Sensing and Decision-Making in Cyber-Physical Systems: The Case of Structural Event Monitoring

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***Abstract*—Wireless sensor networks (WSNs) are being suggested at an increasing rate for structural health monitoring (SHM). The objective is to monitor complex events (e.g., damage) in structures (e.g., an industrial machine, a high-rise building) that is usually carried out with wired-based SHM systems. However, monitoring events with a WSN deployed over large structures is challenging due to WSN constraints (high-resolution data transmission, energy) and the quality of monitoring. In this paper, we attempt to design a cyber-physical system (CPS) of structural event monitoring with WSNs, and propose a novel model-based in-network decision making in the CPS, named MODEM. We think of the idea of generic event detection (like target/object) schemes and enable each sensor to sense and make a simplified local decision (0/1) on the complex events. We then think of the formation of engineering structures, and find that a large physical structure consists of a number of substructures. We enable deployed sensors to be organized into groups in such a way that a group-wise final decision (e.g., 0/1) can be provided for each substructure independently so that the existence of an event (if there is any) in a specific substructure can be identified by WSNs. MODEM is fully distributed in nature, and promises to have the monitoring quality be similar to the original wired-based schemes, and consumes much less energy for transmissions and computations than existing schemes do. The effectiveness of MODEM is shown via both simulations and real experiments.**

***Index Terms*—Wireless sensor networks; in-network processing; decision making; sensor fusion; structural health monitoring.**

I. Introduction

Structural health monitoring (SHM) has received increased attention from diverse domains, including civil, structural, mechanical, and aeronautical (CSMA) engineering, industrial communities, and computer science [1]–[7]. The objective of SHM is to monitor complex events (e.g., damage, crack, corrosion) in a physical structural system (e.g., an industrial machine, a nuclear power plant, a high-rise building, a bridge) by analyzing the dynamics in elements/components of them.

Wired network systems have been dominating SHM tasks since late 1980s, as they are assumed to be reliable. Substantial work has been done by the engineering domains that are generally centralized/global-based [8], [9]. However, manipulating a large structure with wire is cumbersome. Also, we find that these schemes do not seriously handle data collection quality, synchronization errors, etc. In turn, both CSMA and computer science (CS) communities have started research toward developing wireless sensor networks (WSNs) as alternatives to wired systems since 2000s. In 2010s, using WSNs for SHM has received attention at an increasing rate. Reasons include advantages such as low-cost, flexibility, and autonomous decision-making capabilities.

Both CSMA and CS communities have handled numerous challenges/requirements in substantial existing work [2], [4], [5], [10], [11], including sensor deployment, data acquisition, compression, aggregation, and complex-damage detection. However, there is still a lack of quality of monitoring in the work. For example, two data collection methods are given for WSNs, namely, short-range (hop-by-hop routing) and long-range (single-hop) transmission. When given a large scale structure for monitoring, e.g., the Guangzhou New TV Tower (GNTVT) [12], [13] that peaks at 600m above ground or a bridge/tunnel that is longer than several kilometers, even given only a substructure (e.g., a part of the structures), manipulating such systems is cumbersome.

More particularly, based on our experiences with our civil engineering collaborators, we find that these WSN schemes instrument centralized SHM algorithms to obtain the structural raw response data (i.e., vibration, strain) at a high frequency (e.g., 560 Hz or more) for a ‘long enough’ period of time. We also find that some popular existing SHM algorithms, e.g., the ERA, NExT, FFT (see Table I for abbreviations) are made distributed through the idea of ‘divide and conquer,’ multi-level damage localization, and so on [1], [3], [14]–[18]. These algorithms normally work in a round-by-round manner. Each sensor shares the response data with multiple sensors, and then transmits to the BS. The data from each sensor involved is no longer a single value, but a sequence of data having, generally, over thousands of data points at each of the rounds [10]. Although those SHM algorithms solve practical engineering problems, applying them directly within a WSN is quite difficult.

Regarding the situation above, the whole data cannot be either stored or transferred, but must be mined/processed immediately. Some closely related work include different types of in-network processing techniques in WSNs such as data compression, hop-by-hop aggregation [1], [3], [10], [10], [18]. However, they still require complicated signal processing techniques such as matrix computation and system

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identification. Moreover, the ability/quality of event detection (AoED) with them in WSNs is not addressed. We discover that our civil collaborators prefer to use WSN nodes simply as 'data collectors', despite their potential for an autonomous event detection (e.g., 0/1 simplified decision for the complex event, similar to the target/object detection). An autonomous decision-making scheme with the high energy-efficiency and AOED can be promising.

In this paper, we attempt to design a cyber-physical system (CPS) of structural event monitoring with WSNs, and propose a novel model-based in-network decision making in the CPS, named MODEM. As hinted by the recent work [2], [15], we consider that MODEM is a typical example of a CPS, where the performance analysis is carried out under the integration between the CS's cyber system (computation, communication, control in WSNs) and dynamics of physical systems; otherwise, the CPS may provide a suboptimal solution.

In our solution, we use the idea of generic event detection (like target/object) schemes and enable each sensor to sense and work as a local decision maker (LDM) that makes a simplified local decision (0/1) on the complex events. We then think of the formation of engineering structures, and find that a large physical structure consists of a number of substructures. We enable deployed sensors to be organized into groups in such a way that each group of LDMs can cover a substructure independently. A group-wise final decision (e.g., 0/1) is made at a decentralized decision maker (DDM) sensor by simply fusing all decisions from the group of LDMs so that the existence of an event ('1' if there is any) in a specific substructure can be identified by WSNs.

The crucial aspect is that the final decision '0' (zero) made by a DDM is only transmitted to the BS if there is 'no event'. As a result, the total energy and bandwidth cost required for wireless data transmission is drastically reduced. MODEM is fully distributed in nature, and promises to have the monitoring quality similar to the original wired-based schemes. It makes sensing and 0/1 decisions with a equation-based CPS model that has the integration of computation in the WSN and dynamics in the physical process.

In summary, the contributions of this paper are four-fold.

- We formally define the problem of MODEM, which to our knowledge is the first that provides simplified decisions in such a CPS. This task is by no means easy, as it involves knowledge from CSMA engineering domains, process monitoring, and methods from computer science.
- We show a model-based decision-making in the CPS and embed a decision-making algorithm into the on-board computational core of each sensor (such as Imote2).
- To achieve a decision on an event at a substructure in a fully-distributed manner, we propose a low overhead sensor grouping and a group-wise decision fusion technique.
- We conduct an extensive evaluation of MODEM in simulations using real data traces collected by a wired SHM system [12]. We implement a proof-of-concept system using Imote2 sensors running TinyOS, and deploy it on a lab-based structure to validate the decision-making under the event of physical damage. MODEM has the AoED similar to the original wired-based schemes, and achieves low energy cost (at least eight times lower than existing WSN-based schemes under 'no event', and three times lower than under the 'event').

Table I
ABBREVIATION DESCRIPTION

Abbreviation	Full Name
ARX	Auto-regressive model with exogenous inputs [21]
NExT	Natural Excitation Technique [16], [18]
ERA	Eigen Realization Algorithm [1], [16]–[18]
FFT	Fast Fourier Transformation [15], [16]
T	A whole period of SHM operation (i.e., a system run)
$T_d, d \in [1, \rho]$	dth period of monitoring in T
τ	A discrete period (i.e., a round) of monitoring in T_d

The rest of this paper is organized as follows. Section II reviews related work. The MODEM overview and design are in Sections III and IV, respectively. Sections V and VI present the decision making in CPS and decision-making algorithm. Section VII provides substructure-oriented group-wise decision making. Performance evaluations are conducted in Section VIII. Section IX concludes this paper.

II. RELATED WORK

Monitoring or diagnosing the health of industrial machines/equipments and civil structures using WSNs have recently become an active area of research [1], [3], [6], [14], [19], [20]. In the SHM system implemented on the GNTVT [12], the WSN is partially adopted [13]. Existing work mainly focuses on data acquisition and compression methods, reliable data transport protocols, damage detection, and so on [3].

There are various clustering algorithms proposed for WSN-based SHM [2], [3], [17], [18]. Among them, the most interesting one uses distributed processing and cluster-based structural modal analysis. An SHM scheme, SPEM, is verified in an optimal sensor placement algorithm [13]. Indeed, numerous SHM systems have been proposed by the engineering domains, which leverage WSNs to collect raw data. They are generally designed to support centralized/global decision-making in SHM without special consideration to the WSN resource and ability of monitoring.

Challenges like the quality/ability of monitoring (AoED) and long-term monitoring still need to be resolved for WSNs to be widely adopted. For example, a state-of-the-art WSN deployed at the Golden Gate Bridge (GGB) [22] required 9 hours to collect a single round of data that affects the AoED. This large latency may arise from the fact that underlying physical system aspects were designed separately from cyber WSN aspects. Later, DLAC [15] presents a CPS design of SHM with a WSN and a design of a damage localization that effectively reduces the amount of data transmission.

MODEM takes inspiration from the above prominent schemes, and addresses some important issues or gaps.

i) *Data transmission considering the 'event'/'no event' situation.* Typically, the common situation in SHM is that a structural event is a relatively rare event. We thus argue that it is not necessary to always broadcast a huge amount of data over the WSN; after all, the sensors may only need to transmit local decisions to their neighbors or the upstream sensors.

ii) *Complexity of data sensing/decision making*. The popular methods used in wired-based SHM, such as NExT, ERA, FFT,

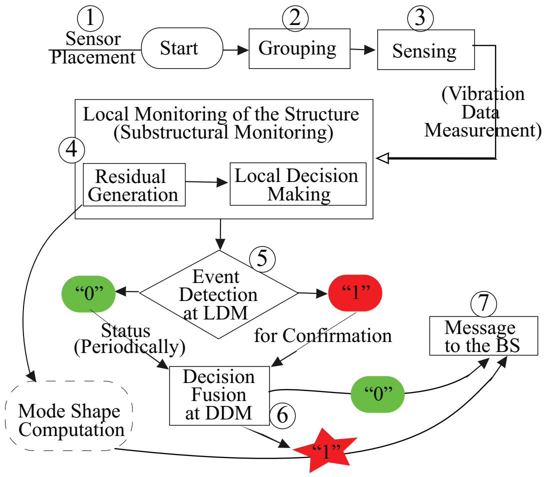


Figure 1. The work flow of MODEM for structural health monitoring.

and genetic algorithms take the heaviest computation to extract structural properties, and take much time to make a decision and forward it to the BS [1], [3], [15]–[18]. By applying them directly in WSNs, the network may suffer from the need for significant energy for communication (with a high message exchange rate) and for decision making.

iii) *Local and long-term SHM*. SHM is still assumed to be a global scheme. What we can do to find a local SHM is to consider the exact formation of civil structures (i.e., substructural orientation). When damage occurs at a particular location, the corresponding substructure is given higher priority by allocating more time to the sensors.

MODEM handles issues above by an in-network decision making and distributed monitoring in order to reach an optimal CPS solution of WSN-based SHM.

III. Overview of Event Monitoring in MODEM

Fig. 1 illustrates a snapshot of the processes involved in the MODEM. After deployment of a WSN (Step 1), the sensors are organized into groups and become ready for the event monitoring operation. Sensors are allowed to sense and get vibration data (Step 3). Amongst all the labeled steps in Fig. 1, the most important contribution of this work is Step 4, in that each LDM uses an embedded algorithm of model-based decision-making. After processing data about structural characteristics, an LDM decides if there is an event by comparing the residuals achieved by a given structural model and a predicted model. Once the WSN starts for T, Steps 4 to 6 repeat in each T_d until T finishes. The in-network decision on the event (1/0) is fused at DDMs in each T_d for a confirmation. If there is a '1' decision (Step 7), meaning that an event happened at a substructure, the DDM located on the particular substructure forwards the decision to the BS. It can then issue a message to all its LDMs for transmitting all of the mode shapes at the request of the BS. Otherwise, DDMs may transmit group information (e.g., connectivity, faults).

IV. MODEM Design: Decision-Making in a CPS

In this section, we design the MODEM. It includes a CPS model and system models. Finally, we figure out the problem.

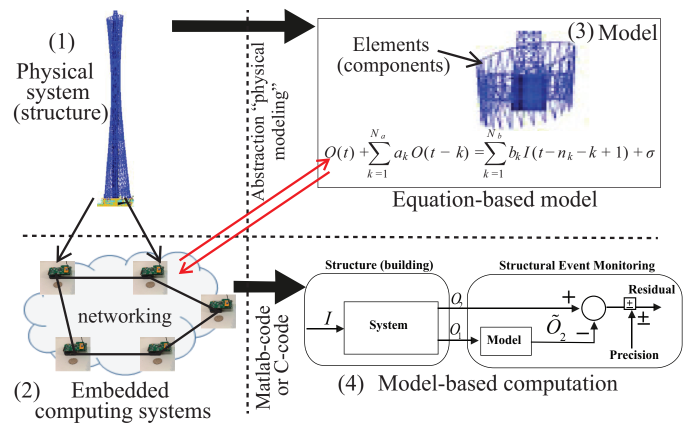


Figure 2. Modeling a cyber-physical system.

A. CPS Model

A major feature of a CPS is the tight combination and coordination of the computational resources and the physical elements. Our CPS model is presented in Fig. 2. There are four parts in the model. (1) The underlying physical structural system consists of the 'physical elements', which are governed by laws in physics as specified by nature, forced excitation, or damage occurrence. (2) There are many computing platforms (sensors), which are capable of sensing, as well as controlling its sensing, transmission, and monitoring tasks. (3) There is the equation given to the sensors that is used to collect structural element state information. The sensors are connected by a communication network (via wireless links). The sensors and the network form the 'cyber' part of CPS, which has to be designed carefully, such that the integrated system achieves certain functionalities. (4) The sensors are given a computation model to make a decision on the structural event.

B. Communication Network Model[1]

Consider a physical structure, such as GNTVT [12], [13] for monitoring, and the WSN topology, as depicted in Fig. 3. The structure consists of a number of substructures as shown in Fig. 3c, represented by Ω_q, where q is the maximum number of substructures. Given a set P of S homogeneous sensors with limited energy, we need to form such a WSN denoted by $W = (V, E)$ over the structure. S sensors are attached to the structure by some location assignment $L = l_1, l_2, \ldots, l_S$, where sensor s_u is placed at location l_u. We adopt an SHM-specific sensor placement model to form the WSN [19], by which we can have sensor nodes like the LDM and DDM deployed. (more detail can be found in Appendix B).

With the placement model, we consider a link quality model regarding dynamic structural environments and interference. According to this model, the strength of a radio signal decays with some power of distance. We let R_{min} and R_{max} denote the communication range for connected region and transitional region, respectively. We take R_{min} as the range that a sensor can easily communicate with 100% packet transmission rate (PRR). We calculate R_{max} based on a statistical link quality on a initial sensor deployment. If a sensor experiences that its R_{max} is more than a threshold value,

[1]Extended details of some parts (models, results, etc.) of the paper can be found in appendices of an online supplemental file.

After the deployment of all sensors, they are organized into (possibly overlapping) $g_i (i = 1, 2, \ldots, K)$ groups. Each group contains a subset of s_m sensors around a substructure for monitoring. g_i is variable, which relies on the WSN density and diameter of a substructure. We assume that the number of groups is great or equivalent to the number of substructures, say, $q \geq K$. In the WSN, each sensor senses periodically to get response measurements (i.e., excitation caused by harmful vibration, heavy wind, load, etc.). Each sensor in a group works as an LDM. After the first election, one of the LDMs in the group is elected as a DDM before T_d finishes. An LDM can adjust its R_{min} according to the connected region based on diameter d, as shown in Fig. 3d. At R_{max}, a DDM can connect to its neighbor DDMs or the BS.

C. Embedded Decision Making

Supposed that each LDM is given a embedded decision-making algorithm, including a computation model. After measurement, each LDM can process and make a decision on an event detected locally and independently (without exchanging messages with its neighbors).

Generally, data fusion is an effective signal processing technique, which is often used for generic WSN applications [23], and can also be used to improve the performance of SHM applications. However, our aim is mainly to focus on embedded decision-making rather than decision fusion. Each LDM makes the following decision (D_j) independently:

$$D_j = \begin{cases} 0 & \text{if there is no event of damage} \\ 1 & \text{if there is an event of damage} \end{cases} \quad (1)$$

The objective of localized detection is to minimize the following energy cost e_{dm} by the system, due to decision-making:

$$e_{dm} = e_{elec}[D_j], \; where \; D_j \in \{0, 1\}, \quad (2)$$

where e_{elec} is the energy required for the computation in order to decide on D_j, which includes a computation model and related equation for capturing structural health proprieties. This is embedded to the sensor. Having D_j reliably at a sensor is subject to a false positive decision. Because the noise from the sensor device is different from the real vibration threshold for a structural event with a high noise level from the measurement, a CPS system is likely to give a false decision when there is no real structural event. In our case, we define the false alarm rate when *there is actually no structural event, but the system detect event.*

D. Energy Cost Model

One of the major objectives is to minimize the energy cost of the WSN. We consider an existing energy model, suggested for clustering in a WSN-based SHM systems [17]. Regarding the model [17], we briefly describe here how energy consumed in transmitting/receiving a packet is computed in our case. Let $cost(s_u)$ be the total energy cost of a sensor in ith group g_i and $cost(g_i)$ be the energy cost of the group of sensors, which is given as follows:

$$cost(g_i) = \sum_{u=1}^{n} cost(s_u) \quad (3)$$

where $cost(s_u) = Er_s(s_u) + Er_c(s_u) + e_{dm}$.

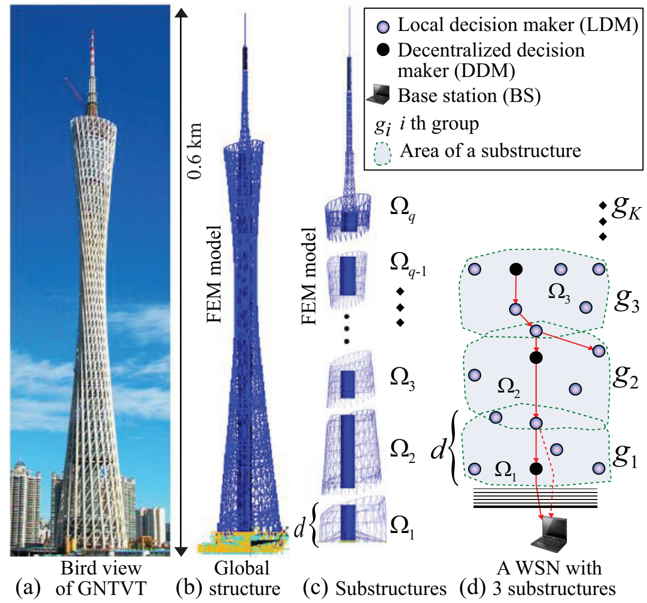


Figure 3. A WSN-based structural health monitoring framework: (a) GNTVT structure; (b) finite element model (FEM) [13] of GNTVT; (c) breaking the GNTVT structure into substructures; (d) sensor grouping.

We describe the terms as follows. i) $Er_s(s_u)$ is the energy required by sensing for N data points; in taking vibration signal measurements, assuming that there is a maximum 40% overlap, $N = (n_a/2+1/2) \cdot c_r$, where n_a and c_r are the number of averages, mainly for denoising purposes. These basically vary from 10 to 20, and are cross-correlational factors [17]. n_a, c_r, and N are set by fixed values on a sensor. ii) $Er_c(s_u)$ is the energy cost per bit for transmission over a link between a transmitter and a receiver, which includes the energy cost for sending and receiving data, and grouping and inter-grouping communication tasks. iii) e_{dm} is given by (2).

E. The Problem in MODEM

Given a set P of S LDMs with limited energy and a BS placed at locations over a physical structure, we find a decision-making algorithm and a substructure-oriented group-wise decision such that ith group g_i of LDMs makes decisions on an event, and a suitable DDM fuses all decisions and makes a confirmed decision in g_i and report to the BS. The objectives are to minimize the total energy cost $cost_T = \sum_{i=1}^{K} cost(g_i)$ and ensure the ability/quality of event detection (AoED).

V. Model-Based Development for Decision-Making in CPS

A. Event Detection Model from CSMA Engineering Domains

Looking into traditional damage detection models, there are many models available, such as NExt, ERA, SVD, and FFT-based. We adopt the most widely-accepted equation-based model, ARX[2] [21], as shown in Fig. 2. The estimation of the ARX model is the most efficient of the polynomial estimation methods, which is defined as follows:

$$O(t) + \sum_{k=1}^{N_a} a_k O(t-k) = \sum_{k=1}^{N_b} b_k I(t - n_k - k + 1) + \sigma. \quad (4)$$

In (4), $O(t)$ and $I(t)$ are the time-series output and the input response data measurements of physical system at sample

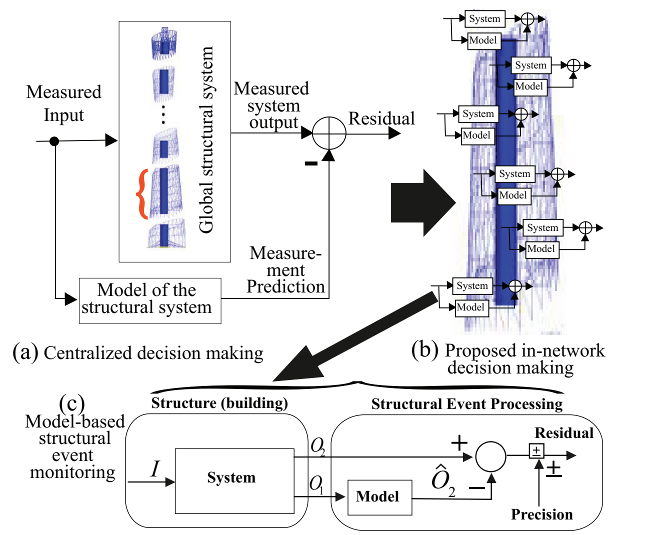


Figure 4. The general concept of model-based technique, and its residual generation for event detection in the CPS: (a) traditional decision making; (b)+(c) in-network decision making (given the substructure marked by '{').

index t, respectively; assume that $I(t)$ is an unknown input (caused by an external ambient or forced excitation). a_k and b_k are the coefficients on previous measurements. N_a and N_b are the orders of the ARX model. n_k is the number of input samples and σ is the residual.

Modified ARX model for WSNs. Like many other models from CSMA engineering, the ARX equation model cannot be applied directly to a WSN. In a wired system, the final results through the ARX equation are computed globally (see Figs. 4a and 2) at the BS, which have no energy limitations. Even the BS needs significant time to finish a round of computations. The BS also delays for all raw measured data from sensors and needs further offline computation.

Model-based system fault detection in the process-monitoring domain has also been used as a broad and dynamic field for over thirty years [24]. We found that when using a model for a higher level of abstraction, the problems of fault detection and structural damage detection using ARX require similar solutions [17]. We modify the ARX equation model with the model in process-monitoring and propose MODEM, which has the following advantages:

i) The combined model is linear, and there is no need to deal with solving nonlinear equations or to wait for a whole given period of measurement.

ii) The model uses polynomials of reasonable order, and there is no need to deal with big size matrices like NExt, ERA. All computations can be done in the time domain.

iii) D_j is taken instead of the mode shape (i.e., a number of vibration patterns at specific frequencies in a structure [13], [16]). However, we ensure that the mode shape can also be computed in MODEM by adjusting the residual, if one wishes.

iv) The confirmation of decisions provide substructural event statuses, which have no need for centralized interaction.

B. Single-Input Multi-Outputs in MODEM

We assume that, manually, an SHM system end user has no access to input data about a physical structural system to create a model for it. The WSN acquires measurements as the structural system's input. To solve this problem, we combine two techniques as follows: *First*, when a sensor acquires measurements of the structural system, we narrow the set of possible inputs. The common input used to perform event detection is a step forward, as it is easily repeatable and creatable. This means that we have two sets of measurements: one used as *input* and the other as *output*, so that the knowledge of the *actual input* of the whole system is not always needed. *Second*, instead of considering the actual inputs for a T_d like the ARX model, we consider part of the measured *outputs* as *inputs*. This approach is derived from the representation of single-input multi-outputs (SIMO) systems using transfer function matrices (M) and a diagonal matrix (H).

Considering each LDM in a group (g_i), the substructural monitoring is shown in Fig. 4b, while Fig. 4a shows the traditional global SHM system where the network monitors the structure as a whole. Fig. 4c illustrates the broader view of the model-based technique at each LDM, in which the actual system output is the result of a predicted system plus damage effects and uncertainty [24].

C. Analytical Damage Event Detection Process

In this subsection, we show analytically the damage event detection process, using the use of two outputs system. Let I be the single input of the system (by following (4)), and let O_1 and O_2 be the multiple outputs, such that $O = [O_1 \quad O_2]$. The transfer function is given as $M = [M_1 \quad M_2]$. Now, a relation between the output and transfer functions is as: $O = M \cdot I$, where $O, M \in \Re^{2\times 1}$.

An equivalent input-output model is given with matrices M and H, consisting of elements that are polynomials in the shift operator; H is a diagonal matrix. In the case, where M_1^{-1} exists, the output obtained by the sensor measurement can be given as follows: $O_2 = M_2 \cdot M_1^{-1} \cdot O_1$, i.e.,$O_2 = H_{21} \cdot O_1$with $H_{21} = M_2 \cdot M_1^{-1}$. But, it can be generalized to n outputs' system by simply splitting n outputs into two sets: $E_1 = [O_1 \quad O_2 \quad \dots \quad O_z]$ and $E_2 = [O_{z+1} \quad O_{z+2} \quad \dots \quad O_n]$.

When we use a model of the undamaged structural system denoted by $\hat{M}$, there are some modeling errors based on the sensor measurements in practice, which are given as $\hat{M} \approx M$, i.e., $M = \hat{M} + \Delta M$, where $\Delta M = [\Delta M_1 \quad \Delta M_2]$. Then, under the undamaged system condition, the following relation is satisfied: $\hat{O} = \hat{M} \cdot I \approx O$. We can define an estimation of the output O_2 using the model and its relation with O_1:

$$\hat{O}_2 = \hat{M}_2 \cdot \hat{M}_1^{-1} \cdot O_1. \tag{5}$$

According to this relation, if there is a damage event D in the structural system, its behavior will change. The event in the structure *is equivalent to a change in the system's parameter, i.e, in* M. For a damage event case, the system behavior could be as follows: $O = (M + D) \cdot I$; where a damage event $D = [D_1 \quad D_2]$. If $D = 0$, there is no damage event in the structural system. As a consequence, in a case, where $(M_1 + D_1)^{-1}$ exists, $O_2 = (M_2 + D_2) \cdot (M_1 + D_1)^{-1} \cdot O_1$. Now we calculate the residual, which gives the change in the behavior of the system. The residual denoted by r is as follows:

$$r = (O_2 - \hat{O}_2) \tag{6}$$

If there is a damage event D at the early stage, $M_1^{-1} \cdot D_1 \ll 1$ is true. Then, the residual becomes as follows:

[2]http://en.wikipedia.org/wiki/Autoregressive_moving_average_model

$$
\begin{aligned}
r &\approx \Big((M_2 + D_2)\cdot M_1^{-1}\cdot\big(1 - M_1^{-1}\cdot D_1\big) - \hat{M}_2\cdot\hat{M}_1^{-1}\Big)\cdot O_1 \\
&\approx \underbrace{\Big(M_2\cdot M_1^{-1} - \hat{M}_2\cdot\hat{M}_1^{-1}\Big)}_{\substack{\to 0 \\ \text{(Corresponding to modeling errors)}}} .O_1 + \\
&\underbrace{\Big(D_2\cdot M_1^{-1}\cdot\big(1 - M_1^{-1}\cdot D_1\big) - M_2\cdot M_1^{-2}\cdot D_1\Big)}_{\text{(Corresponding to damage sensitivity)}} \cdot O_1
\end{aligned} \tag{7}
$$

The residual in (7) is partly subject to modeling errors (left part), which is caused by low sensor location quality and dynamic structural response. If there is a damage event in the structure, the change can be appeared in the right part. We assume that $M_1 \approx \hat{M}_1$ and $M_2 \approx \hat{M}_2$, that is $\Delta M_1 \to 0$ and $\Delta M_2 \to 0$, which is practical, as it is possible to adapt the model to make it fit the real data measurement.

VI. Embedded Decision Making Algorithm

A. *Algorithm Embedded to Each Sensor*

In light of the above analytical detection process, and considering WSN architecture requirements, the model-based technique is designed to utilize the on-board capabilities of a sensor, e.g., the Imote2. Here, we describe the decision making procedures at each LDM. As shown in Fig. 4c, the monitoring of the structure can be broken down into two steps. *First*, as the residual, r is generated, which estimates how far the actual behavior is from the expected one. *Second*, D_j must be taken regarding the structural health status via r.

The analytical model connects the first set of measurements O_1 to the second set O_2 at sample index t so that the frequency domain is given as follows:

$$
\hat{O}_2(t) = \hat{H}_{21}(t)\cdot O_1(t) = \frac{\sum_{k=0}^{N_a} a_k\cdot t^{-k}}{1+\sum_{k=1}^{N_b} b_k\cdot t^{-k}}\cdot O_1(t) \tag{8}
$$

Taking into consideration the resource constraints in a wireless sensor, computations of the model will be done in the time domain. Thus, difference equations will be used to model the structure's behavior as follows:

$$
\hat{O}_2(n) = \sum_{k=0}^{N_a} a_k\cdot O_1(n-k) - \sum_{k=1}^{N_b} b_k\cdot \hat{O}_2(n-k), \forall n > N_b \tag{9}
$$

With the initialization $\hat{O}_2(n) = O_2(n), \forall n > N_b$.

This model leads to the following residual signal denoted by $r(n)$, which has been analytically defined by (4):

$$
\begin{aligned}
r(n) &= O_2(n) - \hat{O}_2(n) \\
&= O_2(n) - \left(\sum_{k=0}^{N_a} a_k\cdot O_1(n-k)\right) - \left(\sum_{k=1}^{N_b} b_k\cdot \hat{O}_2(n-k)\right) \\
&= 0, \forall n < \max(N_a, N_b),\ \text{where n} \leq \text{N}
\end{aligned} \tag{10}
$$

In the case of continuous monitoring, the achieved residual signal denoted by $r(n)$ is compared to a threshold (fixed or dynamic) to detect a change in the system behavior. When an LDM monitors the system at its vicinity intermittently with a noisy measurement, another detection algorithm should be used as the sensor noise, which can be modeled as a Gaussian noise. Then, the effect of the noise in $r(n)$ is reduced, and it receives the same information by taking the expectation of $r(n)$ generation, $r'(n) = E(r(n))$. We consider that the ensemble average of the residual signal for N samples can be estimated by its time average:

$$
R \approx \frac{1}{N}\cdot \sum_{n=\max(N_a,N_b)}^{N} \left(O_2(n) - \left(\begin{array}{c} \sum_{k=0}^{N_a} a_k\cdot O_1(n-k) \\ -\sum_{k=1}^{N_a} b_k\cdot O_2(n-k) \end{array} \right) \right) \tag{11}
$$

where R is the residual number analogous to r.

To provide a perfect structural model embedded in a sensor with low or no measurement noise, *damage in the system would be detected if R is non-zero*. However, in a real deployment, some modeling errors and other perturbations may occur, which may yield a non-zero R for the undamaged system. Therefore, R is compared to a threshold (h).

$$
h = f(amplitude(O_1)) = f\left(\left(\sum_{n=1}^{N}|O_1(n)\right)/N\right) \tag{12}
$$

The analytical expression of h depends on the modeling errors allowed by system operator through the BS. A simple expression would be a linear threshold and the function $f()$ becomes a scaling coefficient that is given as follows:

$$
h = \alpha\cdot\left(\left(\sum_{n=1}^{N}|O_1(n)|\right)/N\right) = h(\alpha) \tag{13}
$$

Hence, the local decision making is follows:

if $|R| > h$, there is a 'damage event' in a structure,
otherwise, the structure is 'safe'.

This delivers a local decision as a binary signal: '0' for an *undamaged structure*, and '1' for a *damaged structure*. The damage sensitivity (extent) is estimated by R/h subject to α.

B. *Complexity Analysis*

We analyze its computational complexity and benefits over existing SHM algorithms. In accordance with (13) that represents R, for N measured samples, and using N_a and N_b coefficients for the transfer function, the embedded algorithm requires the following number of elementary computations:

$$
\begin{array}{ll}
(N - \max(N_a, N_b))\cdot(2 + N_a + N_b) & \text{addition} \\
(N - \max(N_a, N_b))\cdot(N_a + N_b) & \text{multiplication}
\end{array} \tag{14}
$$

To compute h, the algorithm requires:

$$
\begin{array}{ll}
(N - \max(N_a, N_b)) & \text{addition} \\
(N - \max(N_a, N_b)) & \text{multiplication}
\end{array} \tag{15}
$$

Now, as $N \ll \max(N_a, N_b)$, the total number of computational operations is of the order of $N\cdot(N_a + N_b)$. The order of complexity of this algorithm is $O(N)$. The computation cost of commonly used SHM algorithms, such as NExT/ERA, is $O(s_m\cdot e_{NExT} + e_{ERA}(s_m))$. But e_{NExT} and $e_{ERA(s_m)}$ are non-linear functions of s_m and the ERA involves complex matrix computations including SVD (single values decomposition) and matrix inversion. The minimum computation time can be given as $0.4 \times s_m^2 + 1.2 \times (s_m) - 3.6$ in the WSN of Imote2 sensors. FFT-based approaches, e.g., DLAC [15] require $2N\log_2 N$ multiplications and $2N\log_2 N$ additions. These highlight that MODEM significantly reduces the computational cost using Intel Imote2 wireless sensors.

VII. Substructure-oriented Group-wise Decision

In this section, we first propose a substructure-oriented sensor organization (SOSO) algorithm. Then, we provide sensor interaction and the DDM election. Finally, we discuss decision fusion for event detection in substructures.

A. Substructure-Oriented Sensor Organization (SOSO)

Physical substructures are normally identified by wired sensors in civil engineering for substructure oriented monitoring, but it is quite impossible by wireless sensors [19]. Thus, we ignore the structure identification, but we utilize the idea of substructural monitoring. Our focus is to provide substructure-oriented monitoring rather than concentrating on a whole structure, in which length or diameter can be from X00m to Xkm (X=1,2,3..).

To achieve this, we follow an existing WSN-based SHM specific clustering technique [17]. It nicely discusses the structural modal analysis (including mode shape) using clusters. However, it has significant drawbacks, making it difficult to substructure-oriented event monitoring as it did not handle engineering-driven WSN deployment method [19]. We consider the nature of structures, where a substructure can be a part of industrial machinery areas, the area of a number of floors of a building, a long-span of a bridge, one or more sections of an aircraft, and the like [21]. It can be fixed based on the scale of a structure and part or section orientations. In this case, R_{min} is important, which we first adjust to the link quality and then to the diameter of a substructure (see Fig. 3c). We need to organize sensor groups, where at least a group of sensors is required to completely cover the area of a substructure, and sensors in each group are strongly connected. Using the WSN deployment method and the clustering, there is possible that every section of a structure is not covered. Thus, the grouping must therefore meet the following constraints:

- An LDM in a group g_i belongs to the same substructure, and is connected to a DDM.
- An LDM in g_i is within a single hop to multi-hop of a DDM, where it is able to adjust its communication range.
- All of the groups in the network are connected together through the overlapping sensors.

Although satisfying the first constraint is straightforward, it requires domain knowledge from both computer science and CSMA engineering. Before formulating the above grouping problem, we assume that a WSN has already been partitioned according to the substructures they belong to. We therefore only focus on how to further group the sensors in each substructure to satisfy the second and third requirements, and minimize the number of groups. Thus, the problem becomes: given a WSN $W = (V, E)$, find a grouping scheme that can group these V sensors into K groups, denoted as $G = \{g_1, g_2, g_3, \ldots, g_K\}$, subject to the following constraints:

i) $(\cup_{g_i \in G}$, where $s_u \in g_i) = V$

ii) Let the subgraph for group g_i be $W(g_i, E_i)$, where $E_i \in E$. Then, $\forall g_i \in G, \exists s_u \in g_i$, such that there is an edge $e_{uv} \in E_i$ between a sensor s_u and other $s_v \in g_i (s_u \neq s_v)$

iii) $\forall g_i, \exists g_j \in G, (i \neq j),\ g_i \cap g_j \neq \emptyset$ and $\forall G' \subseteq G, (\cup_{g_i \in G'}\ g_i) \cap (\cup_{g_j \in G-G'}\ g_j) \neq \emptyset$

Objective: Minimize $cost(g_i)$

The 1$^{\text{st}}$ constraint is necessary since we wish to find D_j obtained by all sensors. The 2$^{\text{nd}}$ constraint is to ensure that groups are generated. The 3$^{\text{rd}}$ constraint describes that generated groups are overlapped and connected. The detailed justification/proof of the constraints are the same as in [19].

B. Sensor Interactions and the DDM Election

At the initialization, i.e., at the first T_d, each LDM broadcasts a packet in which it announces itself as the DDM, unless it hears such an announcement from another LDM. An important fact is that each LDM uses a table of records for the group. For each LDM in the WSN, a record contains the LDM *id*, a flag hinting whether it is a DDM or not, its current energy level (e_{cur}), and location. When an LDM becomes a DDM, it has extra information in the table, e.g., about neighbor DDM.

At the end of each T_d, each LDM transmits a report to the DDM. The report includes *id*, *decision*, and e_{cur}. Before going to sleep, LDMs wait for an announcement about who is the DDM in the next T_d. After DDM fuses decisions transmitted by the LDMs, DDM confirms the event and announces the next DDM. The packet includes the confirmation on an event detection and the next DDM id. When LDMs receive the announcement, they update the records by *id* of the DDM for the next T_d. They mark the information so that when they wake up in the next T_d, they know which LDM is their DDM.

Under SOSO, group organization is performed once, but a new DDM election is simply performed at the end of each T_d. A sensor node (say an LDM) may enter or leave a group, such as group G_1 over time due to being a boundary sensor, or due to faults in the WSNs, or due to another reason. However, the group G_1 remains in MODEM until a sensor is alive. Thus, the number of LDMs in a particular group of the WSN may vary, but the number of groups in the WSN still remain the same until further group organization or system run. LDMs wake up, connect to the DDMs, and start sensing directly. Thus, this group organization and DDMs election reduces maintenance overhead and offers substructural monitoring.

Remarks. When following optimal clustering like [17], an issue arises: there is a possibility that two or more groups cover a substructure. To tackle this, we take each of the groups as a sub-group and merge all sub-groups (that are covering a part of the substructure) into a single large group, making it suitable for covering the whole substructure.

C. Decision Fusion for Substructure-oriented Monitoring

The decisions made by LDMs of a group are fused at a DDM to create a final decision so as to know whether or not there is a damage event in a substructure. One of the simplest fusion techniques is the use of the voting scheme presented in other WSN applications [23]. Other methods, e.g., distance-based or maximum posterior fusions, may also be used. In MODEM, the local decision made by each LDM is D_j as (1).

Consider that each DDM gets w decisions from its LDMs. An event is confirmed by getting similar decisions from the multiple LDMs. A DDM faces two cases in making a decision:

- If two or more LDMs report the same result (there may have differences in non-binary result, as shown in Table II), i.e., D_j=1. It is computed as follows:

$$\sum D_j \geq \lfloor w/2 \rfloor + 1 \tag{16}$$

Table II
BINARY AND NON-BINARY RESULTS (ACHIEVED FROM THE TESTBED)

Sensor ID	Decision	Difference (in Frequency)
id1	0	Null
id2	1	6.345, 5.346, 5.564,
id3	1	4.456, 5.345, 6.665
id4	0	Null
...	...	...

- If the DDM receives D_j=1 further from the same LDM, DDM may request other LDMs to locate the event. After making a decision, the DDM transmits the final decision for its covering substructure to the BS in a priority manner if D_j=1. The LDM waits for the DDM's announcement before entering into sleep mode.

VIII. PERFORMANCE EVALUATION

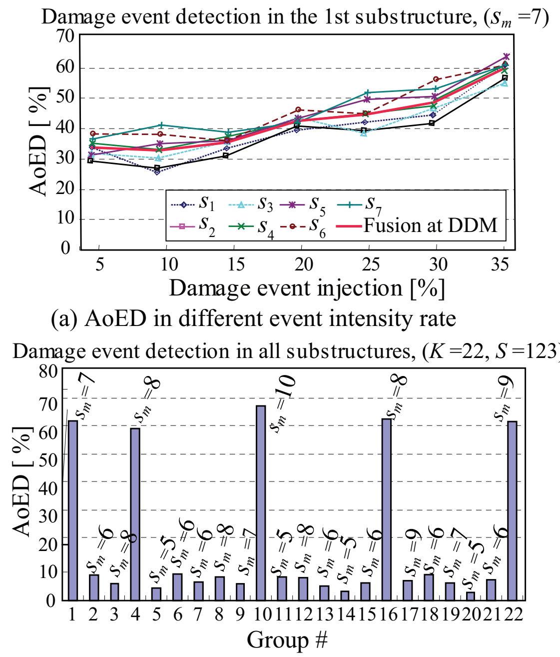
A. Simulation

1) Methodology: We validate the performance of MODEM through a sophisticated building structure model (refer to Fig 3 and [12]). The real acceleration data traces collected by a large number of sensors (800 sensors) deployed on the GNTVT are used. The GNTVT was completed in 2011 and became the tallest TV tower in the world, with a height (H) of 450m of the main tower. A set of 200 sensors is used to monitor the vibration at the transverse direction (z direction). On average, the diameter of each substructure is $d = H/q$, where q is the expected number of substructures, $K \geq q$. The communication range is adjusted with d, $R_{min} \leq d \leq R_{max}$. Note that, for other substructures like aerospace vehicles, industrial machines, K can be much more than q.

Simulations are done with the Matlab Toolbox using a FEM of the GNTVT, adopted from [13] (we have attempted to conduct simulations with the OMNeT++ tool, but have been hindered by the fact that the FEM was not working well). Given different levels of event (damage) injection at different sensor locations (by modifying the input signal randomly in the data sets of (1-5)th sensors, (18-22)th sensors, (41-45)th sensors, (71-75)th sensors, and (95-99)th sensors). Note that it is possible to change at any point on the data using the structural FEM. We model each sensor node with six discrete power levels in the interval {-10dBm, 0dBm} regarding the Imote2's power settings that are tuned within the IEEE 802.15.4.

The objectives of the evaluation are to observe the performance of (i) the AoED as the QoS and (ii) the energy cost in MODEM. AoED is defined by *the intensity of the damage event detected by sensors compared to different percentages of the damage event injection around sensor locations*.

The performance of MODEM is compared to several schemes. (i) **Distributed ERA:** The required computations in the distributed ERA are updated incrementally [1]. It requires fewer wireless transmissions compared to a cluster-based ERA. (ii) **Original ERA:** The structural event detection using ERA [1] is used based on the data collected by the wired SHM system deployed on the GNTVT. (iii) **SPEM**: Sensors transmit all the measured data toward the BS to make decisions and compute mode shapes [13]. (iv) **DLAC**: Sensors use the frequency domain analysis to compute the FFT of a discrete sequence, and aggregate it locally so that they transmit a small amount of data [15]. (v) **Centralized MODEM**: After making a localized decision, the sensors transmit the decisions to the BS for decision fusion, i.e., there is no DDM. But, if the decision is "1", they are required to transmit all of their data.



(a) AoED in different event intensity rate

(b) AoED in different sensor groups

Figure 5. Event monitoring performance: (a) the AoED of the first group of 7 sensors (LDMs) and detection fusion at the DDM; (b) the AoED of 22 groups of 123 sensors in the WSN.

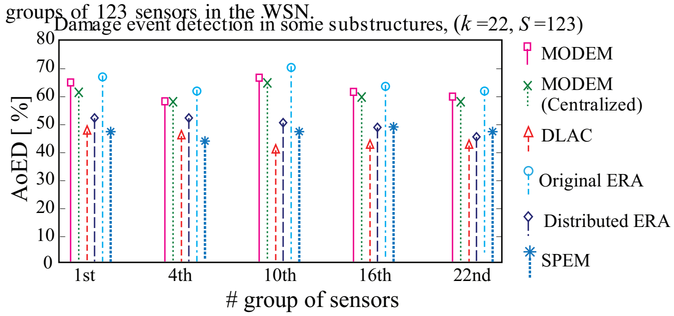


Figure 6. Event monitoring performance: the AoED of different groups of sensors achieved and analyzed in different WSN-based SHM schemes.

2) Simulation Results: Prior to the result processing, we first design the model that links the strain signal and the accelerated signal for the undamaged structure. Then, h is estimated for the different levels of damage sensitivity and decision making, as in (17). The model is determined as a *black box* using the Matlab function *ident*. The *black box* model uses the acceleration signal as an input O_1 called $u(t)$, and the strain signal as an output O_2 is called $y(t)$ in Matlab. Excluding the modeling error, the choice for the model used is of the form given in (9). This is derived from the Matlab

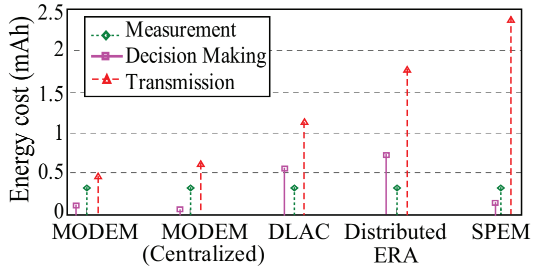


Figure 7. Network performance: the average energy cost of a sensor in each round of monitoring in a T_d in different WSN-based SHM schemes.

toolbox as follows:

$$\begin{aligned}\hat{O}_2(n) &= -0.264\cdot 10^{-9}\cdot O_1(n) + 3.5\cdot 10^{-12}\cdot O_1(n-1) - 1.385\cdot 10^{-10}\cdot O_1(n-2)\\ &\quad + 0.18\cdot 10^{-11}\cdot O_1(n-3) + 1.143\cdot 10^{-10}\cdot O_1(n-4), \forall n > 4 \\ &= O_2(n), \forall n \leq 4\end{aligned} \tag{17}$$

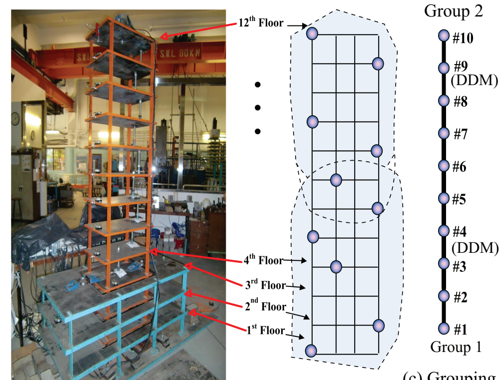
Fig. 5a depicts the AoED in MODEM, obtained by analyzing the results from the 1st group of sensors. Fig. 5b shows the AoED, obtained by groups of 123 sensors, which hints that the damage event information is coming from sensors (group-wise) in different substructures. We find $K = 22$ and $S = 123$ with 25% overlap. Similar to the real system setup, the parameter for residual is separated by R/h for $\alpha = 1$. Since these results are obtained by a damage situation (i.e., '1'), we recover the exact damage information and estimate R/h besides the '1' decision. It is important to mention that AoED from 40% to 50% in an SHM system can be enough for attention in the form of an 'alert'. If it is more than 30%, the situation demands attention. In MODEM, the maximum AoED is about 63% provided by the 22nd group under 35% damage injection in the structure. In a case of a small amount of damage (5% to 10%), MODEM still offers a proper 'alert'.

Fig. 6 shows the AoED achieved in different schemes. Looking into the details, there are remarkable changes (events), detected by the (5-9)th sensors and (18-22)th sensors, as different levels of damage event information has been injected at these sensor locations. We can observe that AoED $\geq$ 65% is in original ERA-based detection, while AoED $\leq$ 53% in distributed ERA, AoED $\leq$ 48% in DLAC, and AoED $\geq$ 59% in centralized MODEM. AoED is around 63% in MODEM, which is close to the original wired-based ERA scheme. It is an evidence that MODEM is superior to other schemes.

Fig. 7 presents the average energy cost consumed by a sensor in each round of monitoring, where $T_d = 5\tau$. This cost is analyzed in the presence of the damage event. We can see that MODEM outperforms other schemes: it achieves a low energy cost, which is roughly at least three to six times lower than other schemes in the presence of a 'damage event'. On an investigation, in the presence of a 'no damage event,' MODEM has at least eight times lower energy cost than that of DLAC, and at least nine times less than that of the distributed ERA, and so on. This is because the amount of computation time and wireless transmission is drastically reduced, and the frequency of transmission is small. All these are achieved by sensor in-network decision-making in the CPS.

B. Experiments on the Physical Structure

1) Proof-of-concept System: We implement the MODEM in TinyOS on SHM mote platforms. In our implementation,



(a) Test building structure (b) Mote deployment (c) Grouping results

Figure 8. (a) Twelve-story test building structure and the placement of 10 SHM motes on it; (b) sensor grouping; (c) DDM selection.

Table III
Identified frequency (Hz) in the undamaged structural system

Exp. \ Sensor	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8	s_9
Experiment 1	18.332	21.233	27.231	21.323	18.212	16.122	19.132	6.434	15.343
Experiment 2	19.212	18.131	26.121	22.121	19.124	17.465	20.466	17.566	16.65

a multi-metric and specialized SHM mote with on-board signal processing and embedded decision making specifically planned for general SHM applications is designed. Each SHM mote is integrated with three main hardware components: a sensor board, an Intel Imote2, and a radio-triggered wakeup with a synchronization module [19]. For an undamaged structure, each mote keeps 20 to 22 bytes of data, but removes other data after each T_d.

The SHM motes run modified TinyOS, and are configured to sample the accelerometers in a synchronized manner at a frequency of 560Hz. We modify the radio-related components in TinyOS 2.0 for time-stamping the packet close to the transmitter. When a mote receives an ACK that the data packet is received by an upper stream mote (i.e., DDM), then data is removed from the buffer, except for the last set of data that remains in the buffer. The Imote2's 3D accelerometer has a resolution of 12-bit, or equivalent 0.97 mg with 3-axis of measurement and $\pm 2g$ of amplitude [16].

We design a twelve-story shear frame structure to verify MODEM under physical damage injection. The structure is shared into two substructures, with each having at least four floors. 10 SHM motes are deployed, according to the 3D location identification on the structure, and are organized into two groups by using the SOSO algorithm.

2) Experimental Results: Study of the AoED. We observe the sensors' identified frequencies in Table III under excitation by using a magnetic shaker and an undamaged structure, obtained by the last set of frequencies remaining in memory. According to different damaged conditions, as shown in Fig. 9a, we summarize the frequency differences in Fig. 9b. We found that the frequencies vary largely as the damage is injected. We consider three damage injection cases: the plates are removed from the first, fifth, and ninth floor, respectively.

r and h are parameters that are required to be passed to the motes at the beginning for accurate decision-making. With reference to (12), we use r as an adaptive threshold for flexibility. The damage sensitivity at different sensors is shown in Fig. 9b, where R/h indicates the sensitivity of the damage,

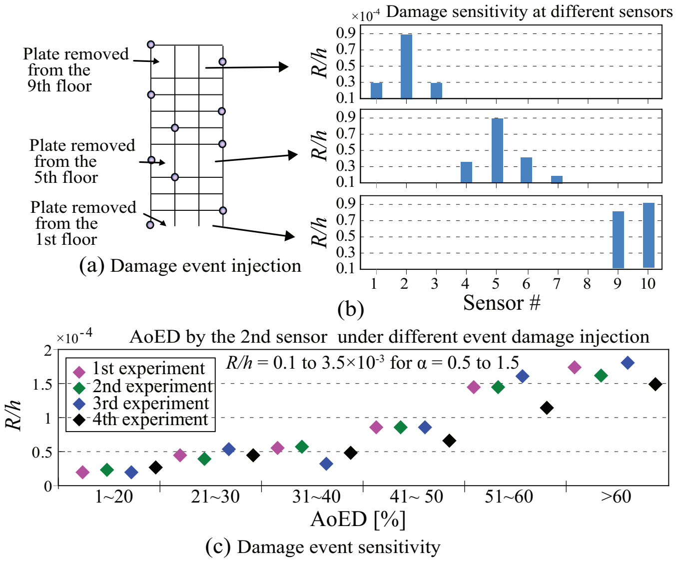


Figure 9. (a) Damage injection; (b) damage sensitivity at sensors estimated by R/h when $\alpha = 1$; (c) damage sensitivity at different experiments.

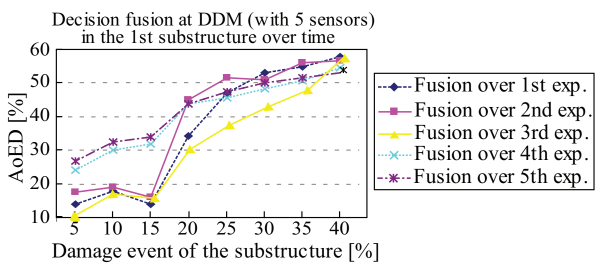


Figure 10. Performance on the event of damage detection.

which is about 0.1×10^{-4} to 0.9×10^{-4}. r is separated by h for $\alpha = 1$. This can justify the form of the threshold used. The AoED of the mote placed on the 2nd floor is depicted in Fig. 9c. We can see that the AoED increases as R/h increases, i.e., the AoED is higher (e.g., $> 60\%$) as R/h is higher.

In the next set of experiments, we analyze some interesting results. We add some noise into the measurements so that the identified frequency difference through r is closer to (even better than) a real structure. We then estimate the AoED that is due to α, R, and h. In MODEM, the motes in the first sensor group are able to provide detection up to getting an *alert* in an SHM system, as shown in Fig. 10. This illustrates sensors' AoED up to 60%. We think that having AoED of more than 50% can be enough in SHM to *alert* the system user in a 'event' situation.

Study of the Energy Cost. The PXA271 fully calculates residual r and decides on D_j via r. The energy consumed by the PXA271 is estimated by the decision-making cost. Fig. 11 exhibits the average energy cost for five rounds of monitoring in the presence of an event, and compares the results with the existing schemes. When estimating the energy cost, we include sensor measurement, computation, and transmission. We calculate the energy cost, $cost(s_u)$, in T_d by summing the energy consumed in all rounds in T_d. By analyzing and comparing with the others in Fig. 11, MODEM saves at least three times the energy (which is more than eight times that under 'no event'), when compared to its counterparts. Also, the centralized MODEM outperforms others, and minimizes

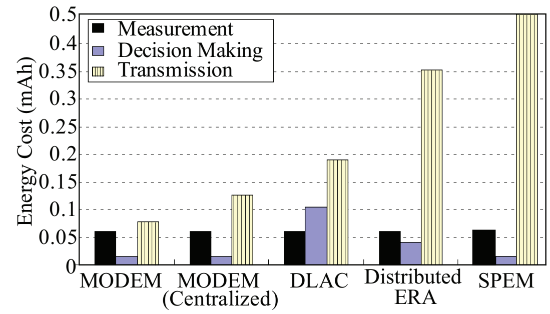


Figure 11. The average energy cost of a Imote2 for five rounds of structural event monitoring under the presence of the damage event.

energy cost from 0.231 mAh to 0.137 mAh. This minimization is mainly achieved by the in-network decision-making that results in a very minimum amount of data transmissions. Since the transmission cost in WSNs is a dominating factor, such reduction in the wireless transmission cost enhances the applicability of WSNs for SHM. (more details about the experimental study can be found in Appendices E and F)

IX. Conclusion

To enhance the applicability of resource-constrained WSNs for SHM and to offer more choices for engineering communities in order to the vitality of structures and public safety requirements, we have devised a computationally inexpensive and cost-efficient CPS design. We proposed MODEM, a comprehensive model-based decision-making scheme for the CPS, which to our knowledge is the first of its kind, featuring a fully-distributed monitoring. Evaluation results achieved via simulations and a prototype SHM system validated MODEM's performance and capacity to make high-quality decisions and improve the applicability of WSNs for SHM by significantly reducing the energy cost.

Our future work includes the following: i) designing application-specific data fusion models; ii) developing SHM-specific sensor scheduling techniques that will wake up sensors in a particular substructure.

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