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Identification of Damage in a Wind Turbine Blade Using Mechanical Measurements and Artificial Neural Networks

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Abstract: Due to the stochastic nature of environmental loadings, a lot of interest is paid in the discovery of possible damages to the involved equipment in modern industry. In wind turbines' blades, the development of a smart structural health monitoring system is essential. In this paper, a large-scale composite wind turbine blade model is designed and used for the detection of several damage scenarios. The process is mainly based on the development of monitoring techniques that exploit the capabilities of artificial neural networks. These techniques can provide the exact position of possible damages, under given external loading scenarios. Moreover, the use of such methods decreases significantly the need for external intervention and at the same time it increases the accuracy of the whole approach. The above processes are simulated using the finite element method. The goal is to develop a neural network that realizes the correlation of measurements with damage patterns. The goal is focused on the solution of inverse problems involving elastically deformable structures, based on remote mechanical measurements. The correlation between measurements and damages, which is much more complicated in comparison to image analysis, is studied by means of neural networks.

Keywords: structural health monitoring, finite element method, wind turbines, artificial neural networks

1. Introduction

Inverse problems related to damage identification on blades of wind turbines are studied here. Data for various damage scenarios are generated by using a high-quality finite element model of the structure. The correlation of measurements with damage parameters has been realized by means of back propagation artificial neural networks (ANNs). The methodology is general and can be extended to other structural health monitoring tasks.

Wind turbines constitute one of the promising devices for harvesting of energy and supporting the green energy policy. Both current designs, namely horizontal and vertical axis wind turbines, include large rotating parts and several smaller parts, i.e., blades, joints, etc., subjected to high wind or other dynamic loadings, which could possibly put at risk the integrity of the whole structure. The arising damage or fatigue effects can decrease significantly the lifetime of the critical components of wind turbine structures, such as the wind turbine blades, and may lead to partial or even total – sometimes catastrophic – failures of the whole system.

In the present investigation, a composite large-scale wind turbine blade model will be considered similar to the one presented in Rentoumis et al. [1]. More specifically, a large-scale wind turbine blade of span, which equals to approximately 25 m, is taken into consideration. The location of installation is the Mount Panachaiko, Peloponnese, Greece. In order to assess the integrity of the blade structure, a damage identification algorithm based on neural networks is considered [2]. The proposed method belongs to the modern physics-based, data-driven methods for treating complex direct and inverse problems in mechanics.

The considered blade is hollow, formed by two separate shells; one on the suction side and one on the pressure side. Aerodynamic principles and structural aspects direct the design of the airfoil considers [3].

The objective of the present paper is the development of a procedure for nondestructive crack and damage identification in wind turbine blades. This methodology can be applied to broader classes of inverse problems, like distributed damage identification and flaw detection. Static mechanical behavior is considered with a finite element model. Several failure scenarios are included in the model for the creation of the required database of predicted results. The inverse is solved by means of a back-propagation trained neural network. The training data are produced by the numerical model (pseudo-experiments).

Crack detection has attracted a lot of scientific interest, and several methods have been proposed in the current literature. For example, in Zhang et al. [4], an automatic system for crack detection during the inspection of tunnels was proposed. Deep learning techniques and a heuristic image postprocessing algorithm were used. From the results, it was shown that this method can be effectively used as a driver of autonomous inspection robots. In Li et al. [5], an automatic robotic inspector for tunnel assessment is proposed. The system consists of an autonomous mobile vehicle, that is, a crane arm, guided by a computer vision-based crack detector, and it has been evaluated in real railway and road tunnels. In Wang and Zhang [6], a new

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method, which is called multidimensional variational decomposition, was proposed for bearing-crack detection. From the results, it is shown that this method can deal with multichannel vibration signals, overcoming the limitations of existing methods. The proposed system is based on unmanned aerial vehicle (UAV) – taken images collected from a commercial wind farm. Automatic detection of cracks on the surface of defects in piles is presented in Protopapadakis et al. [7]. The computational study proves the effectiveness of the proposed method in the identification of the number and location of cracks.

Identification problems belong to the class of the so-called inverse problems where some parameters of the system are unknown, while more than necessary data from the response of the system are available. In the case studied here, unknown parameters are related to the cracks, while input–output data of the structural system are available through measurements or simulations. By considering the structural response, in terms of measured displacements or stresses as the input of the inverse mapping and the related crack parameters as the output, the output error identification problem is formulated and solved. The classical optimization approach is not always advantageous due to the nature of the problem. More specifically, for inverse problems, small variations of a certain structural parameter may lead to either large or small variations in the structural response depending on the position and/or the type of the parameter [2]. Due to this, the problem is considered to be an ill-posed one. Furthermore, due to the nonlinearity of the damage-to-response mapping, the arising optimization problem is usually nonconvex, and thus, the possibility of multiple mathematical solutions exists. In terms of optimization, this corresponds to a problem with several local minima, and thus, the classical optimization may stop at local minima and do not solve the sought inverse problem. In this case, soft computing techniques, such as the neural network approach, which have the ability to overcome local minima, can be adopted.

The methodology used here for the treatment of the inverse problem has been developed and tested for the solution of academic crack identification problems in two- and three-dimensional elasticity in Stavroulaki [2]. In the aforementioned investigation, a two-dimensional specimen is considered that contains one or more unknown cracks. The cracks are described by a certain number of parameters, for instance, the length of a linear crack, and the coordinates of the middle point with respect to the used global coordinate system. Furthermore, it is assumed that certain boundary displacements can be measured for various static, time-periodic, or time-history external loadings. The direct mechanical problem is solved numerically by the boundary element method (BEM), while the identification (inverse) problem is treated by a neural network-based optimization technique. More details can be found in Jensen [3]. Recent investigations of our group present the defect identification of concrete piles by using dynamic test loading and neural networks. For example, Jensen [3] proposed a genetically optimized neural detector for the detection of possible defects in concrete piles. The finite element method was used for the modeling, and from the results, it was shown that useful information about the type and the position of these defects can be obtained. In Bouzid et al. [8], a similar problem is solved by using an ant colony classification algorithm.

Literature on damage identification using mechanical measurements and neural networks of various types is expanding. Visual inspection by using photographs or thermography and further processing with AI methods is an area with considerable activity, as it can be traced in the review articles [9, 10]. In particular, applications focused on damage detection on wind blades using data-driven, AI and digital twins are reported in the review articles [11–16]. Modern approaches involve the exploitation of online data acquisition for SHM, for instance in Alvarez-Montoya et al. [17], Zhang et al. [18], and Lin et al. [19].

Computational modeling is a convenient tool to create data for the initial training of a neural network system in order to solve inverse and damage identification problems. Depending on the degree of accuracy, the investigation may stop at this phase, as it is in the present paper, or continue with fine-tuning by using experimental data. In this context, one has pretrained Artificial Intelligence (AI) systems based on artificial data that are further trained with real-life data. Representative works combining computational modeling by finite element and boundary element methods for the creation of damage scenarios and inverse analysis include these papers [20–31].

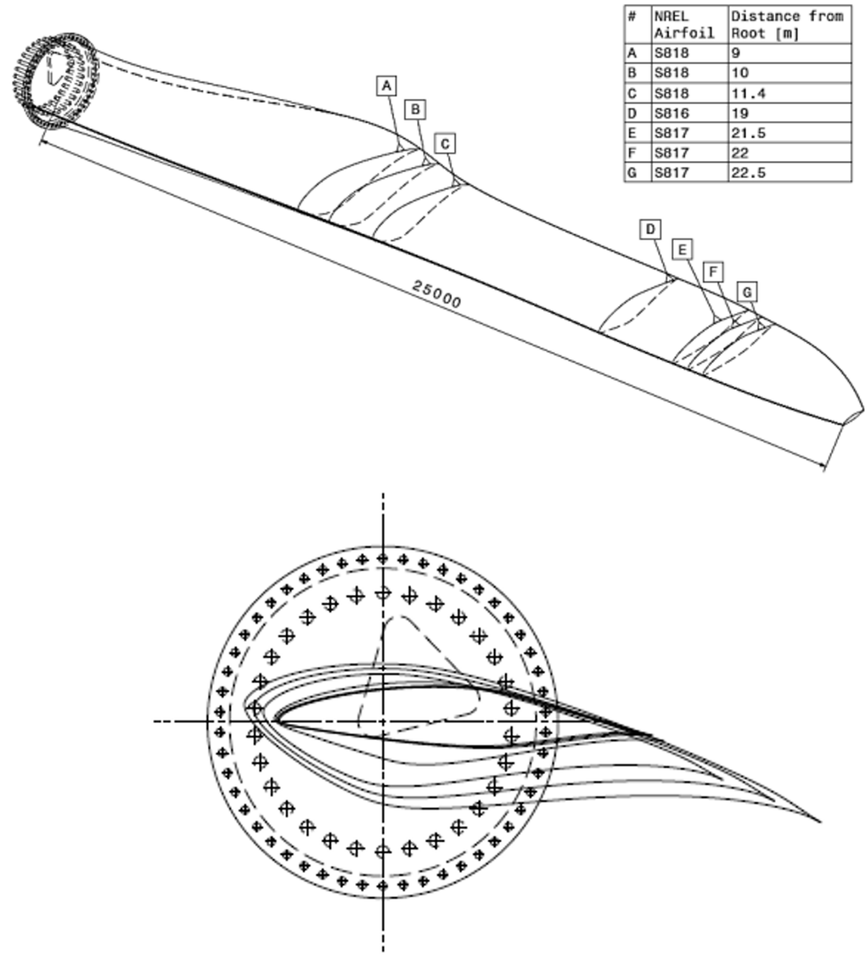
It should be noted that complicated neural networks and AI algorithms are applied for the solution of academic crack identification problems, see Benaissa et al. [32]. Indeed, AI is able to discover difficult correlations between signal and damage patterns, like ones appearing in wave propagation and ultrasound produced by distributed actuators and sensors and nondestructive evaluation (NDT), see Lomazzi et al. [33], Saha et al. [34], Islam et al. [35], Shen and Tian [36], Bandara et al. [37], Nazarko and Ziemianski [38], Yang et al. [39], de Assis and Gomes [40], and Yoon et al. [41]. From the many applications reported in the literature, one can mention here, for example, the aircraft icing detection and characterization problem [42], the prediction of urban gas consumption [43], the underwater backscatter recognition [44], the sonar classifier [45], the classification of marine mammals [46, 47], the financial accounting information processing [48], and the biomedical application on breast cancer diagnosis [49].

A numerical simulation of finite element and BEM was carried out on a specific wind turbine blade with realistic damage scenarios, and from the results, it was shown that the proposed scheme can identify the type and position of the defects in a much more complicated structure is considered in the present investigation, which seems to be the first work using data-driven, neural network-assisted techniques for the solution of crack identification problems in complicated structures based on Computer-Aided Design – Computer-Aided Engineering (CAD-CAE) models. The method can be used for the solution of much more complicated tasks, by using more refined tools of deep learning, in view of modern software developments which allow for easy parametric analysis and neural network evaluation.

2. The Wind Turbine Blade Design

Several airfoil families are available in the industry. The most common airfoils for horizontal axis wind turbines (HAWTs) are NACA 44XX, NACA 23XXX, NACA 63XXX, and NASA LS series (NACA denotes the National Advisory Committee for Aeronautics in the USA, the Federal Agency that created the standards for the named aerofoils). The performance of the above-mentioned airfoils suffers from roughness effects resulting from leading-edge contamination [1]. Furthermore, thick airfoils (with thickness between 16% and 21%) are mainly used in stall-regulated wind turbines. Thus, tip-region airfoils are considered thick enough in order to accommodate overspeed-control aerodynamic devices and to reduce the weight of the structure. On the other hand, thin airfoils, i.e., those with thickness between 11% and 15%, are more suited to variable-pitch or variable-rpm turbines that use full-span blade pitch [1]. In general, the cross section varies along the length of the blade, with greater thickness

Figure 1
Illustration of airfoils location along the blade span and illustration of different pitch angles of airfoils with reference to the root of the blade



used near the root in order to withstand structural and dynamic effects. For this reason, the blade-root airfoil thickness is usually in the range between 18% and 24%. Large thicknesses, greater than 26%, should be avoided, as it result in poor performance characteristics. In 1992, an airfoil family was designed for extra-large blades for turbines rated at 400–1000 kW. This family, which is included in stall-regulated rotors, is composed of the S816, S817, and S818 airfoils. The tip-region airfoil has a Cl, max of 1.1 and a thickness of 16%. The primary outboard airfoil has a Cl, max of 1.2 and a thickness of 21%, while the root airfoil has Cl, max of 1.3 and a thickness of 24% [1].

3. Structural Health Monitoring (SHM)

3.1. Assessment of SHM implementation

Structural failures in wind turbines are caused by several unpredicted reasons, e.g., earthquakes, hurricanes, strong winds, usage of brakes to avoid uncontrolled rotation, and extremely high temperatures. For that reason, a suitably defined system, able to monitor the performance of the whole structure, is necessary. In the case of wind turbines, this need is ubiquitous due to inaccessibility reasons (e.g., offshore structures), fatigue, or even because of the type of loads. An SHM system is a damage identification procedure for the prediction of possible damages of the host structure and is composed of three basic elements, i.e., the signal monitoring, the processing, and the interpretation. Such systems are usually vibration-based since the dynamic response is rich enough and can be used for the detection of internal (hidden) damages [50]. Either eigendynamic characteristics or time-domain response can be used for SHM. Static response can be used in a controlled monitoring sense. Provided that a first data-processing step is used in order to extract eigenshapes from dynamical measurements, the methodology that uses static response can be used as well in combination with dynamic data.

A typical wind turbine blade is shown in Figure 1 and a possible damage on it is depicted in Figure 2. Composite materials that are used in wind turbines' blades have certain advantages, i.e., they improve electrical conductance. However, they exhibit anisotropic properties that make the mechanism behind failures sophisticated. This type of material usually suffers by aging and fatigue Moreover, even a small impact can lead to the creation of cracks, delamination phenomena on the fibers, etc., in situ sensors with intelligent algorithms for online damage detection can be combined in order to achieve high accuracy and reliability for damage identification and monitoring at the minimum cost [48].

Figure 2
A typical crack near the trailing edge of the blade structure

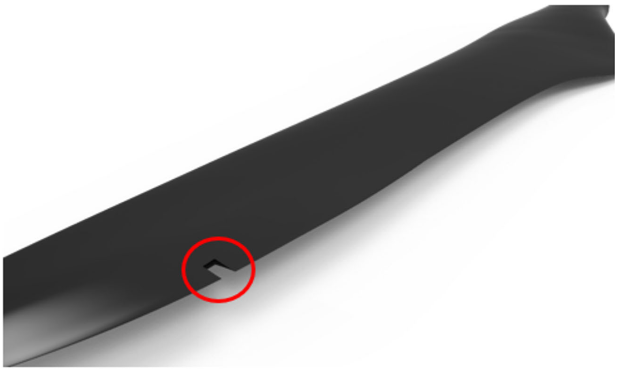
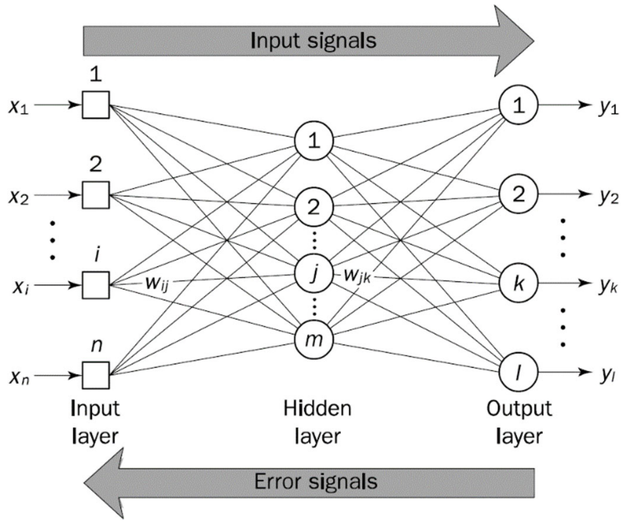


Figure 3
The backpropagation training process



4. Artificial Neural Networks

4.1. ANN introduction

An ANN is an approach of machine learning that attempts to simulate the function of the human's central nervous system, i.e., of the biological neural networks. It is a highly complicated network of interconnected calculating nodes (artificial neurons), which are algorithms of computational intelligence. Neural networks can be used for several applications, such as, among others, for optimization of control parameters [51] and damage identification [20].

With reference to Figure 3, the input (x) – output (y) relation is approximated by a feedforward ANN. A fully connected NN is considered for simplicity. Weights on the links multiply input information. At every node, activation functions (sigmoidal in our case) are used as processing elements. Outputs are approximations of the unknown mapping for every input, provided that the choice of network topology (number of layers, nodes, etc.) and weights are suitable. Topology is defined from the experience of the user, since no theoretical results exist. Weights are defined through training.

There are several ways of learning, and thus training of ANNs, which can be classified into supervised and unsupervised learning. Supervised learning is the process that combines the existence of an external trainer and a number of training data for the model. The most popular method in this direction is the back-propagation method of errors training method. This method calculates the derivative of the errors considering network weights. The derivative is, let's say, fed to the optimization method, which updates the weights, and thus the error is minimized.

Training is based on a representative set of training data, which corresponds to the unknown mapping. Here, training data relate the measurements directly with the failure characteristics. With fixed network parameters (topology and activation functions), the inputs are used and the outputs are calculated. In case an unacceptable error exists, the weights are adjusted to minimize this error. In this way, the neural network adapts itself to learn directly the inverse mapping and in this way it directly solves the inverse problem. In order to have a fair evaluation of the ANN model, 70% of examples are used for training and the remaining 30% are used for evaluation. In this last group, outputs are never used for training. Therefore, comparison of neural network predictions with outputs is a fair indication of a successful neural network. This methodology can be applied for static loadings and measurements of displacements or deformations, which is the case here, for harmonic dynamic loadings, for eigenvalues and eigenmodes, or even for dynamic service loads or testing loadings such as ultrasounds which are used in nondestructive structural evaluation.

4.2. ANN for solution of inverse problems

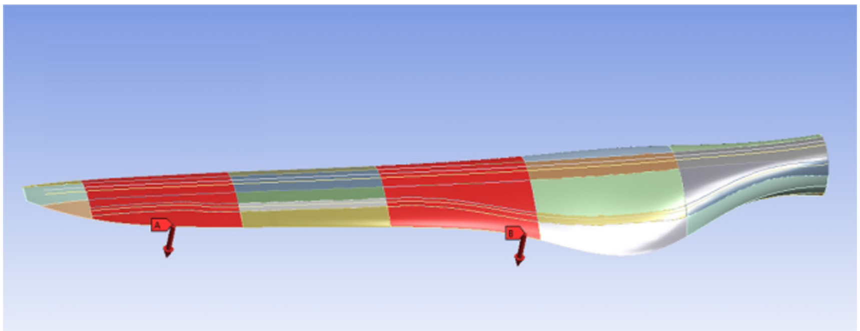
In the present investigation, the model of a blade with an unknown crack is considered. The crack is characterized by a set of parameters $z = [z_1, \ \dots \ z_m]^T$. Here, the coordinates (x, y) of the crack are used as identification parameters. The deformation of the blade for a given static loading b^l, $l = 1, \ \dots, ll$ and for a given crack z is given by the vector $\tilde{x}(z, b^l)$ (loadings are applied on the different areas of the model, see Figure 4, different crack positions are incorporated in various places of the model, as it will be seen in the numerical results). Experimental or numerically calculated results can be used. A finite element model is used here for the production of the results for various crack characteristics. Cracks are modeled as smeared ones, by considering a lower stiffness near their place, similarly to the areas of loading depicted in Figure 4.

Let the total number of different loading cases be l_l, and the mechanical response of the structure with a known crack subjected to the same loading b^l be denoted by $\tilde{x}_0(z, b^l)$. In this investigation, the elements of $\tilde{x}_0(z, b^l)$ are produced by a finite element algorithm. Here, a direct solution to the inverse problem by means of back propagation-trained neural networks is sought. Due to the appearance of nonlinearity in the response vector, if the response is considered as a function of the crack parameters, the classical error minimization approach may lead to non-convex optimization [2].

A multilayer back propagation error-trained neural network is used to learn the previously mentioned inverse relation for a given value of loading vector b^l. The couples of data composed of the vectors $\tilde{x}(z, b^l)$ and the corresponding parameter vectors z are used as training examples. After training, the network reproduces the relation $x \rightarrow z$, i.e., for a given set of measurements $\tilde{x}$ (different from the ones used in training), it gives a prediction for the variables characterizing the internal crack [2].

The procedure can be extended to cover time-varying damage cases, by expanding the database and using a moving window technique or another suitable type of neural network.

Figure 4
Areas of static loadings considered on the wind turbine blade



5. Numerical Results

5.1. Wind turbine blade materials

The blade has a sandwich form for both the external surfaces and the internal spars. The thickness differs from point to point from 0.035 m to 0.1 m, with ore material at the spars, where larger stiffness is needed, and external surfaces, where less material is used.

The model consists of an isotropic elastic polyvinyl chloride plastic – PVC foam, for the core of the blade, and an orthotropic elastic epoxy carbon material with enhanced characteristics in terms of electrical conductance, for the external material. The latter provides distributed sensing ability, which is very useful in similar applications. The total mass of the blade is 3.686, 39 kg. The characteristics and critical values of the materials that were used are given in detail below. The detailed material properties of the foam are given in Table 1, while the ones for the epoxy carbon material are presented in Table 2.

The orthotropic strain limits and the orthotropic stress limits of the epoxy carbon material are given in Table 3.

Table 1
PVC foam material properties

	80
Young's modulus [Pa]	1.02×10^{8}
Poisson's ratio	0.3
Bulk modulus [Pa]	8.5×10^{7}
Shear modulus [Pa]	3.9231×10^{7}

Table 2
Epoxy carbon unidirectional – UD material properties

Density [kg/m^3]	1490
Young's modulus (X direction) [Pa]	1.21×10^{11}
Young's modulus (Y direction) [Pa]	0.6×10^{9}
Young's modulus (Z direction) [Pa]	0.6×10^{9}
Poisson's ratio (XY)	0.27
Poisson's ratio (YZ)	0.4
Poisson's ratio (XZ)	0.27
Shear modulus (XY) [Pa]	0.7×10^{9}
Shear modulus (YZ) [Pa]	0.1×10^{9}
Shear modulus (XZ) [Pa]	0.7×10^{9}

Table 3
Epoxy carbon UD orthotropic strain and stress limits

	Strain [m]	Stress [Pa]
Tensile (X direction)	1.67×10^{-2}	2.231×10^{9}
Tensile (Y direction)	3.2×10^{-3}	2.9×10^{7}
Tensile (Z direction)	3.2×10^{-3}	2.9×10^{7}
Compressive (X direction)	-1.08×10^{-2}	-1.082×10^{8}
Compressive (Y direction)	-1.92×10^{-2}	-1.0×10^{8}
Compressive (Z direction)	-1.92×10^{-2}	-1.0×10^{8}
Shear (XY)	1.2×10^{-2}	6×10^{7}
Shear (YZ)	1.1×10^{-2}	3.2×10^{7}
Shear (XZ)	1.2×10^{-2}	6×10^{7}

More details on the composite structure of the blade, which is based on classical composite materials made of multiple layers, can be found in the literature [1].

5.2. Identification of cracks using ANNs

For the development of the SHM scheme, in order to predict the possible appearance of cracks on the aforementioned blade model, neural networks were used (see Figure 5). The neural network learns the inverse relation correlating displacement measurements from sensors with damage indicators. The data are produced using finite element modeling. In this work, static deformations are used for given loads. Various examples have been considered by taking damage scenarios with different, reduced stiffnesses, at the various areas of the model which are measured at the positions shown in Figure 6. (see Figure 4). Training is accomplished by backpropagation error training algorithm (see Figure 3), by using the previously mentioned measurement – damage couples of data.

In the present investigation, two different cases are examined. The failures (cracks) appear on the surface of the wind turbine blade.

Case 1:

For the first numerical experiment, the control points (points of measurement) on the blade are selected on the central axis of the surface as shown in Figure 6. More specifically, 44 control points are employed for the analysis. A static analysis is performed on the wind turbine in order to obtain the training data for the neural network which is trained using the back-propagation method. A total amount of 40 cracks are used for the training process. Namely, the displacements for each crack are measured at these points in order to train the neural network for the detection of cracks. The same points of measurement are also used for the testing process. The results of the analysis are displayed below.

Figure 5
Structure of the proposed SHM scheme

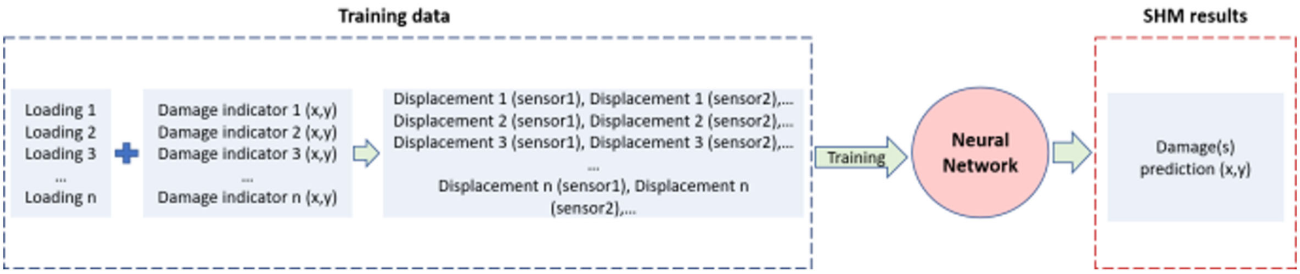


Figure 6
Positions of measurements (control points)

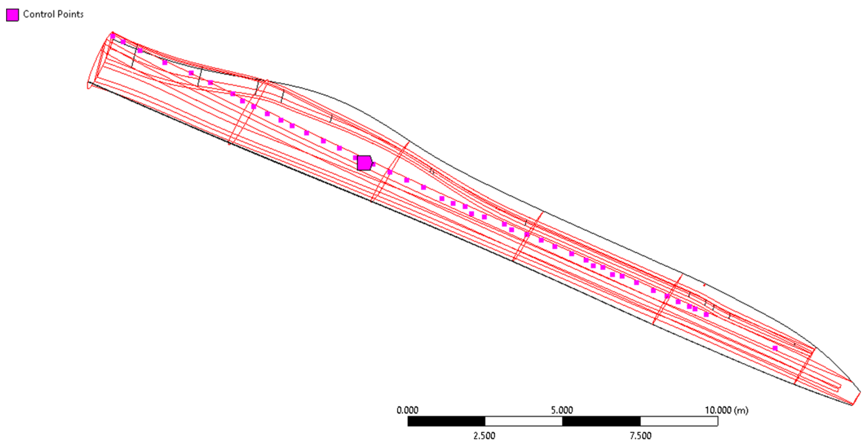
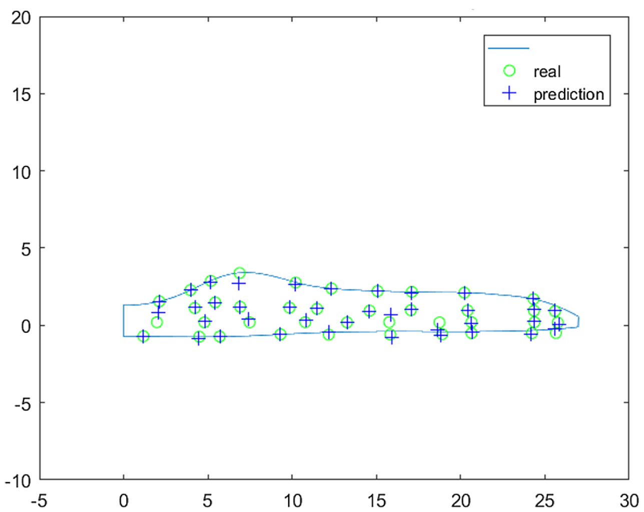


Figure 7
The results from training by the neural network



The results from the neural network are presented in Figure 7. Green circles denote the real position of the cracks, while blue crosses present the predictions of the neural network. From these results, it is clear that the trained network can predict the positions of the recurring cracks very effectively.

A fully connected ANN (cf. Figure 3) has been used with sigmoidal activation functions at the internal nodes. Input layer has 44 entries, equal to the number of measurement points, two internal layers with 50 nodes in each have been used, and 2 outputs are used, depicting the position of estimated crack. The deep learning package of MATLAB has been used for ANN modelling. Training up to an acceptable accuracy needs less than 5 min on a usual PC. Usage of trained ANN needs a couple of seconds.

In Figure 8, one can see the correlation of inputs and outputs for both the model and the neural network prediction, as well as the error of the created system through the deviation of the diagonal line, which represents the error-free cases. Every point corresponds to a different damage example used for training or representation of the neural network model.

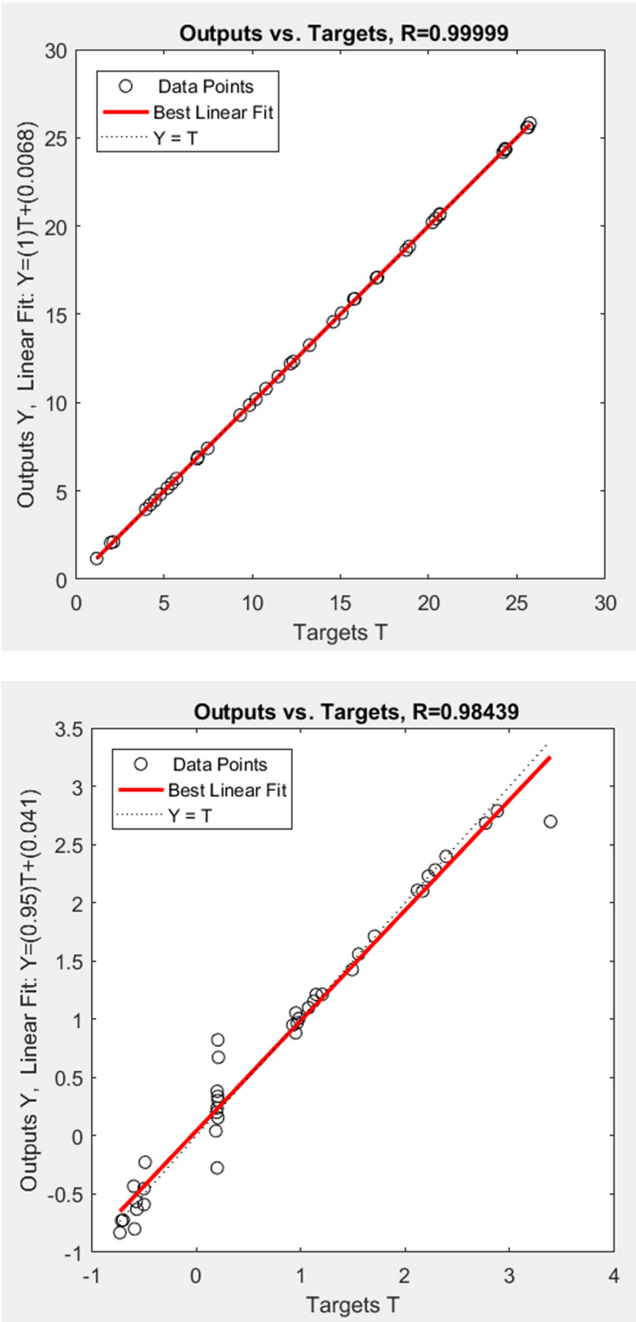
A simulation with the use of 10 unknown cracks is performed. The results are shown in Figure 9. Again, with green circles are denoted the real position of the cracks, while with blue crosses are presented the predictions of the neural network.

In Figure 10, one can see the correlation of inputs and outputs for both the model and the neural network prediction, for case 1. From the results, it is clear that the fitting is not satisfactory, although even warning that something deviates from nominal response could be a useful result within SHM.

Case 2:

For the second case, a set of 105 control points is selected, covering not only the central axis of the surface as in case 1 but also the whole surface of the wind turbine blade, as seen in Figure 11. The same static analysis is repeated in order to obtain the training data for the neural network. A total amount of 40

Figure 8
Correlation of inputs and outputs for both the model and the neural network prediction



cracks are used for the training. Namely, the displacements for each crack are measured at these points in order to train the neural network for the detection of cracks. The same points of measurement are also used for the testing process. The number of measurement points is higher, in comparison to case 1, and evenly distributed along the length of the blade. The ANN has been modified to accommodate this case by changing the input entries to 105 and using 100 nodes at each one of the two hidden layers. The results of the analysis are displayed below.

Figure 9
The results for the first case

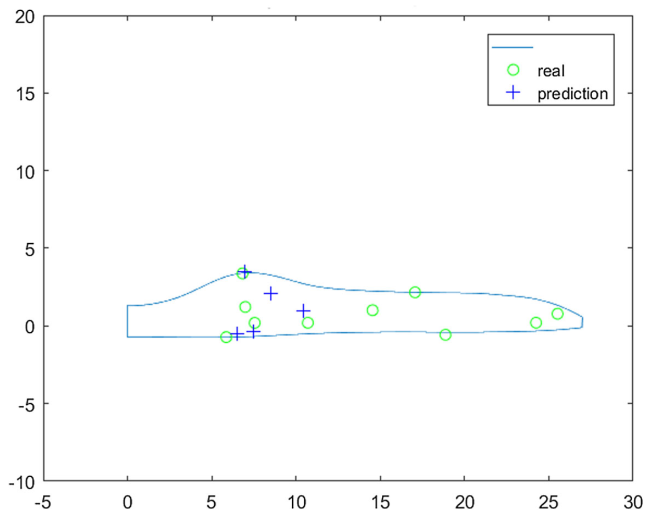


Figure 10
Correlation of inputs and outputs for both the model and the neural network prediction for case 1

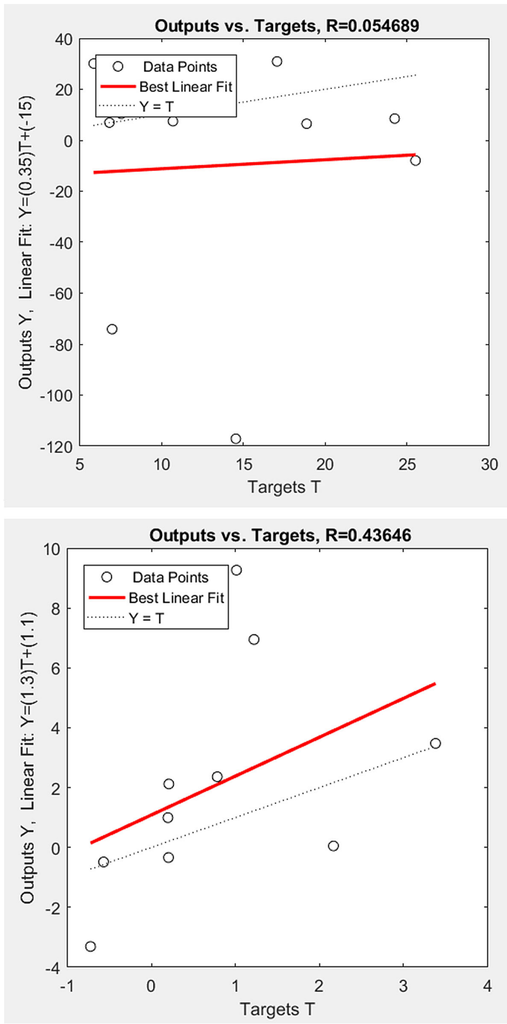


Figure 11
Positions of measurements (control points)

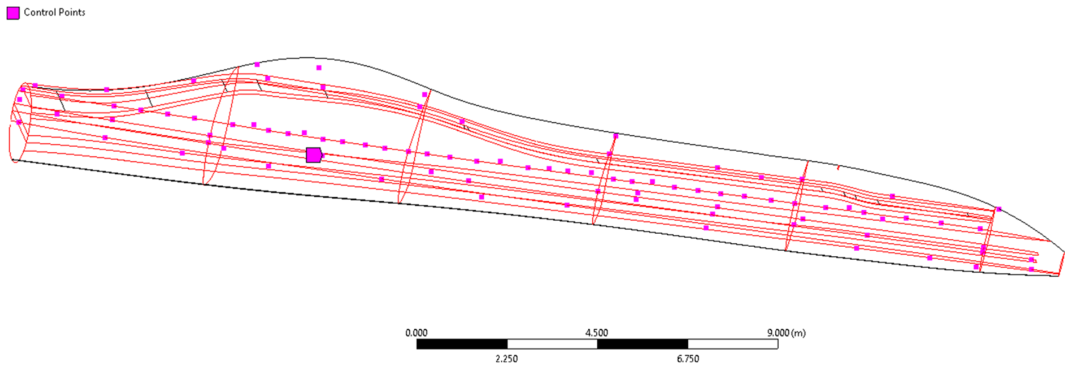


Figure 12
The results from training by the neural network. Real cracks vs. prediction on the CAD model

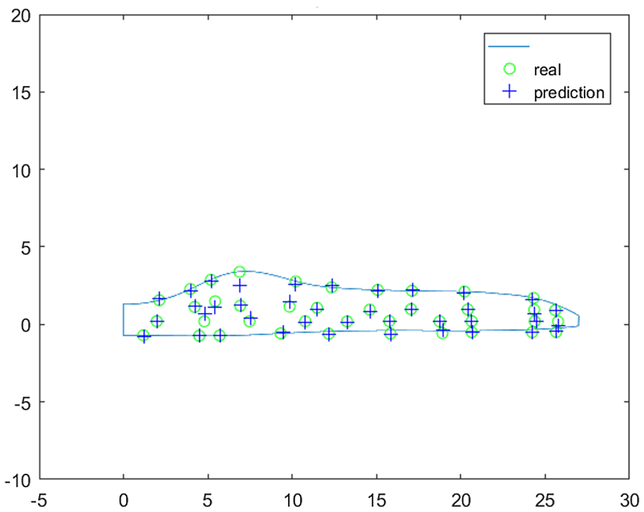
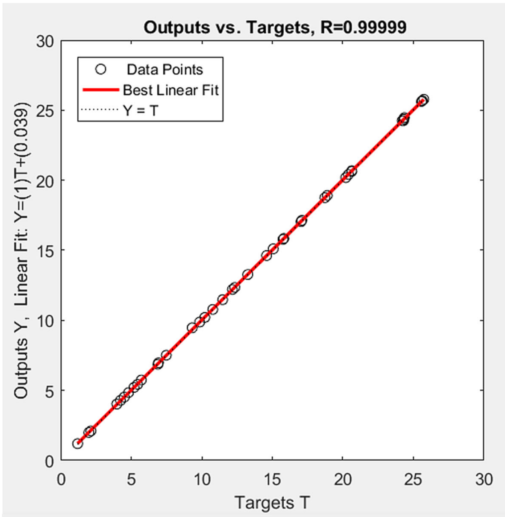
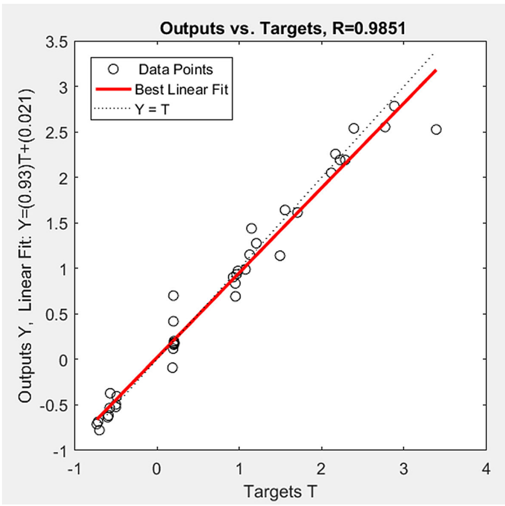


Figure 13
Correlation of inputs and outputs for both the model and the neural network prediction. Target *T* and output *Y* must coincide in case of error-free prediction (points in diagonal line). First picture corresponds to examples used for training, and second picture shows prediction for new examples





The results from the neural network are presented in Figure 12. Again, with green circles are given the real position of the cracks, while the blue crosses denote the predictions of the ANN. It is seen that the trained network can predict even more efficiently the positions of the recurring cracks. The result is expected since more information is provided to the system for the solution of the damage identification problem, cf. [2].

In Figure 13, one can see the correlation of inputs and outputs for both the model and the neural network prediction, as well as the error of the created system through the deviation of the diagonal line, which represents the error-free cases. Every point corresponds to a different damage example used for training or representation of the neural network model.

The same 10 cracks are used for the analysis, and the results are shown in Figure 14. The results here indicate that the training of the network in this second case is more successful.

Finally, in Figure 15, the correlation of inputs and outputs for both the model and the neural network prediction for case 2 is depicted. One can observe that the neural network achieves better fitting in this case.

Figure 14
The results for the second case

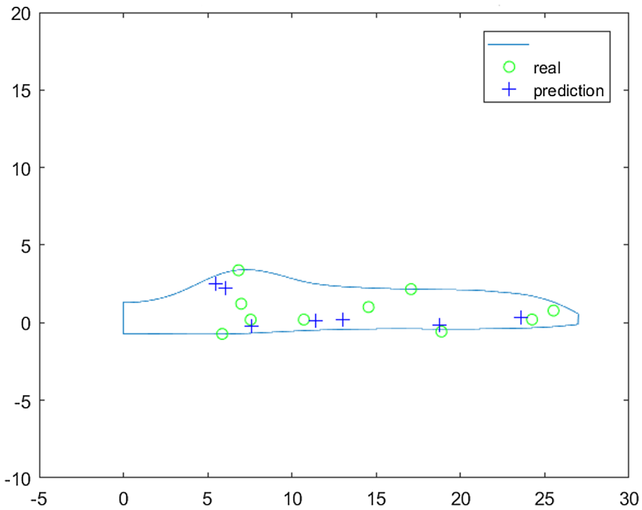
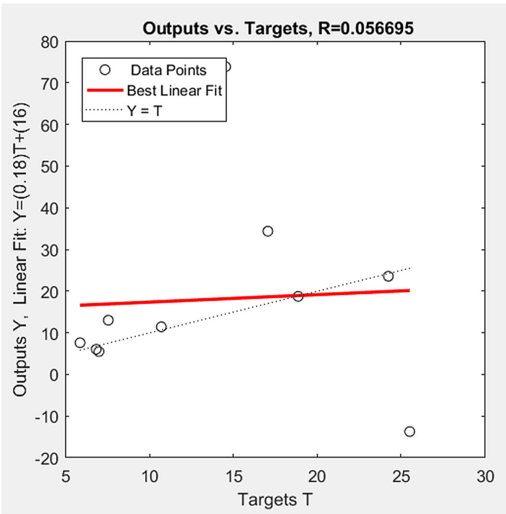
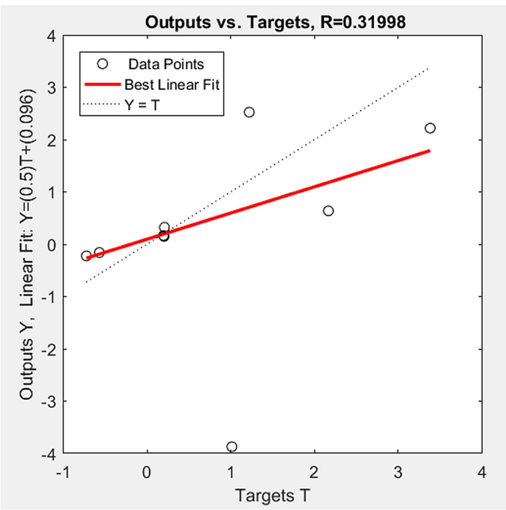


Figure 15
Correlation of inputs and outputs for both the model and the neural network prediction for case 1





6. Conclusions

In the present investigation, a correlation system of measurements and damages was tested. The efficiency of the proposed scheme lies in the ability of the neural networks to learn from examples with unknown correlations and to perform prediction. More specifically, two different cases were examined. The difference lies in the number and the position of the control points. In both cases, measured deformations have been used as input for the damage identification problem. From the results, one can conclude that a suitably trained neural network can predict effectively the positions of the recurring cracks, however, only when the control points are evenly distributed along the surface of the wind turbine blade (case 2). This is expected, as the neural network has better performance in interpolation, rather than in extrapolation.

Previous works on the solution of comparable problems use relative methodology of neural networks, however, on simpler academic applications. Thus, more examples, which in turn means better training, were obtained. In the present investigation, a more complicated CAD model, closer to a real blade, was considered. Although the CAD-CAE model used here is near to real applications, the examples remain academic.

In any case, the proof of concept, which was the objective of the study, was successful, as with a few data and a simple neural network, efficient results were obtained. For more complex applications, a larger amount of training examples might be needed, along with optimization of the network using deep learning. More information can be found in the review papers [52, 53].

It is also worth noting that only static loadings, and a relatively small amount of measurements, were considered. The next step in the present investigation can be the optimization of the neural network characteristics, as well as the consideration of multiple loading which will be applied across every dimension. Moreover, an extension of this work to dynamic loadings with more measurements and the use of modal analysis tools can also be performed.

More complicated AI tools, including deep learning and decision trees, can be employed for the solution of more complicated inverse tasks using a fusion of various measurements (static, dynamic, etc.).

A mixture of initial training based on numerically generated data, as it has been done in this paper, with experimental measurements, is also possible. In fact, usage of pretrained neural networks that can be further refined with additional or experimental data is a widely adopted methodology in various modern applications.

Finally, various stages of damage can be considered, and a plastic neural network approach can be adopted, in order to identify the degree of damage. The resulting neural network model is a kind of digital twin that can be used to monitor the blade throughout its whole life and predict possible damages. In fact, wind turbines suffer from fatigue damage due to extreme loading and weather conditions. In turn, SHM and maintenance tasks become challenging. The application of digital twins in this area is a topic of current intensive research activity. The neural network-based metamodels presented here are a useful tool.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are not publicly available due to privacy concerns. However, anonymous data are available on reasonable request. Requests should be made to the corresponding author Georgios E. Stavroulakis and should include a brief description of the intended use of the data.

Author Contribution Statement

Panagiotis Koutsianitis: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Manolis Paterakis:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualization. **Georgios E. Stavroulakis:** Conceptualization, Validation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration.

References

[1] Rentoumis, M., Koutsianitis, P., Athanailidis, I., Taridis, G., Tselikos, G., Bilalis, N., & Stavroulakis, G. E. (2018). Design and structural analysis of wind turbine blades for structural health monitoring consideration. In *9th GRACM International Congress on Computational Mechanics*, 153–162.

[2] Stavroulakis, G. E. (2013). *Inverse and crack identification problems in engineering mechanics*. USA: Springer.

[3] Jensen, F. M. (2008). *Ultimate strength of a large wind turbine blade*. PhD Thesis, Technical University of Denmark.

[4] Zhang, W., Zhang, R., Wu, C., Goh, A. T. C., Lacasse, S., Liu, Z., & Liu, H. (2020). State-of-the-art review of soft computing applications in underground excavations. *Geoscience Frontiers, 11*(4), 1095–1106. https://doi.org/10.1016/j.gsf.2019.12.003

[5] Li, Z., Jiang, Y., Guo, O., Hu, C., & Peng, Z. (2018). Multi-dimensional variational mode decomposition for bearing-crack detection in wind turbines with large driving-speed variations. *Renewable Energy*, *116*, 55–73. https://doi.org/10.1016/j.renene.2016.12.013

[6] Wang, L., & Zhang, Z. (2017). Automatic detection of wind turbine blade surface cracks based on UAV-taken images. *IEEE Transactions on Industrial Electronics*, *64*(9), 7293–7303. https://doi.org/10.1109/TIE.2017.2682037

[7] Protopapadakis, E., Voulodimos, A., Doulamis, A., Doulamis, N., & Stathaki, T. (2019). Automatic crack detection for tunnel inspection using deep learning and heuristic image post-processing. *Applied Intelligence*, *49*, 2793–2806. https://doi.org/10.1007/s10489-018-01396-y

[8] Bouzid, O. M., Tian, G. Y., Cumanan, K., & Moore, D. (2015). Structural health monitoring of wind turbine blades: Acoustic source localization using wireless sensor networks. *Journal of Sensors*, *2015*(1), 139695. https://doi.org/10.1155/2015/139695

[9] Nguyen, S. D., Tran, T. S., Tran, V. P., Lee, H. J., Piran, M. J., & Le, V. P. (2023). Deep learning-based crack detection: A survey. *International Journal of Pavement Research and Technology*, *16*(4), 943–967. https://doi.org/10.1007/s42947-022-00172-z

[10] Hamishebahar, Y., Guan, H., So, S., & Jo, J. (2022). A comprehensive review of deep learning-based crack detection approaches. *Applied Sciences*, *12*(3), 1374. https://doi.org/10.3390/app12031374

[11] Kong, K., Dyer, K., Payne, C., Hamerton, I., & Weaver, P. M. (2023). Progress and trends in damage detection methods, maintenance, and data-driven monitoring of wind turbine blades: A review. *Renewable Energy Focus*, *44*, 390–412. https://doi.org/10.1016/j.ref.2022.08.005

[12] Bisanti, G. M., Mainetti, L., Montanaro, T., Patrono, L., & Sergi, I. (2023). Digital twins for aircraft maintenance and operation: A systematic literature review and an IoT-enabled modular architecture. *Internet of Things*, *24*, 100991. https://doi.org/10.1016/j.iot.2023.100991

[13] Aguilar, E., Awan, A., Garcia, J., Quach, M., Salei, R., Sevilla, M., . . . , & Sotoudeh, Z. (2024). A digital twin framework for detecting the damage location. In *AIAA SCITECH 2024 Forum*. https://doi.org/10.2514/6.2024-0197

[14] Lai, X., Yang, L., He, X., Pang, Y., Song, X., & Sun, W. (2023). Digital twin-based structural health monitoring by combining measurement and computational data: An aircraft wing example. *Journal of Manufacturing Systems*, *69*, 76–90. https://doi.org/10.1016/j.jmsy.2023.06.006

[15] Shen, T., Wan, F., Song, B., & Wu, Y. (2011). Damage location and identification of the wing structure with probabilistic neural networks. In *Prognostics and System Health Managment Conference,* 1–6. https://doi.org/10.1109/PHM.2011.5939524

[16] Sucharitha, M., Sesha Talpa Sai, P. H. V., Thazha, S. K., Thomas, M., Hunagund, B., & Krishna Anand, V. G. (2024). Damage identification on aircraft wing using convolutional neural network based pattern recognition. In *Intelligent Manufacturing and Energy Sustainability: Proceedings of ICIMES 2023*, 173–182. https://doi.org/10.1007/978-981-99-6774-2_16

[17] Alvarez-Montoya, J., Carvajal-Castrillón, A., & Sierra-Pérez, J. (2020). In-flight and wireless damage detection in a UAV composite wing using fiber optic sensors and strain field pattern recognition. *Mechanical Systems and Signal Processing*, *136*, 106526. https://doi.org/10.1016/j.ymssp.2019.106526

[18] Zhang, M., Pei, Y., Yao, X., & Ge, Y. (2023). Damage assessment of aircraft wing subjected to blast wave with finite element method and artificial neural network tool. *Defence Technology*, *25*, 203–219. https://doi.org/10.1016/j.dt.2022.05.010

[19] Lin, M., Guo, S., He, S., Li, W., & Yang, D. (2022). Structure health monitoring of a composite wing based on flight load and strain data using deep learning method. *Composite Structures*, *286*, 115305. https://doi.org/10.1016/j.compstruct.2022.115305

[20] Efstathiades, C., Baniotopoulos, C. C., Nazarko, P., Ziemianski, L., & Stavroulakis, G. E. (2007). Application of neural networks for the structural health monitoring in curtain-wall systems. *Engineering Structures*, *29*(12), 3475–3484. https://doi.org/10.1016/j.engstruct.2007.08.017

[21] Jeong, I., Kim, H., Cho, H., Park, H., & Kim, T. (2023). Initial structural damage detection approach via FE-based data augmentation and class activation map. *Structural Health*

Monitoring, *22*(5), 3225–3249. https://doi.org/10.1177/14759217221149612

[22] Seventekidis, P., & Giagopoulos, D. (2023). Model error effects in supervised damage identification of structures with numerically trained classifiers. *Mechanical Systems and Signal Processing*, *184*, 109741. https://doi.org/10.1016/j.ymssp.2022.109741

[23] Yang, Y., Zhan, Z., & Liu, Y. (2024). A novel damage identification algorithm by combining the boundary element method and a series connection neural network. *Engineering Applications of Artificial Intelligence*, *133*, 108010. https://doi.org/10.1016/j.engappai.2024.108010

[24] Han, X., Yang, Y., & Liu, Y. (2022). Determining the defect locations and sizes in elastic plates by using the artificial neural network and boundary element method. *Engineering Analysis with Boundary Elements*, *139*, 232–245. https://doi.org/10.1016/j.enganabound.2022.03.030

[25] Di Giacinto, D., Musone, V., & Ruocco, E. (2022). Voids identification by isogeometric boundary element and neural network algorithms. *International Journal of Mechanical Sciences*, *231*, 107538. https://doi.org/10.1016/j.ijmecsci.2022.107538

[26] Amoura, N., Benaissa, B., Al Ali, M., & Khatir, S. (2023). Deep neural network and YUKI algorithm for inner damage characterization based on elastic boundary displacement. In *Proceedings of the International Conference of Steel and Composite for Engineering Structures*, 220–233. https://doi.org/10.1007/978-3-031-24041-6_18

[27] Fujii, S., Ogawa, M., & Hirabayashi, D. (2023). Non-destructive estimation of three-dimensional inelastic strain via nonlinear inverse analysis using displacement. *Mechanical Engineering Journal*, *10*(4), 23-00191. https://doi.org/10.1299/mej.23-00191

[28] Yang, C., Yang, Y., Lin, Y., Wang, B., Qian, Z., & Hirose, S. (2024). Inversion of the shape of defects in composite plates. *International Journal of Mechanical Sciences*, *269*, 109046. https://doi.org/10.1016/j.ijmecsci.2024.109046

[29] Rangoju, S. S. V. D., Polepally, G., Kalap, P., & Pasupuleti, V. D. K. (2023). Structural damage detection through finite element model updating using evolutionary algorithm. *Structural Health Monitoring*.

[30] Thananjayan, P., Ramu, P., & Natarajan, S. (2023). SBFEM and Bayesian inference for efficient multiple flaw detection in structures. *Engineering Analysis with Boundary Elements*, *155*, 226–250. https://doi.org/10.1016/j.enganabound.2023.06.001

[31] Somners, D. M. (2004). *The S816, S817, and S818 airfoils. October 1991 – July 1992.* National Renewable Energy Laboratory Report. Retrieved from: https://www.nrel.gov/docs/fy05osti/36333.pdf

[32] Benaissa, B., Aït Hocine, N., Khatir, S., Kamel Riahi, M., & Mirjalili, S. (2021). YUKI algorithm and POD-RBF for elastostatic and dynamic crack identification. *Journal of Computational Science*, *55*, 101451. https://doi.org/10.1016/j.jocs.2021.101451

[33] Lomazzi, L., Giglio, M., & Cadini, F. (2023). Towards a deep learning-based unified approach for structural damage detection, localisation and quantification. *Engineering Applications of Artificial Intelligence*, *121*, 106003. https://doi.org/10.1016/j.engappai.2023.106003

[34] Saha, N., Roy, P., & Topdar, P. (2023). Damage detection in composites using non-destructive testing aided by ANN technique: A review. *Journal of Thermoplastic Composite Materials*, *36*(12), 4997–5033. https://doi.org/10.1177/08927057231172670

[35] Islam, M., Sohaib, M., Kim, J., & Kim, J. M. (2018). Crack classification of a pressure vessel using feature selection and deep learning methods. *Sensors*, *18*(12), 4379. https://doi.org/10.3390/s18124379

[36] Shen, L., & Tian, L. (2023). A static load position identification method for optical fiber-composite structures based on particle swarm optimization-back propagation neural network algorithm. *Measurement and Control*, *56*(3–4), 820–831. https://doi.org/10.1177/00202940221101673

[37] Bandara, S., Herath, M., & Epaarachchi, J. (2023). Sensory methods and machine learning based damage identification of fibre-reinforced composite structures: An introductory review. *Journal of Reinforced Plastics and Composites*, *42*(21–22), 1119–1146. https://doi.org/10.1177/07316844221145972

[38] Nazarko, P., & Ziemianski, L. (2011). Application of artificial neural networks in the damage identification of structural elements. *Computer Assisted Methods in Engineering and Science*, *18*(3), 175–189.

[39] Yang, Q., Li, G., Mu, W., Liu, G., & Sun, H. (2020). Identification of crack length and angle at the center weld seam of offshore platforms using a neural network approach. *Journal of Marine Science and Engineering*, *8*(1), 40. https://doi.org/10.3390/jmse8010040

[40] de Assis, F. M., & Gomes, G. F. (2021). Crack identification in laminated composites based on modal responses using metaheuristics, artificial neural networks and response surface method: A comparative study. *Archive of Applied Mechanics*, *91*(10), 4389–4408. https://doi.org/10.1007/s00419-021-02015-y

[41] Yoon, J., Lee, J., Kim, G., Ryu, S., & Park, J. (2022). Deep neural network-based structural health monitoring technique for real-time crack detection and localization using strain gauge sensors. *Scientific Reports*, *12*(1), 20204. https://doi.org/10.1038/s41598-022-24269-4

[42] Dong, Y. (2018). An application of Deep Neural Networks to the in-flight parameter identification for detection and characterization of aircraft icing. *Aerospace Science and Technology*, *77*, 34–49. https://doi.org/10.1016/j.ast.2018.02.026

[43] Qian, L., Chen, Z., Huang, Y., & Stanford, R. J. (2023). Employing categorical boosting (CatBoost) and meta-heuristic algorithms for predicting the urban gas consumption. *Urban Climate*, *51*, 101647. https://doi.org/10.1016/j.uclim.2023.101647

[44] Khishe, M., Mohammadi, M., & Ramezani Varkani, A. (2023). Underwater backscatter recognition using deep fuzzy extreme convolutional neural network optimized via hunger games search. *Neural Processing Letters*, *55*(4), 4843–4870. https://doi.org/10.1007/s11063-022-11068-1

[45] Kosarirad, H., Ghasempour Nejati, M., Saffari, A., Khishe, M., & Mohammadi, M. (2022). Feature selection and training multilayer perceptron neural networks using grasshopper optimization algorithm for design optimal classifier of big data sonar. *Journal of Sensors*, *2022*(1), 9620555. https://doi.org/10.1155/2022/9620555

[46] Hosseini Nejad Takhti, A., Saffari, A., Martín, D., Khishe, M., & Mohammadi, M. (2022). Classification of marine mammals using the trained multilayer perceptron neural network with the whale algorithm developed with the fuzzy system. *Computational Intelligence and Neuroscience*, *2022*(1), 3216400. https://doi.org/10.1155/2022/3216400

[47] Saffari, A., Khishe, M., & Zahiri, S. H. (2022). Fuzzy-ChOA: An improved chimp optimization algorithm for marine mammal classification using artificial neural network. *Analog Integrated Circuits and Signal Processing*, *111*(3), 403–417. https://doi.org/10.1007/s10470-022-02014-1

[48] Li, H., Zhou, W., & Xu, J. (2014). Structural health monitoring of wind turbine blades. In N. Luo, Y. Vidal & L. Acho (Eds.), *Wind turbine control and monitoring* (pp. 231–266). Springer.

[49] Qian, L., Bai, J., Huang, Y., Zeebaree, D. Q., Saffari, A., & Zebari, D. A. (2024). Breast cancer diagnosis using evolving deep convolutional neural network based on hybrid extreme learning machine technique and improved chimp optimization algorithm. *Biomedical Signal Processing and Control*, *87*, 105492. https://doi.org/10.1016/j.bspc.2023.105492

[50] Han, S., & Yun, L. (2021). Design and performance of concrete pile strengthened with lengthened steel-tube core: Model tests and numerical simulations. *Mathematical Problems in Engineering*, *2021*(1), 5592296. https://doi.org/10.1155/2021/5592296

[51] Repinaldo, J. P., Faria, A. W., Alves e Silva, R., Koroishi, E. H., & Lara-Molina, F. A. (2020). Neuro-fuzzy modal control of smart laminated composite structures modeled via mixed theory and high-order shear deformation theory. *Latin American Journal of Solids and Structures*, *17*(2), e258. https://doi.org/10.1590/1679-78255873

[52] Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep learning for computer vision: A brief review. *Computational Intelligence and Neuroscience*, *2018*(1), 7068349. https://doi.org/10.1155/2018/7068349

[53] Guo, Y., Liu, Y., Oerlemans, A., Lao, S., Wu, S., & Lew, M. S. (2016). Deep learning for visual understanding: A review. *Neurocomputing*, *187*, 27–48. https://doi.org/10.1016/j.neucom.2015.09.116

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