# Cloud-based Digital Twinning for Structural Health Monitoring Using Deep Learning

Hung V. Dang, Mallik Tatipamula, *Senior Member, IEEE*, and Huan X. Nguyen, *Senior Member, IEEE*

***Abstract*—Digital Twin technology has recently gathered pace in the engineering communities as it allows for the convergence of the real structure and its digital counterpart throughout their entire life-cycle. With the rapid development of supporting technologies, including machine learning, 5G/6G, cloud computing, and Internet of Things, Digital Twin has been moving progressively from concept to practice. In this paper, a Digital Twin framework based on cloud computing and deep learning for structural health monitoring is proposed to efficiently perform real-time monitoring and proactive maintenance. The framework consists of structural components, device measurements, and digital models formed by combining different sub-models including mathematical, finite element, and machine learning ones. The data interaction among physical structure, digital model, and human interventions are enhanced by using cloud computing infrastructure and a user-friendly web application. The feasibility of the proposed framework is demonstrated via case studies of damage detection of model bridge and real bridge structures using deep learning algorithms, with high accuracy of 92%.**

***Index Terms*—Digital Twin, structural health monitoring, cloud computing, Internet of Things, deep learning.**

## I. Introduction

During their lifetime, infrastructure is constantly susceptible to various stimuli such as environmental changes, vehicular loads, chemical actions, and human-induced factors, which cause significantly negative impacts on their conditions. As a consequence, one needs to monitor the civil structures regularly to assess their operational behaviour, detect early structural damage, prevent catastrophic failures, and extend their lifetime. However, the inspection work of infrastructures has been considered laborious and expensive due to their relatively large sizes. The conventional non-destructive evaluation methods such as ultrasonic, thermography, X-ray, and visual inspection can provide detailed information about the state of structures. However, they require experienced labour and ease of access, which often come at the cost of interruption to the operational services. Therefore, it is vital to develop effective structural health monitoring (SHM) techniques to enable cost-effective and proactive maintenance.

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Recently, thanks to notable improvements in technologies such as 5G, Wireless Sensor Networks (WSNs), Internet of Things (IoT), deep learning algorithms, cloud framework, and high-performance computers, a new data-driven paradigm, termed Digital Twin (DT) [1], has emerged and received increasing attention. The DT creates a high-fidelity digital mirror of the physical entity; the former evolves synchronously with the latter throughout their entire life cycle [2]. On the other aspect, the construction process is becoming more and more digitalized with the help of digital design packages such as 3D computer aid design (CAD), building information modeling (BIM), finite element analysis (FEA); thus, it is more straightforward to create digital data related to structures and infrastructures. With these advances, this paper presents a concept of Cloud based Digital Twin for Structural Health Monitoring (cDTSHM) framework aiming to perform continuous monitoring and proactive maintenance through continuous data from physical entities to virtual counterparts. In this way, monitoring service evolves from periodical, generic, and physics-based models to real-time, personalized, and data-driven ones, thus optimizing maintenance strategy, increasing reliability and safety of the structure, and extending its remaining service life. We validate the framework for different case studies of a model bridge in the lab and the real bridge structure Nam O in Vietnam, where the cloud platform is tested and validated to confirm the fast computation of 0.003s per one testing sample while achieving an accuracy of 92%.

The rest of the paper is organized as follows: Section II summarizes related works on DT for structural engineering. Section III presents the key components of the proposed DT-based SHM framework. In Section IV, the proposed approach's viability is validated through two case studies, including a toy model and a 3D steel bridge structure. Finally, the conclusions and perspectives are drawn in Section V.

## II. Related Work

Xu et al. [3] developed a dual fault diagnosis method on the basis of DT and applied the method on a car body-side production line. Their results demonstrated that the digital twin–based method achieved high diagnosis accuracy and had the capability in predicting the trend of production throughput with respect to changes in working conditions and data efficiencies. Wang et al. [4] proposed a DT model for fault diagnosis of rotation machinery, unifying physical knowledge, experimental data, and model updating technique into one model. The study achieved a clear improvement compared to the traditional fault diagnosis method with error rates under 5% in locating fault and assessing its extent. Revetria et al. [5] presented a DT-based real-time monitoring system for mechanical structures to improve the safety of the work environment. The essential components of the system included strain gauges mounted to the structure for deformation measurement, Arduino card for data integration, augmented reality glasses, and FEA Toolbox in the software Matlab for numerical simulation. Knezevic et al. [6] investigated the fatigue life of structures in the energy industry via a DT concept. The workflow of the presented framework included four stages: build of a detailed finite element (FE) model, collection of data from strategically placed accelerometers to calibrate the FE model with real-world conditions, fatigue calculations based on continuous monitoring, and statistical correlation between structural response and environmental loads. Shim et al. [7] presented a DT approach for bridge structure, having the ability to monitor the structural behavior continuously, and assess different facets of the structure timely such as material properties and surface cracking.

Of the other advances, Cloud Computing technology is an exciting field with numerous advantages, including cost efficiency, parallel and high-performance computing, massive storage, and remote access from anywhere via the network, hence, potentially fuelling the SHM tasks. Liao et al. [8] presented a cloud-based open-source framework named SnowFort for SHM using an elaborated decision support system when addressing the massive monitoring data flow. With the help of Cloud Computing, Zhang et al. [9] developed a cyber-infrastructure platform termed SenStore which unifies sensor data, bridge metadata, data mining, data visualization, and data interpretation into one system. In various industries, more and more large companies leverage the DT technology to enhance their complex processes [10]. For example, Predix of General Electric [11] is regarded as one of the leading industrial DT platforms, especially for power plants. Predix allows plant managers and workers to ingest large volumes of sensory data, run analytic models, and perform business rules engine at the same time, thus enabling the detection of abnormal phenomenons and improving plant reliability. For offshore applications such as port infrastructure, offshore structure, floating vessels, Akselos [12] has developed a novel DT framework to carry out real-time risk-based decisions using a massively parallel cloud-based server. The computation is enhanced by using simultaneously multiple solvers. In addition, a decision support system powered by Machine learning (ML) algorithms and deep domain knowledge from engineers, yields fast and accurate assessment about the asset (cracks, corrosion, fatigue, defection). Siemens empower their friendly 3D CAE software Simcenter [13] with DT approach by combining physics-based simulation, closed-loop of data from operation to design, and their IoT platform MindSphere, to perform real-time simulation and achieve more predictive results throughout the product lifecycle. Of all above existing works, there is lack of a unified DT framework that uses Cloud platform to handle continuous data and facilitate the two-way feedback to iteratively improve both the digital and physical structures as one closed system along their life cycle using deep learning algorithms. Thus, our work focuses on the design of such DT platform towards real-time SHM applications.

## III. Digital Twin-based Structural Health Monitoring Framework

### A. General Concept of Digital Twin

A typical architecture of DT involves three main components [14]: physical object, virtual object, and connected data interface (see Fig. 1). There is no universal approach for an optimal DT architecture because each project has different contexts: input data, requirements, budget, and domain. The physical model is built based on the data collected using measurement devices installed on the real objects. As a result, one could obtain a large amount of data, such as functional parameters of the systems (speed, pressure, intensity, quantity), the environmental data (temperature, location, weather) as well as historical data, log files, maintenance records, and so on. In addition, there exist different types of data formats and various communication protocols for data transmission. The digital replica of a physical model could consist of a number of sub-models: mathematical models, numerical models, and machine learning models, which work jointly to mimic the real counterpart and predict its behavior in the future or hypothesis scenarios. By aggregating different techniques, one could construct a smart virtual mirror that could evolve simultaneously and reflect the physical model closely. In terms of data, there exist unavoidable errors in reality, such as device instability, incomplete measurements, and hardware corruption. Therefore, the cleaning process, including duplication technique, handling missing data, rule-based methods, are applied before sending data to the central servers, thus reducing system errors and storage cost. In addition, due to the aforementioned heterogeneous formats of collected data from multiple sources, it is indispensable to adopt clustering methods to ease the information query and data management.

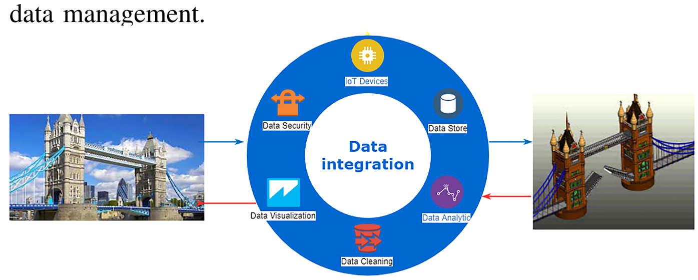


Fig. 1. Main components of a Digital Twin model: physical entity, digital mirror and connected data.

### B. Digital Twin-based Structural Health Monitoring

The eventual purpose of this research direction is to develop a SHM solution for monitoring the structures in a real-time or near real-time manner with high accuracy within a reasonable development/operation budget and maintaining its performance in the long run. To do this, one needs to combine physical and structural expertise [15] with new advanced technologies. Existing methods using only physics-based models normally work with processed data rather than directly with large collections of raw data [16], while ignoring the physics may lead to a low-performance model, which cannot be compensated by increasing the data volume. In order to make development and structure monitoring reasonably affordable

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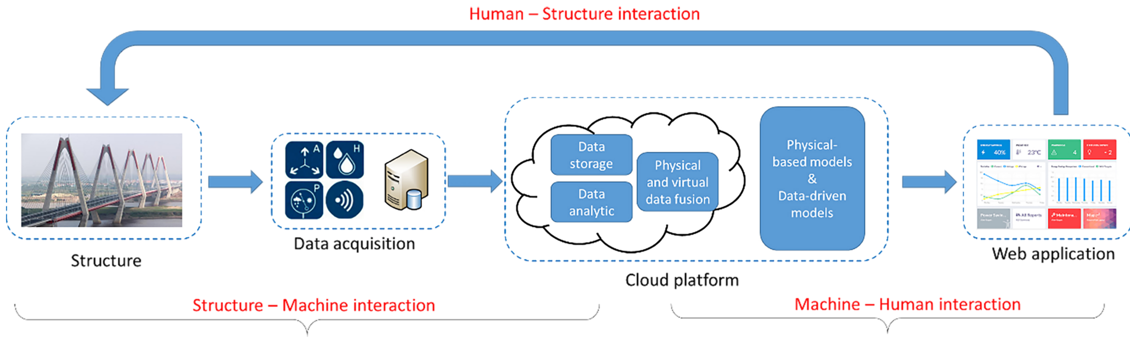


Fig. 2. A Cloud based Digital Twin model

within its whole life cycle, we leverage open-source machine learning libraries to develop data-driven models and to create a friendly and light web application for data visualization. To ensure the accuracy of the framework, the data-driven model is used on top of a mathematical baseline model. In addition, the model is trained based on a database augmented by synthetical data obtained from physics-based numerical models. For near real-time monitoring, cloud and fog computing [17] is adopted. And the long-term performance of the framework is ensured by using transfer learning and periodically retraining the AI models with updated data. Working together, all above components and characteristics form the proposed DT framework for SHM featuring the Structure-Human-Machine interactions as illustrated in Fig. 2. The proposed framework allows engineers to discover defects before they become apparent, improve the control system, and prepare better for preventing sudden damages. Moreover, different scenarios of infrastructures such as structural defects, element replacement, new device installation, and post-damage behaviors can be tested in virtual environment before scheduling and implementing the actual changes. The key differences between the conventional SHM methods and the cDTSHM are listed in Table I. The main components of cDTSHM includes: Physical Structure, Virtual Structure, Cloud based DT platform (see Fig. 2), and a cross-platform SHM web application for users.

*1) Physical Structure:* The physical entity in cDTSHM is divided into four subcategories jointly connected (see Fig. 3): main structural elements, auxiliary elements, external excitation, and measurement devices. The main structural elements play a critical role in assuring the integrity and safety of the structure. They are usually designed according to relevant standards in response to various scenarios of loadings, even extreme cases such as an earthquake or explosion. For an infrastructure such as a bridge, the main structural elements could be foundations, girder, deck, and prestressed cables, whose behavior during operation should satisfy predefined ultimate limit states and services limit states [18]. These requirements can be formulated in the following generic form:

$$F(\alpha, \beta, \gamma, t, \dots) \leq D, \tag{1}$$

where $\alpha, \beta, \gamma$ are time-variant properties of main structural elements such as displacement, deformation, crack, corrosion, material property degradation, $t$ denotes time, and $D$ denotes required threshold value determined in various standards. Furthermore, contractors and designers often aim to optimize the working capacity of structures to increase profitability, leading to optimization problems as follows:

$$\max G(\alpha, \beta, \gamma, t, \dots) \quad \text{w.r.t} \quad F(\alpha, \beta, \gamma, t, \dots) \leq D. \tag{2}$$

where $G(\cdot)$ is the objective/utility function. However, time-variant parameters mostly possess stochastic nature rather than deterministic one, then obtained results with conventional statistic methods usually have large variances. With DT method, current states of the structure are continuously updated, thus reducing uncertainty in parameter estimation and increase the reliability of structural assessment. The auxiliary elements do not directly influence the safety of the structure, but they can provide significant protections for structure and improve users' comfort. For example, paints give an additional protection layer for steel structural elements against corrosion under unfavorable environmental factors such as rain, sun exposure, marine atmosphere. In contrast, an inappropriate auxiliary element can cause heavier loads or introduce unexpected additional restraints to the structure.

The excitation on the structure can have various forms, involving the permanent loads, self-weights of structural elements, live loads, and vehicular loads. It could also be chemical reactions, environmental changes, and accidental events. In general, excitations do not have fixed values but vary over time, then they are modeled by a stochastic process, and in design practice, engineers adopt their statistical values and empirical formulae to determine corresponding behaviors of the structure. Measurement devices consist of sensors, accelerometers, strain gauge, actuators, scanning machines, cameras, and smartphones, that are supported by relevant software (e.g., Labview, Dewsoft for gathering signals from sensors, OpenCV for capturing live video, Trimble RealWork for 3D laser scanning).

The above physical components have inherent dynamic and uncertain properties. Thus, the physical model can be considered as a system of systems and it is a challenging task to model the behavior, patterns, and laws of whole systems with real scenarios.

*2) Virtual Structure:* The digital copy of the physical counterpart is expected to accurately replicate the behavior of the latter in real-world scenarios, predicting evolution in

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TABLE I
KEY DIFFERENCES BETWEEN CONVENTIONAL SHM AND DT-BASED SHM

| | Conventional SHM | cDTSHM |
|---|---|---|
| Concept | Model-based approach | Data driven-based approach. |
| Data source | Monitoring data from physical entities | Monitoring data from physical entities, historical data, simulation data of digital model. |
| Technologies | optimization, statistical methods, FEM | IoT, Big Data, Reduced-order modeling, surrogate model, machine learning model, augmented reality. |
| Data fusion | Synchronize data from different sensing devices | Heterogeneous data in different format, from different sources. |
| Visualization | Table, chart, 2D images | Table, chart, virtual reality, dashboard. |
| Frequency | Periodical monitoring | Continuous monitoring. |
| Services | Damage detection, damage severity, damage localization | Damage diagnostic, crisis warning, asset management, proactive maintenance, decision-making support system. |

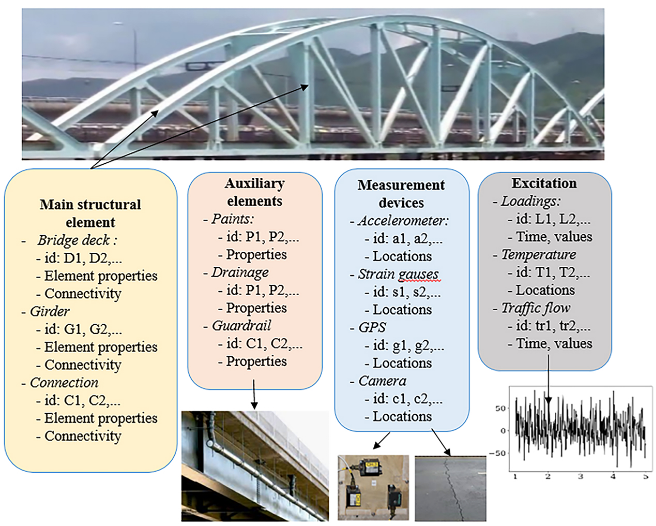


Fig. 3. Four subcategories of physical structure.

the future, and conducting as-if studies. Computed results of the digital model can be formulated as follows [19]:

$$z(x) = y(x) + e = \eta(x, \theta) + \delta(x) + e \tag{3}$$

where $z(x)$ denotes the observational outputs; $y(x)$ stands for model discrepancy-corrected outputs; $e$ is the additional error, accounting for uncertainty in observations; $\eta(x, \theta)$ is the computed results, $\delta(x)$ is the model discrepancy. To obtain $y(x)$, the digital mirror in cDTSHM uses ensemble methods that aggregate multiple computation models ranging across the quick and exact mathematical model, the popular finite element model (FEM), and the promising ML model. The mathematical model makes use of classical mechanic theory and probability theory to calculate the response of the structural element under excitations and analyze their reliability and safety. Although this theoretical model could give a quick and exact solution that serves as a baseline result for other models, it can only be applied for relatively simple structures and require some ideal assumptions. For more complicated structures with a large number of degrees of freedom and complex interactions between elements, one needs to resort to the finite element model which is nowadays the most popular computation method in both the academic and industrial community for modeling from the solid object to fluid and gas phenomenon. At first, FEMs of the structures, including geometry, material, and connectivity, are built with the help of commercial software such as ABAQUS, SAP2000, or open-source program such as Code-Aster, Opensees, in which both elastic and plastic constitutive laws of materials are incorporated, then time and space-dependent behaviors of the structures are obtained via the dynamic analysis from pristine condition to failure scenarios (collapse or local damage). The main drawback of the FEM is their high computational costs. Because of the instantaneous nature of external excitation, it requires a detailed 3D model in FEM using fine space and time discretization to assure FEM results converge to real solutions. However, such small discretization and large size of the structure leads to a huge number of elements and total time steps required, then a paramount volume of computation.

To overcome the intractability of computational time, in cDTSHM, we develop deep learning (DL) models to infer the structure behavior from historical data, measured data, and simulated data obtained from FEM. The deep learning model consists of multiple layers of neurons designed for extracting automatically hierarchical features from raw data. Initially, it takes significant effort to develop an appropriate DL algorithm for SHM applications and train the model with a large quantity of data. The most common DL algorithm in SHM is performed in a supervised way; it means that before training process, each sample $x_n \in \mathbf{x}$ in the data is labeled by the corresponding operational state $s$ of the infrastructure, resulting in a set of pairs $(x_1, s_1), \ldots, (x_N, s_N)$. Then, the DL model will seek a predictor $f(., \theta)$, parametrized by $\theta$ to fit as close as possible to the given labeled data:

$$f(x_n, \theta^*) \approx s_n \quad \text{for} \quad n = 1, \ldots, N. \tag{4}$$

Once the DL model is trained, and its parameters are determined, it provides a rapid and automatic tool to assess operational states of the structure which is suitable for long-term SHM with continuous flow of data. One of the major obstacles with DL methods is the requirement of large associated datasets. If the real data are insufficient, one could resort to the FEM to create synthetic data for the training process.

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The obtained DL models can be updated in an adaptive fashion with data obtained in the future.

In summary, the mathematical model is used to build a baseline model, the FEM model help to formulate the initial behavior of the physical entity and generate synthetic data, the DL model is helpful in rapidly inferring the patterns of structure's behaviors. By combining these models, the cDTSHM is able to create a digital mirror of the infrastructure, executing in parallel mode, thus allowing the prediction of the structural capacity, performing structural health evaluation, and testing different maintenance strategies (see Fig. 4).

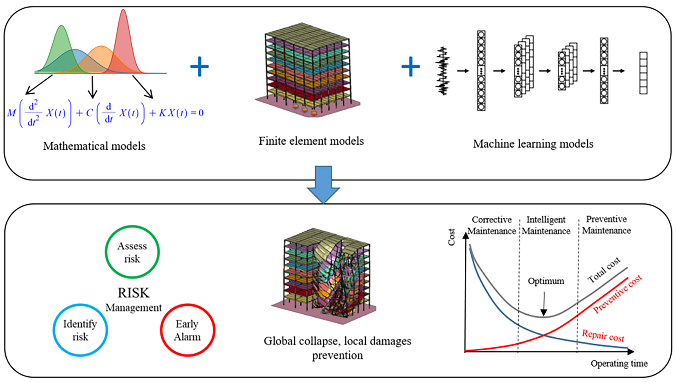


Fig. 4. Digital mirror in DTSHM involving multiple computation models: mathematical, Finite element and Machine Learning ones.

*3) Cloud Computing Platform:* The proposed cDTSHM framework utilises hybrid cloud computing services, which is a mix of the private fog environment and public cloud environment (Fig. 5). On the one hand, it facilitates data access from anywhere in the world via the Internet and provides an elastic environment when dealing with a suddenly increasing flow of data, and calculation resource demand, such as earthquakes, accidents, brittle damage. On the other hand, one could also save significant economic resources because of the reduced requirement for storage. This is due to the pre-processing for raw data, i.e., data cleaning, data duplication, as well as the training of complex digital models, is performed firstly in the private environment, i.e., fog layer. After that, only processed data and trained models are deployed across public cloud environments. Depending on the type of structures and the volume of measured data, further advanced task scheduling algorithms such as parallel or hierarchical ones and more edge devices can be resorted to reduce the requirements of CPU power and memory of the fog layer's local server [20]. Detailed studies about the fog layer's main components and architectures can be found in [17], [21], [22].

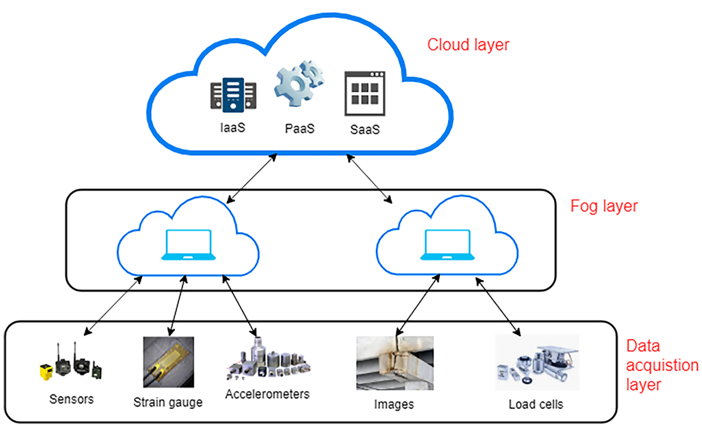


Fig. 5. Illustration of cloud computing framework of cDTSHM.

Besides, it is essential to ensure the security of data communication as DT is able to send recommendations back to the control system, then make intentional adjustments to the structure's operational services. In the hybrid cloud framework, data privacy is ensured by adopting encrypted data communication between the public cloud environment and fog layers, which is more economically profitable than building a whole private framework for single or two civil infrastructures.

Regarding the cloud platform, it includes three modes of service: Infrastructure as a Service (IaaS), Platform as a Service (IaaS), Software as a Service (SaaS). The IaaS acts as a virtual machine made of highly scalable compute resources and cost depending on consumption; the PaaS is used mainly for application, based on which the data analytic and machine learning components of cDTSHM run on the fly, and the SaaS provides smooth services for end-users. In practice, one can run cDTSHM directly on the web browser without any special installation on local devices.

Although the cloud platform is flexible and scalable, there exist constraints to take into account when deploying the cDTSHM application. First, the computation resources required by virtual machines should not exceed the total capacity of the IaaS provider. Second, each cloud user has corresponding priority and resource budget involving time and payment within which their requests should be completed to avoid potential conflicts with other users. These constraints are formulated as follows [23]:

$$\begin{aligned} C^{cpu} &\geq \sum x_i^{cpu}, \quad & C^{RAM} &\geq \sum x_i^{RAM}, \\ B &\geq \sum q_{ij}, & T &\geq \sum t_{ij}. \end{aligned} \tag{5}$$

where $x_i$ is either CPU or RAM requested by a virtual machine, $q_{ij}$ and $t_{ij}$ stand for the payment and required time of the cloud user $i$ for request $j$, and $C, B, T$ are available resources of IaaS provider.

In terms of data storage, owing to the heterogeneous nature and large quantity of the collected data such as time-series data from sensors, tabular information, video, plain texts, the Hadoop distributed framework and Map Reduce are employed to optimize the storage and improve query process. The server is divided into clusters of a number of machines, each performs computation and storage in parallel mode. The scalability of the platform is achieved through the split-apply-combine strategy, i.e. map and reduce, well-known in functional programming. Once the Cloud Computing based platform is set up, initial testing to evaluate its performance over a short period is conducted, where impact of different factors on the data communication process is examined (e.g., distance, data recording time interval, device's battery life, continuous connectivity) and then adjust technical issues to guarantee the stability of communication.

*4) User Application:* The fourth component of the cDT-SHM is a Human-Computer interface, which is a web-based application for real-time monitoring and timely controlling of infrastructure. The application helps explore different types of data in a graphical way by using dynamic charts, live graph, table of critical indexes such as allowable stress, vibration limits, and service temperature threshold. When a problem occurs, for example, measured data exceed value limits, the web service will display a red light alarm on the interface. Besides, a 3D space model window is also introduced on the web application interface for the visualization of the structure's behavior predicted by the digital model. In addition, there are controllable parameters, through which engineers can adjust the infrastructure's operation and maintenance activities based on monitoring information, to improve the operation efficiency and ensure the safety and ease of operations. The

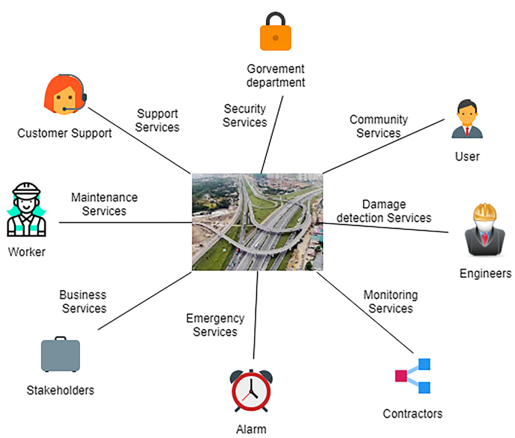


Fig. 6. Various services potentially provided by cDTSHM for different users.

cDTSHM web application is written in Python, using popular web framework Flask and Javascript charting library Chartjs. The application is deployed on the PaaS of cloud computing; the transfer data between cloud servers and web application is realized through the HTTP streaming technique in which data from the server is segmented in chunks, received, and processed further on-the-fly by the client. The web application serves as a collaborative environment for continuously sharing information among different end-users as indicated in Fig. 6. For example, real-time monitoring information is exploited by engineers for early damage detection, by contractors for planning maintenance services, by the government for ensuring security, by other stakeholders for increasing businesses and enhancing the conformity of users. On the other aspect, to avoid conflict among the users, role-based access control is utilized, and if more than one user access to the web application at the same time, the first come first served basis is applied unless priority is indicated.

### C. Implementation

Before building a DT, one needs to clarify the requirements of the project and its relevant constraints, which could relate to physical properties, economics profitability, and environment requirements. Requirements and constraints are translated into well-defined mathematical functions and variables, e.g., as seen in (1), which are iteratively updated over time. Next, a system of measurement devices is installed across the structure to collect data related to the structure and surrounding environments. In general, a uniform placement strategy plus some predefined critical locations are selected for device installation. The layout of devices is updated based on the output assessment of the cDTSHM for further improvement of the system. Then, the measured data are passed to a local server using cable/5G networks and the Internet. On the local server (fog layer), data preprocessing steps are performed to capture relevant information, as well as to remove insensible data before being sent to the cloud, thus lowering the burden of computation and cost financing.

In addition, a numerical counterpart of the physical model is established with as-built input data provided by contractors and corresponding standards. As there is a large number of input parameters with inherent uncertainty, the numerical model needs to be validated, calibrated, and updated to reflect the current state of the physical structure based on various laboratory or in-situ test results and optimization methods. In addition, the driven-data models are also developed with the help of not only current information but also historical data and numerically simulated data. In general, the performance of such models will significantly improve with increasingly available data. Indeed the inference times of the data-driven model and mathematical model are faster than those of the model-based one. Then, the data-driven model will be deployed in a real-time fashion on the cloud service, whereas, the model-based method is periodically carried out to simulate and generate synthetic data, especially in extreme scenarios, which are scarce in reality but could cause substantial damages, such as earthquake and explosion.

The results of data analytics, involving critical monitoring parameters, reliability index, and safety margin, are interactively visualized on a web application, which facilitates the exploration of the structure behavior under external factors such as weather, loading, and human activity. As the infrastructure is a large-scale and nearly immobile entity, the digital-to-physical feedback is indirectly realized through a control and decision-making system. With recommendation system algorithms and condition analysis, the DT is capable of providing appropriate suggestions for failure prevention, early warning, and optimized planning, which traditionally depends largely on the subjective perception of responsible personnel. In short, the data interaction among the triplet structure-machine-human is the core of the cDTSHM (Fig. 2), which brings unprecedented advantages for the SHM applications.

## IV. Case Studies and Results

The first proof-of-concept demonstration is carried out via a simplified toy model as seen in Fig. 7. The toy model is the Sydney Harbour bridge model built by using K'nex plastic rods and connectors. The model has a length of about 2m, consisting of around 800 elements. The model is manually excited by hand-shaking, where its vibration is recorded by using a set of accelerometer sensors MPU-6050 uniformly distributed across the model. The measured signals are subsequently transmitted to a local server through microcontroller

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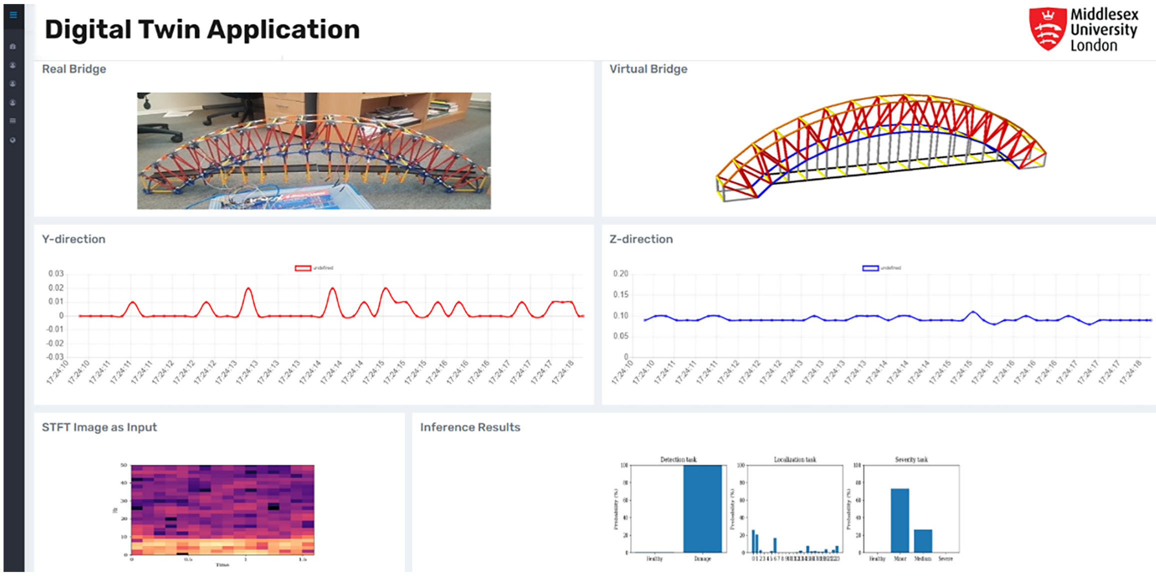


Fig. 7. Web application interface of cDTSHM for SHM of bridges. Further information can be found at https://dt.mdx.ac.uk/?p=1106

boards Arduino Uno, then stored in SQL relational databases on a cloud service, which is Amazon Relational Database Service for this example. These vibration signals are visualized by line charts in a near-real-time fashion. The database for the first example was experimentally obtained by the authors. The damage states were created by randomly removing one (minor damage) or two consecutive (severe damage) chord bars (in yellow/blue color). After that, the bridge was vibrated, its vibration signals at three truss joints (one-quarter, mid-span, and third-quarter points) were then measured for 30 s with a frequency of 100Hz and labeled correspondingly. In total, the size of data is 1000; each data sample consists of three time-series sequences having a length of 3000. After that, to assess the model's structural integrity, two data analytic components have been developed, and both are continuously deployed with the help of a cloud computing platform, which is Amazon Elastic Compute Cloud, herein. The first component is a lightweight mathematical model simply making use of statistic features such as maximum and minimum values derived for a time window of 20 seconds. When these values remain within a given band of safety involving an upper and lower bound, the structure is regarded in a healthy working condition; otherwise, if these extrema cross the safety band, damage likely occurs. A second component is a Deep Learning-based model, which not only classify healthy/damaged states of the structure, but it also can spatially localize damage location and quantize damage severity if the model is trained with appropriate data. The measured vibration signal is converted to a spectrogram image able to represent the signal's properties in both time and frequency domain. After that, the image is fed into a ResNet-34 architecture whose output are probabilities of all possible structural states. The states with the highest probability will be assigned to the current state of the structure. Further details can be found in [24].

The second case study is the validation of the framework for the real structure, Nam O railway bridge located in Da Nang, Vietnam, which is a large-scale steel truss continuous bridge, as shown in Fig. 8. The bridge of more than 60 years old frequently experiences daily unfavorable factors such as the maritime environment, unpredictable tropical weather, and dynamic loadings, rendering in potential loss of stiffness at truss connections. Thereby, a network of triaxle accelerometers are installed at truss connections to collect vibration data, and vibrational-based structural health monitoring is carried out using the deep learning algorithm. The bridge is 300m long, consists of four simply supported spans of equal length (75m each). The width of the bridge is 5m, and its height is 14m. Its material properties are Young's modulus E = 200 GPa, Poisson's ratio = 0.3, mass density $\rho$ = 7850kg/m3, and the modal ratio = 2%. As all the spans of the bridge are identical and designed as a simply supported truss, the identification test was performed only on the first span. The vibration of the bridge is induced by a train composed of four identical vehicles moving at constant speeds, with parameters as follows: the vehicle length is 22.5 m, the distance of wheels is 15.6 m, the mass of vehicle including wheels is 50 tons, and the moving speed is 30m/s.

For the second example, the database is collected both experimentally and numerically. The current state of the bridge was monitored through a set of sensors uniformly installed along its length. Based on measurement data, the dynamical characteristics of the current state of the bridge are determined using reliable and widely used identification methods such as Operational Modal Analysis. Then, a detailed 3D finite element model of the structure is built and updated such that the deviations between modal characteristics, including eigenfrequency values and mode shapes from the FEM and experimental ones are small, specifically, within a predefined tolerance. Because the bridge is still in a healthy operational state, the damaged states and associated data are synthetically created through the 3D Finite element models. It means that artificial connection stiffness losses with various damage

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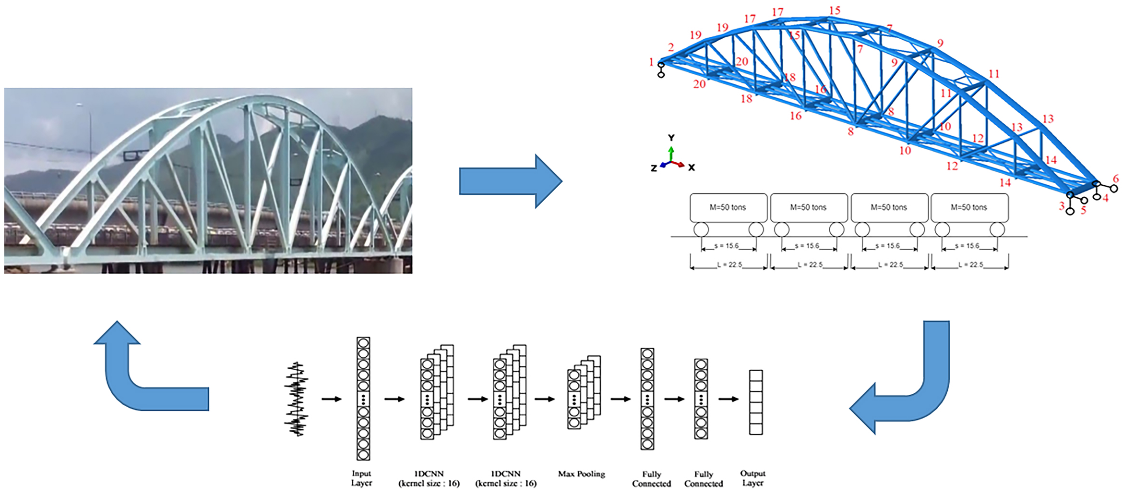


Fig. 8. Architecture of the Deep CNN algorithm designed for structural damage detection.

levels are introduced into an arbitrary truss connection, then finite element analysis is carried out and yields corresponding simulated vibration data. Each vibration data is further labeled by the associated artificial damage state, i.e., damage location and damage level (damage severity). In total, a database of 10000 samples was created to train and validate the data-driven model; the number of samples for each state is equally distributed.

Once the database is already prepared, they are split into three sub datasets, namely, the training set, validation set and testing set to train and validate the deep learning model, which is able to infer the structural state accurately and fast. The foregoing workflow is schematically illustrated in Fig. 9. The details of a FEM is described as follows. The bridge is

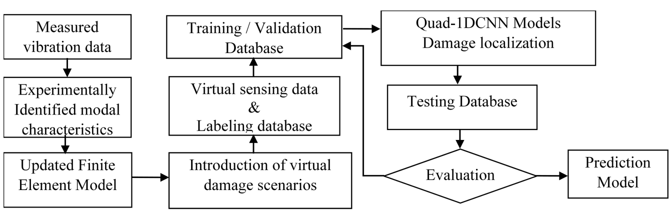


Fig. 9. Workflow of training process for CNN-based SHM.

modeled in the Finite Element software Abaqus [25], using the three dimensional (3D) beam. The element has six degrees of freedom (DoFs) at each node, including three translations and three rotations around the x, y, and z directions. Section properties of structural members are summarized in Table II. In terms of connectivity, the semi-rigid link with rotational spring is applied to model the connection between truss members.

The selected deep learning architecture is the deep 1D Convolution neural network-based method commonly acknowledged by its outstanding performance on local pattern recognition and reduced computational complexity compared to conventional artificial neural networks in various domains [26], [27], [28]. Its configuration included a sequence of layers involving an input layer, two convolutional layers, a max-pooling layer, two fully connected (FC) layers, and a soft-max output layer. The formula of one convolutional layer is expressed as follows [29]:

$$h_k = conv1D(w_k, X) + b_k, \tag{6}$$

where $conv1D(\cdot)$ is the 1D convolution operator, $h_k, w_k$ and $b_k$ are respectively the output vector, weight matrix and bias vector parameters of the kernel $k$, $X$ is the input vector. Once vibration data enter into the network, the 1DCNN layers will extract inner relationships between measured points and their higher derivatives before feeding to the last fully connected layers serving as a classifier.

In terms of the training process setting, the following details are adopted. Adam optimizer is used, the batch size is set to 64, a learning rate is initially set to 1E-4, which is divided by 2 when the validation loss does not decrease for five consecutive epochs, and early stopping is set to 20, which means the training process is stopped after 20 consecutive epochs of no improvement. During the training process, the early convergence problem could be alleviated thanks to using a proper initialization strategy. Here the Kaiming He [30] approach is adopted, in which the weights of each layer are initially selected from a zero-centered Gaussian distribution scaled by $\sqrt{(2/n)}$ with $n$ is the total coming inputs for a given layer. By doing so, for each layer with nonlinear activation such as ReLU function, their weights will have a standard deviation equal to around 1 on average, mitigating the gradient exploding/vanishing problem during the training process of very deep NN models. Another way to address the premature convergence is to maintain the data diversity by using the K-fold cross-validation approach. Instead of using a single training/validation split, the $K$ fold cross-validation divides the database into $K$ equal portions and repeats the training process $K$ times, each time one different part is selected for validation, and the final results are obtained by averaging those of $K$ folds. In this way, the distribution of different structural conditions among sub-dataset is better balanced, thus ensuring data diversity.

Figures 10, 11 and 12 highlight the computed results of the proposed method for damage localization tasks. The evolution

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TABLE II
NUMBER OF PARAMETERS AND THE SHAPE OF OUTPUTS OF EACH LAYER IN THE 1D CONVOLUTIONAL NEURAL NETWORK

| Layer | $1^{st}$ 1DConv | $2^{nd}$ 1DConv | Max Pooling | $1^{st}$ Dense | $2^{nd}$ Dense |
|---|---|---|---|---|---|
| $N \times L$ | $N \times L \times 16$ | $N \times L \times 16$ | $N \times L/4 \times 16$ | $N \times$ 100 | $N \times$ 20 |

$N$ is the number of samples, $L$ is the length of time-series.

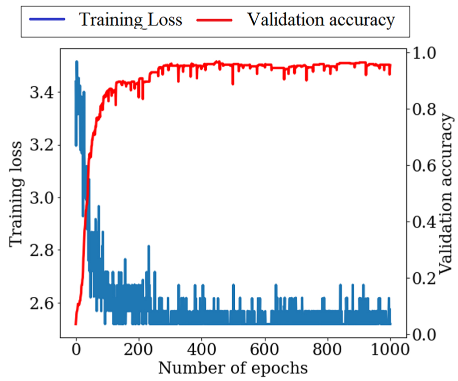


Fig. 10. Evolution of train and validation loss during the training process.

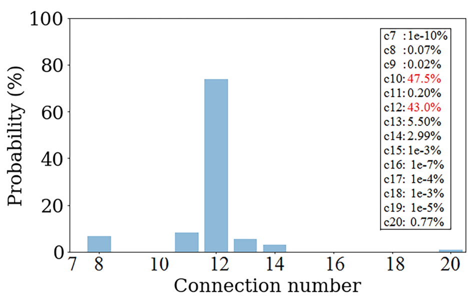


Fig. 11. Predicted probability for all classes at 1DCNN's output layer.

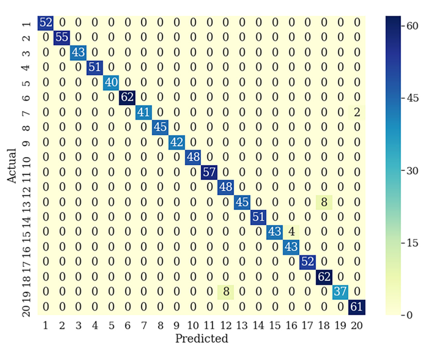


Fig. 12. Confusion matrix of damage localization - Deep CNN algorithms

of training errors and corresponding accuracy on validation with respect to the number of epochs are depicted in Fig. 10. It is noted that the accuracy increases steadily for the first 200 epochs, then surge to a value of 92% at a epoch around 500; after that, no significant improvement is observed. Thus, the converged validation accuracy is taken as 92%, with a small variation of around 1.5%. Once the training process is terminated, the system's parameters are fixed and applied to the testing data set. Fig. 11 presents an example of a test case; the DL model provides the probability associated with every truss connections, the sum of probabilities is equal to 100%. The connection with the highest probability value is identified as the location of damages. Fig. 12 shows the confusion matrix of results calculated on the testing data set in which rows denote the ground truth of test cases, i.e., the actual number of connections subjected to stiffness loss, whereas columns are the damaged connection number inferred by the DL model. As expected from the validation results, the testing result achieves a high accuracy of 91.7%. Moreover, in terms of inference time, it only took 0.003s for one testing sample using a cloud virtual machine with specification of 6-core Xeon CPU and 16 Gb RAM, thus ensuring the required speed of real-time SHM applications. In short, these results confirm the correctness and effectiveness of the SHM method based DL algorithm.

A comparative analysis between cDTSHM with existing SHM frameworks is presented in Table III. It can be seen that the industrial solutions provide most of the functionalities, but with a considerable cost. The framework using only physics-based models are yet able to perform the near real-time capacity. Some data-driven models can only detect the existence of damage yet provide further information about damage location or damage severity. Note that as these reviewed frameworks are not publicly available or the relevant data are censored, quantitative comparisons are not possible.

In the table, one suggests that the development and operational cost of cDTSHM are from low to medium for two reasons: i) the fog layer helps reduce the volume of data stored on the cloud, ii) the data analytic component is built based on free and open-source deep learning libraries. Besides, thanks to the transfer learning technique and a data augmentation strategy combining real data and synthetic data, the cDTSHM can perform multiple SHM tasks with increasing complexity levels ranging from detecting damage existence (level 1) to identifying damage location (level 2) to quantifying damage severity.

## V. CONCLUSION AND FUTURE WORK

A cloud-based DT framework for SHM (cDTSHM) was proposed for real-time monitoring and proactive maintenance of civil structures. The proposed method facilitates two-way mapping between physical structure and digital counterpart, as well as interaction among structure, machine, and human, paving the way towards a real-time intelligent monitoring system. A layer of fog computing was implemented prior to the cloud layer to reduce the data volume and the computational demand for the digital model. The feasibility of cDTSHM was demonstrated through the case studies of structural damage detection in bridges using deep learning algorithms, with accuracy of 92%.

When implementing the cDTSHM, the fidelity of the DL models is one of the main challenges. In addition, the difficulty

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TABLE III
COMPARATIVE ANALYSIS BETWEEN cDTSHM WITH REVIEWED FRAMEWORKS

| Features | Proposed cDTSHM | Shim et al. [7] | Industrial solutions [12] | Qian et al. [31] | Jeong et al. [32] | Tran et al. [16] |
|---|---|---|---|---|---|---|
| Data type | Time-series data | Various | Various | Time-series data | Time-series data | Tabular data |
| Data collection | Semi-Automatic | Manual | Automatic | Semi-automatic | Semi-automatic | Manual |
| Data pre-processing | Fog layer | Local server | Cloud computing | Cloud computing | Cloud computing | Local server |
| Data storage | On cloud | Local server | On cloud | On cloud | On cloud | Local server |
| Data analytic | Data-driven model | Data-driven model | Data-driven model | Data-driven model | Data-driven model | Physic-based model |
| Data visualization | Web application | Desktop program | Web application | N/A | Web application | N/A |
| Security | Good | N/A | Good | N/A | Good | N/A |
| Portability | Multi-devices | PC | multi-devices | multi-devices | multi-devices | PC |
| Budget/costs | Low to medium | N/A | High | N/A | Medium-High | Low |
| Monitoring | Near real-time | Periodic | Near real-time | Near real-time | Near real-time | Periodic |
| SHM level | 3 levels | 3 levels | 3 levels | 1 level | 1 level | 3 levels |

in actively updating the models for facing the future damage scenarios also accentuates the challenge. To address this issue, one uses statistic models as baselines on the one hand and uses 3D numerical simulations for introducing different levels of damages to augment SHM data on the other hand. By doing so, the DL models' performance will always provide better or at least similar results to conventional statistic/numerical models. The second challenge is the scarcity of relevant data. Because most of the data are related to a normal state of the structures; hence, transmitting and storing full data all the time is unnecessary. Thus, one adopts a hybrid scheme to augment SHM database via synthetical data obtained from reliable FEMs as discussed in the second example. Another way to increase the data efficiency is to engineer a hierarchical strategy. Some basic features will be extracted from data to detect the damage existence first; if no damage occurs, data are discarded, or only basic features are stored. In contrast, if the damage is detected, the more advanced feature extractions are adopted for preparing inputs for the mathematical and ML models to perform complex tasks such as damage localization or damage severity.

Although this paper presents promising results, further works can be identified and addressed in the next studies. Currently, the framework works with predefined types of damages, i.e., stiffness reduction; however, in reality, there exist numerous potential defection scenarios such as corrosion, material degradation, etc. Therefore, unsupervised and semi-supervised learning algorithms should be applied to increase the generalization. Another aspect is that the proposed framework only uses vibration data which are not very sensitive to local damages. Therefore, it is usually required a large number of sensors installed along the structure's body to detect the damage localization to some degree of accuracy. It is recommended to apply some breakthrough measurement devices such as optical fiber sensors, which can provide richer information about the structures' behavior, thus extending the framework's capacity.

As the real-world application of cDTSHM is highly complex and dynamically evolving over time, further work can also include: i) Long-term efficiency of cDTSHM on multiple facets (e.g., performance, reliability, practicality, cost financing), particularly when facing the variability/fuzziness of real structure parameters and uncertainty of data acquisition; ii) Relating/learning from DT applications in other domains: useful feedback from the digital replica can be improved by conceiving more other insights (e.g., control functions).

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