Digital Communications and Networks 2 (2016) 97–107

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Digital Communications and Networks

journal homepage: www.elsevier.com/locate/dcan

Big data-enabled multiscale serviceability analysis for aging bridges☆

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A R T I C L E I N F O

Article history:
Received 20 April 2016
Accepted 31 May 2016
Available online 15 July 2016

Keywords:
Hadoop Ecosystem
Bridge
Serviceability
Multi-scale
Reliability analysis
Deep learning

A B S T R A C T

This work is dedicated to constructing a multi-scale structural health monitoring system to monitor and evaluate the serviceability of bridges based on the Hadoop Ecosystem (MS-SHM-Hadoop). By taking the advantages of the fault-tolerant distributed file system called the Hadoop Distributed File System (HDFS) and high-performance parallel data processing engine called MapReduce programming paradigm, MS-SHM-Hadoop features include high scalability and robustness in data ingestion, fusion, processing, retrieval, and analytics. MS-SHM-Hadoop is a multi-scale reliability analysis framework, which ranges from nationwide bridge-surveys, global structural integrity analysis, and structural component reliability analysis. This Nationwide bridge survey uses deep-learning techniques to evaluate the bridge serviceability according to real-time sensory data or archived bridge-related data such as traffic status, weather conditions and bridge structural configuration. The global structural integrity analysis of a targeted bridge is made by processing and analyzing the measured vibration signals incurred by external loads such as wind and traffic flow. Component-wise reliability analysis is also enabled by the deep learning technique, where the input data is derived from the measured structural load effects, hyper-spectral images, and moisture measurement of the structural components. As one of its major contributions, this work employs a Bayesian network to formulate the integral serviceability of a bridge according to its components serviceability and inter-component correlations. Here the inter-component correlations are jointly specified using a statistics-oriented machine learning method (e.g., association rule learning) or structural mechanics modeling and simulation.

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1. Introduction

Public transportation plays an extremely significant role in human society; however, the safety of transportation infrastructure such as bridges is becoming an increasingly critical issue. According to a report from the United States Federal National Bridge Inventory, the average age of the nation's 607,380 bridges is currently 42 years old. One in nine of those bridges is rated as structurally deficient. The American Society of Civil Engineers (ASCE) has given our nation's infrastructure a very poor grade of D+ overall according to the 2013 America's infrastructure report card. Safeguarding the most critical structures is necessary to save citizen's lives and protect the nation's economy foundation.

A complete traditional structural health monitoring (SHM) system includes sensory system, data acquisition and transmission system, data processing and management system, and structural evaluation system [1]. With the development of computing and networking technologies, wireless sensor networks (WSNs) have received extensive attention which are generally composed of multiple wireless smart sensor nodes (WSSNs) and a base station which can be a computer server with ample computation and storage resources. A WSSN consists of a Mote platform (such as Imotes), a sensor board and a battery board. Featured with low cost in installation and maintenance and high scalability, the WSSNs have been deployed on the Golden Gate Bridge by UC Berkeley in 2006 [2] and recently on Jindo Bridge in Korea through a collaborative research among Korea, US and Japan [3]. Researchers

☆This work is jointly sponsored by the National Science Foundation (NSF) with proposal number 1240734 and UTC THEC/CEACSE 2016 Grant Program.

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Peer review under responsibility of Chongqing University of Posts and Telecommunications.

http://dx.doi.org/10.1016/j.dcan.2016.05.002
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have also displayed enthusiasm using wireless smart sensors to monitor full-scale civil bridge structures in [4,5]. Full-scale deployment of WSNs on real bridge structures is transformative because the employment of a wired sensor network still dominates SHM projects. Challenges lay in the availability of the power supply and mature damage monitoring algorithms.

Although there has been some work that adopted data management infrastructure and machine learning techniques for structural monitoring, few platforms have been investigated to seamlessly integrate full spectrum input data. In [6] neural network based techniques are used for modeling and analyzing dynamic structural information for recognizing structural defects. In [7], to avoid the need of a large amount of labeled real-world data as training data, a large amount of unlabeled data is used to train a feature extractor based on the sparse coding algorithm. Features learned from the sparse coding are then used to train a neural network classifier to distinguish different statuses of a bridge. The work in [8] presents a layered big data and a real-time decision-making framework for bridge data management as well as health monitoring. In [9], both supervised and unsupervised learning techniques for structural health monitoring are investigated by considering acoustic emission signals. A data management infrastructure based on NoSQL database technologies for bridge monitoring applications was proposed in [10]. Cloud service infrastructure is also deployed to enhance scalability, flexibility and accessibility of the data management system [11].

In this work, a multiscale structural health monitoring and measuring system [12,13] based on the Hadoop Ecosystem, which is denoted as MS-SHM-Hadoop for simplicity, is investigated. By integrating sensor technology, a wireless network, data-mining based on a big-data platform, and structural mechanics modeling and simulation, MS-SHM-Hadoop is equipped with the following functions: (1) real-time sensory data acquisition, integration, and analysis [14–17]; (2) quantitative measurement of the deficiency of nation-wide bridges; (3) identification of bridge structural faults and quantitative prediction of their life expectancy according to the long-term surveillance of the dynamic behavior of bridges.

The remainder of this paper is organized as follows: Section 2 provides an overview of the proposed MS-SHM-Hadoop system. Section 3 describes the infrastructure and flowchart of MS-SHM-Hadoop; Section 4 introduces the acquisition of sensory data and the integration of structure-related data; Section 5 presents a nationwide bridge survey; Section 6 investigates the global structural integrity of bridges according to structural vibration; Section 7 investigates the reliability analysis for localized critical components; Section 8 employs a Bayesian network to investigate bridge global integrity according to their component reliability, which is obtained in Section 7; and Section 9 concludes the paper.

2. Overview of the proposed MS-SHM-Hadoop

Fig. 1 illustrates the three major inputs for MS-SHM-Hadoop. Sensory data includes the cyclic external load and structural response, and surrounding environmental conditions. The supporting information refers to all bridge-related information such as the bridge configuration database (National Bridge Inventory), transportation status (National Transit Database), and weather conditions (National Climatic Data Center). Structural configurations include the geometric formulation of bridges and construction material description.

We marry big-data with sensor-oriented structural health monitoring and measuring due to the following motivations: (1) Many critical aspects of bridge performance are not well understood. The reasons for this include the extreme diversity of the bridge infrastructure, the widely varying conditions under which bridges serve, and the lack of reliable data needed to understand performance. Meanwhile, as sensors for bridge structural health monitoring are increasingly employed across the country, massive information-rich data from different kinds of sensors are acquired and transmitted to the racks of the bridge management administration database. (2) There exists a high-degree of correlation among bridges data, which can be effectively disclosed by data mining over a big-data platform.

The objectives include: (1) Real-time processing and integration of structure-related sensory data derived from heterogeneous sensors; (2) highly efficient storage and retrieval of SHM-related heterogeneous data (i.e., with differences in format, durability, function, etc.) over a big-data platform; (3) prompt while accurate evaluation about the safety of civil structures according to historical and real-time sensory data.

The accomplishment of the above objectives consists of the following tasks: (1) research samples screening: survey the nation-wide bridge information platform, characterize and screen representative research samples with low safety levels; (2) performance indicators (PIs) determination: evaluate and determine the proper multiple PIs to predict bridge performance in a quantitative manner; (3) data fetching and processing: fetch relevant sensor data from the Hadoop platform, according to the PI requirement, and process the raw sensor data into load effects and load spectrums [18]; (4) multi-scale structural dynamic modeling and simulation: based on historical data of sample bridges, establish finite element (FE) and particle models for global structural analysis and local component fatigue analysis [19]; (5) evaluate the impact of innovative bridge construction methods on bridge performance by instrumenting two new bridges in Tennessee. Bridge construction, design, and materials have changed over time, and these changes may affect bridge performance. For example, accelerated bridge construction (ABC) is a new process in bridge construction and may affect bridge performance [20]. These

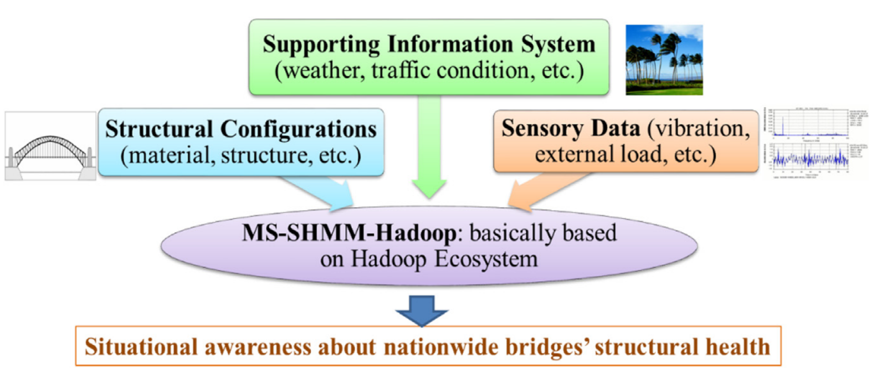

Fig. 1. Three major inputs for MS-SHM-Hadoop.

two new bridges can also serve as a test bed for the proposed activities in this project. (6) Bridge performance evaluation: assess the bridge performance by PIs of the global structure and local critical components [21]. The implementation of MS-SHM-Hadoop involves the following cutting-edge technologies: (1) machine learning including classification, clustering, regression, and predictive analysis, based on general bridge information (e.g., age, maintenance management, and weather conditions, etc.), sensory data, and structural configurations (e.g., bridge material, length, etc.), Bayesian network and stochastic analysis; (2) structural dynamic analysis; (3) signal processing for external load and structure response; (4) a multi-scale strategy ranging from the nationwide bridges survey to specific component structural reliability analysis; and (5) the Hadoop ecosystem to achieve high-scalability including acquisition, fusion, normalization of heterogeneous sensory data, and highly scalable and robust data analysis and information queries.

3. Implementation framework about MS-SHM-Hadoop

3.1. Infrastructure of MS-SHM-Hadoop

Fig. 2 shows the infrastructure of MS-SHM-Hadoop, which consists of the following three modules: the sensor grid (SG) module, the data processing and management (DPM) module based on the Hadoop platform, and the structural evaluation (SE) module based on structural dynamics modeling and simulation. A more detailed description about each module is given below.

The sensor grid (SG) module mainly acquires, pre-processes the raw sensory data and then transmits it to the data processing and management (DPM) module. The mobile computing gateway (denoted as MC for simplicity) coordinates with each other through a wireless network. SensorCtrl is the control-module that tunes the sensor's configurations for better observation of the area-of-interest, which is located through the structural analysis (SE module).

The Hadoop-enabled data processing and management (DPM) module mainly integrates, transforms, classifies, and stores the data with high fault-tolerance and scalability. Based on Hadoop Distributed File System (HDFS) and MapReduce high-performance parallel data processing paradigm [22], R-Connector and Mahout [22] provide powerful statistics and machine learning capability. Inspired by big-table techniques (including row-key, column-key, and time-stamp), HBase [22] efficiently accesses large-scale heterogeneous real-time or historical data. Flume [22] collects, aggregates, and moves a large amount of streaming data (i.e., the sensory data about bridge status) into Hadoop from a variety of sources. Hive [22] provides a data warehouse infrastructure to manage all the data corresponding to bridge serviceability; Pig [22] offers MapReduce-enabled query and processing. Sqoop [22] supports the ingestion of log data, which is related to bridge design and operation such as the bridge configuration (e.g., National Bridge Inventory), transportation status (e.g., National Transit Database), and weather conditions (e.g., NOAA's National Climatic Data Center). In this work, InfoSys manages the external log data. VIBRA stores the cyclic external force load (or vibration signals), which is applied by the wind or vehicles, and the corresponding structural response. The StConD component stores the structure configuration (i.e., geometry configuration and mesh) of civil structure. The EnvD (Environmental data component) keeps circumstance parameters such as temperature, moisture, etc. SenD is a database component that keeps the configurations (e.g., location, brand, mechanism, maintenance schedule, etc.) of sensors attached to the bridges.

Based on structural dynamics theory and signal processing techniques, the SE module mainly uses historical or real-time sensory data to identify the global (or bridge-wise) or component-wise structural faults. In addition, a Bayesian network is employed to formulate the integrity analysis according to components' structural reliability.

3.2. Flowchart of the MS-SHM-Hadoop

Fig. 3 shows the systematic approach of the implementation of the MS-SHM-Hadoop system. Based on the acquired sensory data and bridge-related log data, multiscale structural health monitoring and measurement consist of the following stages: *Stage* 1: nationwide bridges database survey using machine learning techniques; *Stage* 2: global structural integrity analysis using signal processing, and structural dynamics; and *Stage* 3: localized structural component reliability analysis using stochastic methods, or multiscale modeling and simulation.

With reference to Fig. 2, it is observed that: Stage 1 is implemented in the Sensor Grid (SG) module and partially in the Data Processing and Management (DPM) module; Stage 2 is implemented in the DPM module; and Stage 3 is implemented in the Structure Evaluation module.

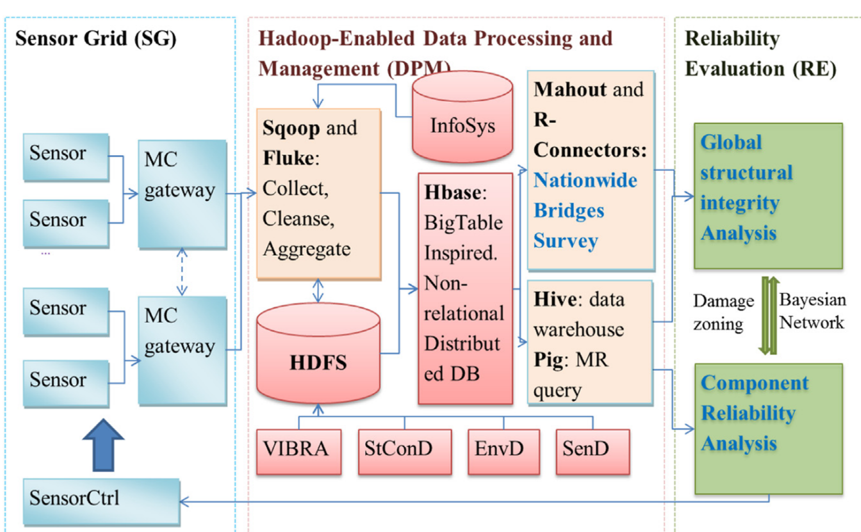

Fig. 2. Infrastructure of MS-SHM-Hadoop.

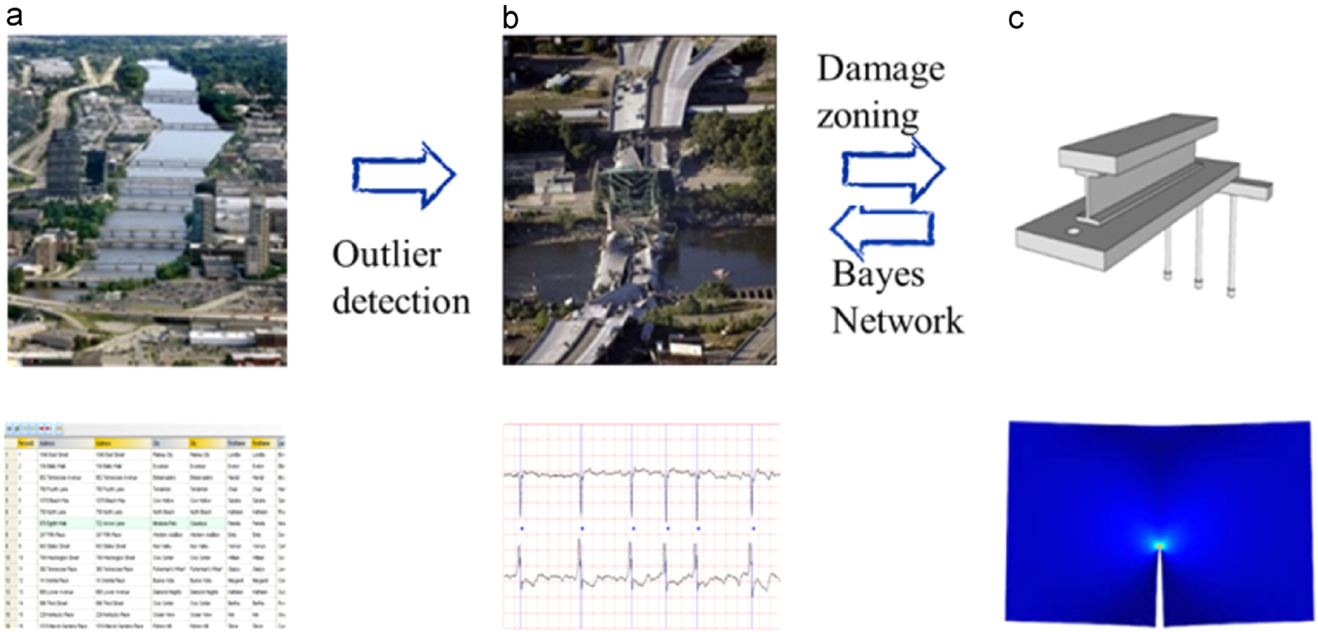

Fig. 3. Flowchart of multiscale structural health evaluation: (a) nationwide bridges survey; (b) global structural integrity analysis; and (c) localized structural component reliability analysis. The bridges' pictures are derived from mnpoliticalroundtable.com.

By surveying the nation-wide bridge status on a big-data platform, Stage 1 aims to obtain a preliminary characterization of the safety level of all the 607,380 bridges in the United States from the National Bridge Inventory (NBI) database. NBI involves dimensions, location, type, design criteria, traffic, structural and functional conditions, and lots of other information. A general screening and prioritization analysis based on weighting considerations is performed to determine the relatively low safety level aging bridges. The serviceability of a bridge is qualitatively determined by a number of overall factors, such as, the year-of-build, structure configuration, construction material, weather conditions, traffic flow intensity and life cycle cost. In this project, cluster analysis is employed to categorize the bridges according to their serviceability.

Stage 2 aims to quantitatively evaluate the global structural health status of the targeted bridges that are characterized with a low safety level from Stage 1. Global structural integrity analysis consists of the following intensive data-based structural dynamics: (1) extraction of the measured structural resonance frequencies from the time-history sensory data via Fast Fourier transformation (FFT) for the targeted bridges; (2) computation of the fundamental natural frequency (e.g., the 10 lowest natural frequencies) of the bridges using the finite-element method (FEM), which gives the upper bound of the solution; (3) computation of the fundamental natural frequency of the bridges using the node-based finite-element method (NS-FEM), which gives the lower bound of the solution; (4) evaluation of the discrepancy about fundamental natural frequencies between the measured and computed ones; (5) establishment of the relationship between the discrepancy of the fundamental natural frequencies and the healthy status of the bridge; and (6) based on the distribution of the discrepancy obtained using a sufficient large number of sensors deployed over the span of the bridge, the possible zones with heavy damage and degradation are identified.

Following the time-domain or frequency-domain algorithm, Stage 3 aims to obtain a precise description about the serviceability of the local components in the heavily damaged zones identified in Stage 2. This is to provide the remaining service life of the bridge, as well as prepare possible strategies for life-prolongation. With the load effects from sensors and computational values from the FE analysis, structural performance indicators are calculated respectively in local scale and global scale. Proper assessment theory, such as the neuro-fuzzy hybrid method [23] or the DER&U method [24] is evaluated and utilized. Finally the structural performance evaluation results are updated to the management system of structural administration to provide professional support for decision making [25].

4. Acquisition of sensory data and integration of structure-related data

Table 1 lists representative sensors in the proposed system needed to acquire the following information: external load; structural response to external load; and environmental

Table 1
List of sensors.

Monitoring data category	Sensor type	Data to be collected
External loading and structural response	Accelerometer	Proper acceleration
	Displacement transducer	Structural displacement
	Strain gage	Strain of the structure
	Laser Doppler vibrometer	Vibration amplitude and frequency
	GPS station	Location of structure and time synchronization
Environmental conditions	Thermometer	Temperature and humidity
	Anemometer and wind-vane	Wind speed and direction
Traffic flow	CCD camera	Vehicle type, throughput, velocity
	Weight in motion	Weight of the still/moving vehicles

circumstance parameters. To provide a localized monitoring data analysis, we adopt a mobile computing (MC) gateway that collects the raw sensory data, pre-processes and sends them to the DPM module via a wired or wireless network. The MC is used to provide real-time analysis of the situation at a specific location on the infrastructure. The MC is carried by a robot or unmanned aerial vehicles (UAVs) to collect the acquired data from the sensors covering a specified area on the bridge. The MC also communicates with the DPM module where further extensive analysis of the collected data is performed. For large-scale monitoring, multiple MCs can be deployed based on the structure of a bridge and communicate with each other to acquire more data from sensors and broaden the monitoring analysis.

Wireless sensor networks (WSNs) play a big role in monitoring the infrastructure health, where data is collected and sent to the data processing management module [26–28]. Despite the benefits that WSNs provide, such as, high scalability, high deployment flexibility of deployment, and low maintenance cost, sensors suffer from computational and energy limitations, which needs to be taken into consideration for extended, reliable and robust monitoring.

Energy-efficient sensors are crucial for accurate long-duration monitoring in SHM systems. On the one hand, to accurately formulate the random process of structural mechanics and detect the potential damage of complex structures in real time, both long-term monitoring and real-time monitoring of these structures by sensor networks are needed. On the other hand, sensors usually have a very limited energy supply, battery power for example, which is consumed by different modules in the sensors, including the sensing module, the on-board data processing and storage module, and the communication module. Therefore, development of methods and strategies for the optimization of the sensors energy consumption is imperative.

In the proposed SHM system, the parameters to be monitored are heterogeneous, such as temperature, wind, acceleration, displacement, corrosion, strain, traffic, etc. These parameters have different spatial and temporal properties, for example, different variation speeds and locations. Depending on the nature of the monitored parameters, some sensors may work continuously while others may work in trigger mode. Based on these observations, the sampling rate in data acquisition and duty cycles [29] in wireless networking is optimized for different types of sensors. Moreover, in some types of data-intensive monitoring, such as wireless video based traffic monitoring, energy consumption on computation for source signal processing and compression might be the same order of magnitude as energy consumption on wireless transmission of the post-processed data. In such scenarios, joint source-channel coding schemes [30] can be developed based on rate-distortion theory to achieve the optimal trade-off between the computation-oriented energy-consumption and energy communication-oriented energy-consumption. To further save energy, sensors can remain in sleep mode or low duty cycle mode. When they are approached by the MC for data collection, they are woken up by the MC or switch from the low duty cycle mode to the high duty cycle mode. Last, the proposed system may incorporate various energy-harvesting sensors to capture and generate power from ambient energy sources such as vibration, strain, wind, solar, and thermal. Bridges are ideally suited to harvest such types of energy [31]. For example, sensors with piezoelectric materials can be mounted or embedded to bridges based on bridge structural information to harvest vibrational/strain energy generated by the passing vehicles to supply the energy for low-power sensors.

5. Nationwide bridges survey

As the major task of the data processing and management (DPM) module, the nationwide bridge survey is dedicated to classifying the nationwide bridges according to their life-expectancy. The Hadoop Ecosystem and deep learning are two enabling techniques for the nationwide bridge survey.

5.1. The features used in nationwide bridges survey

In this work, more accurate features are used in the nationwide bridge survey. Besides material erosion, cyclic and random external loads and corresponding structural responses are the major causes of bridges' aging. A quantitative investigation about the dynamic behavior of bridges will help us to extract the features for structural health. The following governing equation shows the linear dynamics of bridges:

$$\left[M\right]\left\{\ddot{u}\right\}+\left[C\right]\left\{\dot{u}\right\}+\left[K\right]\left\{u\right\}=\left\{L_{traffic}\right\}+\left\{L_{wind}\right\}+\left\{L_{self\_weight}\right\}. \quad (1)$$

where $[M]$, $[C]$, and $[K]$ are mass, damping and stiffness matrices respectively ($[C]=\alpha[M]+\beta[K]$); $\{\ddot{u}\}$, $\{\dot{u}\}$ and $\{u\}$ are acceleration, velocity, and displacement vectors, respectively; external load effects $\{L_{self\_weight}\}$, $\{L_{traffic}\}$ and $\{L_{wind}\}$ are self-weight of bridge, traffic load incurred by moving vehicles, and aerodynamic load incurred by wind, respectively. Load effects are stochastic due to random variations in space and time. Turkstra load combination (add up the peak values) [32] and Ferry Borges–Castanheta load combination (time-scale) [33] are two applicable strategies to model the uncertainty combination of load.

For small or medium scale bridges, traffic load ($\{L_{traffic}\}$), which is determined by the traffic velocity, density, and vehicle weight, dominates the external load effects. For large-scale long span bridges like suspension bridges and cable-stayed bridges, wind load ($\{L_{wind}\}$) dominates the external loads. $\{L_{self\_weight}\}$ is defined by the following equation:

$$\{L_{wind}\}=q[Q(k)]\{u^{*}\}e^{i\omega t} \quad (2)$$

where $q=\frac{1}{2}\rho v^{2}$ is dynamic pressure; ρ is air mass density; v is wind velocity; $k=B\omega/v$ where B is the width of girder of bridge; and $Q(k)$ is aerodynamic force matrix. The dynamic behavior of bridges caused by extreme weather or environmental conditions is not considered in this work.

Fig. 4 shows the features to be used to measure bridges' life-expectancy. Structural dynamics features include bridges' structural configuration (e.g., mass, damping and stiffness matrices), and cyclic external load-effect/structural response (derived from in-house sensors or National Transit Database). The weather information can be derived from NOAA's National Climatic Data Center. The accessory bridges' information such as the age of bridges, maintenance policy, and construction budgets can be found in the National Bridge Inventory database. Particularly, the Nationwide Bridge Sufficiency rating provides training data (https://www.fhwa.dot.gov/bridge/).

As shown in Table 2, the National Bridge Inventory Database uses a series of general features, which includes material and structural types, climatic conditions, highway functional classes, traffic loading, precipitation, and past preservation history (where the data is available) etc., to specify the life-expectancy of bridges. Only five features are presented here. As a measurement of the bridge life-expectancy, the sufficiency rating scales from 100% (entirely sufficient bridge) to 0% (deficient bridge).

5.2. Estimation of the life-expectancy of nationwide bridges using the deep learning method

The goal of nationwide bridge survey is to identify those target bridges that are in risk of short service life. Most of the previous work about the estimation of the bridge life expectancy adopted supervised machine learning methods [34–36] such as linear and

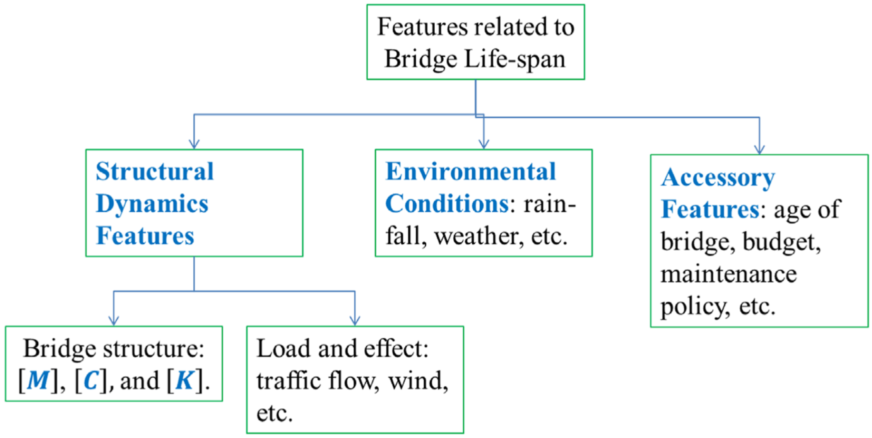

Fig. 4. Classification of features involved in nationwide bridges survey.

nonlinear regression, Markov Chain, Support Vector Machine (SVM), etc. This work emphatically investigates a deep learning algorithm [37].

Fig. 5 shows a flowchart of the deep learning enabled nationwide bridge survey. Compared with many other classifiers, a deep learning algorithm has the following advantages: (1) less or no human supervision is needed; (2) some uninterpretable while constructive features (or intermediate representations) can be directly derived from raw data; (3) less training data is required (this advantage is very important in the addressed project because the archived real world sensory data for highly deficient bridges is limited); (4) the mid layers of the deep networks can be re-purposed from one application to another, and this advantage is the motivation for using a hybrid deep learning method (HDL) which arises by merging multiple different deep learning algorithms to handle heterogeneous raw input data.

To efficiently and accurately classify the observed bridges, a hybrid deep-learning (HDL) algorithm is investigated in this work. HDL is featured with the following techniques: (1) Multiple data with heterogeneous modalities, such as raw stream sensory data like audio/video data, images, textual information like operational data, city-open-data, environment factors, and other hand-designed data is exploited so as to give a panoramic and full-spectrum description about targeted bridge's status. (2) HDL is equipped with different deep-learning algorithms, at least at the lower levels, to learn the features from multiple input data with heterogeneous modality. A Deep Convolutional Neural Network (DCNN) [38] is used to learn from visual media such as video and images because it demonstrates superior performance (high accuracy and fast training speed) on matrix-oriented feature-learning. A Recurrent Neural Network (RNN) [39] is also considered to learn features from streaming data such as acoustic signals or vibration signals because RNN exhibits dynamic temporal behavior (enabled by the directed cycle inside RNN). A Deep Boltzmann Machine (DBM) [40] specializing on learning the high-level features from textual information such as weather conditions, traffic status, and maintenance policy, etc. (3) Deep learning algorithms always learn the upper-level features from lower ones [37] and the input data with heterogeneous modality eventually fuse at the upper layers with somewhat homogeneous modality. Therefore, the HDL uses a unified deep learning algorithm such as DBM in the feature-learning of the upper levels.

5.3. Techniques to boost the nationwide bridges survey

To boost the performance of the nationwide bridges survey, various techniques such as missing data handling, data management optimization, and dimensionality reduction, etc. are employed in this work.

Most of the software packages such as WeibullReg in R or lifereg in SAS can handle missing data. However if there is a relatively large amount of missing data in the input data of statistical model, some data imputation models are applied in this work.

The proposed project employs discrete Hash-tables to formulate the correlation among data, control the data partitioning to optimize data placement, and use in-memory technology [36].

The data involved in sensor-oriented structural analysis is always extremely high-dimensional [41]. As one of our preliminary

Table 2
Sample bridge data from the National Bridge Inventory Database (updated by 2012). (ADT (ton/day): average daily traffic; SR: Sufficiency Rate).

Year built	Structure	Material	ADT	Status	SR
1914	Stringer/Multi-beam or Girder	Steel	660	Structurally deficient	6.5
1940	Tee Beam	Concrete	210	Structurally deficient	47
1965	Stringer/Multi-beam or Girder	Steel	170	Structurally deficient	23.6
1941	Stringer/Multi-beam or Girder	Steel	1320	Structurally deficient	61.3
1975	Tringer/Multi-beam or Girder	Wood	80	Structurally deficient	29.4
1952	Tringer/Multi-beam or Girder	Concrete	1080	Functionally obsolete	69.8
1984	Culvert	Concrete	50	Functionally obsolete	87.5
1940	Stringer/Multi-beam or Girder	Steel	1530	Functionally obsolete	50.8
1950	Stringer/Multi-beam or Girder	Steel	650	Functionally obsolete	78.6
1946	Tee Beam	Concrete	4350	Functionally obsolete	43.9
1982	Stringer/Multi-beam or Girder	Prest. concrete	1010	Good condition	87.4
1999	Box Beam or Girders	Prest. concrete	420	Excellent condition	88
1993	Culvert	Concrete	1020	Not applicable	78.8
1988	Culvert	Concrete	1670	Not applicable	99.4
1970	Culvert	Concrete	990	Not applicable	99.4

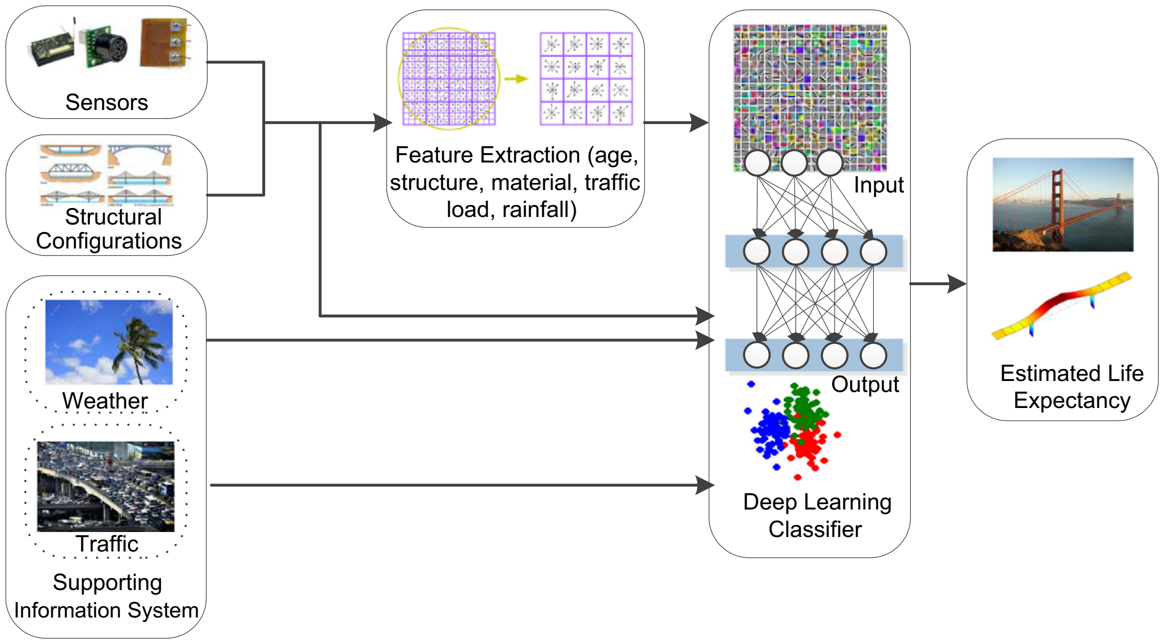

Fig. 5. Flow-chart of the deep-learning-centric nationwide bridges survey (the original pictures appeared in the figure are derived from images.google.com).

achievements, a rank revealing randomized singular value decomposition (R^3SVD) [42] was proposed to reduce the dimensionality of the dataset. As a variance of primary component analysis (PCA), R^3SVD uses local statistical errors to estimate global approximation error.

The preliminary investigations [43,44] demonstrated that A-RSVD scales well to extremely big matrices and is efficient with minimal sacrifices in accuracy due to the following reasons: (1) R^3SVD is based on statistical sampling, which is also applicable to incomplete or noisy data. (2) R^3SVD is able to obtain low-accuracy approximation quickly, which is particularly suitable for many applications where high-accuracy solutions are not necessary but fast decision making is. (3) On the other hand, of most importance R^3SVD is trivially naturally parallelizable.

6. Global structural integrity analysis

The global structural integrity analysis module aims to provide further structural integrity analysis of the deficient bridges identified in Section 5. The objectives are itemized as follows: (1) to apply the big-data and perform quantitative analysis of global structural integrity of targeted bridges; (2) to provide guidelines for more intensive and predictive examination of the bridge at the component level to be carried out at Section 7; and (3) to feed back to the database with integrity analysis results for future use.

6.1. Rational: big-data and inverse analysis

Assessments of the structural integrity from measured data of health monitoring systems are typical inverse problems, with responses of the structure as inputs and the properties (e.g., integrity) of the structure as outputs. Such an inverse problem is in general ill-posed in nature [44]. Various regularization techniques have been developed to overcome the ill-posedness, and it is understood that the sensitivity from input to output is a critical factor for any regularization technique to be effective. The use of big-data has clearly an important advantage as the problem can be made over-posed with more types of inputs available to choose from, and hence improves the sensitiveness [44]. Inverse analysis can be performed using either time-history data [45], and frequency response data [46], or combinations of the two [47]. The big-data from a monitoring system is generally rich in time-history records of responses, which can be transferred to frequency responses via standard Fast Fourier Transform (FFT) techniques. For effective assessment of slender structures like bridges, the global structural integrity relates well to the lowest natural frequencies or to the frequency responses in the lower frequency range. Therefore, we propose to conduct quantitative assessment of the target bridges by using frequency response data extracted from our big-data system.

6.2. Proposed major tasks and general procedures

As illustrated by Fig. 6(a), the proposed procedure for quantitative analysis of global structural integrity of the targeted bridges consists of three major tasks: data query for the response records of the targeted bridges, computer analysis of the rich record data, and assessment on the integrity level of the bridge using the data. In this study, a small number (e.g., 6) of lowest natural frequencies are chosen to establish global structural integrity indicators of the characteristics of the bridges.

Data query for the measured global characteristics of the targeted bridges: To obtain the actual global characteristics of the targeted bridge, the following analysis is performed. (1) Based on the data made available for querying in Section 5, bridges under monitoring are selected for qualitatively integrity assessments. (2) A query is then made to the database for bridges that have a high possibility of a short life, and a list of targeted bridges is created, in the order of urgency. (3) For each targeted bridge, a query is next made for the major excitation events that may have happened to the bridge. Such events include earthquake, wind storms, and major traffic loading at levels closest to the level used in the design of the bridge. (4) For each targeted bridge and each major event, the detailed health monitoring data related to the global responses and behavior is extracted. The data includes the time-history of accelerometers, vibrometers, and strain gauges installed at various locations on the bridge. (5) The Fast Fourier Transform (FFT) is next performed to the time-history data to obtain the frequency response data (f_i^M, if this is not readily available in the database).

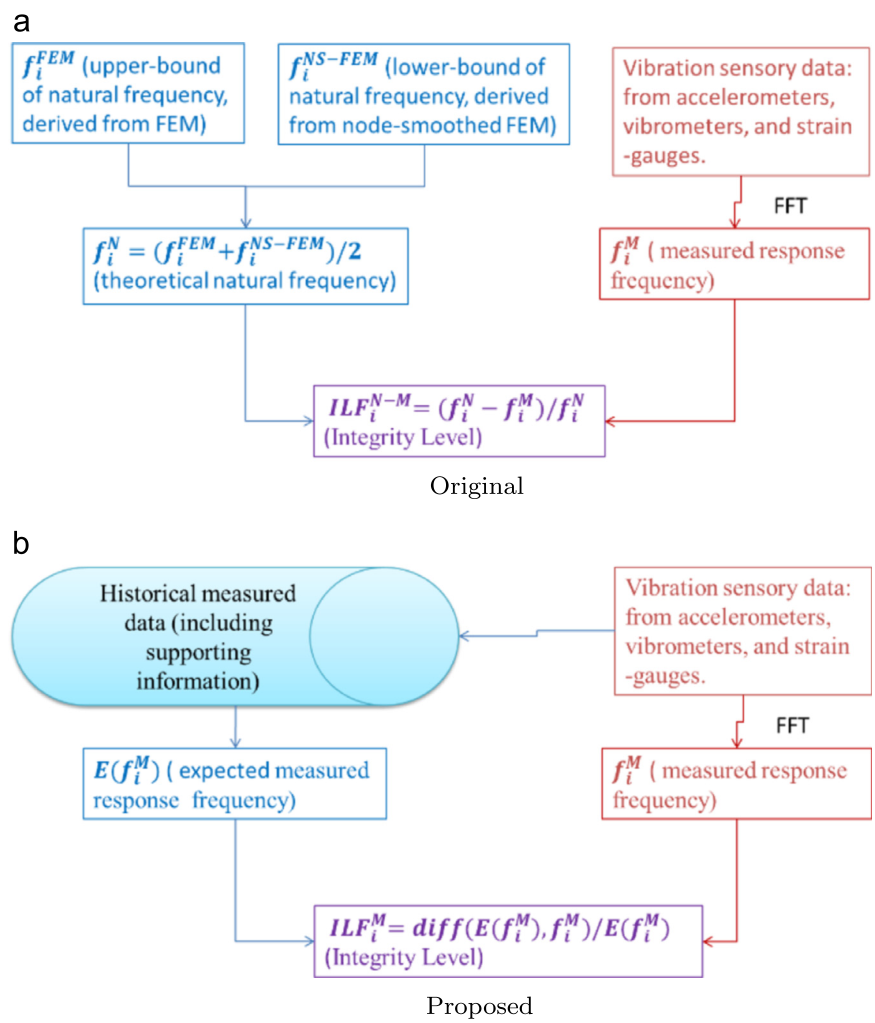

Fig. 6. Global structural integrity analysis with reference to: (a) theoretical response frequency; and (b) historical measured response frequency.

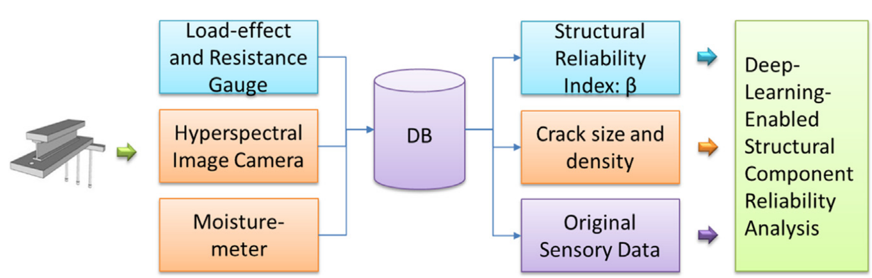

Fig. 7. Infrastructure for component reliability analysis.

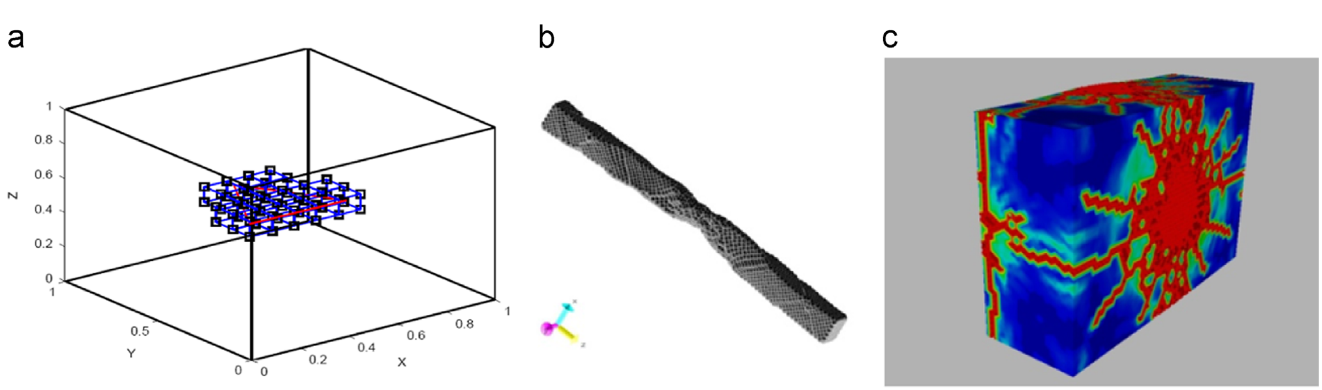

Fig. 8. Modeling and simulation of crack generation and growth: (a) growth of planar crack (X-FEM); (b) deformation of nano-wire (MD); (c)crack generation in concrete block (smooth particle method).

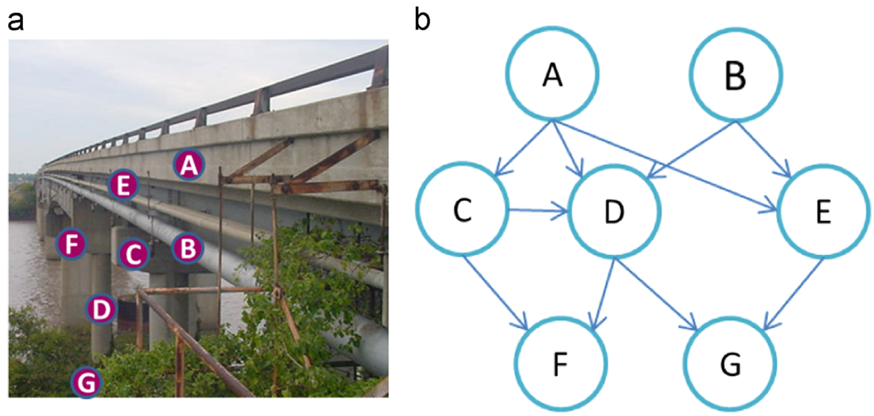

Fig. 9. (a) Bridge's components; (b) Bayesian network for bridge.

(6) Estimate the lowest few fundamental frequencies of the bridge from the frequency response data.

Computer analysis of the same characteristics of bridges: Next, we perform computer analysis to numerically predicate the values of the lowest few fundamental frequencies which consists of the following detailed procedures. (1) Query for proper the finite element mesh from the database. Since our purpose is to compute the lowest fundamental frequencies, a coarse global mesh is sufficient. (2) Query next for the material properties, considering the aging and erosion effects. (3) Query also for data on the supports of the bridge, considering the possible movements and consolidation of the foundations [48]. (4) Perform the finite element method (FEM) to obtain the FEM values of the lowest fundamental frequencies (f_i^{FEM}), which provides the upper bounds of the natural frequencies of the bridge [49]. (5) Perform the Node-based Smoothed Finite Element Method (NS-FEM) to obtain the NS-FEM values of the lowest fundamental frequencies ($f_i^{(NS-FEM)}$), which provides the lower bounds of the natural frequencies of the bridge [50]. (6) As a reference, a query may also be made for the lowest natural frequencies when the bridge was initially designed.

Assessment on the integrity level of the bridges: Finally, we assess the integrity of the bridge by comparing these lowest fundamental frequencies obtained from the monitoring data, and FEM and NS-FEM analyses, as is illustrated in Fig. 6. First, we define the numerical error indicator for the computed natural frequencies:

$$Error_i = f_i^{FEM} - f_i^{(NS-FEM)} \tag{3}$$

which gives a good indication on how accurate the numerical value is. Note that the numerical error can be reduced if a finer mesh is used. Therefore, if the error is too big we can use a fine mesh to reduce the error gap. In general, the average of both the FEM and NS-FEM values gives a good approximation [51]

$$f_i^N = \left(f_i^{FEM} + f_i^{(NS-FEM)}\right)/2 \tag{4}$$

where the superscript N denotes the numerical natural frequency. The integrity level in terms of the rate of frequency reduction (ILF) is defined as:

$$ILF_i^{(N-M)} = \left(f_i^N - f_i^M\right)/f_i^N \tag{5}$$

where the superscript M denotes the measured natural frequency. We know that a degradation of a bridge structure may lead to a reduction of some fundamental frequencies. In addition, we have a general understanding that the frequency is related to the square-root of the stiffness of the structure of the bridge. The integrity level in terms of the rate of stiffness reduction (ILK) indicators is then defined as:

$$ILK_i^{(N-M)} = \left(\sqrt{f_i^N} - \sqrt{f_i^M}\right)/\sqrt{f_i^N} \tag{6}$$

In the end, a criterion (e.g., 10% reduction) can be set to categorize the bridge into the list of bridges to be further studied in detail in Section 7.

As illustrated in Fig. 6(b), integrity analysis is made by comparing the newly observed response signals with the historical response signals.

7. Localized critical component reliability analysis

Different from Section 6, this section mainly focuses on the measurement of structural component deterioration.

7.1. Deep-learning-enabled component reliability analysis

Fig. 7 shows the infrastructure of the component reliability analysis. Just like the nationwide bridges survey, the deep learning technique is employed to digest the input data with heterogeneous modality so as to obtain the reliability of the structural components. Component reliability involves two strategies: structural reliability analysis and observation-oriented method. The former is derived from the probabilistic evaluation of load-effect (denoted as S) resistance (denoted as R). The latter is derived from the direct observation about the component using optical-electro sensors (e.g., hyper-spectral image cameras and moisture meters).

Structural reliability is conventionally measured by reliability index β, which is determined by the limit state function $Z = R - S$. Structural component failure occurs whenever $Z < 0$. If R and S follow Gaussian distributions, the reliability index is a function of the mean and standard deviation of Z, namely $\beta = \frac{\bar{Z}}{\sigma_Z} = (\bar{R} - \bar{S})/\sqrt{(\sigma_R^2 + \sigma_S^2)}$. Commonly used numerical methods to calculate the reliability index include Monte Carlo simulation (random sampling to artificially simulate a large number of experiments and observe the results), first-order reliability method (approximating limit-state function with a first-order function), response surface method (approximating the unknown explicit limit state functions by a polynomial function), Latin hypercube simulation, genetic search algorithm, and subset simulation.

The crack density and size inside or outside the structural component is also an index to evaluate the reliability of the structural component. A hyper-spectral image processing technique and concrete moisture measurement are commonly used techniques to probe crack size and density.

7.2. Probe prolongation strategies via simulating crack initialization and growth

Fatigue failure is a complex and progressive form of local damage which is significantly influenced by many factors such as magnitude and frequency of the loads causing the fluctuating stress, temperature, environment, geometrical complexities, material imperfections and discontinuities [52]. Durability of the bridge structures is mainly dominated by the fatigue behavior of those critical components of the bridge.

In the proposed work, both time-domain and frequency-domain finite-element-based (FEM) [53–55] fatigue analyses are investigated to measure the life expectancy of the bridge component under random cyclic external loads. The former is implemented by formulating the transient solution to the dynamics of the structure. The latter formulates the random cyclic load and structural response using Power Spectral Density (PSD) [56]. Numerically, frequency-domain approaches are more efficient because they do not need to solve the dynamics equation at each time step. However, frequency domain approaches are not applicable for an extremely irregular cyclic load. Both approaches are investigated in the proposed work.

Crack generation and crack growth give us a more in-depth understanding about the fatigue behavior of the material. Fig. 8 (a)–(c) shows our preliminary results in crack generation and growth using extended FEM (X-FEM) [57], molecular dynamics (MD) [58], and smoothed particle methods [59]. Our future work will focus on the application of generalized smoothed particle methods in the modeling and simulation of component fatigue, based on which a potential life prolongation strategy will be discussed.

8. Bridge's reliability analysis based on a Bayesian network

The Bayesian network is a probabilistic graphical model that represents a set of random variables (nodes) and their conditional dependencies (arcs) via a Directed Acyclic Graph (DAG). As one of the major contributions of this work, a Bayesian network is employed to formulate the reliability of the bridge system according to component reliability examined in the previous section (or Section 7).

As illustrated in Fig. 9 (a) and (b), the Bayesian network for bridges has the following features: (1) Each node represents a structural component and takes a discrete value to describe the serviceability (e.g. whether or not the component still functions, or the life expectancy of component, etc.). (2) The topology of the Bayesian network is determined according to the components qualitative relationship. Two nodes should be connected directly if one affects or causes the other, with the arc indicating the direction of the effect. (3) Once the topology of the Bayesian network is specified, the inter-component dependency is quantified. As its creative contribution, the inter-component interactions are jointly formulated according to mechanical interaction (e.g., pin and hanger) and statistical correlation (e.g., two pins not directly related).

It is extremely computationally costly to construct the Bayesian network of a bridge constituted out of tens of thousands of components. Multiple techniques are introduced to reduce the computing complexity. For example, the Bayesian network nodes are classified into essential and non-essential components, only those essential ones will be considered in integrity analysis. The inter-component dependency is either derived from mechanical interaction or "inferred causal interactions" (statistical correlation), and those insignificant inter-component correlations are ignored. In addition, the sub-system, a self-contained system within a larger one, is considered to formulate the Bayesian network into a hierarchy structure.

9. Conclusion and future work

This work proposed a framework to construct a multi-scale structural bridge health monitoring system based on the Hadoop Ecosystem (MS-SHM-Hadoop) to monitor and evaluate the serviceability of bridges. MS-SHM-Hadoop is a multi-scale reliability analysis system, which ranges from a nationwide bridge survey, global structural integrity analysis, to structural components' reliability analysis. As one of its major technical contributions, this system employs a Bayesian network to formulate the integral serviceability of a bridge according to component serviceability and inter-component correlations. Enabled by deep learning and Hadoop techniques, a full-spectrum, sustainable, and effective evaluation can be made to cover the 600,000 nationwide bridges.

As our future work, the proposed system will be employed in monitoring two Tennessee bridges to evaluate the feasibility and performance of this project. One of the bridges was built with Accelerated Bridge Construction (ABC), a bridge construction method that uses innovative planning, design, materials, and construction methods in a safe and cost-effective manner. The other was built with a conventional construction method. The impact of the innovative bridge construction methods on the bridge performance will also be evaluated since bridge construction, design, and materials have changed over time, and these changes may affect bridge performance. For example, the accelerated bridge construction is a new process in bridge construction and may affect bridge's performance [18–20]. A total of up to 25 nodes will be deployed for each of these two targeted bridges to demonstrate the integration of cutting-edge wireless sensors with the big data platform for structural bridge health monitoring.

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