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Development of Digital Twin Concept for Real-Time Detection of Abnormal Changes in Structural Behaviour

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Abstract **–** The paper aims to extend the definition of Digital Twin (DT) concept to be able to identify small severity damages by incorporating mathematical formulations in construction of neural networks. Advanced modelling techniques such as Reduced Basis (RB) method and artificial neural networks were used during the offline stage to develop a DT model to detect abnormal changes in structural behaviour during the online monitoring stage. Finite element model was used with RB model order reduction technique for construction of a low-dimensional space to speed the analysis during the online stage. Different damage scenarios were implemented by reducing the effective stiffness of several structural members to test the ability of the established DT model to detect damages once they have appeared in the structure. In addition, the RB model was used to choose the optimal location of displacement sensors in a physical structure. The RB model was validated against experimental test results for a two-dimensional truss. A neural network was developed and trained to identify the location of damage once it has appeared during the operational stage. The constructed RB model was used again for identification of severity of damage identified by the optimized neural network. It was found that the developed method showed high accuracy in identifying small severity damages during the online stage.

Keywords**:** Damage diagnosis, Deep Learning (DL), Digital Twin (DT), Predictive maintenance, Reduced Basis (RB), Structural Health Monitoring (SHM)

1. Introduction

DT technology is a new technology appeared in the early 21st century. The term DT was introduced in 2002 by Gravies [1] who defined the DT as the digital representation of living and non-living physical assets. By connecting the physical and virtual assets, data are transmitted smoothly, allowing the virtual asset to fully represent the physical asset. In 2019 [2], the concept was introduced in various studies to enhance reinforcement learning using it. The DT concept is widely used in different applications. For instance, DTs are used in manufacturing industries and optimizations of complex systems such as aircraft engines and wind turbines. Recently, several studies have used the term DT not only for monitoring of the current behaviour of assets, but also for predicting the future behaviour of the assets based on the sensory information from the physical assets using different data acquisition systems. In 2019 [3], the DT concept was used in civil engineering field for real time simulation of structural behaviour. In addition, the concept is used for real time damage identification of structures for maintenance purposes [4]. The main usage of DT concept is to simulate the structural behaviour of a system in real-time during its operational phase. However, when the damages start to appear in the structure, the ability of DT model to reflect the current behaviour of the structures decreases. This is due to excessive large computational efforts required to solve the numerical model during the real-time simulation. Due to this, DT models cannot reflect the real condition of the systems. Therefore, these models are no longer twins, but some kind of more distinct numerical relatives [5].

Different variants of Model Order Reduction (MOR) techniques were used for construction of lower dimensional space to accelerate the analysis during the online stage once the sensory information is available. For instance, Reduced Basis Model Order Reduction (RB-MOR) technique is used in different studies for construction of lower dimensional space to overcome computational load/memory requirements in Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD) and accelerate the computational analysis during the online monitoring of structural behaviour [6]. The studies showed that the RB method can reduce the computational effort during the online stage by reducing the dimensional space during the offline stage. However, there is still lack of knowledge of using RB methods to identify the location and type of small severity damage once it has appeared in the structure.

Data-Driven Approach (DDA) such as Machine Learning (ML) is used as an alternative to implement the concept of DT [7]. Deep learning (DL) is a subfield of ML that makes use of hierarchical architectures to learn high-level abstractions from data. DL techniques are based on Neural Networks (NNs), a subset of ML often referred to as Artificial Neural Networks (ANNs) or Simulated Neural Networks (SNNs). Recently, DL algorithms with help of ANNs are used in the context of DT concept for structural damage identification [8]. The studies showed that ANNs can be used for identification of damage location and type once it has appeared during the online simulation. However, the accuracy of the NN networks showed significant decrease with small severity damages.

Previous studies have shown that constructing a higher accuracy NNs using DDA without a mathematical formulation requires a large experimental trial. Moreover, this trial requires a large memory to be saved for later use. Therefore, this paper aims to incorporate a mathematical formulation to decrease the experimental work required for constructing the NN for damage identification. RB-MOR method with ANNs is used herein for developing a new method with specific criteria for establishing a DT model able to simulate structural behaviour quickly during the online stage and identify small severity damages once they have appeared in structure during the online stage.

2. Real-time damage identification using RB-MOR and ANNs

The workflow is divided into two main stages: offline and online stages. In the offline stage, several FEA analyses using ranges of parameters, namely, stiffness of structural members, are used for construction of lower dimensional space. Then, the constructed RB space is optimized again by reducing the sub-space again for construction of Reduced RB (RRB) space to speed up the analysis during the online stage. In addition, the RB snapshots are then used for construction of the NN dataset input. In the online stage, the sensory information is used first to check the accuracy of the constructed RRB space to simulate the behaviour of an initially undamaged structure. This step includes updating the RRB model constructed during the offline stage. Then, the NN is used to identify the damage scenario once the damage appears in the structure during the online stage. The updated RRB model is used again to estimate damage severity in terms of stiffness reduction. Fig.1 shows the workflow used in this research paper.

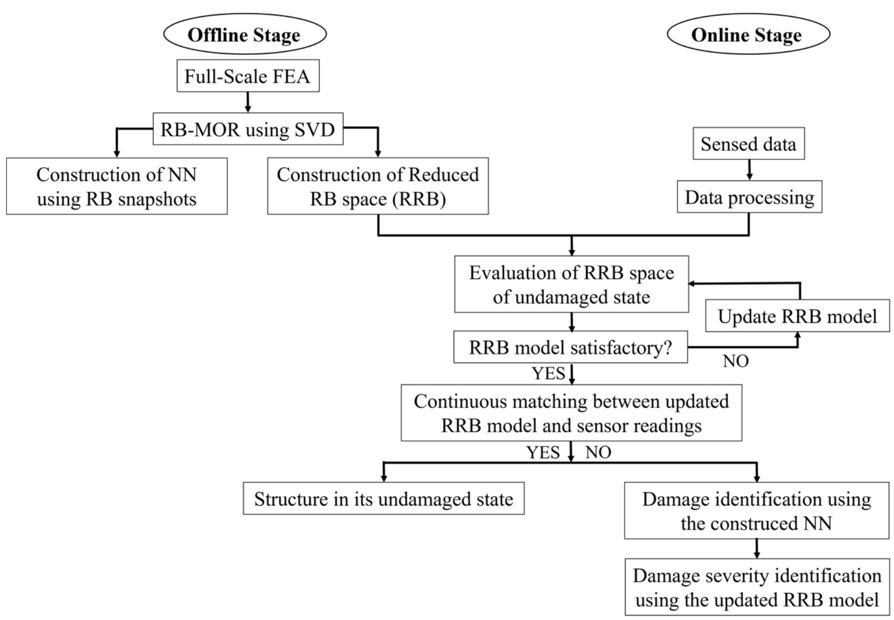


Fig. 1: Methodology flowchart

2.1. Construction of low-dimensional space using RB-MOR method

The strategy of the RB technique is based on the projection of the high-fidelity problem upon a subspace made of specially selected bases functions, representing a set of high-fidelity solutions for a range of chosen parameters. The parameter-dependent problem will be obtained using a suitable transformation of the original PDEs equation, resulting in a in a FE formulation. The accurate high-fidelity approximation of a PDE entails, from an algebraic standpoint, the solution solution of a (large) linear system, whose dimension is given by the number of Degrees of Freedom (DoF) N_h required to to represent the solution over a suitable finite dimensional space. The high-fidelity problem for any parameter $\mu \in \mathscr{P}$. $\mathscr{P}$ is the parameter space, can be represented as following:

$$K_h(\mu)u_h(\mu) = f_h(\mu), \tag{1}$$

where $K_h(\mu) \in \mathbb{R}^{N_h \times N_h}$ - is the μ-dependent stiffness matrix, $f_h(\mu) \in \mathbb{R}^{N_h \times 1}$ – is the μ-dependent force vector and $u_h(\mu)$ is the high-fidelity displacement vector.

The method begins with the offline phase in which a full FEA analysis for different sets of predefined parameters, chosen randomly within a range of values, is carried out. Such a FEA solution of the high-fidelity problem (1) for a specific set of parameters μ, $\mu \in \mathscr{P}$. is called a snapshot This creates a matrix of solutions

$$\mathcal{M} = [u_h(\mu^1)^{N_h \times 1}, \dots\dots\dots, u_h(\mu^N)^{N_h \times 1}] \tag{2}$$

where $\mathcal{M} \in \mathbb{R}^{N_h x N}$ – is the matrix of the N selected snapshots for N selected sets of parameters μ described in vector $S_{N_{RB}}$,

$$S_{N_{RB}} = \{\mu^1, \dots\dots, \mu^N\} \in \mathscr{P} \tag{3}$$

Here $u_h(\mu^1)$ is the high-fidelity solution corresponding to the first selected set of parameters.

The main goal of the RB method is to generate an approximate solution to the problem shown in Eq. (1) that belongs to a low-dimensional space of dimension $N_{RB} \ll N_h$ to accelerate the computational analysis during the online stage. For this purpose, the SVD technique is used to introduce a sub-space of lower dimensions. The SVD is defined as a diagonalization process, it states that any real matrix A can be represented as

$$A = U\Sigma Z^T \tag{4}$$

where $\Sigma = \text{diag}(\lambda_1, \dots\dots, \lambda_p) \in \mathbb{R}^{m \times n}$ is a diagonal matrix of singular values, $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0, p = \min(m, n)$, and $U^{m \times m}$ and $Z^{n \times n}$ are the complex unitary matrices.

$$U = [\zeta_1, \dots\dots, \zeta_m] \in \mathbb{R}^{m \times m} \tag{5}$$

$$Z = [\psi_1, \dots\dots, \psi_n] \in \mathbb{R}^{n \times n} \tag{6}$$

It is common that only a small number of the largest singular values $\lambda_i, 1 \leq i \leq N_{RB}$ is required to accurately approximated the original matrix A while the smaller singular values can be neglected, as well as the corresponding columns in U, leading to the reduced matrix

$$U_{RB} = [\zeta_1, \zeta_2, \dots\dots, \zeta_{N_{RB}}] \tag{7}$$

Columns in U_{RB} are called singular modes and the matrix represents a reduced basis, assumed to be parameter independent, such that for any set of parameters μ, the solution is approximated by a linear combination of

$$u_{RB}(\mu) \approx U_{RB}k(\mu) \tag{8}$$

where $k(\mu)$ – is a vector of generalised variables. The approximate solution u_{RB} can be obtained by replacing the displacement vector in (1) by the approximation introduced in (8) and eliminating k

$$u_{RB}(\mu) \approx U_{RB}(U_{RB}^T K(\mu)U_{RB})^{-1}U_{RB}^T f \tag{9}$$

where the matrix to be inverted has the dimensions N_{RB}, which should be significantly smaller than in the original high-fidelity problem. The smaller dimension of the reduced problem is beneficial for the online stage, in which the unknown parameters are fitted to minimize the difference between the measured displacements and the calculated in Eq. (9). The problem is now formulated as follows: determine the set of parameters μ that minimizes the norm

$$\min_{\mu}\|u_m - u_{RB}(\mu)\| \tag{10}$$

where u_m and u_{RB} are the measured and approximate calculated displacements, respectively.

This paper describes a method that improves the efficiency of the RB space by minimizing the number of orthonormal bases in the matrix U_{RB} during the offline phase. This reduction in the number of bases does not compromise the precision of the reduced space. This can be achieved by using the highest displacement in each mode shape selected to construct a vector from the matrix U_{RB} instead of using the full set of displacements in each mode shape. This reduction in orthonormal basis space requires a smaller amount of information to be updated, which means a smaller number of sensors can be used. In addition, this can be used to predict the optimal sensor location to be placed in the physical structure during the offline stage. An error minimization method is used for finding the unknown parameter that causes any difference between the measured and calculated displacements. Once the RRB space is constructed, it can be used again during the online stage to identify the severity of damage.

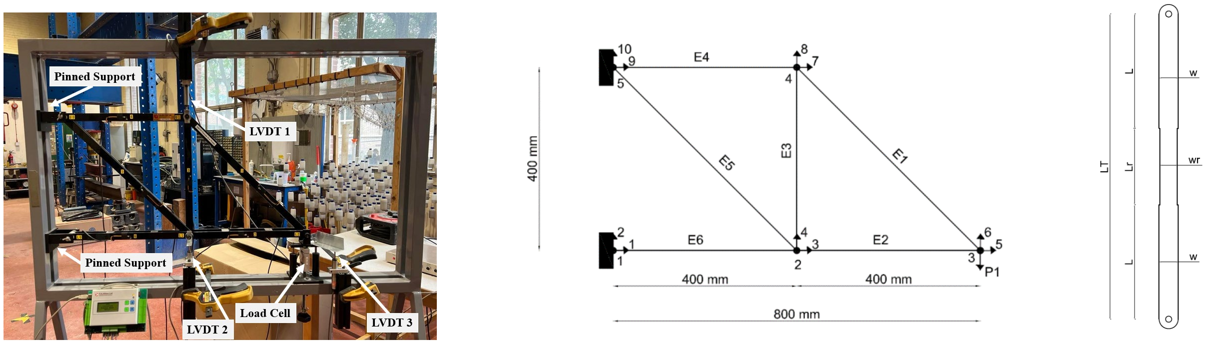
2.2. Artificial Neural Networks (ANNs) for damage identification

NNs are used in this paper for identifying the damage once it has appeared in the structure during the online monitoring. MATLAB toolbox of Pattern Recognition Neural Network is used and modified in this paper. The MATLAB toolbox is a powerful tool for designing and implementing ANNs for various pattern recognition tasks. One of the key elements in designing an NN is setting the weight and bias values for each connection between neurons, which determines the strength and direction of the signal propagation. The second important aspect is the use of hidden layers, which allow the network to learn and represent more complex patterns by combining simpler features from the input. The cross-entropy function is commonly used as a loss function to measure the difference between the predicted output and the true label, allowing the network to adjust its weights and biases through backpropagation to improve its accuracy. Finally, choosing the right activation function is critical for achieving good performance, as it determines the nonlinear relationship between the input and output datasets and affects the network's ability to learn and generalize to new data. By using these aspects, the toolbox enables users to build efficient and accurate models for a wide range of applications.

In this paper, the MATLAB code is modified in two main ways. Firstly, the RB snapshots constructed during the offline phase are used to generate the dataset samples of the NN. This can reduce the experimental efforts required for constructing the NN. Secondly, the code is modified to iteratively search for the optimal number of hidden layers with the goal of increasing the accuracy of the NN without causing over drifting of the dataset samples during the validation stage. The increased accuracy can help to build an NN that can classify inputs with small differences with higher accuracy, thereby identifying small severity damage once it appears in the structure during the online monitoring.

3. Real-time damage identification of 2D acrylic truss

The developed method is tested using 2D truss subjected to concentrated vertical load. The experimental setup is shown in Fig. 2a, and the geometry of the model implemented in the analysis is shown in Fig. 2b. The elements of the truss are made of acrylic material with a Young's modulus of 2500 MPa and a Poisson's ratio of 0.37. One reference specimen and six specimens with a reduced cross-sectional area were manufactured from a different acrylic material (with a measured Young's modulus of $E = 3281$ MPa) for element E3 (Fig. 2b) of the truss, while the reduced area is associated with a stiffness reduction caused by damage of an unspecified nature. Geometries of the specimens and the corresponding axial stiffness reduction calculated using FEA, are summarised in Table 1, and illustrated in Fig 2c.



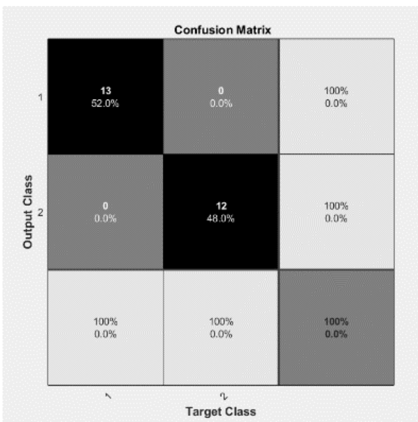
(a) (b) (c)

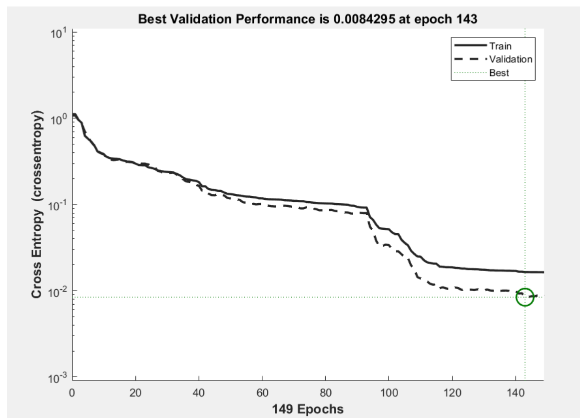
Fig. 2: 2D acrylic truss : a) Experimental setup, b) Geometrical properties of numerical model and c) Geometrical properties of reduced specimens.

Table 1: Characteristics of specimens used in experimental test program.

Specimen	Geometrical properties						No. of samples	Stiffness reduction (%)
	Unreduced width, w, (mm)	Reduced width, w_r, (mm)	Thickness, t, (mm)	Total length, L_T, (mm)	Unreduced length, L, (mm)	Reduced length, L_r, (mm)		
0	25	0	10	400	400	0	4	0
1	25	22.5	10	400	300	100	1	2.81
2	25	22.5	10	400	200	200	1	5.40
3	25	20	10	400	350	50	1	3.50
4	25	20	10	400	300	100	4	6.30
5	25	20	10	400	200	200	1	11.50
6	25	15	10	400	300	100	1	15.68

A simple FE model using six bar elements is used to calculate the displacements of the truss nodes due to a given force $P1$ (Fig.2b). In the offline phase, the FEA with different stiffness EA of the third element was solved to generate a set of snapshots. The SVD method was then applied to construct the RB space. The damaged scenario was introduced numerically by reducing the stiffness of the third element by 2% to 15%. The snapshots were used to build the NN for identification of the presence of damage in element E3 during the online stage. Based on the analysis, the SVD method showed that the first three singular modes have the highest singular values λ, 12.6078, 7.28e-16, and 3.47e-16, respectively. Due to this, the highest displacement in each mode shape was selected to obtain the optimal sensor location (Fig. 2a). The first singular mode was selected for construction of the RB space while the second and third singular modes were neglected. The RB snapshots were used to build the NN during the offline stage to classify the undamaged and damaged cases of the truss. In this case, the nodal displacements corresponding to the location of LVDTs were used to generate the input dataset of the NN with two target output classifications: undamaged and damage in the third element. The analysis showed that two hidden layers with 25 samples were enough to get an accuracy of 100% without causing over drifting of the samples. The output characteristics of the constructed NN are shown in Figs. 3a and 3b. The confusion matrix (Fig. 3a) showed that the constructed NN can identify the two predefined classes with an accuracy of 100%. Fig. 3b showed that the samples were trained 143 times during the training stage with two hidden layers only to find the best validation performance. Fig. 3b shows that the validation stage was performed without causing over drifting of the samples.



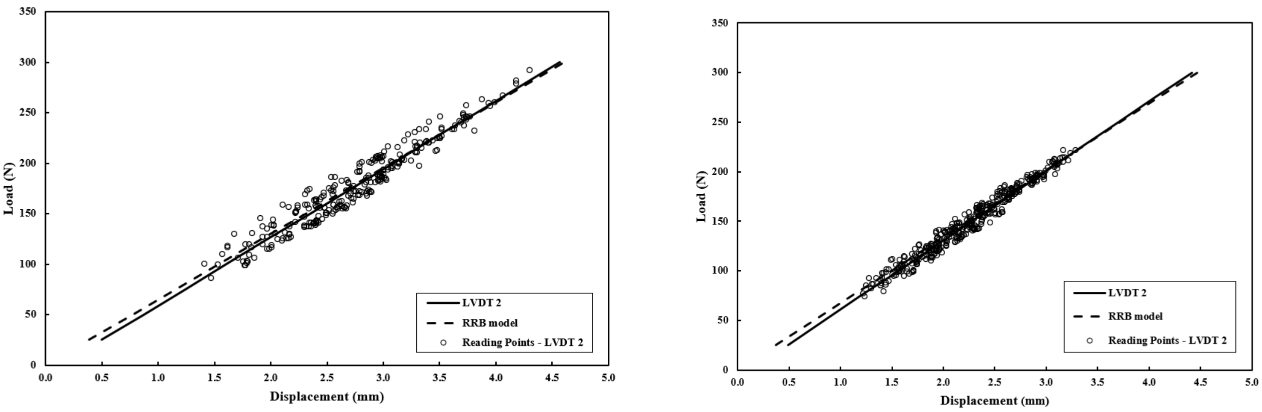


(a) (b)

Fig. 3: Characteristics of the constructed NN: a) Confusion matrix, b) Best Validation Performance

Using the optimization process, the analysis showed that the selected RB space can be reduced by using the highest nodal displacement in the selected first mode shape for construction of the RRB space. Due to this, the vertical displacement of the third node (Fig. 2b) is chosen for construction of the RRB space. Therefore, the LVDT 2 reading is used only during the online monitoring for establishment of the DT model of the truss. The analysis showed that the RRB model accurately predicted the stiffness of the undamaged element, specimen zero (Table 1), with an accuracy of 99.5%. The stiffness of the undamaged element predicted by the RRB model was 816 GPa while a stiffness of 820 GPa was obtained based on the measured Young's modulus. The RRB model is then used to identify the full set of displacement of the undamaged case for a specific load value using the relation shown in (9) to test the ability of the RRB model to reflect the current behaviour of the truss. A value of 300 N was used for $P1$ (Fig. 2b) to validate the RRB model prediction against the experimental test results. The load-displacement curve of the RRB model prediction and LVDT 2 reading of the used specimen zero is shown in Fig.4a. The analysis showed that there is an agreement between the displacement predicted by the constructed RRB model and the displacement measured by LVDT 2.

In the online phase, specimen zero (Table 1) were replaced by the other specified specimens to test the ability of the optimized method to identify the damage and its severity. The three LVDTs were used to monitor the vertical displacements of the three joints and fed the NN to identify the current state of the truss. Once the damage is identified, the RRB model was used again to find the unknown parameter which minimizes the norm of error between the measured and predicted displacements to identify the damage severity. Specimen four was used in this paper as an example to validate the developed method. Based on the analysis, the developed method showed higher accuracy of simulating the current state of the truss. The original prediction of the RRB model was 816 GPa which reflects the undamaged state of the truss. However, once the damage introduced in specimen four was identified by the NN, the RRB model prediction was 766 GPa leading to a stiffness reduction of 6.20% with an error of 1.6% compared with the calculated stiffness reduction introduced for specimen four (See Table 1). The analysis showed that the constructed RRB model was identified the damage severity with an accuracy of 98.5 %. A value of 300 N was used for $P1$ (Fig. 2b) to validate the RRB model prediction against the experimental test results of the used specimen four as shown in Fig. 4b. The analysis showed that the RRB model can reflect the damaged state of the truss with higher accuracy.



(a) (b)

Fig. 4: Load Vs. Displacement curve of RRB model and LVDT 2: a) Specimen zero, b) Specimen four.

4. Conclusion

In this paper, the RB method was incorporated with the DL algorithm, NN, to establish a DT model able to reflect the current behaviour of the structure in real-time. The ability of the developed method to identify the damage and its severity once it has appeared in the structure was tested. The RB model was validated against experimental test results for a two-dimensional truss. Based on the previous results, the following conclusions can be drawn:

- The developed method can be used for establishment of a DT model which is able to reflect the current behaviour of the structure during the online stage.
- The optimized RB space, RRB space, can be used to approximate the current state of the structure during the online stage with an accuracy of 99.5%.
- The optimized NN can be used to identify the damage once it has appeared in the structure with an accuracy of 100%.
- The RRB space can be used to identify the damage severity quickly during the online monitoring once it has been identified by the NN with an accuracy of 98.5%.

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