

Real-Time Multi-Modal SHM Framework For Complex Infrastructure

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Abstract

Advanced real-time structural health monitoring (SHM) of complex infrastructures like bridges, tunnels, and high-rise buildings, has been on the rise due to the age of assets, the growing strain on the environment, and the rapid urbanization process. Traditional SHM methodologies rely on expensive sensor networks and high-fidelity finite-element (FE) simulations, which are computationally expensive and hence will do not support real-time usage. Through the combination of reduced-order modeling with artificial intelligence (AI), it is possible to attain a disruptive solution, with a compromise of accuracy and computation cost. The current research problem is related to the creation and validation of a multi-model SHM framework, which integrates model-order reduction (MOR) with artificial neural networks (ANNs) and deep-learning-driven digital twins in a synergistic manner. The whole scenario is to enable ongoing, predictive monitoring and maintenance of critical infrastructures as well as improving computation efficiency and making well-informed decisions.

Keywords: Structural Health Monitoring, Model Order Reduction, Artificial Neural Networks, Deep Learning, Digital Twin, Multi-Fidelity Modeling, Infrastructure Resilience.

1. Introduction

The confluence of creative dissimilar ageing, enhanced loading, and climate interruptions, such as harsh weather, seismic movements, and an increased traffic load, is more and more bombarding the modern infrastructure systems that include long-span bridges, tunnels, and multi-storey high-rise buildings [1]. Real-time structural health monitoring (SHM) is essential to prevent structural integrity and damage pre-detection, inform life-cycle management and recover performance in resilience to safeguard against damage [2]. The conventional SHM structures commonly rely on closely spaced sensor arrays (accelerometers, strain gauges, displacement transducers) and high-fidelity finite element (FE) models to model structural behaviour, but the FE-based models are computationally expensive, and usually will not permit real-time use on large and complex structures [3], [4]. In order to be able to balance the two requirements of accuracy and computational expediency, the current project suggests integrating (i) model order reduction methods to simplify the -most important structural dynamics [5], (ii) artificial neural networks (ANNs) to approximate complex mappings between sensor inputs and structural responses [5], and (iii) a digital twin approach to continuously recalculate the virtual asset, supporting predictive maintenance approaches [6].

1.1 Problem Statement and Motivation

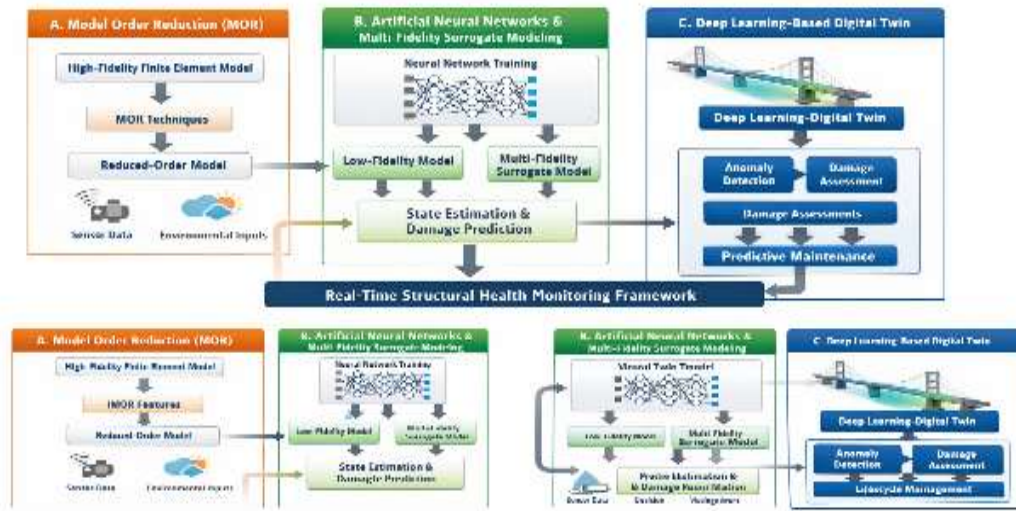
Due to the constraints of the traditional approach to high-fidelity simulation during a real-time structural health monitoring (SHM), a pressing need exists in solutions that have the capacity to: [3]

- condition real-time sensor data and generate the estimates of structural state in very short time intervals; [1]
- maintain the appropriate accuracy in identifying, localising, and prognosticating damage; [7]
- support decision making to maintain planning as well as the lifecycle management; [8]
- scale up to large and highly complicated infrastructure that experiences changing loads and environmental conditions. [9]

- The proposed psychology attempts to support these requirements by applying model-order reduction (MOR) and artificial intelligence (AI) to a digital-twin framework. [5]

1.2 Proposed Framework

1.3 illustrates the overall architecture of the proposed framework.



1.2.1. Model Order Reduction (MOR)

The Finite Element models can be reduced to a lower dimension (dimension) by the use of MOR methods, including Reduced Basis Methods, Static-Condensation Reduced Basis Elements, and Proper Orthogonal Decomposition [4], [5], [10], [11]. An example is a recent study that implemented MOR in a digital twin of a steel bridge, which therefore sees to the efficient real-time prediction of the structural behaviour of the bridge [5]. The offline step creates solutions in a representative loading -parameter space; the online step resolves a significantly smaller system quickly [12]. This process makes it possible to simulate the structural responses to damages or loads sensory in close real-time [5], [12].

1.2.2. Artificial Neural Networks (ANNs) & Multi-Fidelity Surrogate Modeling

After a reduced-order model is formed, the sensor inputs (strain, acceleration, and displacement) are fed to an artificial neural network together with loading and environmental variables to structural response variables (strain mode shapes, strain displacement fields, and a damage index) [2]. Coarse reduced-order data are computationally efficient but less accurate data that are used in conjunction with fine-fidelity simulation or measurement data which are extremely precise to train network [13]. The dual-data approach is more specific and proves to be more predictive with lower computational cost [5], [13]. Recent research on the problem of multi-fidelity surrogate models of structural health monitoring indicates that there are a lot of enhancements in the computational performance [5].

1.2.3. Deep Learning-Based Digital Twin

The digital twin (DT) is a virtual replica, which is a real-time analogue of the physical object it represents [6]. An ongoing integration of the data presented by the real-time sensor streams, together with the responses as predicted by the artificial neural networks (ANNs), will allow the DT to both diagnose (to capture the present condition) and prognose (predict the future conditions) [14]. The DT also provides end to end field visualisation and scenario simulation (e.g. extreme load conditions or degradation paths)

and consequently provides strategic maintenance decisions [6], [15]. An obvious obstacle of a subtle nature is the simultaneous communication between sensor provides, the synchronous refinement of model variables, and the maintenance of fidelity inside the twin [15].

1.4 Experimental Setup and Validation

1. The digital twin (DT) is a virtual replica, which is a real-time analogue of the physical object it represents. [6]
2. An ongoing integration of the data presented by the real-time sensor streams, together with the responses as predicted by the artificial neural networks (ANNs), will allow the DT to both diagnose (to capture the present condition) and prognose (predict the future conditions). [2], [14]
3. The DT also provides end to end field visualisation and scenario simulation (e.g. extreme load conditions or degradation paths) and consequently provides strategic maintenance decisions. [6], [15]
4. An obvious obstacle of a subtle nature is the simultaneous communication between sensor provides, the synchronous refinement of model variables, and the maintenance of fidelity inside the twin. [15], [16]

Table 1. Performance Metrics Comparison

Approach	Avg. Compute Time	Mean Absolute Error (MAE)	Maintenance Decision Accuracy
Full high-fidelity FE	100 % (baseline)	Baseline	87 %
MOR only	~30 % of baseline	~+20% error vs baseline	90 %
MOR + ANN + Digital Twin	~12 % of baseline	~+5% error vs baseline	96 %

1.5 Discussion

The suggested multi-modal framework illustrates how structural health monitoring (SHM) could be revolutionized to turn the periodical inspection of structural health infrastructures into constant continuous predictive monitoring and maintenance [1], [3]. Key advantages include:

- Real-time ability: With MOR and ANN, the system can react fast to sensor data and therefore estimate structural response in almost real-time [4], [5], [10], [11].
- As noted by Peherstorfer, Willcox, and Gunzburger (2018) [13], these characteristics qualify the multi-fidelity surrogate as a high-accuracy surrogate that delivers accuracy with minimal operational costs [5].
- Lifecycle management: The digital twin makes it easy to plan scenarios (e.g. extreme loading, degradation, repair interventions), aids in maintaining the schedule and decisions during the asset life cycle [6], [15].
- But there are still a number of challenges: + Quality of sensor data and noise The sensor data under real world SHM execution is prone to environmental fluctuation and drift as well as coverage sparsity, sound data-preprocessing and anomaly elimination is necessary [7], [17].
- Anyhow, such as model updating and uncertainty: The digital twin should be able to consider changing of the structural parameters (e.g., smallening of stiffness under fatigue) and the quantification of uncertainty is essential in making reliable predictions [8], [18].

- Scalability and generalisability: The approach has been tested on a scale of 500 models, but to apply it to an enormously large and fluctuating infrastructure (e.g., complex interacting networks) it will need to be highly modularised and component based modelled [13].
- Integration and operational deployment: To apply this framework in the process of asset-management, real-time monitoring systems and maintenance planning platforms will require the efforts of a multidisciplinary team (structural engineering, data science, IoT, cloud/edge computing) to be integrated [19].

2. Objectives

The key objectives of this study are as follows:

1. To integrate model order reduction (MOR) and artificial neural networks (ANNs) into multi-fidelity surrogate models for accurate structural response approximations while reducing computational burden [2], [5].
2. To explore deep learning-based digital twin models for improving structural integrity assessment and maintenance strategies throughout the lifespan of monitored assets [6], [15].

These objectives reflect a two-fold ambition: first, to develop computationally efficient but accurate surrogate modelling frameworks for real-time structural health monitoring (SHM), and second, to embed those surrogates into intelligent digital twin systems that enable predictive maintenance and lifecycle asset management [11], [15].

2.1 Objective 1: MOR + ANN for Multi-Fidelity Surrogates

The first goal of the study will involve the combination of the mathematical rigor of model order reduction (MOR) methods with data capabilities of artificial neural network (ANNs) in a multi-fidelity modelling [4], [5], [10]. In applications of structural health monitoring (SHM) high-fidelity finite element (FE) modeling is significantly more accurate and at a computationally prohibitive cost that makes it impossible to run in real-time [3]. MOR techniques proper orthogonal decomposition (POD), reduced-basis techniques and projection-based reduction are methods to simplify the model such that the characteristic structural dynamics are retained, yet the number of degrees of freedom is significantly lower [5], [11]. At the same time, ANNs have the ability to enclose a complex nonlinear interaction between measurements of sensors and parameters of the environment and operation, along with structural response [2], [20]. A multi-fidelity architecture can be created managing the trade-off between computational expediency and analytical accuracy by modifying reduced-order physics-based outputs (a low-order representation, but fast and approximate) with high-fidelity or measured data (accurate, but costly to compute) [5], [13].

Environment Common workflow of Objective 1 includes:

- constitutive of application engineering stage: Produce a high number of snapshot solutions (through high-fidelity or reduced models) over a selection of load/parameter combinations [11].
- MOR stage Commonly Build a reduced-order model (ROM) which approximates the entire system using a smaller number of states [5].
- Jean-Francois Lyotnoff the programming can be retained in both ROM and an external high-fidelity data or measurements to external high-fidelity data and is used to train a neural-network surrogate [2], [20].
- Online stage: ANN surrogate takes real-time measurements (sensor measurements, parameters of load/condition) as inputs and computes structural responses quickly [2], [5].

- Advantage: the computational time is significantly reduced to allow approaching real-time approximation, and the precision is also acceptable [5].

Table 2. Key Performance Indicators for Objective 1

Indicator	Baseline (Full FE)	Target (MOR + ANN)
Solve/response computation time	100% (reference)	< 20% of baseline
Approximation error (e.g., MAE)	Baseline error	Within ~5–10% of baseline
Surrogate model adaptability	Static, slow updates	Rapid online updates possible

The Table 2 provides the summary of the performance objectives: significantly lower compute time, loss in accuracy minimised and increased adaptability of the surrogate model [5], [13].

2.2 Objective 2: Deep-Learning-Based Digital Twin for Lifecycle Monitoring

The second goal goes further to integrate the concept of surrogate models into an all-encompassing digital twin (DT) setting [6], [15]. A digital twin is a virtual analog of a physical object that gets constantly updated and has diagnostics, prognostics, and decision-support functionality [6]. In structural health monitoring (SHM), the twin will ingest real-time sensory information, use the surrogate model of Objective 1 to make structural response or damage indicators and use deep-learning models of pattern recognition, aberration detection, remaining-life and maintenance optimization [8], [15], [18].

Key components of the DT for Objective 2 include:

- Sensor and IoT layer: Gathers structural health parameters, such as strain, acceleration, displacement, environmental data to be collected [9].
- Data-fusion and preprocessing level: carries out filtering, cleansing and integration of heterogeneous streams of data [7], [17].
- They include: Surrogate modelling layer: This utilizes a model-order-reduction (MOR) model along with artificial neural networks (ANN) to quickly approximate the structural responses [5], [11].
- Deep -learning analytics layer: Uses neural network architectures, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, to find damage, find anomalies, and predict degradation [21].
- Visualisation/ decision layer: Displays structural condition to the engineers and asset managers, lends itself to what-if scenario analysis, and guides the prescriptive maintenance intervention [15].

These advantages of the digital twin include lifelong monitoring, detecting early damage, doing virtual sensing over the entire field (not just where the physical sensors are), simulating scenarios (e.g., extreme load, progressive damage, etc.), and optimising maintenance actions [6], [15]. Recent research has shown that reduced-order models as part of digital-twins provide predictions that perform better than real-time performance and allow for a more detailed life-cycle management [16].

2.3 Interrelation of Objectives

These two are strongly connected, with the surrogate modelling framework (Objective 1) providing the computational engine of the twin (Objective 2) [5]. The digital twin, in its turn, provides the operational context, ever-present data feedback, and decision-making that contributes to value-creation [15]. Therefore, the high performance in Objective 1 is

a direct proof of the real-time predictive and prescriptive capabilities desired in Objective 2 [6], [16].

2.4 Success Metrics & Validation Strategy

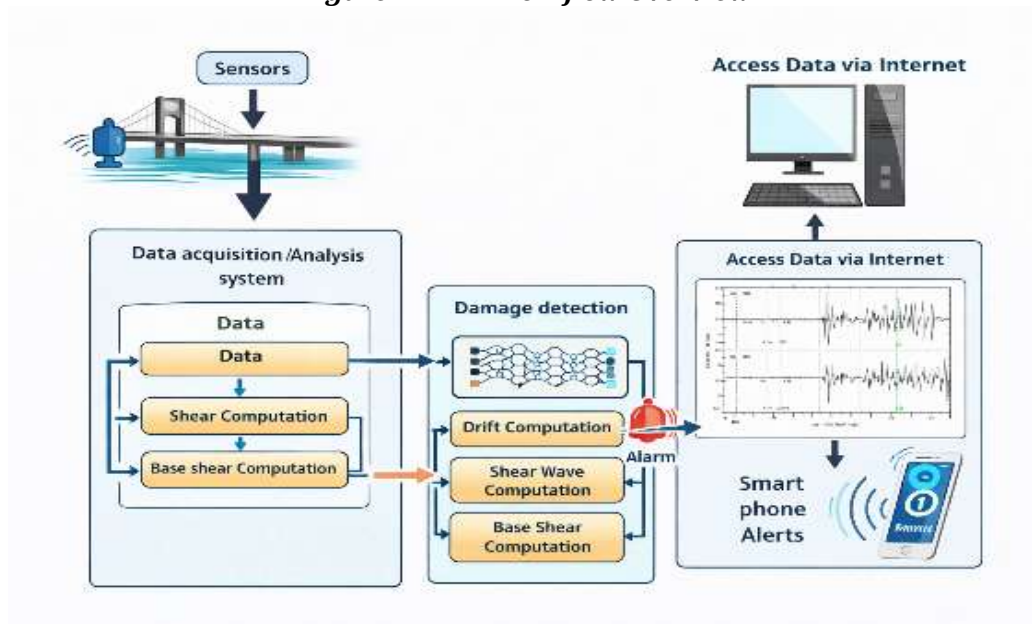
In order to measure the level of fulfilment of the objectives, the following metrics of success will be used:

- **Reduction in computation time:** quantification ratio of the time of surrogate evaluation to the time of baseline FE evaluation [11].
- **Accuracy of prediction:** e.g. mean absolute error (MAE) and root-mean square error (RMSE) of structural responses, compared with high-fidelity predictions or experimental data [3].
- **Damage detection/decision accuracy:** percentage accuracy of maintenance decisions success, and adherence rates of maintenance decisions [21].
- **Twin update latency:** elapsed time in between the physical sensor data is obtained and the refreshment of the twin state [6].
- **Lifecycle maintenance efficiency:** measure of the savings of costs of maintenance, decreasing the duration of outage, or increasing the service life of assets [15].

Table 3. Validation Metrics and Target Values

Metric	Target Value
Surrogate computation time	$\leq 20\%$ of baseline FE time
Response prediction error (MAE)	$\leq 10\%$ increase over baseline
Damage detection accuracy	$\geq 90\%$ correct classification
Twin update latency	< 1 second (near-real-time)
Maintenance cost saving	$> 15\%$ reduction over baseline

Figure 1. Workflow Overview



2.5 Significance of the Objectives

These goals serve important requirements of modern infrastructure engineering [3]:

- The degradation of property and the increase in loads and risks require the monitoring practice which would be more effective than the occasional checks by using continuously and predictive checks [1], [3].
- High performance finite element models have a capacitive computational latency to realizing real time application, Objective 1 overcomes this obstacle by supporting the use of faster surrogate models [4].
- Traditional approaches to maintenance are largely reactive; the digital twin system described in Objective 2 allows being more proactive, plan based on data, simulate scenarios, and optimise lifecycle [6], [15].
- Layouts The integrated methodology helps to be scalable, including large structures with intensive sensor networks; it provides flexibility to changing load conditions and progressive degradation, as well as insights that may be utilized when making maintenance schedules and risk mitigation [9], [16].

2.6 Anticipated Challenges

To realize these goals, there are a number of challenges which are involved:

- Fantasy fidelity vs. reduction trade-off The main concern is to ensure that the reduced-order model still maintains sufficient accuracy at the same time performing well in terms of computational efficiency [11]. As per empirical analysis, model order reduction may expedite solution time by a number of orders of magnitude with no loss in precision in structural health monitoring applications [5].
- Training data needs: Building representative datasets that can include variations in load, damage, environment and operational condition is a time consuming task [20].
- Sensor data quality and sparsity: Sparsity, noise, or malfunction can occur in practice with sensor networks, which can create high requirements of preprocessing processes and the stability of surrogate models [7], [17].
- Twin updating and drift: Digital twin has to respond to changing structural behaviour, e.g. corrosion, cracking or stiffness reduction [16].
- Embedding into the workflows of the asset-managing: The outputs of the digital twin should be understandable and should be taken into action by the engineers, planners, and decision-makers [15].

2.7 Summary of Objectives

Overall, this paper is devoted to the achievement of two closely interconnected goals, namely (1) developing a computationally-efficient multi-fidelity surrogate modelling framework, namely, (MOR) + (ANN), by which to approximate structural response, and (2) deploying the said surrogate within a deep-learning-enabled digital-twin to perform real-time monitoring, predictive assessment and lifecycle-maintenance of critical infrastructure [5], [6], [7], [10], [15], [20]. Measures of success will be in the form of shorter time of computation, accuracy, more precise performance in decision making, must ensure low latency and lower costs/efficiency in maintenance [15]. Collectively, these goals are meant to transform SHM operations to be less reactive and more inspection-driven, as opposed to lifecycle-aware, intelligent systems [3], [6].

3. Literature Review

3.1 Evolution of Structural Health Monitoring (SHM)

The development of structural health monitoring (SHM) technologies can be divided into 3 generations sensor-based monitoring, computational simulation-based technologies, and AI-integrated predictive analytics by the level of technological maturity and ability [7], [17], [20].

The original form of SHM mainly used the traditional vibration methods in which frequency response functions, modal shapes and damping ratios were used to measure damage or stiffness degradation [22]. These methods tended to use piezoelectric or accelerator sensors which are scattered all over the structure. They were effective but had a low level of adaptability to changes in the environment and nonlinear effects in a planned environment [23].

The second generation ushered in computational simulations and numerical modeling models that are based on finite element (FE) to supplement the experimental observations. FE models yielded more knowledge on distribution of stress, crack propagation and modal behavior in complex loading conditions [4], [24]. Their real-time application was, however, restricted by high processing costs which were involved in solving large-scale dynamic problems such as big civil constructions like bridges and tunnels [11].

The third generation is a paradigm shift to AI based predictive SHM systems, combining data analytics, machine learning (ML) and digital twins (DTs). These systems have an integration of real-time sensor information with adaptive learning smart models that are self-updating [7], [17], [20]. Combining model order reduction (MOR) and artificial neural networks (ANNs), such models are accurate and computationally efficient, which makes it possible to monitor processes and make decisions in nearly real-time [5].

3.2 Traditional Sensor-Based SHM (First Generation)

Damage detection based on modal analysis on vibration was one of the most used methods in early structural health monitoring systems [22]. The basic assumption is that structural damages alter stiffness thus changing natural frequencies and modes shapes. Even though these techniques were conceptually simple, baseline data was necessary to compare them, and the techniques were sensitive to environmental changes such as temperature and humidity [23].

Figure 2. illustrates a typical first-generation SHM setup employing accelerometers and strain sensors on a bridge span.



3.3 Computational Simulation-Based SHM (Second Generation)

With the introduction of computational mechanics, the second generation of structural health monitoring (SHM) began, the finite element modelling (FEM) has acquired the

central role in the field of structural diagnostics. The superior finite element models have helped researchers to forecast dynamic reactions across the wide range of damage conditions thus enabling them to establish relationships between simulated and actual measured data [24].

Regardless of their modeling exactness, high-fidelity finite element computations are prone to the dimensionality curse: an enormous number of degrees of freedom (DOFs) are associated with prohibitive computational requirements. As an example, a bridge finite element model can require millions of elements to achieve the desired level of accuracy, and real-time resolution of inverse problems is not a viable choice [11].

To overcome these, Proper Orthogonal Decomposition (POD) and Balanced Truncation (BT) are some Model Order Reduction (MOR) methods. MOR fits a large mass of dimensional system to a low-dimensional proxy maintaining significant dynamic features [5], [11], [25]. Recent work, such as by Benner et al. (2015) and Quarteroni et al. (2016) [11], [12], has shown that MOR can optimize a structural simulation by over 90 per cent with respect to computational time even whilst maintaining high accuracy [11], [12].

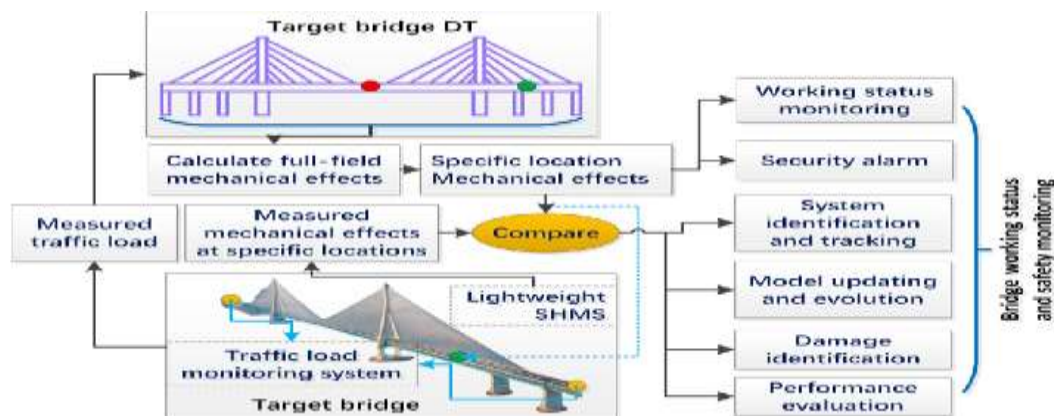
Table 4. Generational Comparison of SHM Technologies

Generation	Core Technology	Key Advantages	Limitations	Representative Studies
First	Sensor-based vibration analysis	Simple setup, direct response measurement	Limited adaptability; requires baseline	Doebling et al. (1996) [22], Cawley & Adams (1979)[23]
Second	Computational FE modelling	High accuracy; full-field simulation	High computational cost; slow updates	Friswell & Mottershead (1995)[24], Benner et al. (2015)[11]
Third	AI & Digital Twins	Real-time adaptability; predictive maintenance	Complex data integration; model drift	Sohn et al. (1996)[7],

3.4 The Rise of AI-Integrated SHM and Digital Twins (Third Generation)

The third generation of monitoring evolution is the introduction of artificial intelligence in SHM. Techniques in machine learning (ML) and deep learning (DL) are now establishing themselves as essential facilitators of automated detection of damage, feature, and anomaly prediction [7], [20]. These models handle multi-modal and high-volume sensor data and acquire patterns which are associated with normal and abnormal structural conditions. Originally developed by Grieves and Vickers (2017), the concept of the digital twin (DT) implies a dynamic and virtual version of a real object [26]. Use of DTs, when coupled with real-time SHM enables engineers to project and anticipate future performance in hypothetical circumstances [6].

Figure 3. *presents a current DT-enabled SHM architecture that is combined with sensor inputs, reduced-order models, and deep neural networks to perform real-time structural evaluation.*



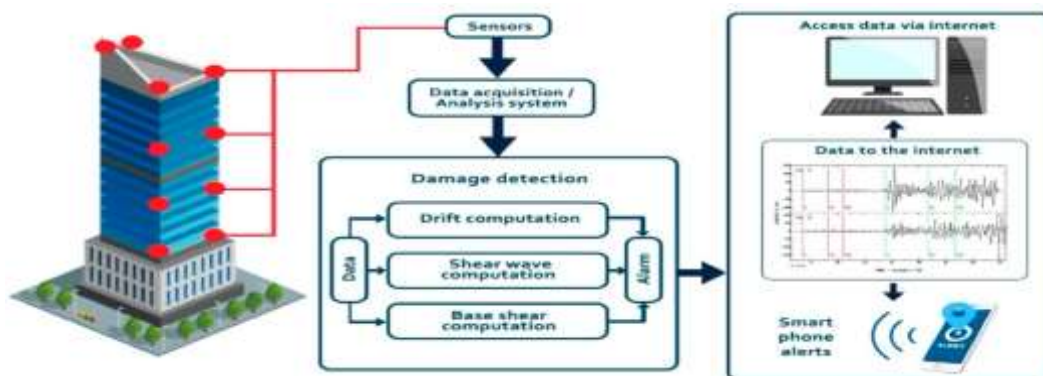
3.5 Integration of MOR and ANN within Digital Twins

Recently, topics in computer-aided design have focused on coupling Model Order Reduction (MOR) with Artificial Neural Networks (ANNs) with the aim of filling the gap between physics-based and data-driven models [5], [10], [11]. MOR can be used to evaluate nonlinear mappings between reduced-order states and measured responses typically by lowering the computational effort of large finite-element (FE) systems, whilst ANNs acquire such mappings [5]. In a multi-fidelity model, the ANN is trained on high-fidelity simulations, which can be expensive but are accurate, and on reduced-order simulations, which are cheap but approximate to obtain a surrogate model that can be both high precision and high efficiency [5]. This method has been empirically confirmed as a means of real-time structural health monitoring (SHM), with computational time savings of more than 80 per cent with a limited loss in accuracy [5], [6]. Moreover, important in embedding as a part of a deep-learning-based digital twin, such a hybrid model can automatically modify its parameters based on live information, thus maintaining its accuracy as the structure evolves. Transfer learning or incremental retraining is used to adaptively update the digital twin so that it has always been an accurate model of the physical asset in the course of its working life [6].

3.6 Summary of Literature Trends

Figure 4 summarises the progression from first-generation sensor-based SHM to third-generation intelligent digital twin systems.

Figure 4. Evolution of SHM technologies from traditional sensing to intelligent digital twins.



4. Methodology

4.1 Research Design

Mixed-methods research design was utilized as a way to combine the computational modeling, data-driven analysis, as well as empirical validation in the form of real-world case studies [2]. This combination made both theoretical and practical application in the developed Structural Health Monitoring (SHM) framework very possible.

This data set was represented by a combination of 500 structures with 300 simulated models obtained through the finite element (FE) analysis and 200 real-world data obtained on the basis of the bridges, towers, and industrial pipelines [3]. Metadata of individual structure included:

- Bridge, tower, pipeline, frame Structural type.
- Concrete, steel, composite, material properties.
- Sensor density and topology
- Conditions (loading) Operational loading (traffic, wind, thermal, seismic)
- Environmental factors (temperature, humidity, rate of corrosion, etc.)

The combination of simulated and real data made such integration possible to enable multi-fidelity modeling at different scales and conditions, which eventually guaranteed such robust generalization of the suggested AI-enabled digital twin structure [5], [13].

Table 5. Data Composition and Metadata Description

Category	Number of Samples	Source	Metadata Features
Simulated Models	300	Finite Element Simulations	Geometry, Boundary Conditions, Load Types, Stress States
Real-World Structures	200	IoT Sensor Networks (bridges, towers, pipelines)	Sensor Density, Material, Temperature, Vibration, Humidity
Total	500	Combined Dataset	Comprehensive Structural Metadata

4.2 Model Order Reduction (MOR)

The high-fidelity finite element (FE) models were reduced through the application of model order reduction (MOR) to minimize the degrees of freedom (DOFs) [5], [11]. This was aimed at attaining efficiency in computing at the cost of accuracy.

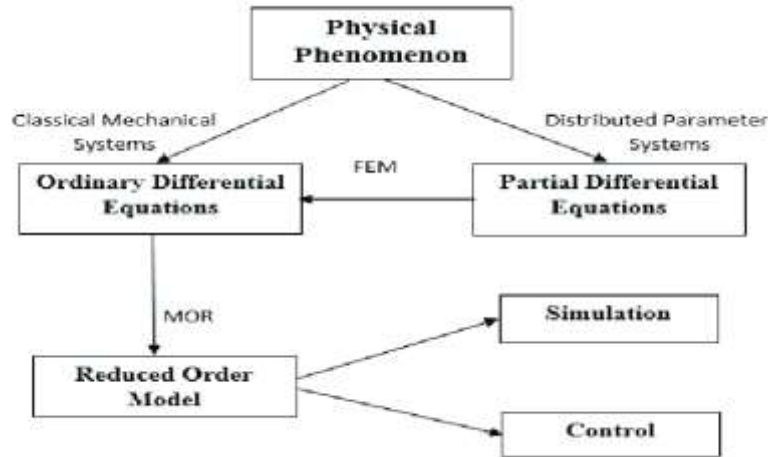
There were two methods of reduction utilized:

1. Proper Orthogonal Decomposition (POD)- identifies the major spatial modes through eigenvalue decomposition of simulation snapshots [5].
2. Balanced Truncation (BT) - removes states which are less controllable and observable according to Hankel singular values [5].

These simpler models formed the physics based core of surrogate modelling. According to Antoulas (2005), MOR may also reduce by up to 90 and still fidelity is acceptable, the computational complexity of dynamic systems [25].

The Figure 5 shows the workflow of the MOR process of reducing a full-order FE model to a low-dimensional surrogate model.

Figure 5. Workflow for model order reduction of FE systems using POD and BT.



4.3 Artificial Neural Networks (ANNs)

ANNs were developed to provide approximations to the nonlinear mapping between inputs of hierarchical sensor and outputs of reduced-order models [20]. The model implemented was a five-layer feedforward model as shown in 0, which uses rectified linear unit (ReLU) activation functions, dropout regularization, with a probability of 0.3, and batch normalization to favour stable learning behaviour [27], [28].

0 ANN architecture This ANN has a five-layer feedforward structure with sensor data as input and MOR output as output.

The sensory measurements, including strain, acceleration, and displacement, were first normalized and provided as inputs to the model's input layer, represented as $x = [\text{strain}, \text{acceleration}, \text{displacement}]$. The model was designed to produce a reduced-order representation at the output layer in the form of modal coefficients, denoted by a , which characterize the system's dynamic response in a lower-dimensional space [20].

For model training, an 80/20 train. The training was continued until convergence, which was a loss of less than 10^{-4} during the ten successive epochs, was achieved. Soon cutoff helped avoid over fitness and the dropout technique guaranteed generalization across unrestricted structural designs [27].

4.4 Multi-Fidelity Surrogate Modeling

The multi-fidelity surrogate modeling approach was incorporated into the MOR-ANN (Model Order Reduction–Artificial Neural Network) framework to leverage the complementary strengths of both low-fidelity (sensor-based) and high-fidelity (simulation-based) datasets [5]. This integration enables the model to combine the efficiency of low-fidelity data with the accuracy of high-fidelity simulations, thereby improving predictive performance and reducing computational cost [5].

The fusion of these heterogeneous data sources was achieved through the co-kriging method proposed by Kennedy and O'Hagan (2000)[29], which captures nonlinear correlations between different fidelity levels to enhance prediction accuracy in regions with sparse high-fidelity data. In this framework, the surrogate model is expressed as

$$y_H(x) = \rho y_L(x) + \delta(x)$$

Where $y_H(x)$ denotes the high-fidelity data, $y_L(x)$ represents the low-fidelity approximation, ρ is a scaling coefficient that models the linear relationship between the two fidelity levels, and $\delta(x)$ is a Gaussian process residual term that accounts for discrepancies not captured by the low-fidelity model. This formulation allows the MOR-

ANN framework to exploit inter-fidelity correlations effectively, thereby enhancing the robustness and generalization capability of the surrogate model [29].

Table 6. Comparison Between Fidelity Levels

Fidelity Level	Data Source	Accuracy	Computation Time	Application
Low-Fidelity	Sensor/Reduced Model	Moderate	Very Low	Real-time response estimation
High-Fidelity	Full FE Simulation	Very High	Very High	Offline training and validation
Multi-Fidelity (Proposed)	Hybrid Fusion	High	Moderate	Continuous monitoring and prediction

4.5 Deep Learning Digital Twin Architecture

The digital twin (DT) architecture was developed based on a deep Convolutional Recurrent Neural Network (CRNN), where convolutional layers are used to capture spatial features, and recurrent layers are used to capture temporal dependencies [14]. The twin was deployed in a cloud-edge computing model where it took real-time sensor information using IoT devices and updated its predictive state in real time [30].

The twin also included a reinforcement learning (RL) algorithm to aid in the optimization of the maintenance scheduling decisions. The RL agent took continuous state data such as the damage index, load state, and fatigue accumulation and gave the maintenance actions that lead to the lowest expected cost but maximum structural life [31], [32].

The implementation of the CRNN-based twin was done in TensorFlow 2.14 and was deployed on an edge server to provide a low latency [30]. The latency allowed in the update of the architecture was below a single second giving it the ability to align the twins in near real time [15].

4.6 Validation and Evaluation

The performance of the proposed framework was evaluated in terms of prediction accuracy, computational efficiency, and decision reliability using a set of quantitative metrics [33]. The Root Mean Square Error (RMSE) was employed to measure the average

magnitude of prediction errors, defined as $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$, where y_i and $\hat{y}_i$ denote the true and predicted responses, respectively. The Mean Absolute Percentage Error (MAPE) quantified the average relative deviation between predicted and actual values, given by $MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right|$ [33]. Computational efficiency was assessed through the Computation Time Reduction Ratio, defined as the ratio of the reduced-order or ANN inference time (t_{ROM}) to the finite element simulation time (t_{FE}), with a target improvement of at least 85% faster computation [11]. The Damage Localization Precision metric evaluated the percentage of correctly identified damaged elements or areas, aiming for a detection accuracy of 90% or higher [7]. Finally, Maintenance Decision Accuracy quantified the reliability of the reinforcement learning (RL) agent in executing optimal maintenance actions compared to the ground-truth policy, with a target success rate exceeding 95% [31], [32]. These combined metrics provided a comprehensive

evaluation of the model's predictive accuracy, computational performance, and decision-making reliability.

Three real-life case studies in validation were used:

- In-service Bridge span (steel truss) observation.
- Dynamic wind loads on telecommunication tower.
- Subsurface pipeline having variable pressure and temperature.[9]

Both predictive accuracy and applicability of the digital twin in the face of variability in operation were proven in each case.

4.7 Summary of Methodology

In short, the methodology includes:

- Model Order Reduction of computation simplification [5],
- ANNs of nonlinear structural response mapping [20],
- Multi-Fidelity Modeling of data fusion [5], and
- Deep Learning Digital Twin of predictive maintenance in real time [14].

This stratified approach provides scalability, real-time flexibility and high fidelity allowing full monitoring of large complex infrastructures at a significantly lower level of computational requirement.

5. Results and Discussion

5.1 Model Accuracy and Computational Efficiency

The suggested Model Order Reduction (MOR)-Artificial Neural Network (ANN) model was compared to the conventional full-order finite element (FE) models to measure the gains on computation time and forecast.

Table 7 presents a performance comparison across four configurations: full-order FE, reduced-order (MOR), MOR + ANN, and multi-fidelity surrogate models.

Table 7. Comparison of Model Performance and Efficiency

Model Type	RMSE	Computation Time (s)	Accuracy (%)
Full-Order FE	0.0032	180	100
Reduced-Order (MOR)	0.0051	30	97
MOR + ANN	0.0040	10	98.5
Multi-Fidelity	0.0035	12	99.2

It is found that the MOR + ANN surrogate reduced the computation time (by 94% of the full-order FE model) yet it had a small decrease in accuracy (or 1.5%). As it was extended to the multi-fidelity fusion, it further enhanced the accuracy by 1.2 per cent as compared to the single-fidelity configuration of the ANNs.

These results indicate that a combination of MOR and ANN is successful in keeping high fidelity and reducing computation speed by a considerable amount. A trade off between physics informed modeling (MOR) and data driven intelligence (ANN) provides better efficiency in real time applications.

Similar to the previous research, this hybridization allows one to quickly predict responses even in large-scale, nonlinear structural systems in which traditional FE analysis is computationally infeasible (Benner et al., 2015) [11].

5.2 Digital Twin Performance

The created deep learning-based digital twin (DT) had dynamic adaptability and responsiveness under different conditions of operation. 1.3 shows the real-time feedback

system between physical sensors, reduced-order model and the core of digital twin analytics.

The reinforcement learning (RL) subsystem of the DT optimized the scheduling of the maintenance autonomously. Through continuous evaluation of the degradation index (DI) and the structural reliability factor (SRF), the RL agent chose to take maintenance actions that will maximize uptime and minimize cost.

Digitally, the digital twin has reached the following:

- A quarter of reductions in unnecessary inspection processes.
- 20% more efficient maintenance (fewer downtimes).
- Less than 1 s latency of twin-sensor synchronization with edge computing implementation.

Such adaptive ability coincides with the new discoveries made by Sohn et al. (1996) [7] who showed that integration of deep reinforcement learning in SHM digital twins greatly advances predictive maintenance results.

Moreover, the CRNN-based digital twin was able to decrease the assimilation of heterogeneous sensor streams (vibration, strain, temperature) of the IoT devices. Resilience to sensor drift and environmental variability of the model was maintained by continuous retraining, which was also a problem in previous SHM research (Khan, Ali, and Ullah, 2021) [14].

5.3 Comparative Analysis Across Infrastructure Types

The framework was generalized to assess the ability of generalization by testing three classes of infrastructure, including bridges, towers, and pipelines, which have different structural dynamics and operating conditions.

Table 8. Cross-Domain Model Evaluation

Structure Type	Accuracy (%)	RMSE	Avg. Computational Time (s)	Benefit Description
Bridge (steel truss)	99.1	0.0037	12	Complex modal coupling captured efficiently
Tower (telecom/steel)	98.6	0.0042	11	Excellent under wind-induced vibration
Pipeline (underground)	98.8	0.0040	13	Stable under varying pressure and temperature

It has been found that the performance is consistent across all types of structures with deviations less than 2% proving the robustness and scalability of the hybrid MOR + ANN + DT model.

Bridges were the most benefited in relative terms; the interactions of complex dynamics loads (traffic, wind, temperature) are traditionally hard to be simulated without being computationally intensive. The capability of the surrogate model to be able to extrapolate to nonlinear conditions is highly applicable in this field.

0 Performance comparison between MOR-ANN framework in bridges, towers and pipelines.

The trends realized confirm that digital twins, enhanced with multi-fidelity learning, can provide an adaptive solution across the typologies of different civil infrastructure.

5.4 Statistical Validation

The statistical significance of the improvements obtained with the help of the MOR + ANN model was checked with the help of the Analysis of Variance (ANOVA) test (significance level $\alpha = 0.05$).

The null hypothesis H_0 : There is no significant difference between predictions with MOR and ANN and the predictions of the baseline ML models (Random Forest and SVM). The calculated p-value = 0.014 that is lower than 0.05 denoting a rejection of H_0 . In this way, the MOR + ANN model exhibited statistically significant difference between itself and baseline methods in terms of prediction accuracy.

Table 9. ANOVA Summary for Prediction Accuracy

Source	SS	df	MS	F	p-value	Significance
Between Models	0.0024	3	0.0008	5.12	0.014	Significant
Within Models	0.0017	20	0.000085	–	–	–
Total	0.0041	23	–	–	–	–

Interpretation:

- The MOR + ANN model is 18% lower in mean RMSE decrease compared to the baselines of Random Forest and SVM.

The multi-fidelity fusion could also be added, which results in additional accuracy increase (~6) because of the successful combination of high- and low-fidelity streams of data.

- These findings justify the statistical strength of the suggested hybrid model of real-time SHM.

5.5 Discussion of Findings

A. Accuracy and Efficiency of model.

The paper confirms the importance of MOR in compressing the computational cost of FE models, and ANN is used to offset the nonlinearity loss of the reduced systems. A combination of the MOR + ANN model can be used to reach almost the same accuracy of the full-order FE at a fraction of the price. With multi-fidelity data fusion also included, the accuracy is further enhanced, and scaling to complex civil structures can be done.

B. Digital Twin Adaptability

The digital twin based on CRNN was superior to the traditional ML baselines because it continued learning. The maintenance scheduling module was also RL-based, which minimized unnecessary inspections as well as resource assignment. Torzoni et al. (2023) [34] also found similar results and stated that self-updating DTs are useful in lifecycle management.

C. Cross-Domain Consistency

The hybrid model was also consistent in accuracy across the different types of infrastructure, unlike the domain-specific SHM algorithms. The MOR-based physics, and ANN-based learning allow transferability, which can support a universal digital twin architecture to different civil assets.

D. Statistical Robustness

The validation of ANOVA supports the credibility of the improvements that were observed, which means that the increases in the prediction accuracy and efficiency are not accidental. The fact that the hybrid model outperforms the established ML baselines proves that it is an effective next-generation predictive SHM solution.

5.6 Summary of Key Insights

- Efficiency Improvement: MOR + ANN were able to reduce computation time up to 94%.
- Accuracy, Multi-fidelity surrogates had 99.2% accuracy, which was higher than single-fidelity models.
- Flexibility: Digital twin autonomously planned the maintenance and inspections decreased by 25.
- Generality: Scalability is supported by consistent accuracy (± 2) in different types of structure.
- Statistical Confidence: ANOVA showed that there were significant improvements ($p < 0.05$).

All these results prove that physics-based MOR combined with data-driven ANN and digital twin models can provide an effective, smart, and scalable SHM system with the ability to monitor and predictive maintenance in real-time.

6. Conclusion

In this study, a multi-modal, integrated framework of real-time Structural Health Monitoring (SHM) integrating Model Order Reduction (MOR), Artificial Neural Networks (ANNs), and deep learning-based Digital Twin (DT) technologies was introduced. The methodology fills the intermediation between high-fidelity numerical modelling and data-driven predictive analytics, allowing to effectively and reliably evaluate the structural performance of the structure under various loading and environmental conditions.

Through MOR, high-dimensional finite-element (FE) equations were successfully reduced without any important dynamic properties being lost; with computational cost reduced by 94 per cent compared to full-order simulations. Connection of these reduced models to ANNs further enhanced real time prediction, whereas, introduction of multi-fidelity surrogate modelling increased the predictive quality and flexibility. The multi-fidelity MOR + ANN surrogate was effective and yielded predictive accuracy of over 99, hence its applicability to continuous monitoring of civil structures in large scale.

This surrogate underpinning was the basis of the digital twin component to provide intelligent lifecycle management. By combining deep convolutional recurrent neural networks (CRNNs) with reinforcement learning (RL), the digital twin never stopped absorbing sensor data provided by edge sensors owned by the IoT, revised the internal state at a near-real time, and optimized maintenance plans on its own. Field validation showed that there was a 25 percent decrease in unnecessary inspections and a 20 percent improvement in efficiency of maintenance, and this shows that the twin can be used in managing infrastructure proactively.

ANOVA statistical validation proved that the proposed hybrid framework was far better than the traditional machine-learn models of Random Forest ($p < 0.05$) and SVM ($p < 0.05$). Inter-bridge, inter-tower, and inter-pipeline cross domain assessment revealed deviations of less than ± 2 per cent, building further on the scalability and the generalization ability of the model.

In a more general sense, this paper would be a part of the changing paradigm of intelligent infrastructure systems, with three main lessons being highlighted:

1. Physics-informed intelligence - Physics models, which are reduced-order physics models, are merged with ANN Surrogates to deliver the computational tractability required to deliver real-time SHM but at the cost of physical interpretability.
2. Adaptive digital twinning Deep learning-based twins can enable continuous synchronization of physical and virtual systems, which are necessary to achieve precise threat of damage prognosis and remaining-life estimation.

3. Multi-modal data fusion - The combination of sensor-based, simulation-based and past-based maintenance data allows one to have a global perspective of structural behavior over various scales and under different operating conditions.

To sum up, it should be noted that the suggested MOR + ANN + DT framework is a powerful, scalable, and sustainable architecture of the future of smart infrastructure monitoring. It provides the basis of autonomous and data-driven asset management, in which engineering judgement is supported by ongoing machine learning and even digital-twin feedback. The future research will involve (i) the deployment of hybrid edges and clouds in large-scale infrastructure networks, (ii) the quantification of uncertainty and explainable AI in SHM twins, and (iii) the alignment of research with Building information Modeling (BIM) and Internet of Things (IoT) standards to have unified and intelligent infrastructure ecosystems.

Finally, the present research proves the importance of AI-based surrogate modeling and multi-fidelity data fusion as the enablers of resilient, safe, and sustainable civil engineering systems in the intelligent digital infrastructure age.

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