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Self-Charging and Self-Monitoring Smart Civil Infrastructure Systems: Current Practice and Future Trends

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ABSTRACT

Next generation of smart infrastructure is heavily dependent on distributed sensing technology to monitor the state of urban infrastructure. The smart sensor networks should react in time, establish automated control, and collect information for intelligent decision making. In this paper, we highlight our interdisciplinary research to address three main technical challenges related to smart infrastructure: (1) development of smart wireless sensors for civil infrastructure monitoring, (2) finding an innovative, cost-effective and sustainable energy resource for empowering heterogeneous, wireless sensor networks, and (3) designing advanced data analysis frameworks for the interpretation of the information provided by these emerging monitoring systems. More specifically, we focus on development of a self-powered piezo-floating-gate (PFG) sensor that uses only self-generated electrical energy harvested by piezoelectric transducers directly from a structure under vibration. The performance of this sensing technology is discussed for different civil infrastructure systems with complex behavior. Subsequently, the proposed data interpretation systems integrating deterministic, machine learning and statistical methods are reviewed. We outline our thoughtful vision for the proposed framework to serve as an integral part of future smart civil infrastructure, which will be capable of self-charging and the self-diagnosis of damage well in advance of the occurrence of failure.

Keywords: Civil Infrastructure Health Monitoring, Smart Cities, Energy Harvesting, Self-powered Sensing, Machine Learning.

1. INTRODUCTION

Degradation is known as the main cause of failures of civil infrastructure systems in the US. In a recent report by the American Society of Civil Engineers (*1*), America's aging infrastructure has received a D+ grade. An estimated $206 billion must be invested each year to raise the overall infrastructure grade and to maintain the US global competitiveness by 2025 (*1*). The losses associated with aging and deterioration in the US infrastructure are significant. However, the challenges of aging infrastructure networks imply the need for developing innovative civil infrastructure monitoring solutions. In the last three decades, notable research has been conducted in the area of deployment of new monitoring technologies for continuous damage assessment and safety evaluation of civil infrastructure. In this context, wireless sensor networks (WSNs) have been increasingly utilized as alternatives to traditional structural engineering monitoring systems (*2*). However, a significant concern for the application of WSNs is about their power supply. Nearly all commercially viable sensors for structural health monitoring (SHM) require an external power source (*2*) (*3*). Periodic replacement of batteries for embedded sensors or use of solar power technology

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would be cost-prohibitive and in some cases impractical. These issues have been exacerbated by rapid development of ‘smart city’ technologies with a global technology market of over $1.5 trillion by as early as 2020 (*4*). The smart city enabling technologies extensively rely on distributed WSNs (*21*). Developing smart sensors that can harvest ambient energy through different techniques for their operation seems to be an attractive solution for tackling this problem (*22*) (*23*) (*24*) (*25*) (*26*). Furthermore, the next generation smart cities will not only be dependent on smart monitoring systems but also advanced data mining frameworks to interpret the generated information.

In this paper, we highlight our interdisciplinary research to address the above-mentioned technical challenges through development of smart and battery-free sensors for civil infrastructure health monitoring and designing advanced data mining algorithms. The focus is placed on a piezo-floating-gate (PFG) sensing technology that harvests its required operation power from the structural vibrations. The functionality of this sensing technology for detecting damage in various structural systems is discussed. Furthermore, the associated data interpretation system integrating deterministic, machine learning and statistical methods are reviewed.

2. OPERATION PRINCIPLE OF THE PIEZO-FLOATING-GATE SENSORS

Our teams at Michigan State University (MSU) and Washington University in St. Louis have been working on development of various aspects of the PFG sensing technology (*3*) (*5*) (*6*). This sensor consists of a floating-gate unit and a piezoelectric transducer. The power consumption is more than two orders of magnitude lower compared to other sensing technologies (80nW power consumption for the latest prototype). The prototype of the sensor is shown in Figure 1(a) (*5*). The die size of the electronics, including floating-gates, is 1.5mm × 1.5mm, which we package into a standard 6mm × 6mm × 0.8mm quad-flat no-leads (QFN). A piezoelectric transducer is used to harvest mechanical energy from a host structure by transforming the applied mechanical loading into electrical power. The open source voltage (V) generated across the piezoelectric transducer can be defined as (*7*):

$$V = \frac{S\,Y\,d_{31}\,h}{\varepsilon} \tag{1}$$

where S, Y, d_{31}, h and ε are the applied strain, Young’s modulus of the piezoelectric material, piezoelectric constant, thickness, and electrical permittivity, respectively.

The sensor has a series of memory cells/gates that are placed adjacent to the computational circuits. The information delivered by the piezoelectric transducer is stored in these gates. In fact, the gates record the duration of strain/voltage events when the amplitudes of the input signals, generated by the piezoelectric transducer exceed certain thresholds. The recorded cumulative durations are periodically read using a Radio Frequency Identification (RFID) scanner. The outputs of the sensor are presented in the form of histograms, in which each bin denotes the cumulative time of the events at a specific, predetermined strain level. One of the main advantages of this sensing system is the fact that it is “response-based”. The whole methodology is based on relative damage as the sensor does not directly measure the absolute value of strain. The rate of variation of strain distributions is related to the rate of damage. Figure 1(b) and (c) present the procedure of obtaining the histograms. Figure 1(b) displays strain/voltage strain history. Each gate number corresponds to a predefined strain/voltage level. Figure 1(c) shows the voltage generated by the piezoelectric transducer in response to a mechanical vibration. Based on the previous studies (*2*) (*3*), (*5-10*), the sensor output can be characterized by a cumulative density function (CDF) (*8*):

$$CDF_{Gaussian}(g) = \frac{\alpha}{2}\left[1 - \operatorname{erf}\left(\frac{g-\mu}{\sigma\sqrt{2}}\right)\right] \tag{2}$$

where μ, σ, α and g refer to the mean of the strain distribution, standard deviation with respect to load and frequency, total cumulative time of the applied strain measured by the entire gates, and the gate number, respectively. The CDF is then transformed into a probability density function (PDF) as follows:

$$PDF(g) = \frac{1}{\sigma\sqrt{2\,\pi}}\, e^{-\frac{(g-\mu)^2}{2\,\sigma^2}} \tag{3}$$

The PDF is defined with respect to two parameters, μ and σ. Structural damage progression can be captured using these parameters. Figure 1(d) schematically illustrates the application of this approach to detect damage progression in a bridge. As illustrated, sensors are distributed over a part of the structure. Based on the relative variations in the

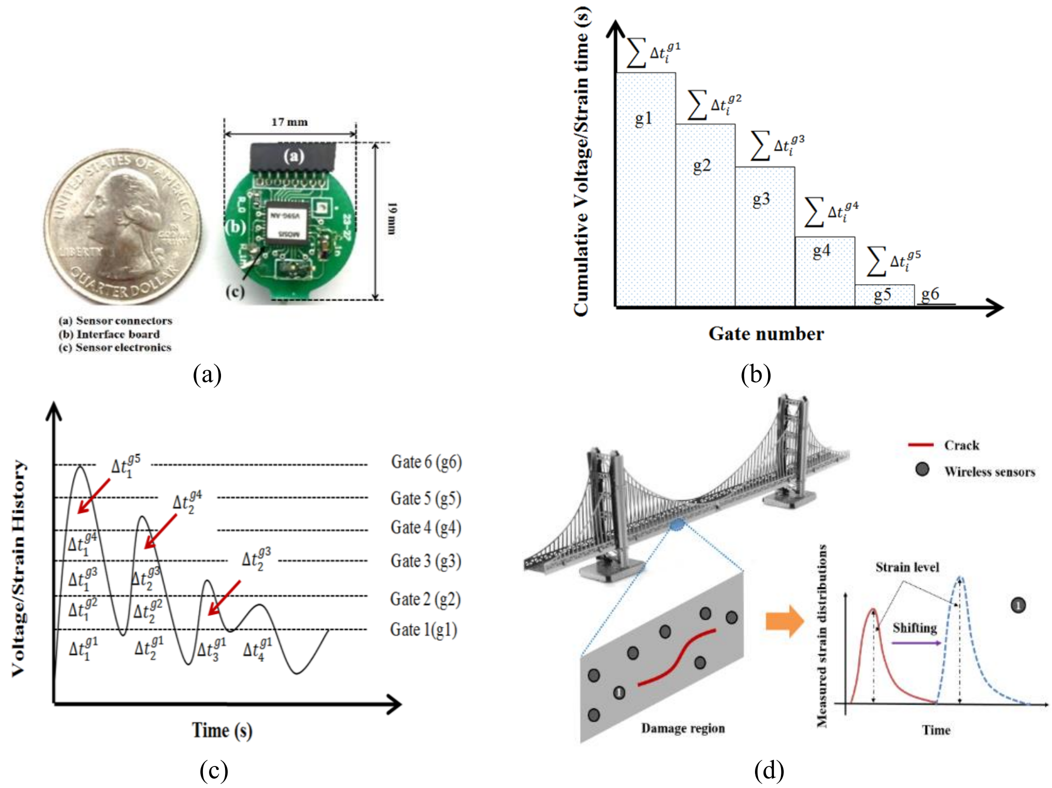


Figure 1 (a) The PFG wireless sensor, (b)-(c) cumulative time counting, and (d) detection of damage progression in a bridge (*9*).

strain response which is represented by PDFs, the condition of the structure can be assessed. The impact of damage can be detected by tracking the shifts of PDFs over time, rather than measuring the damage directly.

3. PERFORMANCE EVALUATION

In this section, we review the performance of the PFG sensing technology for various civil infrastructure systems. Subsequently, problem-specific data interpretation systems integrating deterministic, machine learning and statistical methods are explained. Two major application areas of the PFG sensing technology are discussed here.

3.1. Structural Health Monitoring

The SHM systems are basically designed to provide cost-effective, autonomous, continuous, and reliable condition assessment and damage detection in civil infrastructure systems. We have deployed the PFG sensor for the SHM of various structural systems including: crack growth detection in steel plates under a uniaxial tension mode, distortion-induced fatigue cracking in steel bridge girders, and failure of gusset plate of the I-35W highway bridge in Minneapolis, Minnesota.

3.1.1. Detection of Crack Growth in Gusset Plates

On August 1st, 2007, the I-35W Highway Bridge over the Mississippi river in Minneapolis collapsed, which resulted in 13 deaths and 145 injuries. According to the Center for Transportation Studies (CTS), 111 vehicles are driving on the bridge at the time of the collapse. An investigation by the National Transportation Safety Board (NTSB) concluded that the collapse was caused by the mechanical conditions of the U10W gusset plate shown in Figure 2(a). A major issue with monitoring of gusset plates is that they are generally located in relatively remote and narrow places. This makes it difficult to implement traditional measurement devices such as wired strain gages or ultrasonic testing

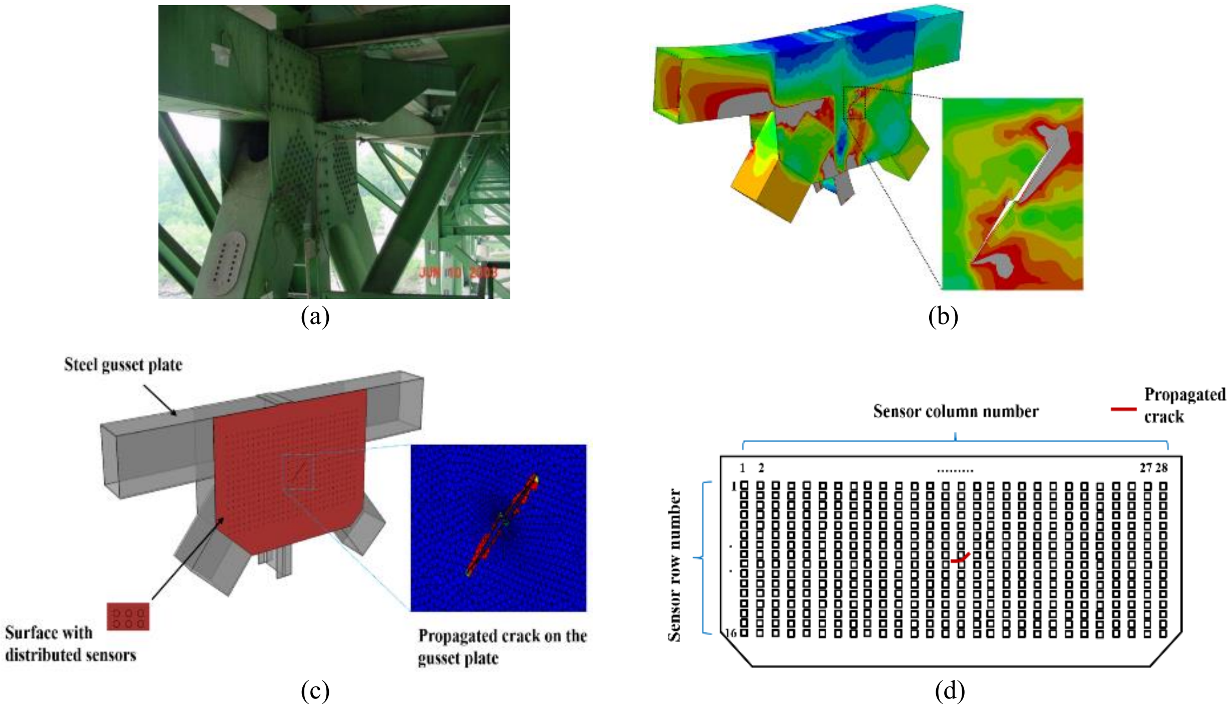


Figure 2 (a) U10W gusset plate, (b) 3D perspective of the studied gusset plate, (c) the gusset plate FE model with a propagated crack, and (d) sensing nodes and crack location on the gusset plate (*2*) (*10*) (*11*).

(UT) devices. In our recent studies (*2*) (*10*) (*11*), we have used the PFG sensing concept to detect crack growth in the U10W gusset plate of the I-35W Bridge. A real-size finite element (FE) model developed to simulate the mechanical response of the gusset plate is shown in Figure 2(b). Damage was introduced by making a crack at the middle of the plate. The propagation direction of the crack was estimated using the extended FE method (XFEM) (Figure 2(c)).

As shown in Figure 2(d), a total of 448 data acquisition nodes were placed on the gusset plate to represent the actual strain-transducers. Then, the cumulative times were calculated, and CDFs were fitted to the data. The CDFs were transformed into PDFs. Figure 3(a) displays the PDF plots corresponding to one of the sensing nodes close to the crack location. It was found that the PDFs located far from the damage zone were fairly identical. In fact, the strain amplitudes of these sensors were not affected by the damage progression as they were located outside the stress concentration area generated by the crack. Also, the shapes of PDFs were significantly changing due to damage progression by approaching the damage zone. For sensors near the crack, the PDFs shift to the left and expand as damage progresses. In other words, the mean of the distribution decreases while the standard deviation increases. However, this is not the case for all sensing nodes. Therefore, an effective sensor fusion model was developed to improve the damage progression identification through spatial measurement. The sensor fusion process integrates and extracts useful information from two or more sensors. Fused multi-sensor data can offer significant advantages in comparison with the data from a single sensor (*2*) (*10*) (*11*). A statistical analysis was performed to investigate the relationship between the PDF parameters of a group of sensors and damage progression. To this aim, different statistical indexes (average, standard deviation (STD), range, minimum, maximum, skewness, and kurtosis) were calculated for different sensor groups. Based on a preliminary analysis, STD plays a dominant role in characterizing the relationship between the PDF parameters of a group of sensors and damage progression. As seen in Figure 3(b), the STD continuously increases with damage progression from D1 to D5. Each data point on the plot represents the STD of a group of sensors for a specific damage state. Later, innovative data interpretation algorithms were developed for more accurate damage detection. This was done by integrating FE and statistical methods with two machine learning approaches called probabilistic neural network (PNN) (*2*), and hybrid genetic programming and logistic regression (GPLR) (*11*). Several features were extracted from the cumulative limited static strain data to be used as damage indicator variables. Effective indicator variables were defined that can simultaneously take into account the effect of an array of scattered sensors. This enables the methods to detect damage at any location in a structure with an organized or a sparse random distribution of the sensors. The data were further polluted with random Gaussian

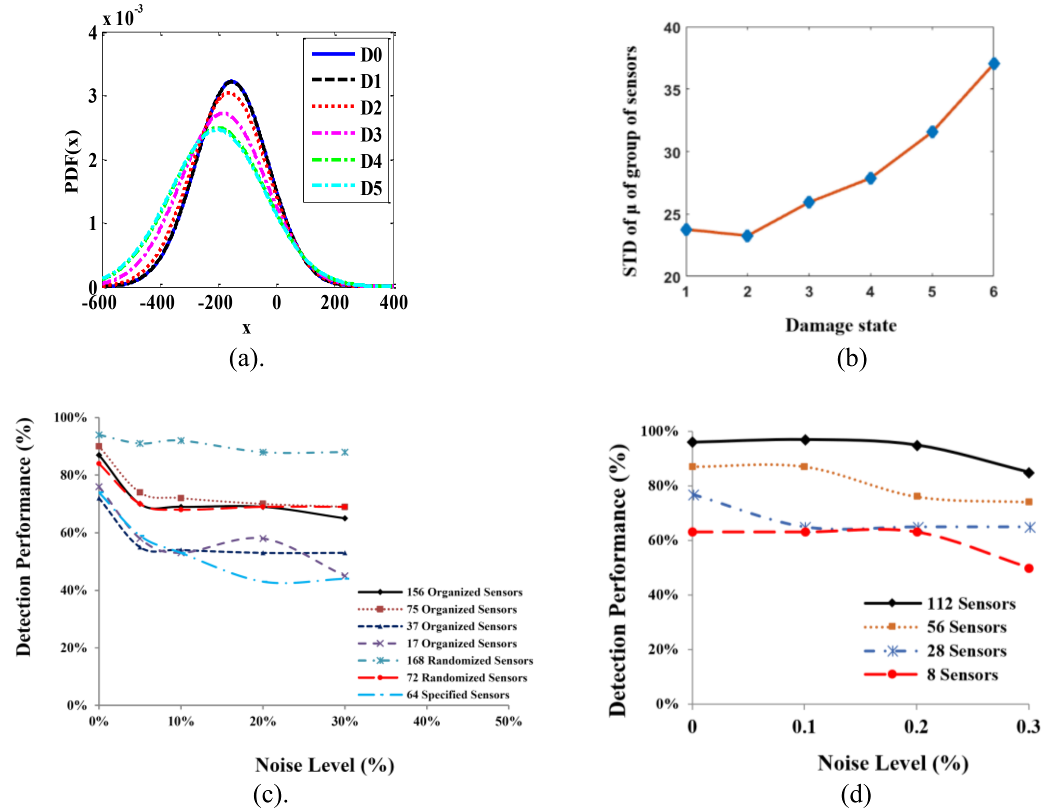


Figure 3 (a) Changes of the PDFs between damage states (*10*), (b) variation of the STD of μ of sensor groups (*10*), (c) PNN results on the testing data (*2*), and (d) GPLR results on the testing data (*11*).

noise to analyze the uncertainties in the predictions (*2*) (*11*). Figure 3(c) and (d), respectively, visualize the best classification results obtained by the PNN and GPLR methods for different number of sensors with various noise levels. It was found that increasing the noise level even up to 20% does not influence the performance of the models (*2*) (*11*).

3.1.2. Damage Growth Detection in Steel Plates

In order to evaluate the proposed method, experimental and numerical studies were performed on a thin steel plate subjected to in-plane tension (*8*) (*12*). Damage was introduced by making notches with different sizes on the plate. Piezoelectric transducers were placed on the surface of the plate to measure the delivered voltage in each damage growth phase (Figure (a)). 3D FE models were developed to extract the strains induced by the dynamic loading (Figure (b)). Thereafter, features extracted from the dynamic strain data for a number of sensing nodes were used to detect the damage progression. The tests were performed at 2 and 5 Hz loading frequencies for 0.05 and 0.08 mm amplitudes (*8*) (*12*). A part of the experimental results for 2 Hz and 0.08 mm displacement is shown in Figure (c). As seen, the shapes of all PDFs change due to damage progression. This indicates that damage growth can be monitored by the changes of PDFs even outside of the high stress concentration regions. The key point is that only PDFs for some of the sensing nodes have a sound relationship with damage progression. These are the nodes that continuously sense higher or lower strains due to the propagation of damage. In these cases, μ decreases and σ increases by transitioning from intact to damaged mode. Accordingly, the PDFs shift left and their width increases due to damage progression. Furthermore, the effect of a group of sensors was investigated. Figure (d) presents the variations of the STD of μ of sensors in one of the defined configurations. The red circles represent the sensing nodes that were included in the analysis (*8*). As seen, the STD of μ increases with damage progression for all layouts including the sensors located along the crack.

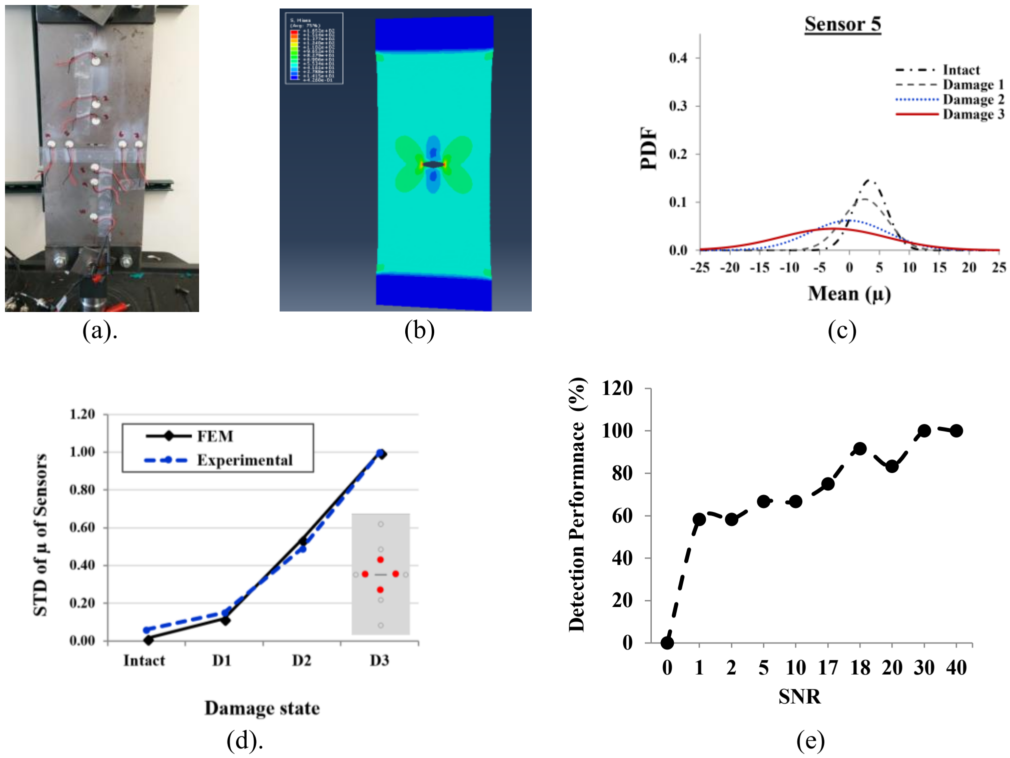


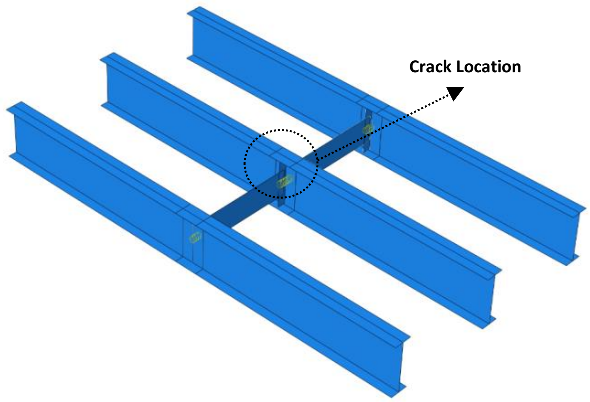
Figure 4 (a) Test setup and sensors locations, (b) the plate FE model, (c) change of PDFs curves due to damage progression, (d) the STD of μ of group of sensors, and (e) the SVM detection results (*8*) (*12*).

In order to improve the damage detection accuracy, another powerful machine learning method called support vector machine (SVM) was deployed (*12*). Several features were extracted from the cumulative voltage decrease for each memory gate, based on the sensor group concept. The obtained features were then fed into the SVM classifier to identify multiple damage states. An uncertainty analysis was carried out to evaluate the reliability of the proposed method. To this aim, the training, testing and validation sets from original sensor signal were polluted with a white Gaussian noise, with different signal-to-noise ratios (SNR) (*12*). Figure 4(e) depicts the best classification results for various noise levels on unseen testing data. Referring to this figure, the performance of the models remains satisfactory for SNR up to 23%.

3.1.3. Fatigue Cracking Detection in Steel Bridge Girders

Fatigue cracking is one of the most important phenomena affecting the structural integrity and performance of welded steel bridges. Out-of-plane distortion is known as the major source of fatigue cracks leading to severe structural deficiency. We proposed a new approach for detection of distortion-induced fatigue cracking of steel bridges based on the interpretation of the data provided by the PFG sensors (*13*) (*14*). As shown in Figure (a) and (b), 3D finite element models were developed, and the structural response of the girder was subsequently obtained. The fatigue life of the girder was determined based on J-integral concept and Paris Law. Several damage states were defined by extending the fatigue crack lengths. The initial crack length was taken 10 mm. The crack length was changed between 10 mm to 100 mm with 10 mm steps. The J-integral concept was used to estimate the energy release rate for each crack state (or length). Thereafter, features representing the PFG sensor output were extracted from the strain data for different sensing nodes to detect the damage scenarios (*13*) (*14*). Furthermore, the effect of group of sensors was used to improve the damage detection performance.

In order to evaluate the information provided by the sensing nodes, the μ and σ values for 400 sensing nodes for different damage scenarios were calculated. The PDF plots for some of these sensors are shown in Figure 6(a) and (b).



(a)

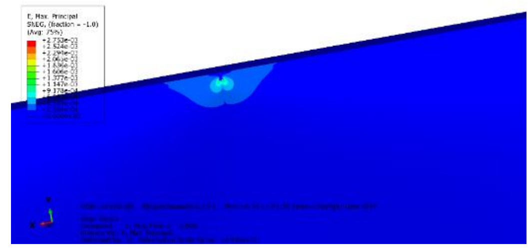
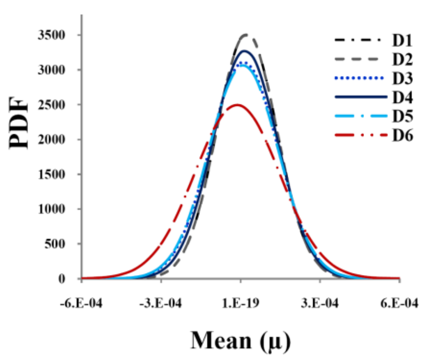

(b)

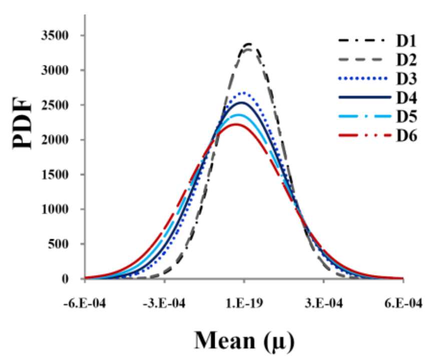
Figure 5 (a) Assembly of the girder model and crack location, (b) the FE results for a crack with length of 20 mm (*13*).

It was found that for the sensors located at the corners and far from the damage location, there was no notable sense of damage as the PDFs (*13*). By getting closer to the damage zone, the strain patterns remarkably change and therefore the shape of the PDFs transforms from D1 (0-1 million cycles) to D6 (5-6 million cycles). Extensive simulations were conducted based on over 70 combinations of the sensors to evaluate the group effect (*13*). Figure 6(d) presents the variation of the descriptive statistics of μ and σ for some of the sensors in the defined configurations. Similar to other case studies, it was observed that the STD of μ and σ of group of sensors increases with damage progression. Including the sensors adjacent to the damage zone resulted in obtaining chaotic trends. This seems to be due to the singularities around the crack. It is possible to localize the damage by checking: (1) which sensors provide chaotic response when included in the analysis and (2) in which locations the incremental rates of the STD of μ and σ of group of sensors notably decreases (*13*).

In addition, SVM damage detection models were developed for different sensor configurations by adding the number of sensors from 1 (single sensor) to 400 (the entire sensor network) (*14*). The total number of data points was 2400 (400 sensing nodes × 6 damage states). The labels to be classified were 6 damage states (D1, ..., D6) each represented the girder condition after 1 million cycles. Figure 7(a) displays the results for the unseen testing sets for different combination of the input parameters. The results indicate that the models using the new data fusion features (*Zs*) provide a satisfactory performance (*14*). Using only the individual sensing features μ and σ resulted in a very low performance.



(a)



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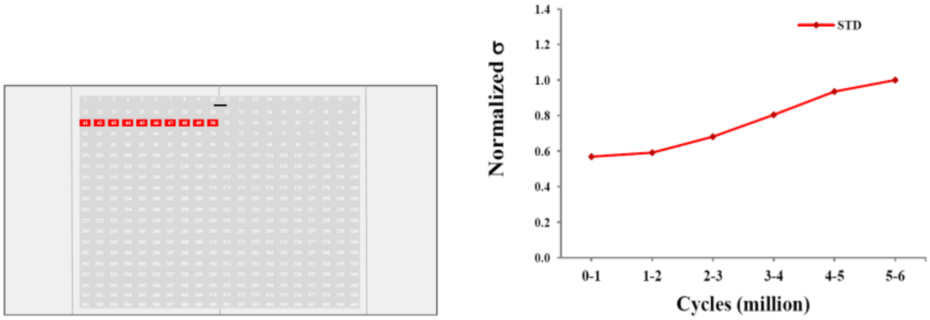
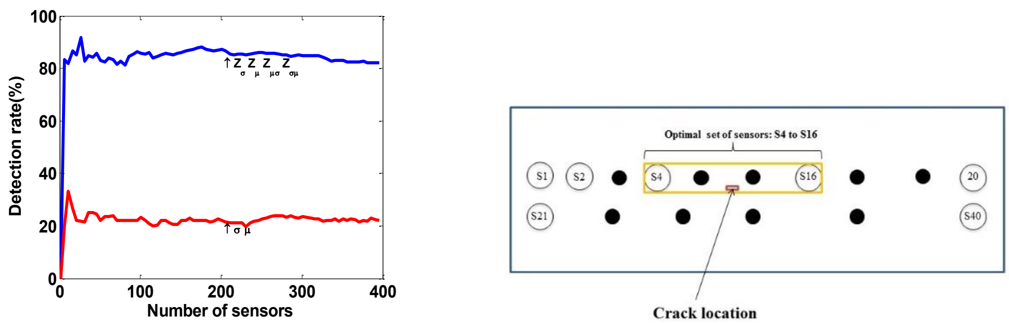


(c) (d)

Figure 6 (a) The PDF plot for sensing node 7, (b) the PDF plot for sensing node 8, (c) sensor combinations, and (d) sensor group effect (*13*).

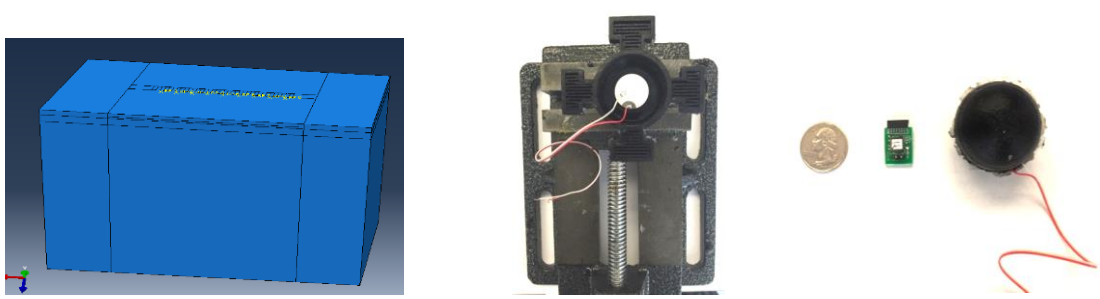


(a) (b)

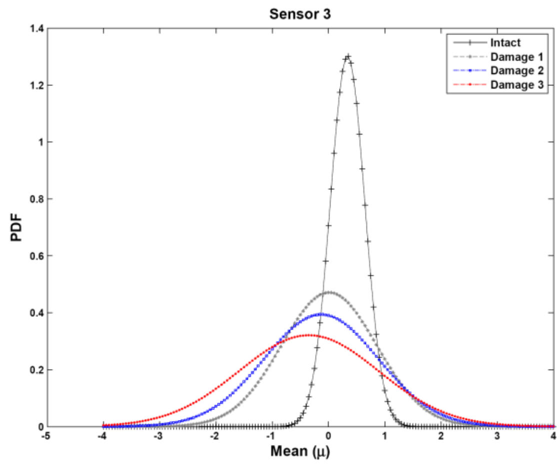
Figure 7 (a) The SVM performance on the testing data, (b) set of sensors with the highest detection rate (*14*).

3.2. Pavement Condition Assessment

Pavement health monitoring plays a key role in pavement management systems. Early repair and maintenance scheduling increase the safe operation and in-service performance of pavement. This can be achieved through an accurate and consistent monitoring of pavement condition. We have verified the performance of the PFG sensors for the continuous health monitoring of asphalt concrete pavements through numerical and experimental studies (*15*). The analyses carried out were divided into two main stages. First, a 3D FE model was developed to obtain the response of the asphalt pavement under moving load, as shown in Figure 8(a). The main goal was to detect the fatigue cracking due to excessive tensile strain at the bottom of the asphalt concrete. Then, an experimental study was carried out to evaluate the performance of the sensors embedded inside an asphalt concrete slab. Damage was introduced by making a notch at the bottom of the asphalt layer.



(a) (b)



(c)

Figure 8 (a) The pavement FE model, (b) packaging fabrication, and (c) changes of PDFs due to damage progression (*15*).

To simulate the movement of the load at the desired speed, a quasi-static analysis was adopted. The sensors were located at a distance of 50.8 mm (2 inches) from the bottom of the asphalt layer (*15*). A spherical packaging system was designed so that it can be tossed in the pavement material during construction or can be used within a mesh network distributed over the base layer (Figure 8(b)). All the electronics already have a small size and the antenna can be miniaturized to fit the desired size. The μ and σ values for each damage state were obtained and then used to plot the PDFs corresponding to each sensor (Figure 8(c)). As seen in this figure, for the experimental study, the values of μ and σ, respectively, decrease and increase due to damage progression. This was in accordance with the FE simulation results. Additionally, the crack propagation process was accurately detected by the sensors (*15*).

4. FIELD STUDY

We have recently deployed a prototype of the PFG sensors on the Mackinac Bridge in northern Michigan, with a target operational life span greater than 20 years (*16*). The prototype is a quasi-self-powered sensor that combines the benefits of self-powered sensing and with the benefits of battery-powered wireless transmission (*17*). Self-powered operation is limited in its ability to wirelessly transmit the stored data over long distances due to high energy requirements (*18*). Therefore, in this case study, self-powered sensors are continuously active and battery-powered transmitters are sporadically active. The combination of the two techniques results in ultra-low average power consumption of the entire system implying that they can be deployed on real-world structures for extended periods of time with relatively low amounts of maintenance (*19*).

We previously demonstrated a backscatter RF interface for data retrieval (*20*), yet in the case of communication in the dense steel structure of the Mackinac Bridge, for long ranges, they are not feasible. Thus, we opted to swap out the backscatter interrogation unit with an active RF link leading to a quasi-self-powered platform since the continuous sensing is self-powered, but the interrogation is not. A preliminary feasibility test using a short-term deployment on the Mackinac Bridge (*16*) was successfully completed and we miniaturized the design to make a more robust platform for an active RF interface, as shown in Figure 4(b). An assembled board with sensors and battery mounted in a weatherproof enclosure is shown in Figure 4(c). To take advantage of the quasi-self-powered architecture, an ultra-deep sleep mode that draw less than 50 nA from the battery (≈35 nA for the TPL5111 from Texas Instruments and another ≈15 nA leakage through bypass capacitors) was enabled. Upon wakeup, the MCU will idle while waiting for a command, if a read command is detected it will pull the data from the PFG sensors, else it goes back to sleep (*17*). In the case of the Mackinac Bridge, the sensors are configured for measuring upwards of two million loading cycles of mechanical strain.

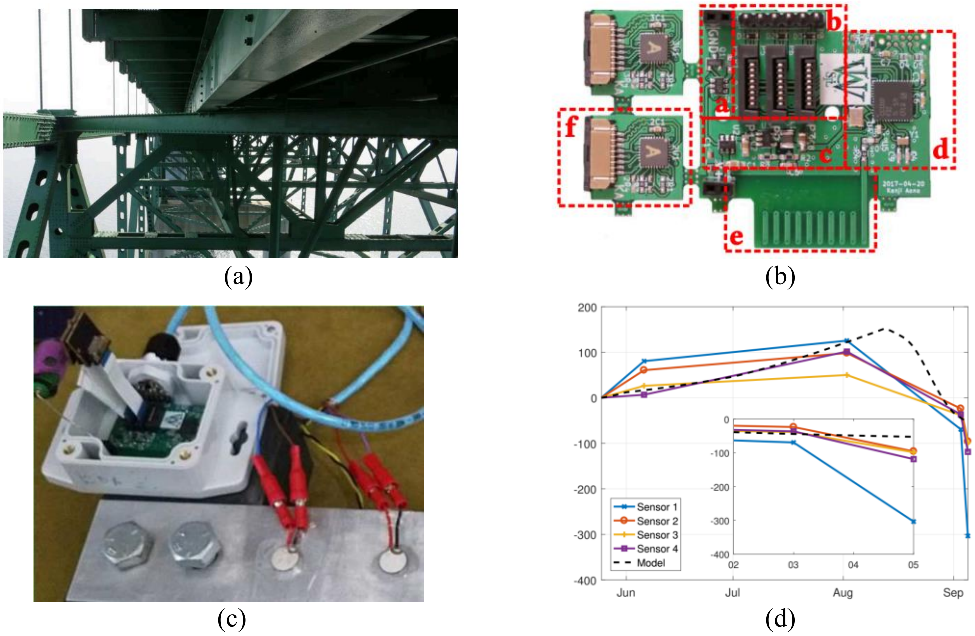


Figure 4 Mackinac Bridge used for the field study, (b) PCB for timer, piezo input, battery management, micro-controller, antenna, and PFG module, and (c) the assembled sensing unit (*20*), (d) data from four sensors installed on the Mackinac Bridge (*16*).

The data collected by four sensors between May 25th and September 5th of 2017 are presented in Figure 4(d) (*16*). The dashed black line shows expected results from model. The inset of Figure 4(d) shows the data collected before and after the Mackinac Bridge Labor Day Walk (on Sep. 4th), which drew a crowd of over 25,000 people, much greater than usual traffic on the bridge. It shows that during the event the sensors logged a much larger amount of data than it had in the days before. The deviation from the model trace, which is based on monthly traffic statistics, highlights the extra strain that the Labor Day Walk placed on the sensors (*16*).

5. CONCLUSIONS

In this paper, we presented an overview of our interdisciplinary research in the area of smart, wireless, and battery-free sensors for civil infrastructure health monitoring and designing advanced data interpretation frameworks. Different applications of the self-powered PFG sensing technology were discussed. The performance of the PFG sensors has been evaluated on different civil infrastructure systems including detection of cracks in steel plates, distortion-induced fatigue cracking in steel bridge girders, failure of gusset plates, and pavement condition assessment. Extensive numerical and experimental studies have been conducted to assess the capabilities of this sensing technology. Robust machine learning techniques such as PNN, GPLR and SVM have been deployed to improve the damage detection accuracy. Furthermore, an effective sensor fusion model was developed to improve the damage progression identification through spatial measurement. The results indicate that the proposed sensing paradigm and associated data interpretation methods are efficient in detecting different damage states in civil infrastructure systems. Moreover, we presented a design case study where the PFG sensors were prototyped for field deployment on the Mackinac Bridge in northern Michigan. The prototype was designed to continuously operate over a duration of 20 years and with a transmission range greater than 100 m. More research is needed to verify the efficiency of the proposed SHM techniques for real structures. In addition, the effect on the environmental conditions and season variability on the sensor and on the piezoelectric transducer should be investigated in depth.

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