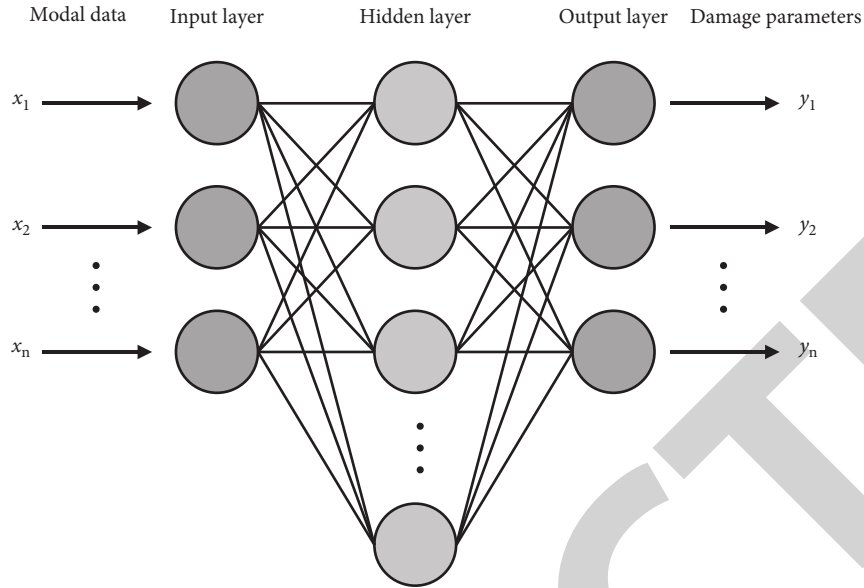


FIGURE 2: Flow chart of structural damage identification of BP neural network.

to neuron NO. k from the output layer; $f(\cdot)$ is the transfer function of neuron in a hidden layer; ω_{ji}^1 is the weight from no. i neuron of the 1st layer (input layer) to no. j neuron of the hidden layer; b_j is the bias value of j neuron in the hidden layer; n_1 is the number of neurons in the input layer; n_2 is the number of neurons in the hidden layer.

After the neural network model is set up, the modal parameters are taken as the input variables of the neural network, the structural damage index is taken as the output variables, and the neural network can master the nonlinear mapping between the input variables and the output variables by using the self-learning ability of the neural network, so as to realize the damage assessment.

Based on the above theory, the process of bridge structural damage identification is shown in Figure 2.

3.2. Numerical Simulation and Analysis. The feasibility of this method is verified by simulation analysis of two common bridge structures.

3.2.1. A Simply Supported Structure Simulation. A simply supported beam bridge structure is taken as the research object. The length of the simply supported beam structure is 10 m, and the whole bridge is divided into 20 units. The elastic modulus of the material is 3.45×10^4 MPa. Considering that first-order modal data is easy to be collected in actual engineering, only first-order modal data is used for simulation analysis. The preset damage degree is 5%–20%, the damage is set as single damage, and the damage simulation is realized by stiffness reduction. The single damage is set for each unit from unit 2 to unit 19 in sequence, and a total of 72 groups of data are obtained. The structure diagram of simply supported beam is shown in Figure 3.

Matlab software is used to compile the program and the parameters of the neural network are set. The number of

iterations is set to 1000, the training accuracy is set to 10^{-3} , and the learning rate is set to 0.01 [20]. The 72 training sets obtained through the modal analysis of case 1 are randomly shuffled by the developed program, and the input variables and output variables in the training set are still corresponding one by one. The first 60 sets of data sets are taken as training sets, and the remaining 12 sets of data sets are taken as test sets. The results and graphs are output after the operation. Columnar convexity exists at both sides of the original damage cells in the 12 test sets, and the damage position of each test set can be automatically output. The Z-coordinates of different heights in the 3D histogram correspond to different damage degrees, which respectively correspond to the true damage values of the 12 test sets in Figure 4.

It can be seen from Figure 4 that the trained neural network can predict and output the damage degree of the test set, where the true value is the stiffness damage degree preset in advance. If the structural units are divided more carefully, the Z coordinate of the damage in Figure 4 will be more prominent.

3.2.2. Numerical Simulation of Continuous Beam Bridge. Taking a 3-span prestressed concrete continuous girder bridge with an equal section as the research object, the bridge length is 106 m, and the span layout is 30 m + 46 m + 30 m. The main beam concrete is C50 grade. The elastic modulus of concrete is 3.45×10^4 MPa. The bridge finite element model is divided into 106 elements, and the damage simulation is realized by stiffness reduction. The first-order modal data which is easy to collect are used for analysis. As the bridge is divided into many units, only the first span and the middle span are used to set structural damage, and even units within the range of units in Table 1 are selected for damage location. After sorting out, there are 84 data sets in total, and the damage degree is shown in Table 1.

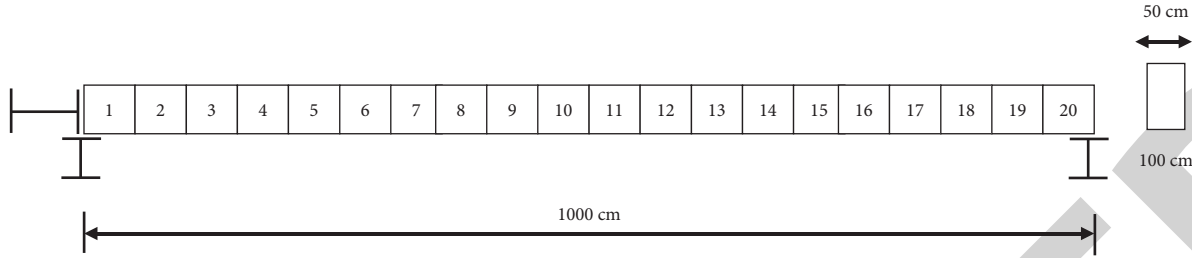


FIGURE 3: Diagram of a simply supported beam structure.

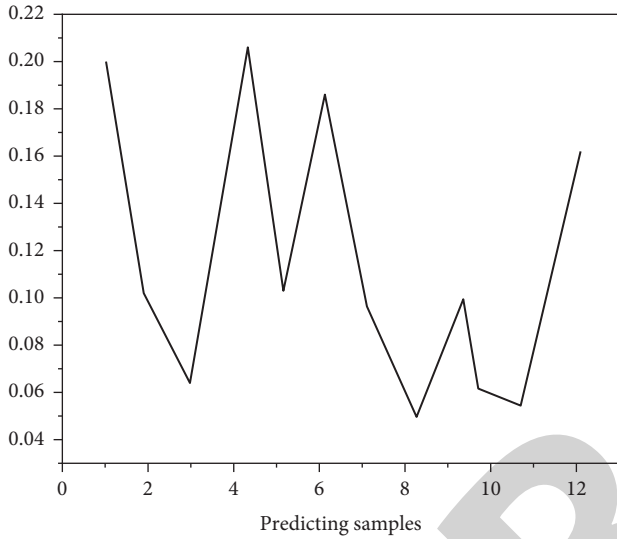


FIGURE 4: Comparison between test set data and actual data of simply supported beams.

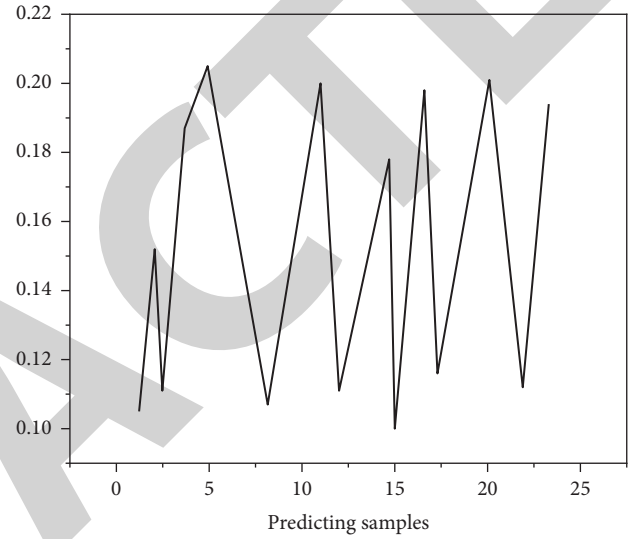


FIGURE 5: Comparison of the test set data and the actual data of the continuous beam.

TABLE 1: Damage degree table.

The degree of damage (%)	The damage position
10	Unit 6~unit 24; unit 36~unit 70
15	Unit 6~unit 24; unit 36~unit 70
20	Unit 6~unit 24; unit 36~unit 70

4. Results and Discussions

24 groups of test sets are calculated through the program, and the output results are shown in Figure 5.

Columnar convexity exists in the original damage unit of the 24 test sets, which can automatically output the damage position of each test set. Corresponding to different damage degrees, the corresponding true damage values of 24 test sets are in Figure 5. It can be seen from Figure 5 that the directions of the bar chart are positive and negative, which is because the mode parameters of the continuous beam have different directions in different spans. When damage occurs, it is greater than or less than no damage. The waveform of the original preset damage appears very obvious exciting convexity, which can accurately identify the location of the damage. By comparison, it is found that the damage identification effect of a continuous beam bridge is slightly worse than that of a simply supported beam, which is caused

by the failure of neural network training for all units' damaged data. If the training set density is added, the prediction effect can be significantly improved and the prediction is more accurate.

The results of finite element simulation are used to verify the developed program. The program is accurate in identifying the damage position of two common bridge structures, namely, simple-supported beam, and continuous beam, and the fitting degree between the predicted value and the real value can reach 0.97, indicating that the program has certain feasibility for structural damage identification.

5. Conclusions

In the research, the application of a distributed network in bridge structure safety inspection is proposed. The safety problems of large bridge structures are becoming more and more prominent, which puts forward higher requirements for the development of intelligent detection technology. It is feasible and sensitive to use the curvature of modal data as a damage index. And after combining with the neural network, the damage location and degree of bridge structure can be accurately identified. In the future, this method can be combined with bridge health monitoring and replace the manual repetitive data analysis and processing, automatically output results, and avoid calculation errors. Especially

in terms of long-term stability, it is very suitable for the needs of long-term monitoring of bridges and other projects. It has great application potential and prospects in realizing the monitoring of the entire life cycle of bridges, long-term health monitoring, and safety assessment of bridges.

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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References

- [1] K. Bugarová, E. Mošková, and J. Šimíčková, "Increasing the resilience of transport enterprises through the implementation of risk management and continuity management," *Transportation Research Procedia*, vol. 55, no. 3, pp. 1522–1529, 2021.
- [2] J. O. Park, S. H. Park, K. S. Kim, W. J. Park, and J. H. Kim, "Bridge monitoring system based on lora sensor network," *Journal of the Computational Structural Engineering Institute of Korea*, vol. 33, no. 2, pp. 113–119, 2020.
- [3] F. Y. Chen and C. Y. Liu, "Air passengers' continued use intention of the airport e-gate system: a perspective with perceived benefits," *International Journal of Business and Management*, vol. 16, no. 1, p. 100, 2020.
- [4] Wang, Z. Wei, Z. Jing, Z. Hui, and Lei, "Assessing effect of grassland resources policies using ahp and fuzzy comprehensive evaluation: a case study of ningxia hui autonomous region, China," *Ecological Economy*, vol. 16, no. 03, pp. 51–59, 2020.
- [5] J. Wang, X. He, F. Shao, G. Lu, and Q. Jiang, "A Real-Time Bridge Crack Detection Method Based on an Improved Inception-Resnet-V2 Structure," *IEEE Access*, vol. 9, no. 99, p. 1, 2021.
- [6] S. H. Li, J. Y. Feng, W. He, R. H. Qi, and H. Guo, "Health Assessment for a Sensor Network with Data Loss Based on Belief Rule Base," *IEEE Access*, vol. 5, no. 99, p. 1, 2020.
- [7] A. Miyamoto, "Knowledge-based systems for the assessment and management of bridge structures: a review," *Journal of Software Engineering and Applications*, vol. 14, no. 09, pp. 505–536, 2021.
- [8] Y. J. Jang, J. W. Jin, J. H. Lee, S. I. Lee, and K. W. Kang, "Long-term durability of offshore wind turbine composite blades based on nonlinear load behavior due to pitch movement," *Journal of Mechanical Science and Technology*, vol. 34, no. 6, pp. 2347–2355, 2020.
- [9] X. Qiao, K. Guo, G. Li, L. Zhao, F. Y. Li, and C. Gao, "Assessing the collapse risk of stipa bungeana grassland in China based on its distribution changes," *Journal of Arid Land*, vol. 12, no. 2, pp. 303–317, 2020.
- [10] M. Zeeshan, J. P. Sajeevan, H. K. Bhoomika, and B. M. Nagesh, "Railway security management system (bridge vibration) based on gsm," *International Journal of Engineering Research in Africa*, vol. 10, no. 12, pp. 8–10, 2020.
- [11] F. Li, D. Yin, C. Zhu, F. Wang, N. Jiang, and Z. Zhang, "Effects of kaolin addition on mechanical properties for cemented coal gangue-fly ash backfill under uniaxial loading," *Energies*, vol. 14, no. 12, p. 3693, 2021.
- [12] L. Wang, W. Shi, Z. Ying, and Q. Zhang, "Semi-active eddy current pendulum tuned mass damper with variable frequency and damping," *Smart Structures and Systems*, vol. 25, no. 1, pp. 65–80, 2020.
- [13] X. Li, Y. Xiao, H. Guo, and J. Zhang, "A bim based approach for structural health monitoring of bridges," *KSCFE Journal of Civil Engineering*, vol. 26, no. 1, pp. 155–165, 2022.
- [14] Y. Shi, H. Liu, X. Zhang, Q. Li, and X. Guo, "Wear identification of vibration drilling bit based on improved lmd and bp neural network," *Mathematical Problems in Engineering*, vol. 2020, no. 4, pp. 1–9, 2020.
- [15] N. M. Barkoula and J. Karger-Kocsis, "Review processes and influencing parameters of the solid particle erosion of polymers and their composites," *Journal of Materials Science*, vol. 37, no. 18, pp. 3807–3820, 2002.
- [16] G. Dhiman, V. Vinoth Kumar, A. Kaur, and A. Sharma, "Don: deep learning and optimization-based framework for detection of novel coronavirus disease using x-ray images," *Interdisciplinary Sciences: Computational Life Sciences*, vol. 13, no. 2, pp. 260–272, 2021.
- [17] J. Jayakumar, B. Nagaraj, S. Chacko, and P. Ajay, "Conceptual implementation of artificial intelligent based E-mobility controller in smart city environment," *Wireless Communications and Mobile Computing*, vol. 2021, pp. 1–8, Article ID 5325116, 2021.
- [18] J. Chen, J. Liu, X. Liu, X. Xu, and F. Zhong, "Decomposition of toluene with a combined plasma photolysis (cpp) reactor: influence of uv irradiation and byproduct analysis," *Plasma Chemistry and Plasma Processing*, vol. 41, no. 1, pp. 409–420, 2020.
- [19] P. Ajay, B. Nagaraj, R. A. Kumar, R. Huang, and P. Ananthi, "Unsupervised hyperspectral microscopic image segmentation using deep embedded clustering algorithm," *Scanning*, vol. 2022, pp. 1–9, Article ID 1200860, 2022.
- [20] G. Veselov, A. Tselykh, A. Sharma, and R. Huang, "Special issue on applications of artificial intelligence in evolution of smart cities and societies," *Informatica*, vol. 45, no. No.5, p. 603, <http://www.informatica.si/index.php/informatica/article/view/3600>.