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Wireless Sensor Placement for Structural Health Monitoring Trade-off Modal Independency and Energy Efficiency

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ABSTRACT

Optimal sensor placement is essential to design an effective structural health monitoring (SHM) system for a large-scale structure. Due to some attractive features of wireless sensor networks (WSNs), the extensive utilization of WSN-based SHM systems is promoted. When finding the optimal wireless sensor placement (OWSP), the performance of the WSNs is emphasized except the performance of data because wireless sensors are generally equipped with limited energy resources and bandwidths. Unfortunately, the two objectives are in conflict with each other and difficult to be optimized simultaneously. In the paper, the OWSP is formulated as a multi-objective optimization problem with the aim of finding a wireless sensor configuration trade-off modal independency and energy efficiency while maintaining the connectivity of the whole WSN. A multi-objective firefly algorithm (MOFA) is developed to find the Pareto front in the OWSP. A directive movement strategy is employed to drive fireflies to fly toward the Pareto front, while the nondirective movement approach is introduced to keep the diversity of the firefly population. Numerical simulation of a cable stayed bridge is performed to demonstrate the effectiveness of the MOFA. The results indicate that the developed MOFA is capable of capturing the Pareto optimal wireless sensor configurations with high accuracy and efficiency. Many wireless sensor configurations are provided to meet the demand of excellent modal independency or the requirement of high energy efficiency.

1. INTRODUCTION

Structural health monitoring (SHM) provides an effective approach for the safe operation of existing or newly built civil infrastrucures (Faravelli *et al*. 2014; Yang and Nagarajaiah 2014). Over the last several decades, successful implementation of long-term SHM systems on full-scale bridges has been widely reported (Zhou, *et al*. 2016).

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Wireless sensor networks (WSNs), which are featured with ease of installation, wireless communication, onboard computation, battery power, relatively low cost, and small size, have emerged as new paradigms of SHM (Jo *et al*. 2012). At present, WSN-based SHM systems have been successfully implemented on many full-scale bridges, such as the Golden Gate Bridge in the United States (Pakzad 2010), the 2nd Jindo Bridge in Korea (Jang *et al*. 2010), and the New Carquinez Bridge in the United States (Kurata *et al*. 2013). An excellent survey on the present stat-of-the-art research on the WSN-based SHM can be traced in Zhou et al. (2013a). It is well known that the reliability and serviceability of the evaluation results depend heavily on the quality of measured data, which in turn are determined by the sensor network. In the cases, the optimal sensor placement (OSP) plays a fundamental role for an effective SHM system.

For the OSP of tethered sensor networks in SHM, a large number of research efforts have been made. On one hand, many widely used optimization criteria have been proposed. Emblematic examples are the Effective Independence (EfI) method (Kammer *et al*. 1991), the modal assurance criterion (MAC) method (Carne and Dohrmann 1995), the modal kinetic energy (MKE) (Salama *et al*. 1987), and the information entropy indexes (Papadimitriou 2005; Zhou *et al*. 2015). On the other hand, a large number of optimization methods have been developed. Swarm intelligence algorithms show more excellent performance when compared with the deterministic optimization algorithms and sequential sensor placement algorithms. The genetic algorithm (Yao *et al*. 1993), the simulated annealing algorithm (Chiu and Lin 2004), the particle swarm optimization algorithm (He *et al*. 2014), the monkey algorithm (Yi *et al*. 2012), the wolf algorithm (Yi *et al*. 2014), the glowworm swarm optimization algorithm (Zhou *et al*. 2015b) and the firefly algorithm (Zhou *et al*. 2015a) have been adopted and improved to find the optimal sensor configuration. For more information, one can refer the literature Yi and Li (2012).

When the WSN is applied in the SHM system, the problem of optimal wireless sensor placement (OWSP) becomes more complicated. Except the effectiveness of the measured data is concerned, the performance of the WSN, like the lifetime, the connectivity, the energy efficiency, and the serviceability, is emphasized since the wireless sensors are generally integrated with limited energy, limited communication capacity, and limited computer power. Hada et al. (2012) proposed a near-optimal algorithm based on the Lagrangian heuristic method for minimizing the total cost of a WSN for the health monitoring of railway structures. Onoufriou et al. (2012) presented a two-step methodology to optimize the number of sensors and their locations to satisfy specific structural engineering requirements while adhering to the energy limitations imposed by a WSN. Bhuiyan et al. (2012) studied the methodology of sensor placement optimization for SHM that addresses the quality of sensor placements, communication efficiency, and network robustness. Fu et al. (2013) performed a study to optimize wireless sensors placements for SHM in terms of the quality of system identification and energy costs. A min-max, energy-balanced routing tree and an optimal grid separation formulation were proposed to minimize the energy consumption as well as provide fine grain measurements, which provides valuable reference for WSNs placement in SHM. Zhou et al. (2013b; 2013c) developed a two-phase node arrangement method to handle the energy consumption, data capacity, and deployment cost of WSNs in SHM. Liu et al. (2015) provided a wireless sensor deployment optimization scheme for SHM, in terms of both energy consumption and modal identification accuracy.

Previous researches generally model OWSP as a single objective optimization problem. As a matter of fact, the two aims of high quality of measured data and high performance of network are hard to achieve simultaneously. The objective of high quality of measured data tends to place sensors on positions with intense structural responses. However, the objective of high performance of network concentrates on the loads of each sensor nodes. In this paper, the OWSP is formulated as a multi-objective optimization problem. The quality of measured data is specified as the modal independency, and the performance of network is measured by the variance of the normalized total energy consumption of each sensor node. The multi-objective firefly algorithm (MOFA) is adopted to find the Pareto optimal wireless sensor configurations.

2. PROBLEM FORMULATION

2.1 Modal independency

The MAC, which provides a simple metric to verify the linear independence of the mode shapes, is defined by

$$MAC_{mn} = \frac{\phi_m^T \phi_n}{\sqrt{\left(\phi_m^T \phi_m\right)\left(\phi_n^T \phi_n\right)}}, \quad (1)$$

where ϕ_m and ϕ_n represent the m^{th} and n^{th} column vectors in model matrix Φ, respectively, and the superscript T denotes the transpose of the vector. With this definition, the values of the *MAC* range from 0 to 1, where 0 indicates that the modal vector is easily distinguishable and 1 indicates that the modal vector is fairly indistinguishable (Yi *et al*. 2011).

2.2 Energy efficiency

The condition that the sensor nodes are within the range of data transmission is the basic requirements of WSNs connectivity. The electromagnetic interference relates to the environment of the WSNs used and is difficult to model. The wireless node performance includes several aspects like the energy, the central processing unit, and the transmitting power. In this paper, the WSNs connectivity is simplified as that two nodes are able to communicate with each other if the Euclidean distance between them is not longer the maximum of their transmission ranges d_{max}. The index *DTL* is employed to describe the WSNs connectivity and expressed as

$$DTL_{kl} = \begin{cases} 0 & \text{If wireless sensor } k \text{ and } l \text{ is in the routing and } d_{kl} \le d_{max} \\ 1 & \text{Otherwise} \end{cases}, \quad (2)$$

where DTL_{kl} represents the connectivity between wireless sensors k and l in the data transmission routing and d_{kl} is the Euclidean distance between wireless sensors k and l.

Generally, the wireless sensors are powered by batteries with limited energy resources. The energy balance mechanism which deals with the balance of energy consumption in the network so that the network lifetime can be prolonged as much as possible is particularly important. The energy balance mechanism involves the energy-efficient routing and the energy-aware wireless sensor placement. In WSNs-based SHM systems, the data transmission routing is predetermined in most occasions. So the main challenge is to deploy the wireless sensors properly such that the energy consumption of each wireless sensor is uniform.

A wireless sensor, typically, contains sensing unit, processing unit, and transceivers. The energy consumption of sensor itself (e.g. calculating, waiting and so on), which depends on the sensor hardware architecture and the computation complexity, is another meaningful topic and not considered here. So it is assumed that the energy cost can only happen when transmitting or receiving packets. The energy consumption for transmitting and receiving are formulated as (Kalpakis *et al*. 2003)

$$E_t = \alpha q + \beta q d^2 \quad ,(3a)$$
$$E_r = \eta q \quad ,(3b)$$

where E_t represents the energy consumption for transmitting a packet with the size q to a distance d, E_r is the energy consumption for receiving a packet with the size q, α and η denotes node specific energy consumption coefficients in the transmitter circuitry and receiver circuitry, respectively, and β is the energy required to transmit per bit over a per unite distance in different cases. The total energy consumption of wireless sensor k is

$$E_k = E_{t,k} + E_{r,k} \quad ,(4)$$

where E_k represents the total energy consumption of wireless sensor k, and $E_{t,k}$ and $E_{r,k}$ denotes the energy consumption for transmitting and receiving of wireless sensor k, respectively.

Defining the normalized total energy consumption of wireless sensor k in data transmission routing as

$$\overline{E}_k = \frac{E_k}{E_{\max}} \quad ,(5)$$

where E_{max} is the maximal total energy consumption of a single wireless sensor in the WSN. By this way, the normalized total energy consumption ranges from 0 to 1.

Then, the variance of the normalized total energy consumption is used for indicating the balance of energy consumption and given by

$$EBM = \mathrm{var}(\overline{E}_k) \quad ,(k=1, \ldots, N), (6)$$

where *EBM* denotes the variance of the normalized energy consumption, var(·) represents the variance operator, and *n* is the total number of wireless sensors in the WSN.

2.3 Optimization function

The first objective function is

$$f_1 = MAC_{mn}\,(m \neq n),(7)$$

The second objective function is

$$f_2 = \left[\max(DTL) + \lambda EBM\right] \times \mathrm{L}_0\ ,(8)$$

where *λ* is a coefficient to make the *EBM* be comparable with *DTL*, and $\mathrm{L}_0 \in \boldsymbol{R}^{m\times m}$ denotes the transform matrix composed of ones and maps the digit to a matrix.

3. MULTI-OBJECTIVE FIREFLY ALGORITHM

3.1 Coding system

By referencing the GA code, a one-dimensional binary coding system is adopted in the MOFA. A firefly, such as the chromosome in the GA, represents a feasible solution. Its location is coded by a permutation. In the permutation, the index represents the number of DOFs and the value of an element indicates the condition of the DOF. If the value of the *π*th element is 1, which indicates that a sensor is located on the *π*th DOF. Conversely, if the value of the *π*th element is 0, no sensor is placed on the *π*th DOF. The length of a permutation represents the number of candidate DOFs and the total number of 1 in a permutation is equal to the sensor number. In a one-dimensional binary coding system, the Hamming distance (Hamming 1950) is employed to describe the distance between firefly i and firefly j.

3.2 Directive movement

The hybrid movement scheme including the directive movement (DM) and the nondirective movement (NDM) is proposed to improve the convergence speed and avoid falling into local optimization. The selecting of DM or NDM is governed by a parameter *ξ* that is generated randomly in each step. The parameter *ξ* is normalized in the interval [0, 1]. If *ξ* is greater than a predetermined parameter *v*, the DM is used; otherwise, the NDM is utilized.

Because the influence of each DOF on the objective functions in Eqs. (7) and (8) is difficult to predict, the relocation of incongruous sensors in the DM is performed by the randomly searching. At first, each firefly search *h* new locations nearby in *h* directions; and then, the firefly moves to the non-dominant position, which is extracted from these *h* locations.

3.3 Nondirective movement

The NDM selects the locations for the random redeployment of incongruous wireless sensors. The process of the NDM is as follows:
Step 1: Calculate the difference between the permutations of firefly i and firefly j

$$\Delta X_{ij} = X_i - X_j \text{ ,(9)}$$

Step 2: Randomly select δ_{ij} elements from ΔX_{ij} with a value of 1 and change these elements to -1; randomly select δ_{ij} elements from ΔX_{ij} with a value of -1 and change these elements to 1. The operated ΔX_{ij} is represented by $[\Delta X_{ij}]$.

Step 3: Replace the permutations of firefly i by

$$X_i \leftarrow X_i + [\Delta X_{ij}] \text{ ,(10)}$$

3.4 Survival of the fittest

Fireflies in the last iteration and fireflies in this iteration are combined into one population. The non-dominated sorting is performed in this population. The level of these fireflies, which is not dominated, is set as 1. The level of these fireflies, which is only dominated by the fireflies in the first level, is set as 2. The level of these fireflies, which is dominated by the fireflies in the first level and the second level, is set as 3. This process is repeated until the levels of all fireflies are determined. Half part of fireflies with low levels in the population is eliminated, and these fireflies with good fitness are survivals.

4. NUMERICAL EXAMPLE

4.1 Bridge description

The bridge employed for numerical simulation is a full-scale, cable-stayed bridge benchmark problem organized by the Center of Structural Monitoring and Control at the Harbin Institute of Technology (http://smc.hit.edu.cn), as shown in Fig. 1. The bridge comprises a main span of 260 m and two side spans of 25.15 m and 99.85 m each. The total length and width of the bridge are 519 m and 11 m, respectively. To understand the behavior of the bridge, an updated three-dimensional finite element model is also provided. Modal analysis has been conducted, and the results are employed to extract OWSP.

Fig. 1 Overview of the cable-stayed bridge

4.2 Results and discussion

Because the longitudinal dimension of the long-span bridge is significantly larger than the remaining two dimensions, the linear WSN, in which the wireless sensors are individually deployed in a straight line on the girder, is adopted. The wireless sensors in the WSN are uniform and have the capabilities of sensing, receiving and transmitting; the parameters are listed in Table 1. The radio of the wireless sensor is capable of adjusting the transmitting power to reach an adjacent wireless sensor at a distance less than d_{max} . The sink is placed on the right end of the main girder. The data are transmitted by a multi-hop using single-line routing.

Table 1 The parameters of wireless sensors

Parameters	Packet size	d_{max}	α	υ	η
Value	100	120	45×10^{-9}	10×10^{-11}	60×10^{-9}
Unit	bit	m	J/bit	J/bit/m^2	J/bit

The optimization results with different wireless sensor numbers found by the MOFA are shown in Fig. 2. In all four cases, the values of f_2 are much less than 1, which indicates that the connectivity of all extracted WSNs is ensured. The proposed MOFA can explore the Pareto front and shows high performance in solving multi-objective optimization problems. Customers can select proper sensor configurations from the Pareto front according different demands.

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