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Layout optimization of wireless sensor networks for structural health monitoring

Khash-Erdene Jalsan[*1], Rohan N. Soman[2], Kallirroi Flouri[1], Marios A. Kyriakides[2], Glauco Feltrin[1] and Toula Onoufriou[2]

[1]Structural Engineering Research Laboratory, Empa, Swiss Federal Laboratories for Materials Science and Technology, Ueberlandstrasse 129, 8600 Dübendorf, Switzerland
[2]Department of Civil Engineering and Geomatics, Cyprus University of Technology, 2-8 Saripolou Street, Achilleos Building 1, 1st floor, 3036 Limassol, Cyprus

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Abstract. Node layout optimization of structural wireless systems is investigated as a means to prolong the network lifetime without, if possible, compromising information quality of the measurement data. The trade-off between these antagonistic objectives is studied within a multi-objective layout optimization framework. A Genetic Algorithm is adopted to obtain a set of Pareto-optimal solutions from which the end user can select the final layout. The information quality of the measurement data collected from a heterogeneous WSN is quantified from the placement quality indicators of strain and acceleration sensors. The network lifetime or equivalently the network energy consumption is estimated through WSN simulation that provides realistic results by capturing the dynamics of the wireless communication protocols. A layout optimization study of a monitoring system on the Great Belt Bridge is conducted to evaluate the proposed approach. The placement quality of strain gauges and accelerometers is obtained as a ratio of the Modal Clarity Index and Mode Shape Expansion values that are computed from a Finite Element model of the monitored bridge. To estimate the energy consumption of the WSN platform in a realistic scenario, we use a discrete-event simulator with stochastic communication models. Finally, we compare the optimization results with those obtained in a previous work where the network energy consumption is obtained via deterministic communication models.

Keywords: SHM; WSN; multi-objective layout optimization; energy estimation; discrete-event simulation

1. Introduction

For the last decade, Wireless Sensor Networks (WSNs) have been successfully employed as an alternative monitoring technology in Structural Health Monitoring (SHM) systems (Pakzad *et al*. 2008, Rice *et al*. 2011). In contrast to the conventional wired systems, WSNs offer numerous advantages such as flexible installation, scalable deployment, and unobtrusive communication at a lower cost for both short- and long-term deployments (Feltrin *et al*. 2010). However, the limited energy resource (batteries) of the wireless sensor nodes imposes severe restrictions on the network performance factors, particularly on the monitoring period. Consequently, many research studies

∗Corresponding author, Student, E-mail: khash.jalsan@empa.ch

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have been devoted to improve the energy efficiency (or network lifetime) of WSNs using various approaches at different levels. At the node hardware level, low-power hardware components are integrated to satisfy stringent energy constraint of the WSN-based systems, whereas at the network level, energy-efficient communication protocols have been developed to prolong the network lifetime. Furthermore, smart monitoring applications conserve energy by employing sleeping, or event detection mechanisms.

Recently, the network layout (sensor node locations) optimization has gained much attention from the research community as a strategy to prolong the network lifetime (Younis and Akkaya 2008). The objective of this approach is to find physical locations of the sensor nodes on the monitored structure such that the network lifetime is extended due to the optimized communication scheme. The layout optimization approach is most effective when the energy consumption of communication is relatively higher than the energy consumption of other operations such as sensing and data processing. Indeed, in typical WSNs, the power consumption of a radio transceiver is significantly higher than the power consumption of other components such as sensors and microcontrollers.

Besides influencing the energy consumption, the network layout directly affects the quality of the extracted information (information quality) from the measurement data, since the sensor node locations coincide with the measurement points. As the purpose of a monitoring system is to obtain high quality information, it is more effective to optimize the network layout along with the information quality.

The combination of the information quality and the energy consumption aspects into one optimization problem has been investigated for generic (Krause *et al.* 2006) and application-specific (Jourdan and de Weck 2004) domains. These layout optimization methods are based on the assumption that the required information of interest is spread over the target area uniformly, or the measurement data is spatially correlated with the distance between their measurement locations. In SHM, however, the measured response of a structure is a function of a complex system involving a large number of structural elements and the complete integration of these elements to form the whole structure. Thus, there is no significant spatial correlation, and the desired information is not uniformly spread over the monitored area.

Furthermore, reliable a priori knowledge of a civil structure can always be achieved using models. Therefore, it is more effective to predict the sensor placement quality using a structural model and optimize the locations before the deployment. In the literature, a number of sensor placement methods have been developed to maximize the information quality (Meo and Zumpano 2005). However, these methods are developed for wired monitoring applications and therefore do not consider the constraints imposed by WSNs.

To overcome the issues in wireless SHM systems, a layout optimization method has been developed (Li *et al.* 2010). In this approach, first, an optimal layout with respect to the information quality is obtained using the Effective Independence (EFI) method (Kammer 1990), a traditional optimal sensor placement method, and then the similar layouts with respect to the result of EFI are explored to find a better alternative in terms of energy consumption. Although the method combines the WSN and SHM multi-disciplinary aspects into a single layout optimization problem, the sensor locations and the wireless network are optimized separately in two phases. As a result, this approach ignores other energy-efficient layouts that still satisfy the application requirements. Instead, as an improved strategy, more layouts that are satisfactory must be investigated, and the optimal layout with respect to both information quality and network lifetime must be selected as the final deployment layout.

The WSN layout optimization is an NP-hard problem (Krause *et al.* 2006). Therefore, exhaustive search techniques are impractical to solve layout optimization problems. Moreover, the underlying problem structure or the gradient of the objective functions is unknown. Hence, the evolutionary algorithm is a practical approach to solve such problems. For instance, Genetic Algorithm (GA), a common evolutionary algorithm, has been successfully applied in a layout optimization problem(Jourdan and de Weck 2004). Although the optimization study provides important aspects of the GA application to the layout optimization, the over simplified WSN models, such as the ideal communication models, degrade the practicality of the proposed approach.

In WSN layout optimization, realistic energy estimation is the most challenging and critical part due to the high complexity of WSNs. The energy estimation of WSN involves all significant energy-consuming components and their complex interactions and operations. Although it is possible to measure precisely the energy consumption of these components, the required radio transmission power and communication protocol behavior are non-trivial to predict due to the stochastic communication behavior. In the literature, there are studies that deterministically estimate the energy consumption with several simplifying assumptions (Fu *et al.* 2012, Jourdan and de Weck 2004, Li *et al.* 2010). On the contrary, a more realistic energy estimation approach is to use a discrete-event network simulator that can predict the behavior of the stochastic communication protocols with high precision (Shnayder *et al.* 2004). However, this fine-grained energy estimation is usually achieved with a high computational cost. When using an evolutionary algorithm, it is desirable that the energy estimations are sufficiently fast to analyze as many layouts as possible.

The contribution of our work is two-fold. First, we design a multi-objective layout optimization framework, where the end user is able to determine the trade-off between energy consumption and information quality considering the application requirements. Second, a discrete-event simulation is proposed to estimate stochastically the energy consumption of a WSN in the layout optimization. A simulation case study is presented to evaluate the proposed approach with a layout optimization of a wireless SHM system comprised of multi-type sensors. Finally, we compare our WSN model with the model proposed in a previous work where the energy estimation employs deterministic communication models. The challenge of optimizing the layout of such a WSN is that the different types of sensor nodes affect both the network lifetime and the information quality of the monitoring system in different ways.

2. Multi-objective layout optimization framework

An overview of the proposed multi-objective layout optimization framework is depicted in Fig. 1. Before the optimization process, structural and WSN models are developed based on the priori knowledge such as the physical properties of the monitored structure and the surrounding environment. The optimization process starts with a GA exploring design space and evaluating the objective functions according to the developed models. Once the result is obtained as a set of Pareto-optimal solutions, the end user selects the final deployment from the result based on the application requirements and domain expertise. Finally, the WSN is deployed on the monitored structure according to the selected layout.

In the following sections, we describe the problem formulation and the search method employing GA.

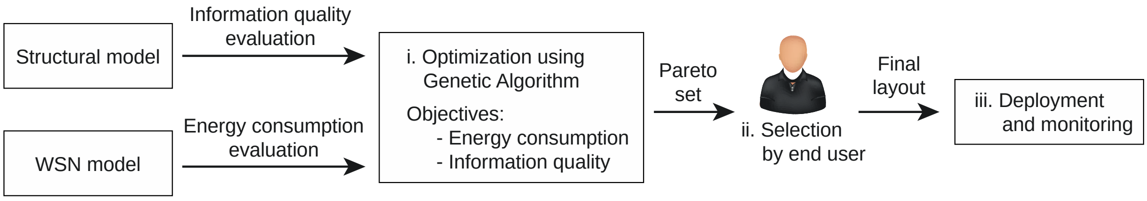


Fig. 1 Multi-objective WSN layout optimization framework for SHM

2.1 Layout optimization problem formulation

The aim of WSN layout optimization is to select particular physical locations on the monitored structure such that the resulting WSN exhibits optimal performance. The sensor node locations are selected from a set of n discrete candidate locations $C = \{(x_1, y_1, z_1), \ldots, (x_n, y_n, z_n)\}$ defined in a 3-dimensional Cartesian coordinate system. The candidate locations are fixed in advance by considering the installation restrictions of the sensor nodes on the monitored structure. In addition, the number of deployed sensor nodes is also fixed according to the application requirements. Then, the feasible design space X is the power set of C, containing all possible subsets with a cardinality of k, where k is the number of deployed sensor nodes.

WSN layout optimization is formulated as a generic multi-objective problem that simultaneously optimizes antagonistic objectives. In multi-objective optimization, the objective functions conflict with each other, i.e., solving for one objective function degrades the other objectives. Consequently, multiple globally optimal solutions exist in such type of problems, and the problem should be formulated and solved differently from the single-objective optimization problems.

Let $J = \{J_1, J_2, \ldots, J_m\}$ be a set of objective functions to be minimized. The optimization result minimizing J consists of a set of optimal solutions, the so-called *Pareto-optimal* solutions. Pareto optimality is a concept to describe the multiple optimal solutions of a multi-objective optimization problem. A feasible design vector u is said to dominate (or preferred to) another design vector v ($u \prec v$), if and only if, $\forall i.\ J_i(u) \leq J_i(v)$ and $\exists j.\ J_j(u) < J_j(v)$. A solution is Pareto-optimal if it is not dominated by any other solution in the design space (Konak *et al.* 2006), i.e., it is impossible to improve an objective of Pareto-optimal solution without degrading any other objectives. Formally, a set of Pareto-optimal network layouts $X^*$from the design space X can be defined as

$$X^* = \left\{x^* \in X : \neg\exists x \in X \prec x^*\right\} \tag{1}$$

X^* may consist of any number of Pareto-optimal layouts in addition to the *utopia* points $\{u \in X : \forall i.\ \forall x \in X.\ J_i(u) \leq J_i(x)\}$, which is the optimum for a single objective function ignoring the other objectives.

2.2 GA for network layout optimization problem

An analytical solution for X^* is difficult to obtain due to the non-linearity, absence of convexity, and the complex dynamics of the objective functions. Since X is discrete and *categorical* (no intrinsic ordering to the sensor node absence and presence), it is difficult to apply classical optimization approaches based on the objective function gradient. A well-suited approach to overcome this issue is to employ derivative-free metaheuristic optimizers (Custódio *et al.* 2012, Zhang *et al.* 2008). Although metaheuristics do not guarantee that the global optimum solution is reliably found, studies show that common evolutionary metaheuristics, such as GAs, provide acceptable results (Guo *et al.* 2004, Jourdan and de Weck 2004).

As any GA explores the design space by operating on the design variable, the design variable must be coded into a suitable structure called *chromosome* in the GA terms. Since the set of candidate locations C is predefined in advance by the domain expert, the binary coding is a simple and efficient way for coding the design variables for the layout optimization. Here, the design variable x is a bit vector indicating the sensor node presence on the candidate locations: $x = (x_1, x_2, \dots, x_n)$ where the bits 0 and 1 correspond to the absence and presence respectively. Note that the design variable is a categorical variable.

A GA runs according to the steps below:

Step 1. Randomly generate an initial population, P_0, in order to start from an average point in general.

Step 2. Execute the main loop until the stopping condition is reached. Such a condition can be the number of iterations or the running time that is exceeded.

Step 2.1. A new population, Q_i, is generated from the parent population, P_i, using the mutation and crossover genetic operators.

Step 2.2. The individuals in P_i and Q are evaluated according to the objective functions in J.

*Step 2.3.*The individuals are sorted according to their Pareto ranking, and the highest-ranking individuals are selected for the next parent population P_{i+1}.

*Step 3.*The last iteration result P_i consists of Pareto-optimal solutions that can be used for the next step of the optimization framework.

Despite no guarantee that the last P_i represents the true Pareto front X^*, it is a reasonable approximation preserving the computational time and resource. The main issue in a GA design is to select appropriate values for the mutation rate, crossover probability, and the population size parameters. This parameter tuning process requires a number of preliminary runs to observe the convergence behavior for specific parameter values from which the best values can be selected for the final GA run. Another issue is to decide on the stopping condition of GA. Our strategy was to empirically estimate the GA iteration number from similar but smaller layout optimization studies (Jalsan *et al.* 2012). In these cases, the problem sizes are sufficiently small that the exhaustive search can be used to obtain the true Pareto front. Subsequently, GA is applied to the same problems to observe the iteration count until it provides an acceptable Pareto front.

3. Objective functions

In the following sections, the information quality and energy estimation formulations are discussed. The information quality is formulated as a ratio of the placement quality metrics of acceleration and strain sensors. To estimate the WSN energy consumption, a discrete-event simulator is used. Since a fast simulation execution is desired in the optimization search, we discuss a technique that speeds the simulation process.

3.1 Information quality formulation

The formulation of information quality (or sensor placement quality) depends on the monitoring application type and requirements. Two types of monitoring applications are common in SHM: modal identification using vibration and fatigue assessment using strain. In this work, we focus on modal identification applications. With appropriate information quality metrics, the proposed optimization framework can be used in fatigue assessment or other types of monitoring applications as well.

The studies mentioned in the introduction are largely limited to homogeneous networks with a single type of sensor. In order to allow an optimal use of resources, a network consists of multi-type sensors, specifically accelerometers and strain gauges, can be used for modal identification applications (Soman *et al.* 2014). In multi-type sensor networks, the orthogonality of the modal vectors cannot be exploited as in single-type sensor networks. Therefore, approaches that do not rely on the orthogonality of the modal vectors, namely Modal Clarity Index (MCI) (Natarajan *et al.* 2006) and Mode Shape Expansion (MSE) (Levine-West *et al.* 1996), are employed to quantify the sensor placement quality.

The optimization problem studied by Soman *et al.* (2014) is solved using GA with a weighted sum of the MCI and MSE. The weighted sum approach requires that the weighting of the objectives must be set in advance to the optimization. When the end user does not have enough a priori knowledge about the problem, it is difficult to set the effective values of the weighting parameter.

In this study, we assume that the end user has no particular preference on the measurement types; instead, the best combination of both measurement types is desired. Hence, the information quality objective function J_I is defined as a ratio of the MCI and MSE metrics described bySoman *et al.* (2014)

$$\operatorname*{argmin}_{x \in X} J_I(x), \quad \text{where } J_I(x) = \frac{MSE(x)}{MCI(x)}. \tag{2}$$

The ratio of MCI and MSE represents a MSE error gain per unit MCI value, and minimizing Eq. (2) leads to the best combination of both measurement types. This formulation overcomes the issues arising in the weighted sum approach.

3.2 Energy consumption formulation

The energy consumption of a WSN determines its lifetime. Assuming that all sensor nodes operate to obtain satisfactory information, the lifetime of the first-depleted node determines the network lifetime. Therefore, we want to minimize the maximum energy consumption of the *i*-th sensor node

$$\operatorname*{argmin}_{x \in X} J_E(x), \quad \text{where } J_E(x) = \max(\{E_i : \forall\, i. x_i = 1\}), \tag{3}$$

where J_E is the objective function and E_i is the total energy consumption of *i*-th sensor node. Considering that the sensor network exhibits same behavior over the operating period, E_i can be approximated by the energy consumption of one-round data collection process.

In this work, the energy consumption is estimated using a discrete-event network simulator. In a discrete-event simulation, the whole WSN is simulated to estimate the energy consumption of individual nodes according to the monitoring application and communication protocols. The advantage of a discrete-event simulator is that the energy estimation can be performed with real-life complex network protocols that are difficult to analyze with closed-form expressions.

The simulation execution time of the discrete-event simulation is an important factor to obtain effective optimization results. In typical WSN simulators, the one-round execution time of a non-trivial WSN is in the order of seconds. Since the layout optimization algorithm needs to explore a large design space, the overall optimization performance degrades due to the limited optimization time. To improve the optimization performance, a fast estimation method of the energy consumption is presented in Section 3.2.1. Finally, the communication model of a multi-hop data collection network is described in Section 3.2.2.

3.2.1 Fast energy consumption estimation approach

Common sensor network simulators are relatively slow for a layout optimization due to the detailed simulation granularity (Egea-López *et al.* 2006). Such detailed simulations can be even unfeasible when the optimization design space is non-trivial. Therefore, the simulation granularity must be set to a proper level to balance the execution speed and estimation accuracy.

In this study, a top-down approach is used to determine the simulation granularity: i) the simulated monitoring program is divided into a set of tasks that are further divided until the energy consumption of such a task is constant, which is referred to as a *primitive task*; ii) the energy consumption of a primitive task is calculated independently from the simulation process; iii) a discrete-event network simulator executes the monitoring application with a simulation granularity of primitive tasks for one-round data collection to count the number of executed primitive tasks; iv) the approximate one-round energy consumption of a sensor node E is defined by

$$E = \sum_{i=1}^{n} n_i \cdot W_i + E_0, \tag{4}$$

where n_i is the executed number of the i-th primitive task; W_i is its energy consumption calculated independently from the simulation; and E_0 is the residual energy consumption due to other non-significant components on the node hardware circuit.

By definition, a primitive task has a constant energy consumption (W given in Eq. (4)) that is obtained independently from the optimization process. Thus, a fine-grained energy profiling, such as low-level node hardware simulation, can be employed to calculate W. If a node has n number of energy-significant components, and a component has a fixed number of predefined power states, the energy consumption of a primitive task is given by

$$W = \sum_{i=1}^{n} \sum_{j=1}^{m_i} P_{i,j} \cdot t_{i,j}, \tag{5}$$

where $P_{i,j}$ is the power consumption of i-th component in its j-th power state, and $t_{i,j}$ is the time spent in the corresponding power state. $P_{i,j}$ is measured from the target sensor node using current measurement tools, e.g., current shunt and an oscilloscope, whereas $t_{i,j}$ is obtained through an energy profiling of a wireless sensor node.

3.2.2 Communication model

A multi-hop data collection network is simulated, where each node is capable of measuring the monitored phenomena and transmitting the measurement data to the sink node S_0 via the other sensor nodes in the network. Let $G_x = (S, L)$ be a particular WSN topology induced by layout x, where $N = \{N_0\} \cup \{C_i : \forall i.\ x_i = 1\}$is a set of nodes, and $L = \{RSS_{i,j} : \forall i.\forall j\}$ is a set of signal strength estimates between each pair of nodes. Here, $RSS_{i,j}$ denotes the signal strength from node N_i to node N_j. Given a data collection tree $T = (N_0, N \setminus N_0, P)$ rooted at N_0, where

$P = \{(i, j) : RSS_{i,j} > t\}$, packets are relayed according to the route P and received at the sink nodeS_0.Here, t is the minimum threshold of the received signal power.

In wireless networks, single-hop reliable communication is handled by a Media Access Control (MAC) protocol. We consider a contention-based MAC protocol, particularly the Carrier-Sense Multiple Access (CSMA) protocol, which is the most common MAC protocol in WSNs. A typical CSMA protocol assesses the channel before a transmission, and transmits a packet if no ongoing transmission is detected. If busy channel is detected, CSMA retries assessing the channel.

For simulating the CSMA protocol, accurate modeling of the signal propagation, channel and physical layer are crucial. The signal strength at the receiver can be calculated as $RSS = P_{\mathrm{tx}} - PL$, ignoring the antenna loss and other constant effects. Here, PL is the expected path loss in dB, and P_{tx} is the transmitted signal power. The exact prediction of PL on a monitoring site is difficult due to fading effects, specifically multi-path due to reflection and shadowing due to obstruction. An approach is proposed byRappaport and Sandhu (1994) to model the signal loss at the receiver as a combination of the loss due to free-space propagation and the loss due to fading effects, given by

$$PL = PL_0 + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma, \tag{6}$$

where PL is the mean path-loss over d distance,PL_0 is the free-space path loss for d_0 reference distance, n is a path-loss exponent, and X_σ is a zero-mean log-normally-distributed random variable with standard deviation σ in dB. The model parameters, namely n, d_0, and σ^2, are experimentally defined for various environments and can be found in the literature (Sohrabi *et al.* 1999).

Typical WSNs operate on single wireless channel that is shared among the sensor nodes. Thus, a transmission can be interfered by other ongoing transmissions. Since the received signal is the sum of all ongoing signals, the decoding ability of the receiver depends on the power of the useful signal. A way to quantify the signal quality is Signal-to-Interference-plus-Noise Ratio (SINR). Here, we use the additive interference model that quantifies the SINR by

$$SINR = \frac{RSS}{I + N}, \tag{7}$$

where I is the interference power (sum of interfering RSS), and N is the noise power (Iyer *et al.* 2009). Since signal-decoding success solely depends on $SINR$, the radio physical layer is often modeled as a function of $SINR$. For a particular radio transceiver, each $SINR$ value can be mapped experimentally to the Packet Reception Rate (PRR) value, which can be used to simulate the physical layer in the network simulator.

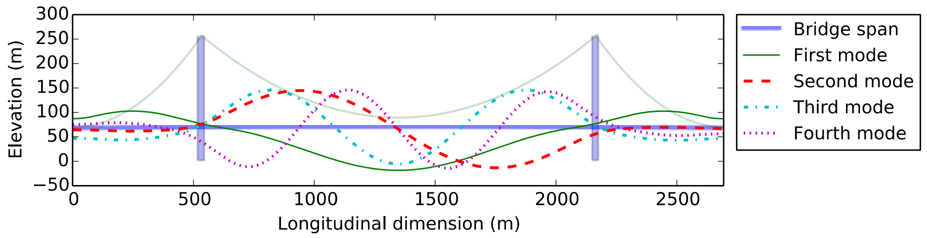
4. Case study: layout optimization of bridge monitoring system

The proposed methodology has been evaluated with a layout optimization of a specific SHM system. The SHM system is designed for a modal test application (Soman *et al.* 2014) that employs multi-type sensor measurements, specifically acceleration and strain measurements. The optimization goal is to obtain the Pareto-optimal network layouts X^* that simultaneously minimize the network energy consumption (J_E) and maximize the information quality (J_I) objectives. In the following sections, we present the monitoring application followed by the optimization setup and results.

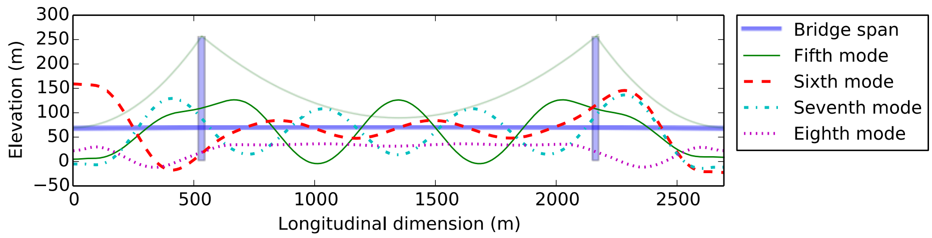
4.1 Monitoring setup

The monitored structure is a 2694 m long suspension bridge that has three spans (535/1624/535 m) and two pylons (254/254 m). The candidate sensor locations (453 for acceleration sensors and 452 for strain sensors) are located along the longitudinal direction of the bridge spans. We assume that the first eight bending modes are of interest, and therefore the number of deployed sensor nodes is fixed to 17. Fig. 2 displays the bending modes that were considered for evaluating the network layouts in Section 4.3. The mode shapes were computed using the model presented in (Soman *et al*. 2014).

The wireless sensor nodes perform acceleration or strain measurements depending on the attached sensor. To effectively measure the vibration modes of interest, the sampling frequency and duration of both types of measurements were set to 64 Hz and two seconds respectively. Once the measurement is done, the data is transmitted to the sink node via multi-hop network. The sink node location is assumed to be fixed to one end of the bridge and plugged into unlimited energy source. This assumption is legitimate when the WSN has to transmit a high amount of data to a remote database using the Internet connection provided by a cellular network.



(a) Bending modes 1 to 4



(b) Bending modes 5 to 8

Fig. 2 First eight bending mode shapes of the monitored bridge

4.2 Optimization setup

As discussed in Section 3.1, the ratio of MSE and MCI is used to formulate the objective function for the information quality (see Eq. (2)). A Finite Element (FE) model of the bridge developed by Soman *et al.* (2014)is used to evaluate J_I of a particular network layout for the first eight bending modes.

For calculating the network energy consumption J_E, Eq. (3) is adopted. First, a power model of the target sensor node is developed from the current measurements of the sensor node platform, including the radio transmission for different power levels (Tables 1 and 2, respectively), assuming that the supply voltage is 3 V during the operating period. Second, three main energy-consuming tasks on the sensor nodes are considered: i) measurement, ii) send, and iii) receive. The send task is further divided into three sub-tasks: i) channel assessment, ii) back-off, and iii) transmission.

Table 1 Current measurement of the sensor node platform

	Active (mA)	Sleep (mA)		Active (mA)	Sleep (mA)
Microcontroller	5.1	0.002	Strain gauge	16	0
Accelerometer	2.6	0	Radio transceiver*	9.2	0

*Active mode of the radio transceiver represents the listen, receive, and channel assessment mode

Table 2 Current measurement of the radio transmission for different power levels

Signal power (dBm)	4	3	2	1	0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11
Current (mA)	22	21.5	21	20.6	20.2	18.3	18.1	16.3	16.1	15.9	14.4	14.1	13.9	13.8	13.6	12.7

The energy consumption of these tasks is considered constant and therefore calculated according to the power model and the sensor node specification. Finally, in order to estimate the energy consumption E of individual nodes, a discrete-event WSN simulator is used, namely TinyOS Simulator (TOSSIM) (Levis *et al.* 2003).The simulator executes the node software with a simulation granularity of the derived tasks.

In the TOSSIM simulator, the routing tree is formed as the Shortest-Path Tree of which the logical distance between adjacent nodes is specified by the estimated signal strength. Considering the signal strength as the distance instead of the Euclidean distance is legitimate because the energy consumption does not depend directly on the Euclidean distance, but rather on the required signal strength. The CSMA MAC protocol, radio physical layer model, and the propagation model given by Eqs. (6) and (7) are integrated into the TOSSIM simulator. The radio propagation model is used with the parameter values n = 2.5, PL_0 = -30 dB, and X_σ = 3 dB (Sohrabi *et al.* 1999). The physical layer model uses a PRR-SINR curve analytically derived for the radio transceiver complying the IEEE 802.15.4 standard (Huang *et al.* 2011).

The simulation process starts with the booting of all sensor nodes at a random time. Afterwards, the measurement starts on the sensor nodes, which is followed by the transmission of a packet containing the measurement data to its parent node. If a node receives a packet from its child nodes, the packet is forwarded to the parent node as well. Once all packets arrive at the sink node, the one-round simulation process stops, and the energy consumption of each sensor node is calculated.

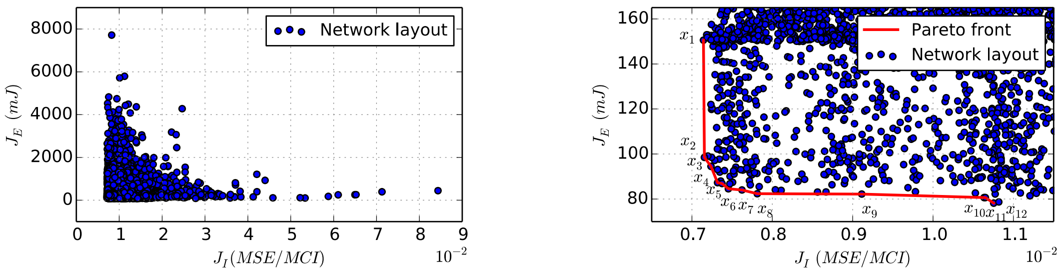
Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb *et al.* 2002) is employed due to its applicability to multi-objective optimization problems. We set the NSGA-II parameters, the crossover probability of two individuals, the mutation probability of an individual, and the population size, to the commonly used values of 0.9, 0.05, and 16 respectively.

4.3 Simulation results

The GA evolution process is depicted in Figs. 3(a) and 3(b) for the individual objective functions J_I and J_E respectively. GA evolves to the next solutions by mutating and mating the current good solutions. The convergence of J_I (Fig. 3(a)) replicates such behavior, a systematic evolution to the optimal solution. However, in case of J_E, the evolution does not follow a specific pattern; instead, it merely resembles a random search. We believe that this is due to the high complexity of WSN energy estimation. For instance, moving one sensor node to another location can completely change the network topology and most importantly the packet routing, which strongly influences the energy consumption of a node. Moreover, the random input to the objective function evaluation can contribute to the poor J_E convergence.

The GA runs for 1000 generations exploring 16000 network layouts. The fitness values (the objective function values) of the layouts evaluated in all generations are shown in Fig. 4(a). The energy consumption varies by two orders of magnitude, indicating that the layout is indeed an important factor for the energy efficiency, and therefore for the network lifetime.

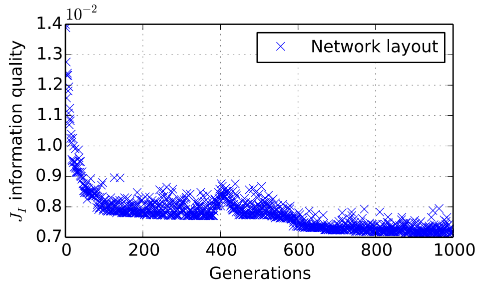
The optimization produces 12 Pareto-optimal layouts, Fig. 4(b). Figs. 5(a)-5(c) show the most significant Pareto-optimal layouts as a deployment on the bridge plan. Layout x_1, which maintains the best information quality, is comprised of 15 acceleration nodes and one strain node. If the energy consumption of 150.5 m J is within the given energy budget, $x_1$is considered the optimal layout. In contrast, the most energy-efficient layout x_{12} has achieved half as much network lifetime as layout x_1 with a balanced packet forwarding load and minimized packet retransmissions. Additionally, the layout x_{12} does not include a strain gauge due to its significantly higher energy consumption than that of an accelerometer. Finally, a balanced trade-off between the energy consumption and information quality can be achieved with layout x_6, which favors a configuration that is similar to x_{12}.



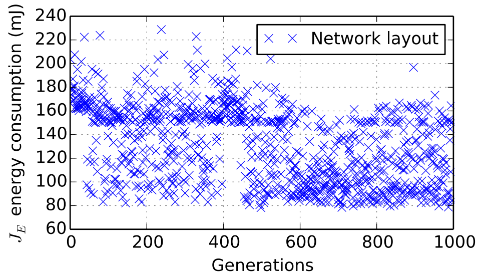
(a) Overall exploration

(b) Pareto front

Fig. 3 Layout distribution over the objective function range

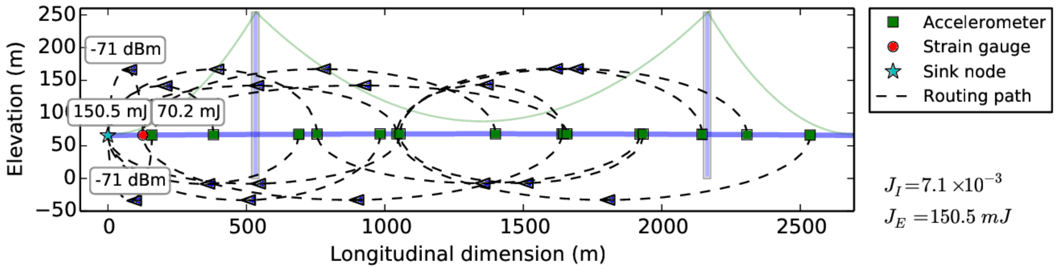


(a) J_I – Information quality

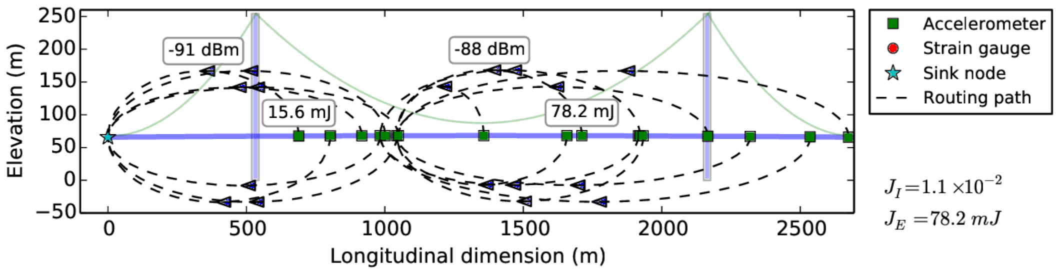


(b) J_E – Energy consumption

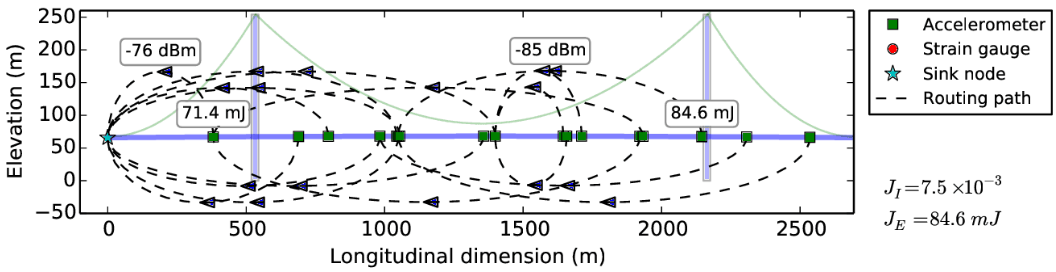
Fig. 4 GA convergence over the iterations



(a) Pareto-optimal layout x_1



(b) Pareto-optimal layout x_{12}

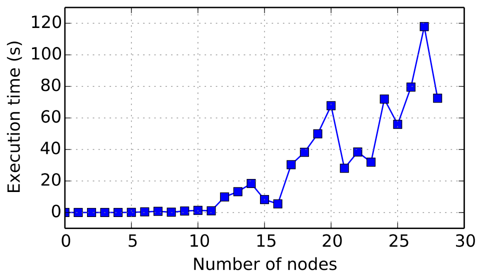


(c) Pareto-optimal layout x_6

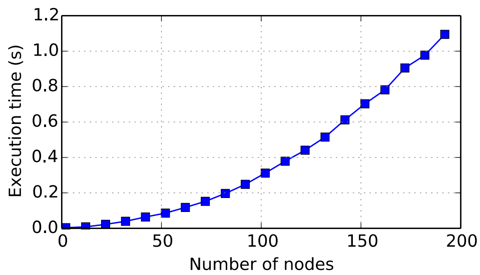
Fig. 5 Most significant layouts (the most and least energy-consuming nodes marked)

In order to evaluate the advantage of fine-grained discrete-event simulation, we compared the optimization results to those obtained by deterministic WSN models. The two energy estimation approaches produce different Pareto-optimal layouts, Figs. 5(b) and 6(c). In the layout produced by the deterministic WSN model, the energy consumption of the individual sensors is significantly lower than that of the discrete-event simulation. Additionally, the sensor nodes are gathered around the sink node. These are due to the absence of packet collisions and retransmissions in the deterministic energy model, which significantly reduces the energy estimation accuracy of real-life WSN systems. Furthermore, the sensor nodes located at different distances to the sink node have exactly the same amount of energy consumption because of the same discrete power level of radio transmission. Both layouts favor more acceleration nodes than strain nodes, possibly due to the higher energy consumption of strain sensors.

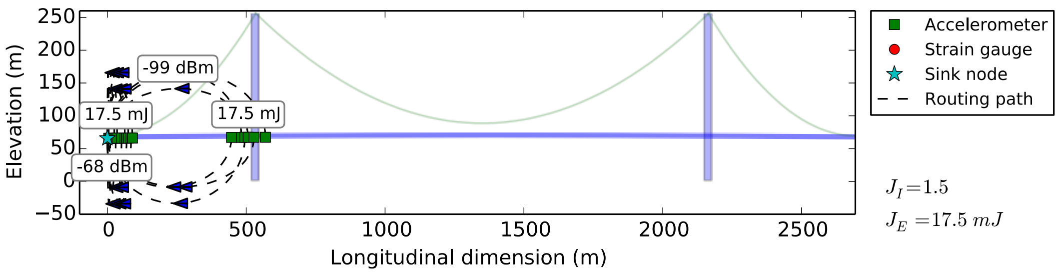
In Figs. 6(a) and 6(b), the execution time is depicted as a function of the number of simulated sensor nodes. Both execution times represent the exponential or polynomial growth; however, the growth is faster in the discrete-event simulation case, whereas a relatively slower growth is observed in the deterministic model case. In addition, the execution time of discrete-event simulation is non-monotonic, which may indicate that the execution time depends on not only the number of sensor nodes, but also on the other factors such as the network topology and the number of packet retransmissions.



(a) Execution time of discrete-event simulation



(b) Execution time of the deterministic energy model



(c) Most energy-efficient Pareto-optimal layout obtained with the deterministic energy estimation model

Fig. 6 Comparison of energy estimation methods

5. Conclusions

In this work, a layout optimization methodology for SHM systems is presented, particularly modal test applications employing multi-type sensors. A multi-objective layout optimization framework is proposed to obtain a set of Pareto-optimal solutions from which the end user selects the final deployment layout. The energy consumption is estimated using the discrete-event simulation to predict the behavior of the communication protocols with high precision. The simulation granularity is adopted to increase the execution running time.

A case study has been conducted to evaluate the feasibility of the proposed methods. In the case study, a layout optimization of a real bridge monitoring is presented using multi-objective GA from which a set of Pareto-optimal solutions was obtained. A power model of a specific sensor node platform has been developed and used within the TOSSIM simulator to estimate node energy consumption. The optimization yields 12 Pareto-optimal solutions with different network lifetime and information quality values that can be used for deciding on the final deployment layout.

The multi-objective layout optimization of wireless SHM systems is feasible with the application of GA and discrete-event simulation. The GA provides a satisfactory result given that the objective functions provide consistent ranking for the investigated layouts. However, a further analysis is required to evaluate the optimization performance such as the population diversity. Even though the discrete-event simulation notably increases computational complexity, it provides accurate energy consumption estimation since the realistic CSMA MAC protocol and radio physical layer are considered. As the discrete-event simulation incorporates random input, a single simulation result cannot reflect the average performance of a layout. Therefore, a Monte-Carlo method where a number of replications are simulated for the layout to obtain the empirical distribution function can be employed.

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