International Journal of Energy, Information and Communications
Vol.6, Issue 4 (2015), pp.35-44
http://dx.doi.org/10.14257/ijeic.2015.6.4.03

Survey of Sensor Placement Methods for Structural Health Monitoring

Jaesung Park and Yujin Lim[1]

Department of Information Security, Department of Information Media
University of Suwon, San 2-2, Wau-ri, Bongdam-eup, Hwaseong,
Gyeonggi-do, 445-743, Korea
{jaesungpark,yujin}@suwon.ac.kr

Abstract

Structural health monitoring (SHM) systems use various sensors to diagnose the health of a structure in real time. Recently, wireless sensors are getting more attention because it can give a SHM system more flexibility than wired sensors. In this system, to identify the dynamic behavior of a structure, the minimum number of sensor nodes needs to be deployed while providing adequate amount of information to reduce the cost of a system and avoid the duplication of information. Therefore, an optimal sensor placement (OSP) becomes an important engineering issue to minimize the number of sensors and increase the accuracy of the assessment based on the sensor measurements. In the networking and computer science communities, the optimal sensor placement (OSP) problem has been one of the key research topics on wireless sensor networks (WSNs). Even though there have been a lot of proposals for the OSP in the context of WSNs, they focus on satisfying the requirements of various applications using WSNs, such as area coverage, network connectivity, network longevity, and data fidelity, without considering the SHM requirements from the civil engineering domain. Therefore, the sensors located at the optimal positions satisfying the network requirements may not provide valuable information to judge the health of a structure. Therefore, in this paper, we survey the OSP methods considering the requirements of the civil engineering and discuss their key ideas. In addition, we introduce notable WSNs deployed for the SHM in the field.

1. Introduction

Monitoring the health of a structure is important to detect critical damages of the structure in advance. To assess the health of a structure, most structural health monitoring (SHM) systems have used wired data acquisition systems to collect data from sensors located at various positions of a structure. However, it usually takes long time to install wired data acquisition system. In addition, a wired data acquisition system may not be installed at a critical position of a structure. A wireless sensor network (WSN) is attracting much attention as a data acquisition system for a SHM system because it can be installed, operated and managed in a cost effective and flexible manner [1, 2].

However, even though wireless data acquisition has many advantages, it is difficult to achieve reliable data transmission and time synchronization [3]. One of the most important issues to use a WSN as a data acquisition system for SHM is the optimal sensor placement (OSP) problem. To reduce the cost of a system while providing adequate amount of information for a SHM system to identify the dynamic behavior of a structure, the minimum number of sensor nodes needs to be deployed. Therefore, an optimal sensor placement becomes an important engineering issue to minimize the number of sensors and increase the accuracy of the assessment based on the sensor measurements.

[1] Corresponding author

ISSN: 2093-9655 IJEIC

In the networking and computer science communities, the optimal sensor placement problem has been one of the key research topics on WSNs. There have been a lot of proposals for the OSP in the context of WSNs. Good surveys could be found in [21-23]. However, they focus on satisfying the requirements of various applications using WSNs, such as area coverage, network connectivity, network longevity, and data fidelity, without considering the SHM requirements from the civil engineering domain. Therefore, the sensors located at the optimal positions satisfying the network requirements may not provide valuable information to judge the health of a structure. Therefore, we focus on the OSP methods considering the requirements of the civil engineering. However, we note that this survey is not exhaustive. In the point of view of the civil engineering, a finite element (FE) model for a structure is constructed to obtain optimal sensor locations. The FE model should be accurate enough to capture the behavior of the structure. Using the FE model, the modal analysis is performed to derive the structural characteristics such as vibrations, damping ratio, and eigenfrequencies.

The rest of the paper is organized as follows. In Section 2, we survey and discuss the various OSP methods for the SHM. In Section 3, we present notable case studies that use WSNs for the SHM in the field. Then, we conclude the paper in Section 4.

2. Sensor Placement

Mathematically, as is noted in [4], the OSP problem is considered as an integer optimization problem. Let us denote the total number of degrees-of-freedom (DoFs) of a structure is n, the number of target mode shapes is m, and the number of sensor nodes is s. We also denote the mode shape matrix as Φ ($\in R^{n\times m}$). Then, the OSP problem is to select s out of n rows of Φ so that the reduced matrix Γ ($\in R^{s\times m}$) whose row i indicates the mode shape measurement results from a sensor i meets a given selection criteria [5].

The linear optimization problem is the NP hard combinatory integer problem. Therefore, searching exhaustively whole the search domain to find an optimal set of sensor positions becomes computationally prohibitive as n and m increases. To resolve the problem, a lot of methods have been proposed by taking various approaches. For example, the sub-optimal addition methods are proposed in [6,7]. The genetic algorithms is used in [8, 9], and the monkey algorithm is used in [10]. A Bayesian approach is taken in [11], and a multiple optimization approach is adopted in [12].

The evaluation criteria for the goodness of sensor locations determines the effectiveness of a given sensor placement [4, 13, 14]. Modal assurance criterion (MAC) [6], probability-based damage detection criterion [11], singular value decomposition [15], Fisher information matrix criteria [16, 17], and measured energy [18] are most commonly used criteria for the SHM applications.

- Modal Kinetic Energy(MKE) Method

  MKE provides a measure of contribution of each DoFs to each of the target mode shapes [16]. The kinetic energy of a sensor node i for a target mode shape n is given as

$$\mathrm{MKE_{i,n}} = \phi_{\mathrm{i,n}} \sum \mathrm{M_{i,j}} \phi_{\mathrm{j,n}},$$

  where $\phi_{\mathrm{i,n}}$ is the ith coefficient in the corresponding mode, $\mathrm{M_{i,j}}$ is the (i,j) elements of the FE model mass matrix. According to the $\mathrm{MKE_{i,n}}$, sensor locations could be selected so that the amount of contribution of each sensor is as large as possible. Since MKE provides the goodness of each DoF to represent the most relevant features of a structure, it is often employed at the first stage of an OSP to identify potential sensor locations.

- Effective Independence (EI) and its Variants

EI method has been used often for modal testing and modal update [14]. EI method considers not only the amount of information provided by a measurement point but also the dependence between mode shapes when it selects a sensor position. Technically, EI method analyzes the covariance matrix of the estimate error for an efficient unbiased estimator. It is shown in [16] that the optimal sensor locations that can provide the best estimates of the modal states can be obtained by maximizing the determinant of the Fisher Information Matrix.

However, EI method could select the locations whose energies are low. In this case, important information may be lost consequently. In [19], a driving-point residue (DPR) method is combined with the EI method to select those locations with high energy contents. To achieve the goal, the authors in [19] extend the effective independence distribution vector obtained by EI method by multiplying the amount of contribution of a sensor location by the corresponding DPR coefficient.

- Minimum Modal Assurance Criterion (minMAC) Method

In [6], the modal assurance criterion is used to judge the goodness of sensor locations. If we denote Φ as the matrix of target mode shapes, the MAC between modal vector Φ_i and Φ_j is defined as

$$\Psi_{i,j} = \frac{\left(\Phi_i^T \Phi_j\right)^2}{\left(\Phi_i^T \Phi_i\right)\left(\Phi_j^T \Phi_j\right)}$$

where Φ_i and Φ_j is the *i*-th and *j*-th column vector of Φ, respectively. The larger $\Psi_{i,j}$ becomes, the more correlation there is between Φ_i and Φ_j. It means that two modal vectors are hardly distinguishable if $\Psi_{i,j}$ approaches to 1. A sensor position is determined so that the maximum off-diagonal terms of the MAC matrix are minimized.

A forward-backward combinatorial minMAC is proposed in [4] by extending the idea of [6]. They note that when the minMAC is applied, the off-diagonal terms of the MAC matrix do not decrease monotonically as the number of sensors increases. To overcome the problem, the authors combine the forward addition minMAC method and the backward deletion minMAC method.

- Modal Strain Energy – Adaptive Genetic Algorithm (MSE-AGA) Method

A MSE-AGA method is proposed in [20] whose computation time is short while providing multiple optimal indexes. To achieve the objective, they combined the modal strain energy (MSE) method with the adaptive genetic algorithm (AGA). The MSE-AGA is composed of three steps. A suitable modal order is selected by the modal participation factor. Then, the initial sensor locations are selected by the MSE so that the location with high modal energy index becomes a candidate position. Finally, the AGA is applied to determine the optimal number of sensors and their optimal locations. The AGA uses the MAC as a fitness function so as to guarantee the root mean square and the maximum of the off-diagonal elements are small.

- Bayesian Approach

In [11], a new performance metric for the OSP based on the Bayesian decision theory is proposed. Unlike the other approaches that do not make any assumptions on the probability distribution of the states to be estimated a priori, they include a priori information to optimally infer system parameters. Specifically, they formulate the OSP problem using the Bayesian decision theory under a given global detection rate or global false alarm rate. In their objective function to be optimized, the relationship between the local versus distributed sensor coverage, the distributed damage occurrence, and the costs of the false positive and the false negative are included. By explicitly incorporating the goal of the application into the object function, the Bayesian approach is expected to be applicable to various SHM systems.

- Uniform Design (UD) Method

In [7], authors presented an optimal sensor placement method for structural vibration measurements. They devised four fitness functions to quantify the similarity between the real mode shapes and the measured mode shapes. Given a set of sensor positions, the corresponding fitness values are calculated, which are used to decide whether the positions of sensors are optimal or not. Therefore, to obtain an optimal set of sensor locations, the number of tests increases exponentially with the number of sensors and the number of potential sensor locations, which makes it less attractive to be applied for engineering applications. To overcome the experimental complexity, they used the uniform design theory [21] to reduce the number of experiments while managing the accuracy of the test results relatively high. In other words, the authors in [7] allocate experimental points so that they are scattered uniformly in the experimental domain using the UD method. Since the UD method reduces the number of experiments by ignoring the high-order interactions, there are places where sensor nodes are not located. Thus, interpolation method is used to derive the mode shapes at those points.

- Optimal Sensor Placement Strategy (OSPS)

In [12], an optimal sensor placement strategy (OSPS) is proposed through multiple optimizations. Let Φ be the mode matrix obtained from the finite element model of a structure. Then, the OSPS is composed of three steps. Using the QR factorization of the Φ into an orthogonal parts and a triangular parts, initial sensor locations are obtained. At the second stage, the optimal sensor positions are found by a sequential sensor placement (SSP) method. The authors proposed two types of SSP. In a forward SSP (FSSP), sensor nodes are added one by one so that the amount of reduction in the maximum off-diagonal elements for a new sensor node becomes the highest given the optimal sensor positions that have been found in the previous steps. On the contrary, a backward SSP (BSSP) works in the opposite way. After placing sensor nodes at all the degrees-of-freedom of the structure, BSSP removes one sensor node at a time. Since the location of a sensor node is determined iteratively, the corresponding sensor locations are suboptimal. Thus, at the final stage, the sensor locations are optimized globally by the generalized genetic algorithm. Unlike the other sensor placement methods that try to find the optimal sensor locations under the assumption that the number of sensors is given, the authors in [12] also provide an OSPS toolbox for a civil engineer who does not familiar with writing an optimization program to obtain the optimal sensor locations intuitively by varying the number of sensors.

- Sensor Placement using EI Method (SPEM)

  A sensor deployment module using EI is proposed in [22]. This is the first interdisciplinary attempt that integrates the constraints from the civil engineering and the requirements from the computer science that are imposed on WSNs for the sensor placement. Among the various sensor placement methods from the civil engineering, the SPEM uses the EI method that assesses the importance of sensor locations by the determinant of the Fisher Information Matrix (FIM). However, the EI method does not consider the constraints imposed on WSNs. For example, to evaluate the health of a structure, the data measured by sensors should be delivered to a data collection point in time. To overcome the deficiency, SPEM includes the computer science (CS) optimization module. The CS optimization module evaluates the sensor locations and the FIM weights obtained by the EI method by considering the requirements of a WSN such as traffic routing, energy efficiency, and topology control. SPEM is validated with the data from Ting Kau bridge and through real experiments on Guangzhou New TV tower. Even though, SPEM could improve the sensor network design for the SHM with the interdisciplinary knowledge, the fully centralized approach may not assure the fidelity of the network if faults occur on a sensor node or communication links.

- energy SPEM

  In [23], the SPEM is improved by considering the amount of the energy consumption of a sensor node. In SPEM, sensor locations are determined so that the determinant of the FIM (Q_{FIM}) is maximized. Denoting E_{max} as the maximum energy used by a sensor in one round of data transmission, the authors in [23] propose a new objective function (Q_{FIM}/E_{max}) to be maximized so that the energy consumed by a sensor node is minimized.

- Sensor Placement using EI Method (FTSHM)

  A fault-tolerant wireless sensor placement method for the SHM (FTSHM) is proposed in [24]. They note that the optimal sensor positions obtained by EI cannot provide the fault-tolerance for the SHM because it does not consider the characteristics of a WSN. Wireless sensors are prone to faults and communication links between sensors are unreliable. Therefore, even though sensors located at the optimal points can measure critical data, a monitoring center may not acquire necessary data in time because of the loss of data in a WSN, which cold neutralize the SHM system. They also note that the generic topologies of a WSN such as random, uniform, grid, or tree may not be suitable for the SHM because sensors located at those positions may not provide meaningful information for the SHM.

  To overcome the difficulties, they propose FTSHM that takes two steps for sensor placements. First, they deploy primary sensors using the EI method to consider the requirements of the civil engineering. Then, considering networking requirements of a WSN such as ensuring network connectivity and reliable data delivery, they deploy the backup sensors called repairing points (RPs) under the environment where *N* primary sensor locations are given. Since highly possible RPs are searched in a distributed manner by limiting the search scope to a cluster, it can avoid problems caused by the methods operating in a centralized manner.

The brief summary is given in Table 1.

7. Case study

There have been notable WSNs deployed for the SHM in the field. In [25], a WSN for the SHM is designed and tested on the south tower of Golden Gate Bridge in San Francisco. They deploy 64 MicaZ sensor nodes. Each sensor node has a 512KB flash memory and does not provide link-level retransmission. The sensor nodes collect vibration data. The measurement frequency is tuned to fill up the flash memory, which is collected from every sensor nodes one at a time. They identify the problem of acquiring data whose quality is sufficient enough for the SHM. They provide the solution for accurate data acquisition, high frequency sampling with low jitter, and time synchronization. From the experiments on the real world structure, they point out future research topics on WSNs for the SHM. Small packets do not

Table 1. Optimal Sensor Placement Methods for the SHM

Method	Types	Description
MKE[16]	Engineering Approach	Kinetic energy of a sensor node for a target mode shape is used to select a sensor position in a way that the contribution of each sensor is as large as possible.
EI and its variants [14, 16, 19]	Engineering Approach	Optimal sensor locations providing the best estimates of the modal states are obtained by maximizing the determinant of the Fisher Information Matrix.
minMAC [4, 6]	Engineering Approach	Modal assurance criteria (MAC) is used to decide the goodness of the sensor locations. Sensor positions minimizing the maximum off-diagonal element of the MAC matrix are selected.
MSE-AGA [20]	Engineering Approach	Modal strain energy is combined with the adaptive genetic algorithm which uses the MAC as the fitness criteria to reduce computation time to find the optimal sensor positions while providing multiple optimal indexes.
Bayesian [11]	Engineering Approach	Bayesian decision theory is used to formulate the OSP problem which incorporates explicitly the relationship between the local versus distributed sensor coverage, the distributed damage occurrence, and the costs of the false positive and the false negative.
UD [7]	Engineering Approach	To overcome the experimental complexity, the uniform design theory is used to reduce the number of experiments while maintaining relatively high accuracy level of the test results.
OSPS [12]	Engineering Approach	Multiple optimization method is devised to find the optimal sensor locations. After finding initial sensor locations through the QR factorization of the mode matrix of a structure, sequential sensor placement method determines an optimal sensor position one at a time. Finally, the genetic algorithm is applied to determine the globally optimal sensor locations
SPEM [22]	Combined	SPEM is an interdisciplinary approach for an OSP problem that integrates both the constraints from the civil engineering and the requirements imposed on a WSN from the computer science domain.
energy SPEM [23]	Combined	SPEM is improved by considering the amount of the energy consumption of a sensor node.
FTSHM [24]	Combined	Primary sensor locations satisfying the requirements from the civil engineering are determined by the EI method. Then, the backup sensors are positioned to meet the requirements imposed on a WSN such as ensuring network connectivity and reliable data transfer from a sensor to a sink.

fully exploit underlying transmission bandwidth and increasing the size of a packet does not help much. In addition, they underscores that heavy traffic prevents the system from estimating link quality correctly, and it causes a problem in the routing function.

A SHM benchmark problem for high-rise slander structure is developed by ANCRiSST (Asian-Pacific Network of Centers for Research in Smart Structures Technology) and ISHMI (International Society for Structural Health Monitoring of Intelligent Infrastructure) [26]. The Guangzhou New TV Tower (GNTVT) is used as a testbed. More than 700 sensors of 16 different types are implemented to monitor the GNTVT not only for the in-construction phase but also for the in-service phase. The objectives of the benchmark problem come in three folds. First, it aims to provide an open platform to the researchers and practitioners and exchange their innovative strategies. The second objective is to apply various algorithms to the real high-rise slender structures and examine the reliability of the techniques. Lastly, the benchmark problem is to close the gap between the algorithms and the practice in the SHM. The first phase of the benchmark has four study tasks, and further phases will be identified and developed gradually.

A Structure-Aware Self-Adaptive WSN system (SASA) is developed to monitor underground structures [27]. A SASA is designed to achieve two goals. A SASA should rapidly detect the collapse area of coal mines. In addition, a SASA should be able to detect the structure of a sensor network to maintain the system integrity. To satisfy the design requirements, a SASA regulates the hexagon mesh topology among the sensor nodes and devises a collaborative mechanism to detect structural variations based on the beacon messages. A prototype of the SASA is composed of 27 Mica2 sensor nodes and is applied to the D. L. coal mine to detect holes. 27 Mica2 motes are deployed manually at the predefined positions with an interval of 3 meters. In their experiments, they showed that a SASA could locate the holes accurately. Based on the experimental results, they underscore that since the beacon interval can tradeoff between the communication quality and the processing latency, it should be selected carefully considering the application workload.

In [1], a multi-hop wireless sensor data acquisition system for the SHM (called Wisden) is devised and its performance is tested on a large seismic test structure used by civil engineers. In their system design, the authors consider the requirements of the structural monitoring and the characteristics of real structures. In theory, the sampling rate of 50Hz is assumed to be sufficient to capture the dominant modal frequencies of structures. However, they point out that the typical real civil structures have high damping characteristic. A SHM system for these structures needs higher sampling rates. Since sensor nodes are limited in the wireless transmission bandwidth, the processing power and the memory size, the high sampling rate requirement imposes a great challenge on the design of Wisden. Considering the design requirements, a Wisden is designed to collect and reliably deliver time-synchronized data to a sink node. To achieve its design goal, a Wisden provides tree topology self-configuration, reliable data transfer not only in a hop-by-hop manner but also in an end-to-end fashion, data synchronization, and data compression. By testing a Wisden on a full scale model of an actual hospital ceiling, it is shown that Wisden can deliver time synchronized vibration data reliably at a sampling rate of as high as 200Hz.

The D3S which is a cross institutional research group in Treno, Italy developed a SHM system for a heritage building Torre Aquila in Treno Italy [28]. They develop customized hardware and software services on top of their TeenyLIME middleware [29] instead of on top of the operating system. The software services include data collection reconciling data rates and reliability requirements, data dissemination, and time synchronization. They deploy 17 sensor nodes including a sink node that can access the external WiFi network. The locations of the sensors are selected a priori to detect the deterioration of the structure early. Using the data obtained from 4 months of operation, the authors show that the data loss rate is less than 0.01%. In addition, through the analysis of the energy consumption, they assert that a single sensor node is expected to operate beyond one year.

On the contrary that most of works on WSNs for the SHM focus on the above-water structures, the feasibility of an underwater wireless sensor network (UWSN) for the health monitoring of offshore civil structures is studied in [30]. They validated the communication aspect of UWSNs. Specifically, the network communication topology and in-network processing algorithms for two offshore structures - Middelgrunden and Horns Rev offshore wind farms in Denmark - are simulated by Aqua-Sim [31].

A BriMon is designed for railway bridge monitoring in India [32]. Since there are as many as 120,000 bridges spread over large geographical area, a system that is not only easy to deploy but also requires minimal maintenance is required. The first design requirement can be satisfied by adopting wireless sensors operated by battery. However, for minimal maintenance, the lifetime of the deployed nodes should be as long as possible while providing critical information on the health of a bridge in time. To tackle the challenge, BriMon focuses on the low energy consumption and a novel event detection mechanism to balance the conflicting requirements. BriMon introduces a beaconing train and high gain external antenna at a designated node on a bridge. The designated node detects the beacon messages sent by the beaconing train before the train passes the bridge under monitoring. By gaining time to wake up the other sensor nodes before a train approaches a bridge, BriMon could fulfill very low duty cycle of a sensor node while measuring the health of a bridge accurately. In their prototype, each node equipped with four AA batteries could run 1.5 years approximately. Moreover, unlike the other approaches that use sensor nodes or the other networks to transfer the measured data at each sensor node to a central controller, BriMon uses the train itself for the data transfer.

8. Conclusion

In this paper, we surveyed the optimal sensor placement methods to use a WSN as a data acquisition system for the SHM. We also present several cases that use WSNs for the SHM in the field to show that a WSN is a cost-effective and viable platform for structural health monitoring.

However, there are other important issues to adopt a WSN as a data acquisition system for the SHM and these issues are often interconnected, which means that the design to address one issue can influence on the operation of the other issues. Therefore, an integrated optimal design process taking all the issues into consideration is needed to design more flexible, robust, efficient, and economic data acquisition system for the SHM using WSNs.

Acknowledgement

This work was supported by the GRRC program of Gyeonggi province. [(GRRCSUWON2015-B3), Development of Cloud Computing-based Intelligent Video Security Surveillance System with Active Tracking Technology]

References

[1] J. Paek, K. Chintalapudi, R. Govindan, J. Caffrey, and S. Masri. A Wireless Sensor Network for Structural Health Monitoring: Performance and Experience. Proceedings of the Second Workshop on Embedded Networked Sensors, **(2005)** May 30-31; Sydney, Australia.

[2] N. Xu, S. Rangwala, K.-K. Chintalapudi, D. Ganesan, A. Broad, R. Govindan, and D. Estrin. A Wireless Sensor Network for Structural Monitoring. Proceedings of the Second International Conference on Embedded Networked Sensor Systems (SenSys '04), **(2004)** November 3-5; Baltimore Maryland, USA.

[3] P. Nie and Z. Jin. Requirements, challenges and opportunities of wireless sensor networks in structural health monitoring. Proceedings of International Conference of the IEEE Broadband Network and Multimedia Technology (IC-BNMT'10), **(2010)** October 26-28; Beijing, China

[4] D. S. Li, C. P. Fritzen, and H. N. Li. Extended minMAC algorithm and comparison of sensor placement methods. Proceedings of the SEM 26th Conference and Exposition on Structural Dynamics, **(2008)** February 4-7; Orlando, US.

[5] C. Papadimitriou, Optimal sensor placement methodology for parametric identification of structural systems. Elsevier Journal of Sound and Vibration, vol.278, no.4-5, pp.923–947 **(2004)**.

[6] T. G. Carne, and C. R. Dohrmann. A modal test design strategy for model correlation. Proceedings of the SEM 13th International Modal Analysis Conference, **(1995)** February 13-16; Nashville, US.

[7] Z.N. Li, J. Tang, and Q.S. Li, Optimal sensor locations for structural vibration measurements. Elsevier Applied Acoustics, vol.65, no.8, pp.807-818 **(2004)**.

[8] W. Liu, W.-C. Gao, Y. Sun, and M.-J. Xu, Optimal sensor placement for spatial lattice structure based on genetic algorithms. Elsevier Journal of Sound and Vibration, vol.317, no.1-2, pp.175–189 **(2008).**

[9] F. Kang , J.-J. Li, and Q. Xu, Virus coevolution partheno-genetic algorithms for optimal sensor placement. Elsevier Advanced Engineering Informatics, vol.22, no.3, pp.362–370 **(2008)**.

[10] T.-H. Yi, H.-N. Li, and X.-D. Zhang, Sensor placement on canton tower for health monitoring using asynchronous-climb monkey algorithm. IOP Science, Smart Materials and Structures, vol.21, pp.1-12 **(2012)**.

[11] E. B. Flynn, and M. D. Todd, A bayesian approach to optimal sensor placement for structural health monitoring with application to active sensing. Elsevier Mechanical Systems and Signal Processing, vol.24, no.4, pp.891–903 **(2010)**.

[12] T.-H. Yi, H.-N. Li, and M. Gu, Optimal sensor placement for structural health monitoring based on multiple optimization strategies. The Structural Design of Tall Special Buildings, vol.20, no.7, pp.881–900 **(2011)**.

[13] T. G. Carne, C.R. Dohrmann. A modal test design strategy for model correlation. Proceedings of SEM International Modal Analysis Conference, **(1995)** February 13-16; Nashville, US.

[14] M. I. Friswell, and J.E. Mottershead, Finite element model updating in structural dynamics, Kluwer Academic Publishers **(1995)**.

[15] R. A. Horn, and C. R. Johnson, Topics in matrix analysis, Cambridge University Press **(1991)**.

[16] D. C. Kammer. Sensor placement for on-orbit modal identification and correlation of large space structures. Proceedings of the IEEE American Control Conference, **(1990)** May 23-25; San Diego, US.

[17] M. Basseville, A. Benveniste, G. V. Moustakides, and A. Rougee, Optimal sensor location for detecting changes in dynamical behavior. IEEE Trans. Automatic Control, vol.32, no.12, pp.1067–1075 **(1987)**.

[18] G. Heo, M. L. Wang, and D. Satpathi, Optimal transducer placement for health monitoring of long span bridge. Elsevier, Soil Dynamics and Earthquake Engineering, vol.16, no.7–8, pp.495–502 **(1998)**.

[19] M. Meo, and G. Zumpano, On the optimal sensor placement techniques for a bridge structure. Elsevier Engineering Structures, vol.27, no.10, pp.1488-1497 **(2005)**.

[20] C. He, J. Xing, J. Li, Q. Yang, R. Wang, and X. Zhang, A combined optimal sensor placement strategy for the structural health monitoring of bridge structures. Hindawi International Journal of Distributed Sensor Networks, vol.2013 **(2013)**.

[21] K.-T. Fang, D. K. J. Lin, P. Winker, and Y. Zhang, Uniform design: theory and application. American Statistical Association and American Society for Quality, Technometrics, vol.42, no.3, pp.237-248 **(2000)**.

[22] B. Li, D. Wang, and Y. Ni. High quality sensor placement for SHM systems: refocusing on application demands. Proceedings of the IEEE International Conference of Computer Communications (Infocom'10), **(2010)** March 15-19; San Diego, US.

[23] M. Najeeb A, and V. Gupta. Energy efficient sensor placement for monitoring structural health. Proceedings of International Electronic Conference on Sensors and Applications (ECSA), **(2014)**June 1-16.

[24] M. Zakirul A. Bhuiyan, G. Wang, J. Cao, and J. Wu. Deploying wireless sensor networks with fault-tolerance for structural health monitoring. Proceedings of the IEEE 8th International Conference on Distributed Computing in Sensor Systems (DCOSS'12), **(2012)** May 16-18; Hangzhou, China.

[25] S. Kim, S. Pakzad, D. Culler, J. Demmel, G. Fenves, S. Glaser, and M. Turon. Health monitoring of civil infrastructures using wireless sensor networks. Proceedings of International Symposium of the ACM Information Processing in Sensor Networks (IPSN'07), **(2007)** April 25-27; Cambridge, US.

[26] http://www.cse.polyu.edu.hk/benchmark/.

[27] M. Li, and Y. Liu. Underground structure monitoring with wireless sensor networks. Proceedings of the IEEE International Symposium on Information Processing in Sensor Network (IPSN'07), **(2007)** April 25-27; Cambridge, US.

[28] M. Ceriotti, L. Mottola, G. P. Picco, A. L. Murphy, S. Guna, M. Corrà, M. Pozzi, D. Zonta, and P. Zanon. Monitoring heritage buildings with wireless sensor networks: The Torre Aquila deployment. Proceedings of the IEEE International Conference on Information Processing in Sensor Networks (IPSN'09), **(2009)** April 13-16; San Francisco, US.
[29] P. Costa, L. Mottola, A. L. Murphy, and G. P. Picco. Programming wireless sensor networks with the TeenyLIME middleware. Proceedings of the ACM/USENIX International Conference on Middleware (Middleware'07), **(2007)** November 26-30; Newport Beach, US.
[30] J. Li, S. Jang, M. Zuba, J.-H. Cui, and Y. Zhu. Feasibility of underwater sensor networks for lifetime assessment of offshore civil structures. Proceedings of the IEEE Oceans, **(2012)** October 14-19; Hampton Roads, US.
[31] P. Xie, Z. Zhou, Z. P, H. Yan, T. Hu, J. Cui, Z. Shi, Y. Fei, and S. Zhou. Aqua-Sim: an NS-2 based simulator for underwater sensor networks. Proceedings of the IEEE/MTS Oceans, **(2009)** October 26-29; Biloxi. US.
[32] K. Chebrolu, B. Raman, N. Mishra, P. K. Valiveti, and R. Kumar. Brimon: a sensor network system for railway bridge monitoring. Proceedings of ACM 6th International Conference on Mobile Systems, Applications, and Services (MobiSys'08), **(2008)** June 17-20; Breckenridge, US.