# Sensor Optimization Using an Evolutionary Strategy for Structural Health Monitoring in High Temperature Environments

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**Abstract:** In a high temperature environment, it is challenging to perform structural health monitoring (SHM), which has become a required task for many important civil structures in harsh environments. A SHM system in high temperature environments requires a large number of sensors for different data resource measurements, for example, strain and temperature. The accuracy of the measurement is highly dependent on the trade-off between the number of sensors of each type and the associated cost of the system. This paper introduces a sensor optimization approach based on an evolutionary strategy for the multi-objective sensor placement of structural health monitoring in high temperature environments. A single-bay steel frame with localized high temperature environment validates the multi-objective function of the evolutionary strategy. The variance between the theoretical and the experimental analysis was within 5 %, indicating an effective sensor placement optimization using the developed genetic algorithm, which can be further applied to general sensor optimization for SHM system applications in high temperature environments.

**Keywords:** Sensor optimization; Structural health monitoring; Evolutionary strategy; High temperature environment.

## 1. INTRODUCTION

Structural health monitoring (SHM) is becoming popular for many important infrastructure such as tall buildings, long bridges, hospitals, offshore facilities, and nuclear power plants. The health condition of the structures can be analyzed based on collected data from sensors on structures. This information could help the users to allocate resources for associated maintenance and avoid severe fatality. However, in high temperature environments, such as in fire, the lightweight sensors in an SHM system would be very vulnerable to damages.

A high temperature environment requires special sensors with associated high cost. Current practices of extensive redundancies of sensor placement for an SHM system in high temperature environments results in a high-cost and unaffordable system to be widely applied. To search for an affordable solution for these conditions, a SHM system needs to reduce the total number of sensors while maintaining an acceptable monitoring accuracy at the same time. Therefore, it becomes critical to apply a sensor placement optimization before the sensor installation for sensor location, sensor types and number (cost), and measurement accuracy.

A sensor optimization problem, either static or dynamic, is a convex optimization [1] and it has been proved to be NP-hard, which could result in a long execution time depending on the problem size. Even with a powerful computer, the number of sensor candidates has to be reasonably small to get an exact solution [2,3]. Improving efficiency is needed for sensor optimization problems to get exact solutions [4]. Thus, instead of an exact solution, local search methods can be applied. For the control and damage detection of dynamic structures, either local information-theory-based [5-8] or information-based [9-10] sensor placement optimizations can be applied. These local search methods depend on optimizing control function of the fisher information matrix (FIM) or its variants using structural dynamic properties, such as structural frequency-mode shapes, strain energy, and structural curvature. These optimization methods emphasize either the controllability or observability of the system and are usually applied for placement of wireless acceleration sensors on structures. In addition, the computational performance of these local search approaches is suboptimal and not guaranteed to be minimum since these algorithms reduce the sensor number in an iterative manner.

Global search methods can also be applied such as genetic algorithm (GA) [11-14] and swarm intelligence method [5]. In addition, various intelligent algorithms have also been developed as good tools for wireless sensor placement in a regular environment with consideration to optimize power consumption and signal strength, such as the monkey algorithm and glowworm swarm optimization algorithms [16-18].

However, in high temperature environments, multiple sensor types will be involved such as strain sensors, temperature sensors, and vibration sensors, and the major task of optimization is to determine the optimized number of each sensor type. None of these applications consider more than one type of sensor for SHM application in harsh environments.

In this paper, we introduce a new approach based on evolutionary strategy to solve the sensor selection problem for SHM application in high temperature environments where multiple types of sensors are a necessity. The developed algorithm uses a fitness function with consideration of the trade-off between the sensor number/type and the measurement accuracy with a weight factor, which can better serve as decision-making criteria.

The organization of the remaining paper is as follows: Section 2 introduces the developed evolutionary strategy, which can be used for sensor optimization of general SHM systems in high temperature environments. Section 3 conducts a case study using a single-bay steel frame structure. Section 4 provides the conclusion and outlines the potential future work.

## 2. EVOLUTIONARY STRATEGY-BASED SENSOR PLACEMENT OPTIMIZATION APPROACH

Evolutionary strategy (ES) is a population based stochastic optimization technique. ES is based on ideas of adaptation and evolution, in particular focusing on the selection and mutation operation. Fig. 1 shows the ES approach as a flow chart.

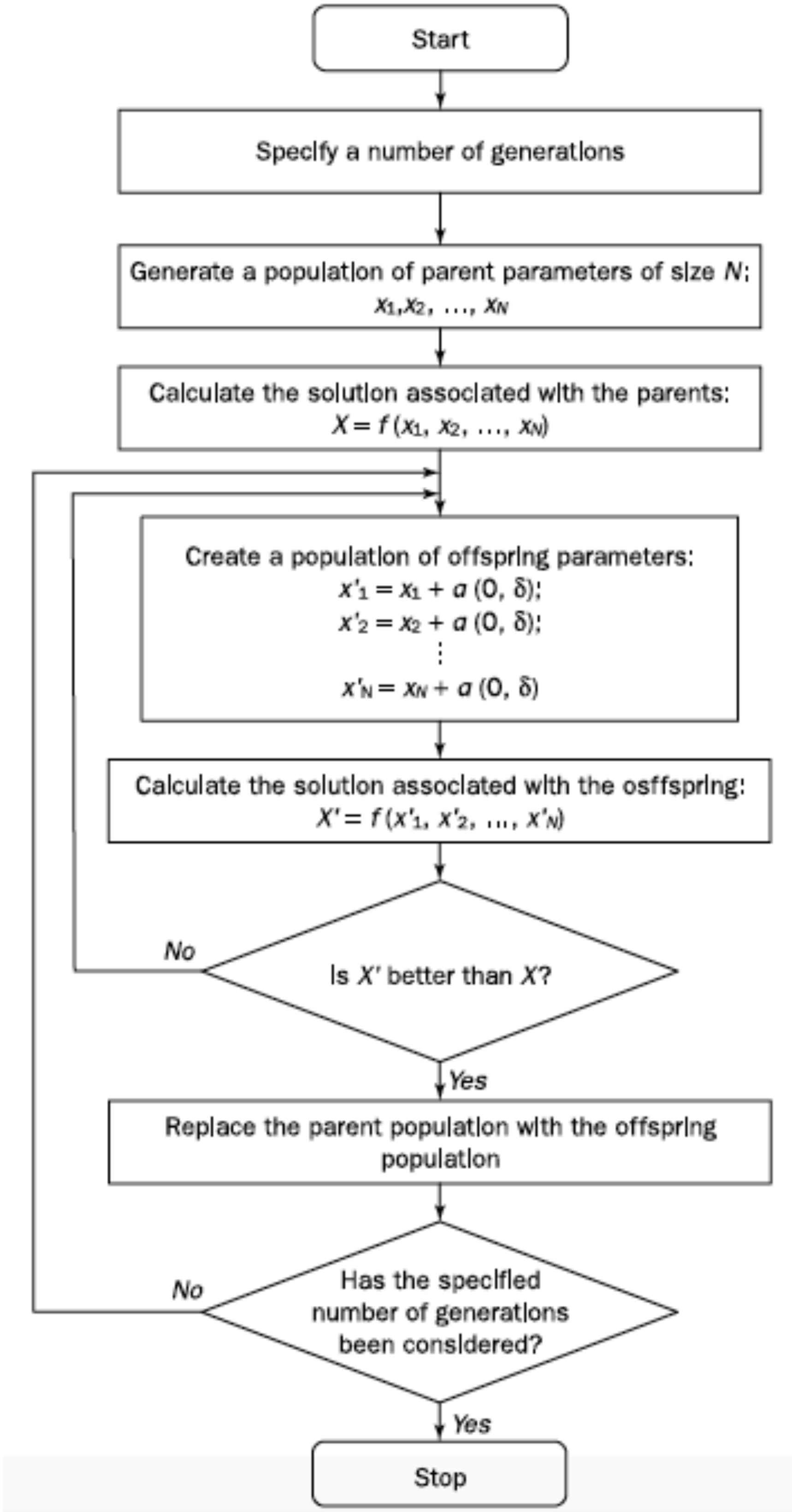


Fig. 1 Steps in Evolutionary Strategy [21]

There are different variants of ES but the canonical version, also referred to as the (1+1) evolution strategy includes the following steps [19]:

Step 1: Initialization of the population.

Step 2: Evaluation of the population.

Step 3: Create population with offspring parameters.

Step 4: Calculate the solution associated with the offspring.

Step 5: If offspring population is better than parent population, then replace parent population with offspring population; if not, then go to Step 3.

Step 6: If number of generations specified has been reached then stop, otherwise go back to Step 3.

The canonical algorithm was implemented and the following parameters were used:

- Population size: 500
- Number of generations: 5000

The optimization function used was the cost of the temperature sensors and the strain sensors as follows:

$$C(n,m) = \frac{1}{(\sum n)*b+(\sum m)*c} \tag{1}$$

where $\sum n$ is the sum of the temperature sensors based on the sensor location n, and $\sum m$ is the sum of the strain sensors based on the strain sensor locations, b is the unit price of the temperature sensors, and c is the unit price of the strain sensors. More details regarding the cost function and the associated linear interpolations of the temperature and strain measurements can be found in [14].

## 3. CASE STUDY

With the required measurement accuracy known, then the total number of sensors, the types of sensors to be applied, and the locations of the associated sensors can be optimized using the developed evolutionary strategy. A case study has been performed on a one-floor and one-bay steel frame with simulated localized high temperature. More details of the steel frame and temperature loading area can be found in reference [20].

Fig. 2 shows the measurement accuracy changes with the increase number of sensors with four different temperatures including 212 °F (100 °C), 575 °F (300 °C), 932 °F (500 °C), and 1292 °F (700 °C). At a temperature of 212 °F (100 °C), a measurement accuracy of 84.3 % will require three sensors.

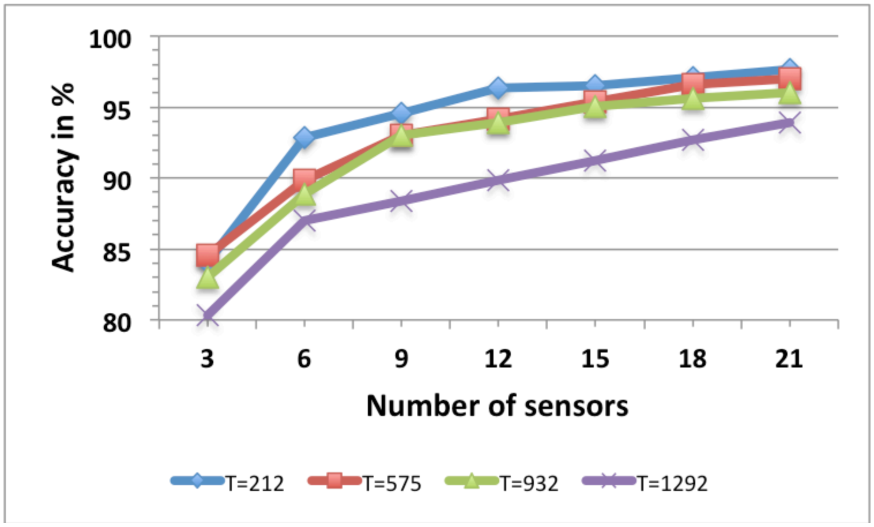


Fig. 2 Number of sensors vs measurement accuracy

Table 1 shows the suggested sensor layout for the three sensors at 212 °F (100 °C) with 84.3 % of required measurement accuracy obtained from the evolutional strategy as discussed in Section 2. The distance between each possible sensor node is 2 inches (5cm).

Table 1 Suggested sensor layout with 84.3% of required measurement accuracy

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To validate the effectiveness of the developed method for sensor placement optimization of SHM system in high temperature environments, laboratory experiments were performed based on the case study as shown in Fig. 3(b). A tube furnace made by Thermo Scientific (Model: Lindberg/Blue M) was used to provide a temperature change environment for validation. It had three temperature zones that can be programmed and operated independently, which were programmed to have the same temperature increase profile in this validation test. The temperature in the furnace was increased at a rate of 18 °F/min (10 °C/min) from 72 °F (room temperature, 22 °C) to 1292 °F (700 °C) by an interval of 180 °F (100 °C). At each temperature level, the test paused for 10 min to ensure that the temperature distribution is stable both inside and outside the furnace. Vertical load was applied on the top beam by the displacement-controlled actuator of 4.6 kips (20.46 kN) to 10 kips (44.48 kN).

To validate the effectiveness of the developed algorithm for sensor placement optimization, a comprehensive sensing network was applied on the steel frame for two temperature sensors and six strain sensors as shown in Fig. 3(a) for the detailed locations of the installed sensors. This validation test used sensors developed in reference to [20] for simultaneous high temperature and large strain measurements. The temperature sensors used long-period fiber grating (LPFG) and the strain sensors used movable extrinsic Fabry–Perot interferometer (EFPI) large strain sensors. Ceramic adhesives that can endure high temperatures up to 2012 °F (1100 °C) were used to attach optical sensors on the surface of the column flanges.

Fig. 4 compares the measurement accuracy changes as simulated fire temperature increases from the experiments and that from the theoretic analysis obtained by the algorithm. At the temperature of 212 °F (100 °C), the measurement accuracy is predicted to be 84.3 % and the actual measurement accuracy from the experiment is 88 %. The measurement accuracy at 1292 °F (700 °C) was expected to be 79.6 % from the training, and the measured accuracy through experiments is 76 %. A variance less than 5 % between the theoretical and the experimental analysis indicates a very effective sensor placement optimization using the developed algorithm.

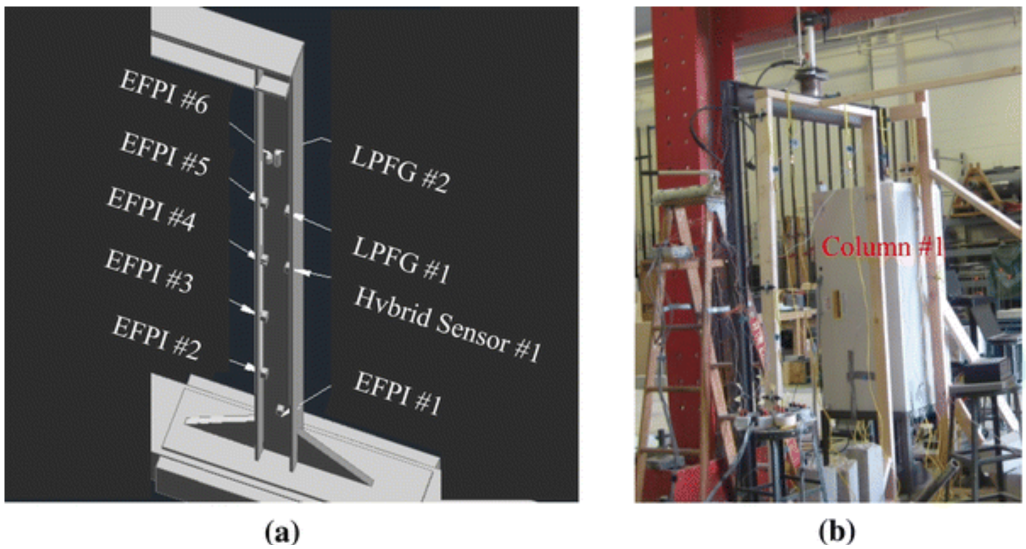


Fig. 3 Experimental sensor layout (a) and scene (b)

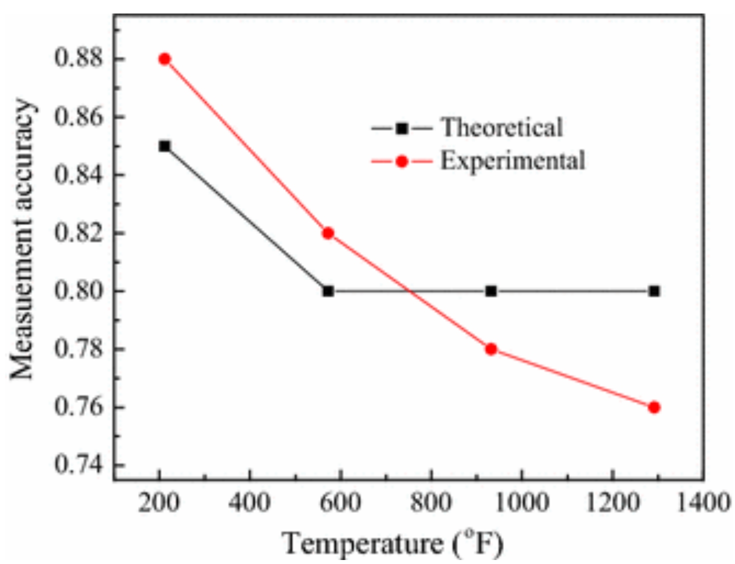


Fig. 4 Comparison between theoretic and experimental results

## 6. CONCLUSIONS AND FUTURE WORK

This paper outlines an effective evolutionary strategy approach for sensor placement optimization with consideration of the tradeoff between measurement accuracy and cost of the system. The authors conducted a theoretic analysis to develop the algorithm followed by laboratory validation experiments. In high temperature environments structures will require multiple types of sensors with different cost consideration. The evolutionary strategy developed in this article can optimize the sensor placement for structural health monitoring in high temperature environments using a fitness function with the consideration of parameters from multiple types of sensors. The laboratory experiments validated the results of the developed algorithm for sensor placement optimization of SHM system in high temperature environments using the single-bay one-story steel frame case study. The sensors placement layout based on the developed algorithm with two temperature sensors and six strain sensors yielded a measurement accuracy of 76 % in a fire environment of 1292 °F (700 °C), which is very close to the expected value of 79.6 % obtained by the numerical analysis. The current algorithm is applicable for one-dimension (1-D) problems. Future work will apply this method to multiple dimension problems such as structures in three dimensions (3-D) and include more parameters to be considered such as vibration and moisture if needed.

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