SOURCE: *Proceedings of the 2008 ASCE Structures Congress*, Vancouver, Canada, April 24-26, 2008.

Distributed Model Updating in Smart Wireless Monitoring Systems

Authors:

Andrew Zimmerman, University of Michigan, Ann Arbor, MI, atzimmer@umich.edu
Jerome P. Lynch, University of Michigan, Ann Arbor, MI, jerlynch@umich.edu

ABSTRACT

A wireless sensor integrates a radio to facilitate the exchange of data by wireless communications. In recent years, wireless sensors have rapidly matured with current platforms offering performance levels on par with traditional tethered sensors. The elimination of extensive wiring typical of tethered monitoring systems keeps the cost of wireless monitoring systems low. In addition to the inclusion of a radio, most wireless sensors include low-power microcontrollers in their hardware design. The inclusion of computational resources allows the sensor to autonomously process data, a revolutionary concept not previously seen in tethered structural monitoring systems. In this paper, the distributed computing resources inherent to a wireless structural monitoring system are leveraged to conduct model updating. A parallelized version of simulated annealing model updating procedures is embedded in a network of wireless sensors for autonomous execution. Automated model updating by a wireless monitoring system allows the system to keep analytical models current for long-term health monitoring of the structure.

INTRODUCTION

On August 1, 2007, the I35 Mississippi River Bridge in Minneapolis, Minnesota collapsed without warning resulting in the death of 13 motorists. The bridge was flagged in 1997 by Federal Highway Administration (FHWA) inspection guidelines as “structurally deficient” after corrosion, fatigue cracking in steel members and dysfunctional bearings had been detected [1]. In the United States, approximately 20% of the national bridge inventory has been classified as structurally deficient over past years [2]. In addition to the I35 bridge, other bridges in the United States have been reported to partially or totally collapse; from 1989 to 2000, over 134 bridges have collapsed [3]. While rare, failure of critical highway bridges underscores the need for improved inspection procedures and long-term maintenance strategies.

Many benefits can be derived from permanent monitoring systems installed within highway bridges. First, response data offers engineers with opportunities to use more objective metrics to track structural performance. These metrics would augment the visual inspection methods currently in widespread use [4]. Measured structural responses are often used to update analytical (*e.g.* finite element) models of the structure to ensure the model accurately predicts behavior under future loading scenarios. Better understanding of structural response to loading allows for improvements in design methods (*e.g.* codes) and bridge management strategies. Furthermore, response data can be screened for signs of structural damage as has been proposed for structural health monitoring (SHM) [5]. Despite these benefits, few bridges in the United States have permanent monitoring systems installed. A reason for the lack of technology adoption is cost.


(a) (b) (c)

FIGURE 1 – (A) WIRELESS SENSOR PROTOTYPE BY WANG [10]; (B) GEUMDANG BRIDGE, KOREA [11]; (C) VESTAS 5MW WIND TURBINE, GERMANY [13].

Typical monitoring systems employ extensive wired infrastructures to physically connect sensors installed in the structure to centralized data servers. This wiring can require significant labor to install in addition to incurring high initial costs. In buildings for example, a permanently installed structural monitoring systems can cost thousands of dollars on a per channel basis [6]. While such costs represent only a small fraction of a structure's total construction cost, they are sufficiently high to keep the technology out of reach for most structural owners.

In recent years, wireless sensors have emerged as lower cost substitutes for tethered sensors [7]. Replacement of wired communication channels with wireless ones render structural monitoring systems cheaper and easier to install. Wireless sensors were first proposed for use in civil structures by Straser and Kiremidjian [8]. Since their seminal work, a number of academic and commercial groups have proposed a variety of wireless sensor prototypes for structural monitoring [9]. For example, the wireless sensor prototype proposed by Wang *et al.* [10] (Figure 1a) has been successfully deployed worldwide on many large-scale civil structures including bridges [11], buildings [12] and wind turbine towers [13]. Two recent structures monitored by the proposed wireless structural monitoring are presented in Figure 1; namely, a concrete box girder bridge in Korea (Figure 1b) and a 5 MW wind turbine in Germany (Figure 1c).

EMBEDDED DATA PROCESSING

A unique feature of wireless sensors is the inclusion of low cost microcontrollers in their hardware design. Microcontrollers are necessary to take place digital data sampled by the analog-to-digital converter and to packetize the data for communication by the radio. The microcontroller can also be utilized to process sensed data; sensor-based data processing represents a major paradigm shift since traditional monitoring systems centralize the processing of data to a single location (*e.g.* at the system data server) where ample computing resources exist. In a wireless structural monitoring system assembled from a network of wireless sensors, processing power and memory is spatially distributed across the network. Hence, new approaches to computing are necessary for this highly distributed computing platform.

The wireless sensor prototype by Wang *et al.* [10] has an extensive software library that allows the wireless sensor to process its own measurement data. A summary of the algorithms embedded within each sensor node are summarized by Table 1. The majority of these algorithms use data collected at the sensor itself as input and do not require data from other wireless sensor nodes in the network. However, recent work by Zimmerman *et al.* [12] has explored the embedding of peak picking, random decrement and frequency domain decomposition modal methods where data must be exchanged between sensors to accurately quantify the modal

Algorithm	**Application**
Fast Fourier Transform (FFT)	- Modal analysis
Peak Picking (PP)	- Modal frequency identification
Wavelet Transform (WT)	- Damage detection - Decorrelation prior to compression
Autoregressive (AR) Modeling	- System identification - Damage detection
AR Exogenous Input (ARX) Modeling	- System identification - Modal analysis
Singular Value Decomposition (SVD)	- Modal analysis - Principle component analysis
Kalman Filter (KF)	- State estimation - System identification - Feedback control
Linear Quadratic Regulation (LQR)	- Feedback control

TABLE 1 – SUMMARY OF THE LIBRARY OF ALGORITHMS EMBEDDED WITHIN WIRELESS SENSORS DESIGNED FOR STRUCTURAL HEALTH MONITORING

characteristics (*e.g.* mode shapes) of the structure. Their work highlights the technical challenges associated with distributed data processing in a wireless sensor network where limited wireless bandwidth is available and each node is battery powered (*i.e.* operates on a nonrenewable energy source). Hence, their approach emphasizes minimization of communication in order to preserve the quality of the wireless communication channel and to maximize the operational life expectancy of a battery pack.

DISTRIBUTED MODEL UPDATING BY A WIRELESS SENSOR NETWORK

While there are several methods available for translating raw sensor data into an estimate of damage, one common technique involves comparing system properties in an unknown state of health (damaged or undamaged) to those in a known undamaged state. Given response data from an instrumented system, it is feasible to iteratively adjust the parameters of an analytical model such that the model predicts responses that match results obtained experimentally. This model updating approach can be used to detect damage in a structural system by periodically searching for changes in model parameters that can be linked directly to suboptimal system performance. Since models decompose the structural system into discrete elements, damage can not only be detected, but localized through direct association with a particular model element.

Many approaches to model updating have been proposed over the years; in this study, simulated annealing (SA) is selected to stochastically search a model parameter space to find the optimal vector of parameters that minimize the difference between the true and model-predicted structural behavior [14]. SA mimics the annealing process of materials in physics; a system is slowly cooled from a molten state such that it assumes the global minimum energy state amidst a nearly infinite number of possible molecular configurations. In model updating, the energy state to be minimized is the difference between the model and the true system output while system configurations are represented model parameters. The parameter space is randomly searched for a set of parameters that offer the minimum (*i.e.* global minimum) energy state. A set of model parameters are accepted if it offers a lower energy state; however, this approach often prematurely converges to local minima. Therefore, to provide the search with a higher probability of finding the global minimum, the Metropolis criterion is used which occasionally accepts a higher energy state when the annealing temperature is high (*i.e.* at the search outset) [15].

SA model updating is attractive for implementation on a wireless sensing network. With limited resources available at any one node, the method must be implemented in a distributed fashion. While parallel SA techniques have been developed for distributed computing environments, most of these methods rely on communication between processing nodes taking place before and after each generated state in the search tree. This creates a constant demand for communication and limits the effectiveness of these methods when implemented within wireless sensor networks. By taking advantage of the fact that the annealing process typically rejects more energy states than it accepts, (especially as the algorithm converges toward a solution), the SA procedure can be parallelized. Specifically, this is done by breaking up the traditionally serial SA search tree (which is continuous across all temperature steps) into a set of smaller search trees, each of which corresponds to a given temperature step and begins with the global minimum values for the preceding step. Each of these smaller trees can be assigned to any available node on the network thereby allowing them to run concurrently. Because wireless sensor networks can enjoy ad-hoc topologies, these search trees can be distributed in real-time to any available processors in the sensing network.

Within this distributed SA methodology, each node is capable of independently beaconing the network, looking for idle computational units. In this way, an ad-hoc assignment of tasks can be propagated through the network, with each node making itself available for reassignment when its computations are complete. This type of ad-hoc assignment is useful in large networks where numerous computational tasks (stemming from either the same or different computational models) may be assigned simultaneously. Since ad-hoc reassignment of tasks allows individual nodes to drop from the network mid-task, this type of ad-hoc computation is also valuable in systems where sensor or communication reliability may be in question.

In the implementation used in this study, the user can assign an optimization task to any one sensing unit, along with an initial temperature, T_0. This sensor can then search the wireless network for other available computational nodes, passing on optimization tasks to the first available node, along with the current global minima and the next temperature step, T_1. This process continues until no available nodes remain. If the initial node finishes its part of the computation without finding a solution, it will alert its successor node that it has not solved the problem, and will make itself available for future task reassignment. As the parallelized search progresses, updated global state information is disseminated downwards through the network, allowing all inherited nodes to maximize the effectiveness of their search at a given temperature. Specifically, when a node detects a new global minimum energy state, it will propagate this information downward to the node directly below it in the search tree (its child). If the propagated information represents a new global minimum at the successor (child) node, this node will then restart its iterations with the new global minimum state information and inform the node directly below of its updated state information. Otherwise, if a message received from a parent node does not represent a new global minimum (*i.e.* if the child finds a lower valued state faster than the parent), the child node will merely restart its iterations given its current state information, without passing anything on to its successor. In this way, it is assured that each temperature step is thoroughly searched given the global minimum state information from the preceding temperature step. Given the parallelism inherent to this implementation, there is a

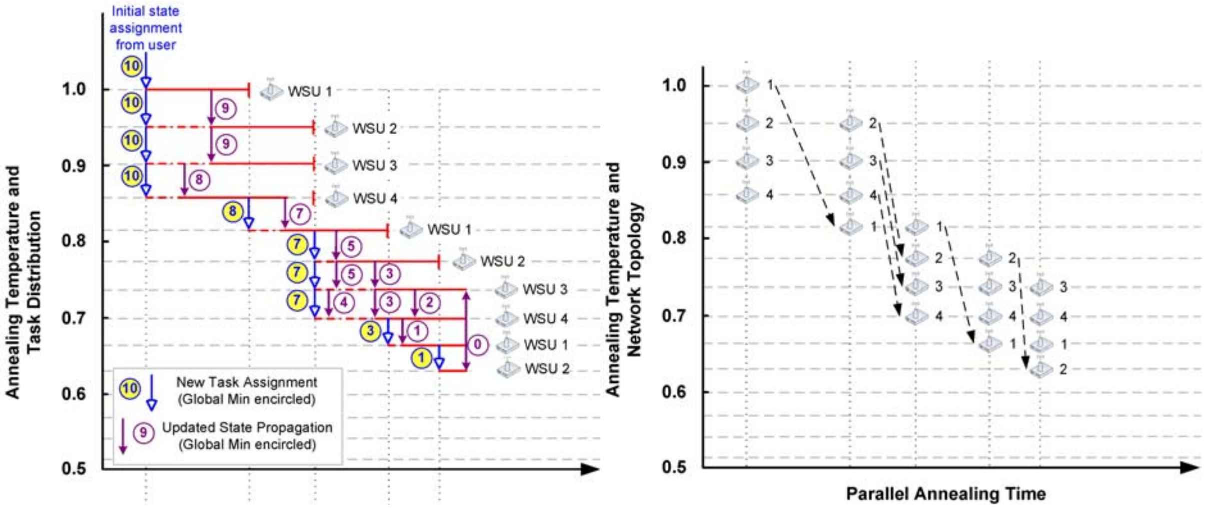

FIGURE 2 – DISTRIBUTED IMPLEMENTATION OF SIMULATED ANNEALING IN A WIRELESS SENSOR NETWORK: (LEFT) TASK DISTRIBUTION VERSUS ANNEALING TIME; (RIGHT) NETWORK TOPOLOGY VERSUS ANNEALING TIME.

natural increase in the total number of randomly generated states at all times which increase the probability that a “better” solution will be found at a lower temperature step.

This parallel method may seem somewhat wasteful at high temperatures, but as the search algorithm converges on a solution, it becomes decreasingly likely that a new global minimum state will be found at a given temperature step. Thus, especially as the search nears completion, successive nodes are all truly running in parallel and the number of computational nodes assigned to the task weighs heavily on the amount of time saved by parallelization. A sample simulated annealing process is presented in Figure 2. In this figure, the evolution of task assignments and network topologies is presented for a four node wireless sensor network (where each wireless sensor is denoted as “WSU”).

DAMAGE DETECTION BY MODEL UPDATING

For experimental purposes, a small three-story aluminum structure is constructed and its base is connected to a unidirectional modal shaker. Each floor is instrumented with one accelerometer oriented in the direction of the lateral excitation. The wireless sensor proposed by Wang *et al.* [10] is used to record accelerometer data. Figure 3 presents a picture of the base-excited laboratory structure; note that one wireless sensor is mounted to each level. Embedded within each wireless sensor is a lumped mass shear structure model with the mass and stiffness of each floor a parameter to be varied. Model updating is performed after the structure has been excited with broad-band white noise at the base of the structure. Wireless sensors stochastically search the parameter space to find an optimal set of floor mass (it is assumed the mass is the same on every floor) and lateral floor stiffness (it is assumed that the stiffness varies from floor to floor): m, k_1, k_2, and k_3.

The objective function to be minimized in this study is a weighted average between differences in the identified modal frequencies of the structure and modal assurance criteria (MAC):

FIGURE 3 – THREE STORY TEST STRUCTURE UPON WHICH WIRELESS SENSORS ARE INSTALLED. MODEL UPDATING IS PERFORMED BY THE WIRELESS SENSOR NETWORK.

$$E = \alpha \cdot \sum_{i=1}^{n} \left(\frac{\omega_{ai} - \omega_{ei}}{\omega_{ei}} \right)^2 + \beta \cdot \sum_{j=1}^{n} \frac{\left(1 - \sqrt{MAC_j}\right)^2}{MAC_j} \qquad (1)$$

where ω_{ai} and ω_{ei} are the i^{th} analytical and experimental modal frequencies, n is the number of modes, MAC_i is the modal assurance criteria of the i^{th} mode, and α and β are weighting constants determined experimentally to properly account for differences in the magnitudes between the two objective functions. For this paper, α is taken to be 0.4 and β is taken to be 0.6. The MAC is defined by Allemang and Brown [16] as (where ϕ_i is the i^{th} mode):

$$MAC_i = \frac{\left(\phi_{ai}^T \phi_{ei}\right)^2}{\left(\phi_{ai}^T \phi_{ai}\right)\left(\phi_{ei}^T \phi_{ei}\right)} \qquad (2)$$

Once the undamaged structure has been tested, damage is induced in one of the base columns by gradually reducing the column section at the first story. Reduction increments of 25%, 50%, 75%, and 100% are used, with a full model update being performed between each increment. Section reductions of the column are introduced by cutting the column. Once data has been collected for each increment of damage, results are compared and changes in floor stiffness are looked at as indications of structural damage. Table 2 shows the model updating results obtained for varying degrees of column damage. It can be seen that when significant damage was induced in a column, the model updating procedure was able to detect and localize the induced damage.

CONCLUSIONS

This study explores new computational tools that allow wireless monitoring systems to interrogate response data for damage detection. Specifically, a parallel simulated annealing model updating procedure is embedded. This approach allows for ad-hoc network topologies to

	1st Floor Stiffness	2nd Floor Stiffness	3rd Floor Stiffness	1st Floor Change	2nd Floor Change	3rd Floor Change
0%	2.88 lb/in	3.45 lb/in	4.21 lb/in	--	--	--
25%	2.89 lb/in	3.48 lb/in	4.18 lb/in	0.4%	0.9%	-0.7%
50%	2.31 lb/in	3.47 lb/in	4.18 lb/in	-19.8%	0.5%	-0.7%
75%	2.30 lb/in	3.46 lb/in	4.27 lb/in	-20.1%	0.3%	1.4%
100%	1.59 lb/in	3.70 lb/in	3.93 lb/in	-44.7%	7.3%	-6.7%

TABLE 2 – SUMMARY OF SIMULATED ANNEALING MODEL UPDATING RESULTS AS REPORTED BY THE WIRELESS SENSOR NETWORK.

form and for stochastic searches to occur in a parallel fashion using a large number of wireless sensors. For validation, a simple three-story shear structure is used; the SA analysis conducted by the wireless sensor network is effective in identifying changes in the first floor stiffness as damage was introduced. Future work in this area will include further validation of the damage detection capabilities of the wireless monitoring system and exploration of more complex structural models.

ACKNOWLEDGEMENT

The work presented in this paper has been supported by the National Science Foundation (NSF) through grant numbers CMMI 0726812, CMMI 0724022 and CMMI 0421180. The authors would also like to acknowledge the assistance offered by R. Andrew Swartz, a Ph.D. candidate in the Department of Civil and Environmental Engineering at the University of Michigan.

REFERENCES

[1] MnDOT, *Interstate 35W Mississippi River Bridge Fact Sheet*, http://www.dot.state.mn.us/i35wbridge/pdfs/factsheet.pdf (accessed on: December 15, 2007).

[2] FHWA, *Status of the Nation's Highways, Bridges, and Transit: Conditions & Performance*, Report # FHWA-PL-03-004, Federal Highway Administration, Washington, D. C., 2003.

[3] Wardhana, K. and Hadipriono, F. C., "Analysis of Recent Bridge Failures in the United States", *Journal of Performance of Constructed Facilities*, Vol. 17, No. 3, 2003, pp. 144-150.

[4] Wenzel, H. and Pichler, D., *Ambient Vibration Monitoring*, Wiley, West Sussex, U.K.

[5] Doebling, S.W., Farrar, C.R. and Prime, M.B. “A Summary Review of Vibration-based Damage Identification Methods,” Shock and Vibration Digest, Vol. 30, No. 2, 1998, pp. 91-105.

[6] Celebi, M., *Seismic Instrumentation of Buildings with Emphasis on Federal Buildings*, Report # 0-7460-68170, United States Geological Survey, Menlo Park, CA, 2002.

[7] Lynch, J.P. and Loh, K., “A Summary Review of Wireless Sensor Networks for Structural Health Monitoring.” *Shock and Vibration Digest*, Vol. 38, No. 2, 2006, pp. 91-128.

[8] Straser, E. and Kiremidjian, A. S., *Modular, Wireless Damage Monitoring System for Structures,* Report # 128, John A. Blume Earthquake Engineering Center, Stanford, CA, 1998.

[9] Spencer, B.F., Ruiz-Sandoval, M.E.,and Kurata, N. “Smart Sensing Technology: Opportunities and Challenges,” *Journal of Structural Control and Health Monitoring*, Vol. 11, No. 4, 2004, pp. 349-368.

[10] Wang, Y., Lynch, J. P. and Law, K. H., "A Wireless Structural Health Monitoring System with Multithreaded Sensing Devices: Design and Validation", *Structure and Infrastructure Engineering*, Vol. 3, No. 2, 2007, pp. 103-120.

[11] Lynch, J. P., Wang, Y., Loh, K., Yi, J. H. and Yun, C. B., "Performance Monitoring of the Geumdang Bridge Using a Dense Network of High-Resolution Wireless Sensors", *Smart Materials and Structures*, Vol. 15, No. 6, 2006, pp. 1561-1575.

[12] Zimmerman, A.T., Shiraishi, M., Swartz, R.A. and Lynch, J.P. “Automated Modal Parameter Estimation by Parallel Processing within Wireless Monitoring Systems,” *Journal of Infrastructure Systems*, 2008, in press.

[13] Rolfes, R., Zerbst, S., Haake, G., Reetz, J. and Lynch, J. P., “Integral SHM-system for Offshore Wind Turbines using Smart Wireless Sensors,” Proceedings of the 6th International Workshop on Structural Health Monitoring, Stanford, CA, 2007, pp. 1889-1896.

[14] Levin, R. I. and Lieven, N. “Dynamic Finite Element Model Updating using Simulated Annealing and Genetic Algorithms,” *Mechanical Systems and Signal Processing*, Vol. 12, No. 1, 1998, pp. 91-120.

[15] Metropolis, N., Rosenbluth, A. W., Rosenbluth, M., Teller, A. H. and Teller, E. "Equation of State Calculations by Fast Computing Machines," *Journal of Chemical Physics*, Vol. 21, No. 6, 1953, pp. 1087-1092.

[16] Allemang, R. J. and Brown, D. L., “A Correlation Coefficient for Modal Vector Analysis,” *Proceedings of the 1st International Modal Analysis Conferenece (IMAC I)*, 1982, pp. 110-116.