

## **POST-SEISMIC DAMAGE ASSESSMENT OF STEEL STRUCTURES INSTRUMENTED WITH SELF-INTERROGATING WIRELESS SENSORS**

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### **ABSTRACT**

Wireless sensors have been proposed for use in structural health monitoring systems because they offer low-installation costs and automated data processing functionality. A wireless sensor prototype is described for use in large-scale civil structures situated in zones of high seismic activity. When networked together, the distributed computational resources of the wireless sensor network can be leveraged to automate the process of screening post-seismic ambient response data for signs of structural damage. To validate the performance of the proposed wireless monitoring system, a three-story half-scale steel structure is instrumented with a wireless monitoring system assembled from a network of six wireless sensors. Attached to the wireless monitoring system is a heterogeneous array of sensing transducers including strain gages and accelerometers. White noise and seismic ground motion records are applied to the base of the structure using a shaking table. Autoregressive time series models are calculated by the wireless sensors using structural response data. Pattern classification methods are then adopted to classify the structure as damaged or undamaged using the autoregressive time series coefficients as feature vectors. To simulate damage in the structure, the steel columns are modified at the base of the structure with reduced column sections. The proposed damage detection methodology is shown to be capable of identifying the reduced column sections as damage.

### **Introduction**

Civil infrastructure systems remain vulnerable to damage over their operation life spans. Structural damage can be introduced into a structure from a number of sources including normal wear and tear and excessive live loading (*e.g.* seismic and blast loads). Structural health monitoring has been proposed by the structural engineering community to assist owners in monitoring their structures for signs of deterioration. To produce a structural health monitoring system, two components are needed: an underlying monitoring system and damage detection

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algorithms. The structural monitoring system is responsible for the reliable collection of response data measured using sensors installed in the structure. Once data is collected by the monitoring system, damage detection algorithms are necessary to automate the task of interrogating the data for signs of structural distress and deterioration. Today, the majority of structural monitoring systems offered by the commercial sector are tethered. Extensive lengths of coaxial wire are installed in the structure to provide a direct communication link between sensors and a centralized data repository. Unfortunately, the installation and maintenance of wires in complex civil structures can be expensive; published data suggests the cost of structural monitoring systems can be in excess of a few thousand dollars per sensor channel (Celebi 2002).

Wireless sensors have the potential to radically change how future structural health monitoring systems are deployed. Initial interest in wireless sensors was prompted by the use of wireless communication for data transfer in the monitoring system. Clearly, the elimination of extensive lengths of wire give wireless monitoring systems the advantage of easier installations and substantially reduced costs. The excitement that surrounds wireless sensors is not due solely to their cost advantages; rather, wireless sensor designs require embedded computing components (*e.g.* microcontrollers) for autonomous operation in the field. Microcontrollers included in wireless sensors can be utilized to perform local data processing at the sensor itself. This computing feature is what sets wireless sensors apart from traditional sensors interfaced to a cable-based monitoring system. In particular, the computing power integrated with wireless sensors can be used to screen structural response data for signs of structural damage.

Many researchers have explored the use of wireless sensors within structural monitoring and structural health monitoring systems. For example, Straser and Kiremidjian (1998) are early proponents for the adoption of low-cost wireless sensors in structural monitoring systems. Since their seminal study, a wide range of academic wireless sensor prototypes have been proposed by Lynch (2002), Casciati *et al.* (2003), and Shinozuka (2003). In addition to these efforts, other researchers have explored the application of generic wireless sensor solutions offered by the commercial sector to civil structures. A wireless sensor platform particularly popular, termed the Mote system, was developed at UC-Berkeley and commercialized by companies such as Crossbow and Intel. Researchers such as Ruiz-Sandoval, Spencer Jr., and Kurata (2003) and Glaser (2004) have applied Crossbow MICA Mote wireless sensors to monitor lab structures.

In this study, a wireless monitoring system assembled from wireless sensor prototypes proposed by Wang, Lynch and Law (2005) is installed upon a half-scale steel structure in the laboratory. The test structure is mounted to a shaking table where base excitations are applied including white noise and various seismic ground motions. The performance of the wireless monitoring system is assessed by comparing structural response data collected by the wireless system to that collected by a traditional wired data acquisition system. To illustrate the self-interrogation capabilities of the wireless sensors, an autoregressive (AR) model fitting algorithm is embedded in the computational cores of the wireless sensors. A damage detection method proposed by Sohn and Farrar (2001) is adopted to identify structural damage in the test structure based on the AR model coefficients calculated by the wireless sensors. Damage is introduced by reducing the cross section of two columns at the base of the structure.

### **Three-Story Laboratory Test Structure**

A three-story half-scale steel structure is designed and constructed at the National Center

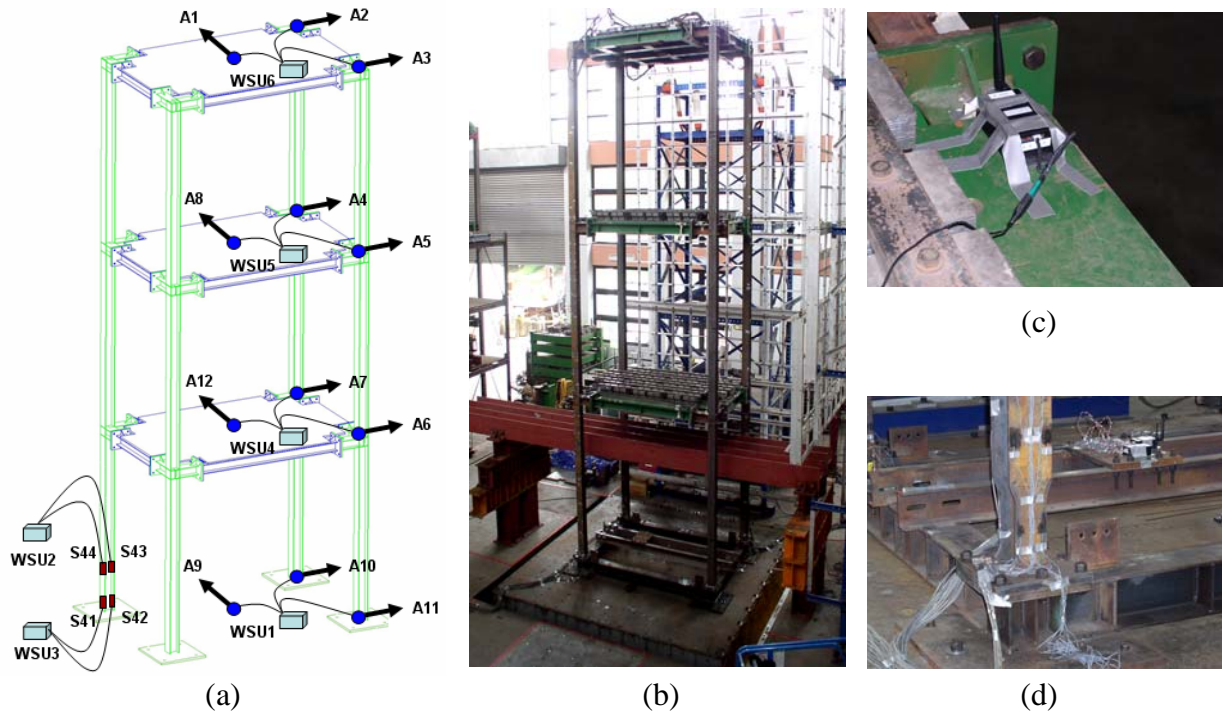


Figure 1. Three-story test structure: (a) instrumentation strategy, (b) test structure mounted to the laboratory shake table, (c) wireless sensors installed, and (d) reduced column section

for Research on Earthquake Engineering (NCREE) in Taipei, Taiwan. As shown in Fig. 1a and 1b, the three-story structure consists of a single bay with a 3 m by 2 m floor area and inter-story heights of 3 m. The structure is constructed using H150x150x7x10 steel I-beam elements with each beam-column joint designed as a bolted connection. To apply additional dead load upon each floor, concrete blocks are fastened until the total mass of each floor is precisely 6,000 kg. The entire structure is constructed upon a large-scale shaking table capable of applying base motion in 6 independent degrees-of-freedom. The floor area of the shaking table is 5 m by 5m.

To monitor the response of the structure excited by various base excitations, a wireless monitoring system is installed. The wireless monitoring system consists of wireless sensor prototypes initially proposed by Wang, Lynch and Law (2005). Designed explicitly for structural monitoring applications, the wireless sensors employ commercial off-the-shelf electrical components, including an 8-bit low-power microcontroller, 16-bit multi-channel analog-to-digital converter, and long-range wireless transceiver. When fully assembled as shown in Fig. 2a, the wireless sensing unit is both low-cost (less than \$200 per unit) and compact (10 cm x 6 cm x 2 cm). The wireless sensor offers end-users a transparent 4-channel sensing interface to which any type of analog sensor can be attached; to date, accelerometers, strain gages, linear displacement transducers and geophones have all been successfully used. Once data is collected by the internal 16-bit analog-to-digital converter, the digitized response data can be stored in the wireless sensor's microcontroller (Atmel ATmega128) and 128 kB static random access memory (SRAM) bank. The role of the ATmega128 microcontroller is twofold: first, software embedded in the microcontroller is needed to coordinate the activities of the wireless sensor. Second, the computing authority offered by the microcontroller can be used for self-interrogation of structural response data. The final element of the wireless sensor design is the



Figure 2. (a) Fully assembled prototype with battery power source revealed, and (b) interface circuit for metal foil strain gages.

inclusion of the long-range 2.4 GHz Maxstream XStream wireless radio. This radio is capable of line-of-sight communication ranges of 180 m when operated indoors. Fully assembled, the wireless sensor is powered by 5 AA batteries that are estimated to have a life expectancy of over 1 year when wireless sensor use is duty cycled (Wang, Lynch and Law 2005). The performance attributes of the wireless sensor are summarized in Table 1.

In total, six wireless sensors are installed in the test structure. Of the 24 available sensor channels, 16 channels are employed. As shown in Fig. 1a, three accelerometers are installed at each level of the structure. For example, on the top story, the three accelerometers interfaced to wireless sensor WSU6 are labeled as A1, A2 and A3. Wireless sensors WSU1, WSU4, and WSU5 each record the lateral acceleration response of the structure base, first and second floors, respectively. Accelerometers A1 through A8 are microelectromechanical systems (MEMS) Crossbow CXL02 accelerometers. The CXL02 accelerometers, with an acceleration range of  $\pm 2g$ , noise floor of 0.5 mg and sensitivity of 1 V/g, are particularly well suited for structural monitoring applications. For accelerometers A9 through A12, the Crossbow CXL01 MEMS accelerometer is selected. The specifications of the CXL01 are similar to those of the CXL02 except that the acceleration range of the sensor is  $\pm 1g$ . To measure strain in one of the structure's columns, four 120  $\Omega$  metal foil strain gages with gage factors of 2 are mounted at the column base. To measure the change in resistance of each strain gage, two wireless sensors (WSU2 and WSU3) are utilized. Unlike the accelerometers, the metal foil strain gages do not modulate strain measurements upon a voltage signal. Rather, a Wheatstone bridge amplification

Table 1. Performance specifications of the wireless sensor prototype.

Attribute	Specification
Sensing Channels	4
Sample Rate	100 kHz
Sensor Inputs	0 – 5 V
Memory for Embedded Algorithms	128 kB
Memory for Data Storage	128 kB
Clock Frequency	8 MHz
Radio Carrier Band	2.4 GHz
Communication Range (outdoor/indoor)	180 m/ 5 km
Power Source (Lithium-ion recommended)	5 AA Batteries
Power Consumption (radio off/radio on)	150 mW/ 380 mW

circuit proposed by Lynch (2002) is adopted to convert changes in the foil resistance to measurable voltage signals. The proposed interface circuit for metal foil strain gages is shown in Fig. 2b. The strain gages are labeled as S41 through S44 in Fig. 1a.

### Seismic Base Excitation

The first objective of this study is to assess the accuracy of the wireless monitoring system. To quantify the wireless monitoring system accuracy, a traditional wired monitoring system is installed in parallel. Accelerometers and metal foil strain gages are installed in identical locations to the sensors employed by the wireless monitoring system. To measure acceleration, Setra 141A capacitive accelerometers are placed at locations A1 through A12 (see Fig. 1a) and are interfaced to the wired data acquisition system. The Setra 141A accelerometers can measure accelerations in a  $\pm 4g$  range with a noise floor of 0.4 mg. Four strain gages are mounted adjacent to the gages mounted at locations SG41 through SG44; these four gages are interfaced to bridge circuit channels of the data acquisition system. The laboratory data acquisition system consists of multiple Pacific Instrument Series 5500 data acquisition chassis. Each 5500 chassis offers high-resolution data acquisition on 16 channels.

To excite the steel structure, various base excitations are applied by the shaking table. Table 2 summarizes the excitations during the laboratory study. It should be noted that the white noise and seismic ground motion records are applied uni- and bi-axially. The direction oriented parallel to accelerometer A9 is denoted as the Y-direction while the orthogonal direction (aligned with A10) is denoted as the X-direction.

The response of the test structure to the Chi-Chi 1999 earthquake TCU082 seismic ground record is shown in Fig. 3. Although the response of the structure is measured at all of the sensor locations, the response measured at sensor location A1, A3, A6 and SG42 are presented in Fig. 3. When comparing the response of the structure measured by the wireless and wired monitoring systems, nearly identical results are observed. It can be concluded that the wireless monitoring system is suitable for accurately recording the seismic response of civil structures.

### Two-Tier Time Series Damage Detection Methodology

While many researchers have proposed the use of modal frequencies as a primary damage indicator, the method lacks sensitivity in structures where environmental factors also contribute to modal frequency shifts (Doebeling *et al.* 1996). To fully account for the environmental and operational variability of structures, a damage detection methodology based

Table 2. Applied ground excitations during dynamic testing of the steel structure

Excitation	Y-Direction	X-Direction
White Noise (Uniaxial)	-	60 gal RMS
White Noise (Uniaxial)	-	100 gal RMS
White Noise (Biaxial)	200 gal RMS	100 gal RMS
White Noise (Biaxial)	100 gal RMS	50 gal RMS
Kobe 1995	50 gal RMS	100 gal RMS
Chi-Chi 1999 (TCU076)	80 gal RMS	100 gal RMS
Chi-Chi 1999 (TCU082)	80 gal RMS	100 gal RMS
El Centro 1940	50 gal RMS	150 gal RMS

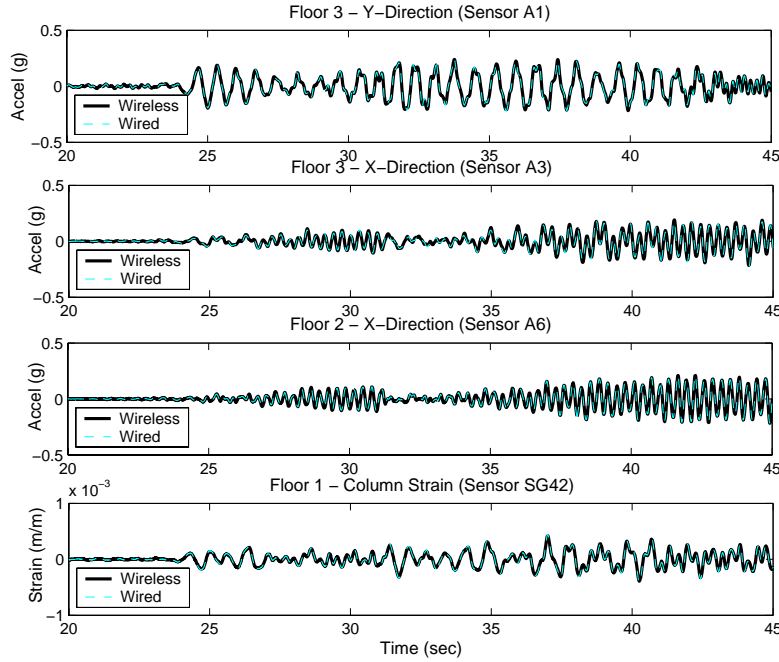


Figure 3. Response of the test structure to Chi-Chi TCU082 strong ground motion record

upon a pattern recognition framework is proposed by Sohn and Farrar (2001). Their method begins with the stationary response time-history of the structure at a single measurement location. Using the response data,  $y$ , an autoregressive (AR) time series model is fit to the data.

$$y(k) = \sum_{i=1}^p a_i y(k-i) + r_{AR}(k) \quad (1)$$

The residual error of the fitted AR time series model,  $r_{AR}$ , and the structural output,  $y$ , are then used to fit a second autoregressive with exogenous input (ARX) time series model.

$$y(k) = \sum_{i=1}^a \alpha_i y(k-i) + \sum_{j=0}^b \beta_j r_{AR}(k-j) + \varepsilon_{ARX}(k) \quad (2)$$

The final residual error of the ARX model,  $\varepsilon_{ARX}$ , is identified as the damage sensitive feature of the proposed method.

To accommodate for environmental variability, AR-ARX time series models are determined for the structure in its undamaged state when exposed to different operational conditions. These AR-ARX time series models form a database of baseline models describing the structure in its undamaged state. When the structural response is recorded for the structure in an unknown state (damage or undamaged), an AR time series model is fit to the structural response data. The coefficients of this AR model are then compared to the library of AR-ARX coefficients corresponding to the undamaged structure. The undamaged AR-ARX model pair closest (based on the Euclidian distance of the AR coefficients) to that of the AR coefficients of the unknown structure, is selected from the library. If the structure in the unknown state is not damaged, then the AR-ARX model pair corresponding to the undamaged structure will fit the response data of the unknown structure well. If the selected AR-ARX model pair does not fit the data well, then the structure is identified as damaged. The metric for determining the quality of

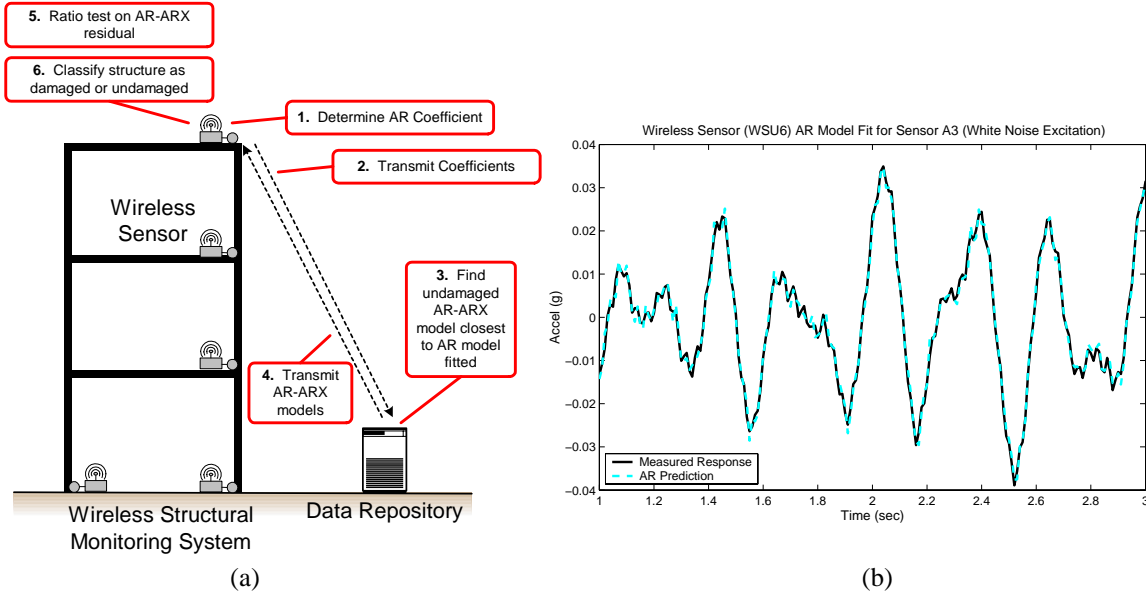


Figure 4. (a) Implementation of the AR-ARX damage detection strategy in a wireless monitoring system, and (b) AR model calculated by the wireless sensor at A3

the model fit is the standard deviation of the ARX model residual error. The ratio of the standard deviation of the ARX model residual error when using the unknown structure's response data as input to the standard deviation of the AR-ARX database model residual error is determined.

$$\frac{\sigma(\varepsilon_{ARX})}{\sigma(\varepsilon_{ARX-DB})} \geq h \quad (3)$$

Damage is concluded when the ARX error standard deviation is above an established threshold,  $h$ . Sohn and Farrar (2001) provide guidance on how to appropriately select the order of the AR and ARX models (as designated by the number of coefficients used in each) as well as setting the damage ratio threshold.

The AR-ARX time series damage detection method is well suited for automated execution by a wireless monitoring system. The damage detection method is implemented in the wireless monitoring system installed in the laboratory test structure. As shown in Fig. 4a, the computational power of the wireless sensor is used to calculate AR models to unknown (damaged versus undamaged) structural response data. After the AR coefficients are determined, the wireless sensor will wirelessly transmit the coefficients to a data repository where the database of AR-ARX model pairs corresponding to the undamaged structure are stored. The repository will select the appropriate AR-ARX model pair based on minimization of the Euclidian distance between the AR coefficients. After the closest AR-ARX model pair is selected, the coefficients of the AR-ARX model pair are transmitted to the wireless sensor. Using the stored response data previously used to fit the AR model, the wireless sensor will determine the residual error of the AR-ARX model pair. Using Eq. 3, damage is diagnosed when the ratio of the standard deviation of the AR-ARX model pair residual error exceeds an established threshold.

The wireless sensor is therefore asked to determine AR models for the response data it

collects. Embedded in the computational core of the wireless sensor is the numerically stable Burg's method for determination of the AR coefficients (Lynch *et al.* 2004). The end user of the system is free to select the number of AR model coefficients to be calculated. To illustrate the accuracy of the AR model fitting algorithm embedded, Fig. 4b presents the AR predicted response of the roof acceleration (at sensor location A3) compared to the true response. The AR model calculated in this example has 10 coefficients.

### **Validation of the Embedded AR-ARX Damage Detection Method**

With each wireless sensor capable of accurately fitting AR models to structural response data, the AR-ARX damage detection method is tested using the wireless monitoring system installed upon the steel test structure. First, the structure is excited in its undamaged state using white noise base excitations. For each sensor location, AR time series models are calculated using 10 coefficients ( $a_i$ ). Using the response data and the residual error of the fitted AR model, a second ARX model is calculated. In this study, the ARX models are calculated using 8 coefficients ( $\alpha_i$ ) for the structural response and 4 coefficients ( $\beta_i$ ) for the AR model error. For each AR-ARX model pair in the central data repository, the standard deviation of the AR-ARX model residual error ( $\sigma(\varepsilon)$ ) is also stored. In this study, well over 24 AR-ARX model pairs are determined using structural responses to uni- and bi-axial white noise base excitations applied to the undamaged structure. To ensure the AR-ARX model database is populated by models fit to response data corresponding to various operational conditions, the four different white noise excitations in Table 2 are utilized. After determining a large number of AR-ARX model pairs at all of the sensor locations for the undamaged structure, they are assembled into separate databases for each sensor location. The databases are stored remotely on the monitoring system data repository.

To validate the AR-ARX damage detection method, first the structure in an undamaged state is excited using white noise base excitations. After each excitation, all of the wireless sensors are commanded to determine AR models using the structural response data locally stored. After selecting an AR-ARX model pair from the database, the wireless sensor response data is used as input to the AR and ARX models. The residual error is then determined and compared to the residual error stored for the AR-ARX model pair in the database. As shown in Fig. 5 for sensor location A1, A3, A6 and SG42, when response data from the undamaged structure is used in the AR-ARX damage detection method, the standard deviation ratio of the AR-ARX residual error is approximately 1; this is an expected result since the structure is undamaged.

To introduce damage in the steel structure, the flanges of the column where the 4 metal foil strain gages are mounted are cut resulting in a reduced cross section in the column. A picture of the damaged column is shown in Fig. 1d. With the structure damaged, the structure is again base excited using white noise records and the damage detection methodology carried out at each sensor location. After each wireless sensor determines an AR model using its response data, the closest AR-ARX model pair is wirelessly obtained from the remote database. It is anticipated that the closest database AR-ARX model pair will not accurately predict the response of the damaged structure. As a result, the standard deviation of the AR-ARX model pair residual error, when using the damage structure response as input, will exceed that corresponding to the undamaged structure's response data used to initially fit the database model. As seen in Fig. 5, for sensor location A1 and A3, the roof acceleration response seems particularly sensitive to the

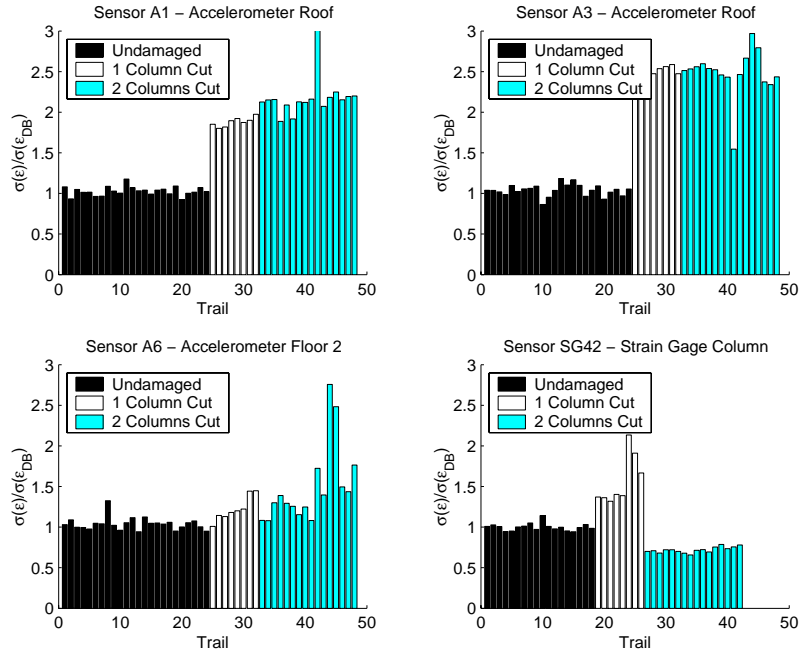


Figure 5. Ratio of AR-ARX two tier model residual errors for 4 selected sensor locations (A1, A3, A6 and SG42)

damage introduced at the base of the structure; the standard deviation ratio at both locations is over 2 for trials 25 through 32 (which correspond to eight different base excitations applied to the damaged structure). While sensor locations A1 and A3 are capable to identify the column section reduction, the accelerometer at location A6 appears to lack the same sensitivity to the damage. This lack of sensitivity results in a standard deviation ratio only slightly elevated for the damaged structural response data. When considering the strain gage (SG42) installed in the immediate vicinity of the structural damage, we see the AR-ARX damage detection method is able to identify the reduced cross section with standard deviation ratios spanning from 1.4 to 2.1.

Next, a second column is cut in a similar fashion to the first column. With two column sections reduced, the AR-ARX damage detection method is again applied at each sensor location. Similar to the findings of the first damage scenario, sensor locations A1 and A3 are able to identify the structure as damaged as seen for trials 33 to 48 (again corresponding to sixteen different white noise base excitation records). Sensor location A6 is able to identify the structural damage for some of the trails with residual error standard deviation ratios exceeding 1.5 for some of the trials. However, the strain gage at location SG42 experiences a reduction in the standard deviation ratio well below 1.

## Conclusions

This work has explored the use of wireless sensors as building blocks of future structural health monitoring systems. Installation of wireless sensor prototypes upon a half-scale steel test structure validates the accuracy of the novel wireless monitoring system. In addition, an AR-ARX damage detection method has been embedded within the wireless monitoring system for autonomous execution. In the proposed damage detection methodology, each wireless sensor is

responsible for calculation of AR model coefficients for comparison to a database of AR-ARX model pairs on the undamaged structure. To validate the approach, the embedded damage detection algorithm is shown to exhibit sufficient sensitivity to identify column damage at many sensor locations. Future work is intended to better identify how the standard deviation of the AR-ARX model residual error changes with damage as a function of sensor location. This future pursuit will lead to improvements in the proposed embedded damage detection method.

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