Ultrasonic Sensor Placement Optimization in Structural Health Monitoring Using CMA Evolutionary Strategy

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Abstract

Ultrasonic guided wave technology is one of the commonly used methods in monitoring the health conditions of aerospace, civil, and mechanical infrastructures. Sensor network scale and sensor distribution are very important issues, which greatly affects the sensor network performance as well as the structural health monitoring (SHM) system cost. To improve the state-of-the-art from commonly used empirical sensor distribution, a quantitative sensor placement optimization method with covariance matrix adaptation evolutionary strategy (CMAES) and a damage detection probability model is presented in this paper. The miss-detection probability of a sample problem with 12 sensors improves by 11% from an arbitrary random sensor distribution. CMAES algorithm assessment is also carried out with algorithm parametric study and a comparison with another evolutionary strategy algorithm. Finally, the trade-off relation between optimized sensor network performance and the number of sensors is obtained.

1 INTRODUCTION

Structural health monitoring (SHM) is the process of implementing a damage detection strategy for aerospace, civil, and mechanical infrastructures. Damage detection, localization, assessment, and structure remain life prediction are four levels of structural health monitoring objectives. Most of the structural components are natural waveguideds. This provids the ultrasonic guided waves with trememdous opportunety to interrogate the health condition of the structures through wave excitation, propagation, and detection. Ultrasonic guided wave based methods have been recognized as a major part of SHM research. In a passive ultrasonic monitoring situation, sensors are used to detect the ultrasonic signals emitted from a damage event, either a crack propagation or an object impact. In an active ultrasonic monitoring situation, actuators are used to generate ultrasonic waves in a structure. The wave propagates in the structure and carrying out the material and structural information to the detection sensor. If a damage occurs in the structure, the signal will be affected. By using advanced signal processing and decision making algorithms, the damage can be detected, localized, and assessed.

Much efforts have been directed in the areas of wave propagation mechanics study, and sensor design and optimization. Few works have been reported on the sensor network level design and optimization using binary coded GAs for fixed sensor locations (Worden,2001; Guo, 2004). The work presented in this paper aims at developing a quantitative sensor placement optimization methodology for passive ultrasonic sensor network performance enhancement and cost reduction. Wave propagation and sensor design charateristics are abstracted into a damage detection probability model, which serves as a basis for the sensor placement optimization.

Genetic and evolutionary algorithms are population based searching algorithms, in which the exploration of searching space is guided by selection and genetic operators such as cross over and mutation (Back, 2000). Within a short time since its emerging, GEA has achieved an exponetially increasing applications in many fields. Covariance matrix adaptation evolotionary strategy (CMAES) developed by Nickolaus Hansen is particularly capable of solving problems with highly nonlinear, concave, and rugged search landscapes (Hansen, 2005). Sensor network configurations are optimized toward minimum miss-detection probability with CMAES in this paper. CMAES algorithm assessment is also carried out with algorithm parametric study for example the algorithm reliability assessment with random seed analysis, algorithm parametric sweet spot exploration with population size and parent number tuning. An algorithm comparison with another evolutionary strategy algorithm is also discussed in the paper. Finally, the relation showing the trade off between optimized performance and the number of sensors is obtained. The approximated Pareto optimum front provide very important information for real sensor network designs.

2 THEORIES

2.1 A PROBABLISTIC DAMAGE DETECTION MODEL

The ultrasonic wave propagation characteristics are governed by the theories of mechanics, material properties, and structural boundary conditions. The basic concept of passive ultrasonic sensor structural health monitoring is shown in Figure 1. When a damage occurs in the structure, ultrasonic signals will be generated from the damage location and propagate along the plate. The damage event is detected successfully if the wave is detected by a sensor and classified to be a damage event. Therefore, a complete model needs the charateristics of the processes of wave generation, propagation, and detection (Rose,1999). A detailed wave mechanics study is needed for complicated structures and structure oriented sensor and actuator design. The sensor network optimization will then base on the performance of each sensor.

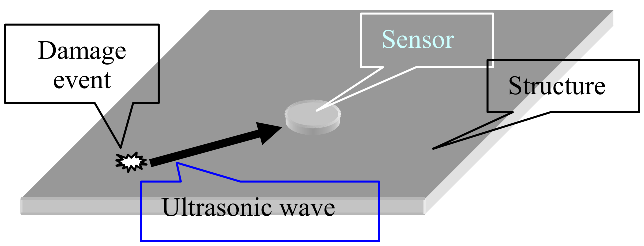

Figure 1: Ultrasonic passive sensor damage monitoring scheme

In this model, the sensor network optimization is separated from the detailed wave mechanics study and individual sensor design. For the case of an isotropic structure, the waves propagate in all the directions with the same velocity. When material attenuation is negligible, the wave energy attenuation is only due to the increase of wavefront scale. In this case, the signal is assumed to be proportional to the reciprocal of the distance between the sensor and the damage event. Based on this assumption, a statistic model is developed to represent the effective region of the sensor.

Equation 1 shows that each sensor has a confident monitoring region defined by a circle with R_1 radius. The damage detection probability decreases with distance until it reaches R_2. When the distance is larger than R_2, the damage event signal is no longer resolvable from the system noise and the sensor loses its effectiveness totally in this region. An example of a sensor effective region is shown in Figure 2.

$$P(x,y,x_0,y_0)=\begin{cases}1 & when \quad R<R_1\\ \dfrac{R_1}{R} & when\, R_1<R<R_2\\ 0 & when \quad R>R_2\end{cases} \tag{1}$$

Here, $R=\sqrt{(x-x_0)^2+(y-y_0)^2}$

(x,y) is the position of the damage event, and (x_0,y_0) is the position of the sensor.

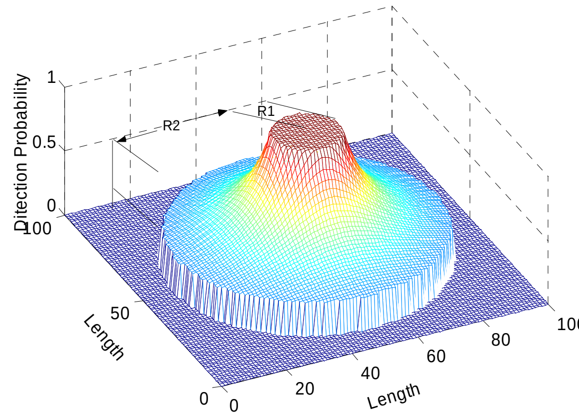

Figure 2: Sensor damage detection probability distribution

The entire effectiveness of a sensor network is the joint effect of all the sensors. Based on the theory of probability, the sensor network sensitivity at a certain point is the union probability of all the sensors.

$$P(x,y)=\bigcup_{i=1}^{SN}(P(x,y,x_i,y_i)) \tag{2}$$

Equation (2) can be implemented as a sequence of union probability of two probabilistic events through Equation (3).

$$\begin{aligned}&\bigcup(P(x,y,x_1,y_1),P(x,y,x_2,y_2))\\ &=P(x,y,x_1,y_1)+P(x,y,x_2,y_2)\\ &\quad -P(x,y,x_1,y_1)\times P(x,y,x_2,y_2)\end{aligned} \tag{3}$$

Sensor network performance can be evaluated by its damage detection probability for the entire structure. Case history study information is used as the guidance in the sensor placement optimization. When the normalized damage distribution on the structure is $P_d(x,y)$, the damage detection probability for the entire structure is defined in Equation (4).

$$DDP=\iint_{Stucture\ region}P(x,y)P_d(x,y)dxdy \tag{4}$$

Here, the normalization of $P_d(x,y)$ is expressed as

$$\iint_{Structure\ region} P_d(x,y)dxdy = 1 \quad (5)$$

To enhance the performance of the sensor network is equivalent to minimize the miss-detection probability (MDP).

$$MDP = 1 - DDP \quad (6)$$

In numerical implementation, grids of sample points are used to evaluate MDP in a 2D space. The integration can be reduced to a summation at the sample points.

$$MDP = 1 - \sum_{j=1}^{SPN} P(x_j, y_j) P_d(x_j, y_j) \quad (7)$$

The minimization of MDP is essentially to place the sensors at the structural hotspots defined by case history damage distribution. For many real applications, the information of structural hotspots is not available or not precise. The overall damage detection objective is to increase the coverage of the sensor network. In this case, Equation (7) reduces to Equation (8).

$$MDP = 1 - \frac{\sum_{j=1}^{SPN} P(x_j, y_j)}{SPN} \quad (8)$$

For most of the real applications, constraints in sensor position should be considered. For example, the sensors installed in the region with high damage susceptibility are not preferred to prevent the sensor from being damaged. The other example is some structural geometric constraints produce some infeasible sensor locations. The constraints should also be handled in an optimization problem.

2.2 CMA EVOLUTIONARY STRATEGY

CMA evolutionary strategy (CMAES) is a heuristic optimization algorithm. The initial population is generated by sampling a normal distribution with user specified mean value and standard deviation of each decision variable. Offspring generation, selection and recombination, covariance matrix adaptation, and step size control are four key operators in the process of evolution. A searching iteration stops when user specified convergence or any other stop criterion is met.

2.2.1 Offspring Generation

A new population is sampled from a normal distribution specified by

$$x_k^{(g+1)} \sim N(m^{(g)}, (\sigma^{(g)})^2 \mathbf{C}^{(g)}) \quad (9)$$

for $k = 1,2,\ldots,\lambda$

Here, λ is the population size; $x_k^{(g+1)}$ is the k^{th} sampled individual of generation (g+1). $N(m^{(g)}, (\sigma^{(g)})^2 \mathbf{C}^{(g)})$ is a multivariate normal distribution in generation (g). $m^{(g)} \in R^n$ is the mean value of decision variables in generation (g); $\sigma^{(g)} \in R_+$ is the “overall” standard deviation, which is also termed step size; $\mathbf{C}^{(g)} \in R^{n\times n}$ is the covariance matrix. *n* refers to the number of decision variables.

2.2.2 Selection and Recombination

Selection and recombination are used to determine the mean value of the distribution for generation (g+1).

$$m^{(g+1)} = \sum_{i=1}^{\mu} w_i x_{i:\lambda}^{(g+1)} \quad (10)$$

Here, $x_{i:\lambda}^{(g+1)}$ is the i^th best individual in generation (g+1). The first μ individuals in fitness ranking are chosen for recombination. Different weights can be assigned to each selected individual to enhance selective pressure. Generally, the recombination takes all the μ selected parents into account. The recombination weights should satisfy Equation (11).

$$\sum_{i=1}^{\mu} w_i = 1, w_1 \geq w_2 \geq \cdots \geq w_\mu > 0 \quad (11)$$

$$\mu_{eff} = \left(\sum_{i=1}^{\mu} w_i^2\right)^{-1} \quad (12)$$

A *variance effective selection mass* defined from the recombination weights is expressed in Equation (12). This paramter is a measurement of the selective pressure in CMAES. The value of μ_{eff} is in the range [1 μ]. When the population size of a problem is given, smaller μ_{eff} represents higher selective pressure. At the extreme case when $\mu_{eff} = \mu = \lambda$, there is no selection at all; when $\mu_{eff} = 1$, only the best individual is selected for offspring generation.

The algorithm parameters introduced in this section are population size (λ), parent number (μ) and recombination weights (w_i).

2.2.3 Covariance Matrix Adaptation

The covariance matrix describes the shape of the variable distribution. The goal of covariance matrix adaptation is to fit the search distribution to the contour lines of the objective function to be minimized.

$$\begin{aligned}\mathbf{C}^{(g+1)} &= (1-c_{\text{cov}})\mathbf{C}^{(g)} \\ &+ \frac{c_{\text{cov}}}{\mu_{\text{cov}}}(\mathbf{p}_c^{(g+1)}\mathbf{p}_c^{(g+1)^T} + \delta(h_\sigma^{(g+1)})\mathbf{C}^{(g)}) \\ &+ c_{\text{cov}}(1-\frac{1}{\mu_{\text{cov}}})\sum_{i=1}^{\mu}\frac{w_i}{(\sigma^{(g)})^2}(x_{i:\lambda}^{(g+1)} - m^{(g)})(x_{i:\lambda}^{(g+1)} - m^{(g)})^T\end{aligned} \quad (13)$$

In Equation (13), three contribution terms are considered for **C** matrix adaptation.

The third term $\sum_{i=1}^{\mu}\frac{w_i}{(\sigma^{(g)})^2}(x_{i:\lambda}^{(g+1)}-m^{(g)})(x_{i:\lambda}^{(g+1)}-m^{(g)})^T$ is an estimator for the distribution of selected steps. The first term $\mathbf{C}^{(g)}$ carries the information of the previous generations into to the covariance matrix of generation (g+1). This term is particularly useful and important for fast search with small population size. $\mathbf{p}_c^{(g+1)}$ is an evolution path used in to exploit the correlations between consecutive steps. Equation 14 is the detailed expression of evolution path.

$$\mathbf{p}_c^{(g+1)} = (1-c_c)\mathbf{p}_c^{(g)} + h_\sigma^{(g+1)}\sqrt{c_c(2-c_c)\mu_{eff}}\,\frac{m^{(g+1)}-m^{(g)}}{\sigma^{(g)}} \quad (14)$$

The algorithm parameters introduced here are learning rate for covariance matrix update (c_{cov}), learning rate for evolution path update (c_c), and weighting between the evolution path update and estimator of distribution update (μ_{cov}).

2.2.4 Step Size Control

A cumulative path length control method is used in CMAES to update the step size $\sigma^{(g)}$ of each generation. In this method, a conjugate evolution path is constructed according to Equation (15). Then, $\sigma^{(g+1)}$ is generated with Equation (16).

$$\mathbf{p}_\sigma^{(g+1)} = (1-c_\sigma)\mathbf{p}_\sigma^{(g)} + \sqrt{c_\sigma(2-c_\sigma)\mu_{eff}}\,\mathbf{C}^{(g)-\frac{1}{2}}\frac{m^{(g+1)}-m^{(g)}}{\sigma^{(g)}} \quad (15)$$

$$\sigma^{(g+1)} = \sigma^{(g)}\exp\left(\frac{c_\sigma}{d_\sigma}\left(\frac{\left\|\mathbf{p}_\sigma^{(g+1)}\right\|}{E\left\|N(\mathbf{0},\mathbf{I})\right\|}-1\right)\right) \quad (16)$$

Two algorithm parameters introduced here are learning rate for cumulation of step size control (c_σ) and damping parameter for step size update (d_σ).

2.2.5 Parameter Settings

Suitable algorithm parameterization is always important for the performance of genetic and evolutionary algorithms in the aspects of searching efficiency, global optimization quality, and algorithm reliability. The algorithm parameters used in CMAES are λ , μ , w_i , c_{cov} , c_c , μ_{cov} , c_σ and d_σ . Fortunately, a set of default parameter setting is given in the algorithm, which is tested to be a robust setting applicable to a wide range of functions to be optimized (Hansen 2005). The default settings for population size, parent number and recombination weights are expressed in Equation (17), Equation (18), and Equaiton (19) resepectively.

$$\lambda = 4 + \lfloor 3\ln n \rfloor \quad (17)$$

$$\mu = \lfloor \lambda/2 \rfloor \quad (18)$$

$$w_i = \frac{\ln(\mu+1)-\ln i}{\mu\ln(\mu+1)-\sum_{j=1}^{\mu}\ln j} \quad \text{for } i = 1,2,\ldots,\mu \quad (19)$$

2.2.6 Stop Criteria

CMAES provides a suite of stop criteria including the maximum stop fitness, maximum number of function evaluation, maximum number of iteration, decision variable change threshold, fitness change threshold. Stop criteria indicating algorithm divergence are also provided, for example, the upper limit of decision variable change, the upper limit of function fitness change, etc.

2.2.7 Boundary and constraint handling

The boundary handling methodology provided in CMAES is to replace the random generated value with the corresponding boundary value of the decision variable when the sampling is out of bound. The lower boundary is used if the value is less than the lower boundary. The upper boundary is used if the value is larger than the upper boundary. In the numerical experiment, in order to exploit the diversity of the searching space, the initial step size is set to be half of the boundary range. A large portion of the samples is out of bound and then set to the boundary value. Therefore, premature convergence sometimes happens at the boundary value. To solve this problem, the "sticky boundary" is modified to a "reflection boundary" in the work presented in this paper. Instead of using the boundary value, the symmetric value with respect to the boundary is used in the modified "reflection boundary" when the sampled value is out of bound. Each decision variable within a newly generated offspring experiences the reflection boundary check before the offspring is used for function fitness evaluation.

Constraints can also be handled in CMAES with a user defined penalty function in the objective function or simply discard the infeasible solution and generate new offspring until the population size is met.

3 A SAMPLE SENSOR NETWORK DESIGN PROBLEM

3.1 MONITORING PROBLEM DESCRIPTION

In this sample problem, normalized sensor and structure scale is used. The monirtoring region is 100x100 in arbitrary unit. The sensor performance parameter R_1 and R_2 are 3 and 40 respectively.

The case history damage distribution is shown in Figure 3. The damage distribution is normalized such that the summation of the probability in a 100x100 sample grids is 1. In this sample structure, the damages are most likely to happen in two elliptical areas at two sides and the center of the plate.

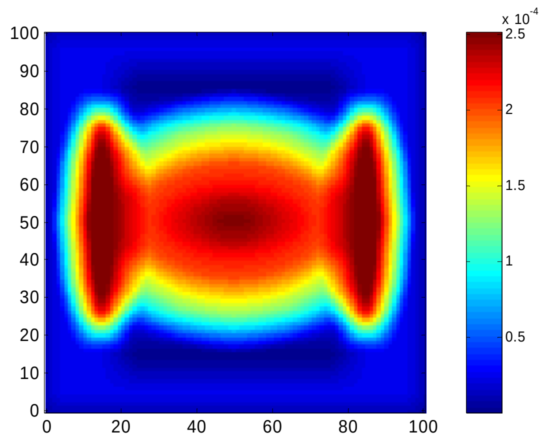

Figure 3: Damage probability distribution

3.2 OPTIMIZATION PROBLEM FORMULATION

The optimization problem is to minimize the MDP function in Equation (8) when the the number of sensors is given. When the sensor number is N, 2N real decision variables will be considered for the x and y coordinate positions of these sensors. Real coded evolutionary strategies are used. No other constraints are used besides the boundaries of the monitoring region. The mathematical formulation of this optimization problem is in Equation (19).

Minimize $f(X,Y)=MDP(X,Y)$ (19)

When $X_{lb} \leq X_i \leq X_{ub}$ $i=1,2,...,N$

$Y_{lb} \leq Y_i \leq Y_{ub}$ $i=1,2,....N$

Here for this particular problem $X_{lb}=Y_{lb}=0$, and $X_{ub}=Y_{ub}=100$.

3.3 SENSOR PLACEMENT OPTIMIZATION RESULTS AND ALGORITHM PARAMETRIC ANALYSIS

3.3.1 Sensor Network Placement Optimization with Default Parameter Settings

The default algorithm parameter setting is used for the sensor placement optimization when the number of sensors used is 12. According to Equation (17-19), the population size, parent number and recombination weights are listed in Table 1.

Table 1: Algorithm parameters

Number of Sensors	12
Number of variables	24
Population size	13
Parent number	6
Recombination weights	[0.3818 0.2458 0.1663 0.1098 0.0660 0.0302]

The evolutionary search stops when the maximum standard deviation of the decision variables is smaller than 0.25. This represents the convergence of the sensor placement configuration. The evolution history of the best fitness value of each generation for one run is plotted versus the number of function evaluation in Figure 4. At the beginning of the search, the step size of the decision variables are large, the variation of best fitness values change dramatically. Because the offspring generation is sampled from a normal distribution derived from the selected parents, it does not guarantee that the best fitness found in the new generation is better than the previous generation. Therefore, in CMAES, the best fitness value of each generation usually does not decrease monotonically, which is different from some evolutionary algorithms with deterministic selection operators. In addition, the best ever found solution is not necessarily within the final generation.

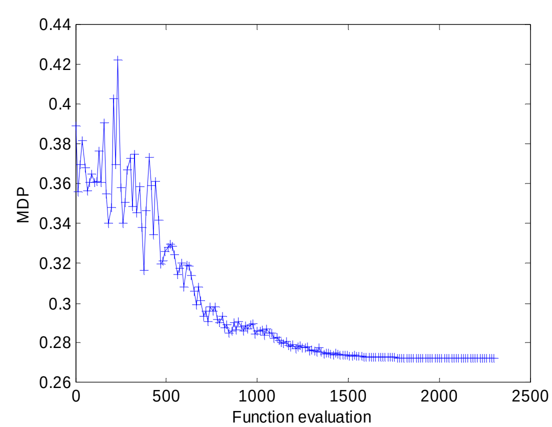

Figure 4: The evolution history of the best fitness value of each generation

The best fitness value of MDP found in this run is 27.24%. This means that the 12 sensor system can detect 72.76% of the damage events occurred on this structure. Although this number is somehow not very satisfactory, the performance is fair for the limited sensor sparse array system. In addition, the evolutionary algorithm improves the performance of the sensor network by decreasing the MDP by about 11% from arbitrary sensor placement configurations to the best configuration find in this run. The sensor network sensitivity distribution of the optimized configuration is shown in Figure 5. This figure shows that the sensor placement result from the CMAES optimization generally fits the structure hotspot. The corresponding miss-detection probability distribution is shown in Figure 6. It is found that the four corners of the hotspot area are not well covered by this 12 sensor network configuration.

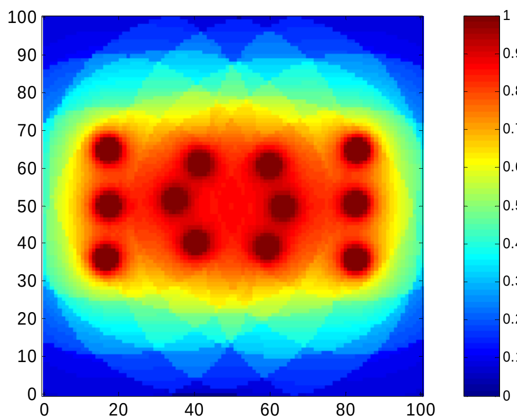

Figure 5: Sensor detectability distribution of the best sensor configuration found in one run of CMAES

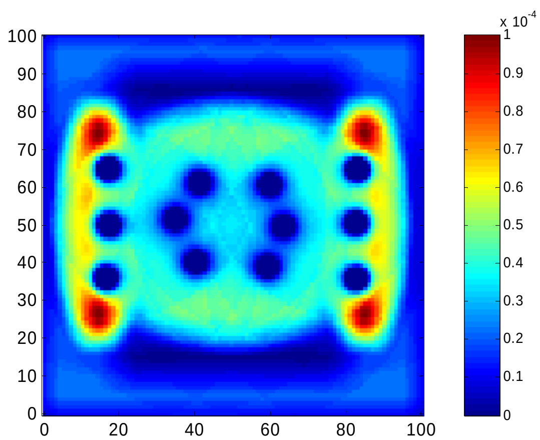

Figure 6: Damage miss-detection probability distribution

3.3.2 CMAES algorithm reliability analysis

40 different random number seed runs are used to evaluate the reliability of this CMA evolutionary strategy. The best ever found minimum miss-detection probability (MDP) and the minimum MDP in the last generation are evaluated for the test runs. The corresponding number of function evaluations for the best ever found solution and the number of function evaluation for algorithm convergence are also recorded. Although the best ever found solution is not guaranteed to be found in the final generation, it is always close to the last generation. This means that the selection process of the algorithm indeed drives the solution toward the best in the process of its evolution. The mean value and standard deviation of these four results are listed in Table 2. Very small standard deviations of the optimized MDP value is observed from the 40 runs. In addition, the standard deviation of the number of function evaluation toward convergence is also comparably small to the average number of function evaluation. Therefore, the CMAES with default parameter setting has a good performance in terms of its reliability for this problem.

Table 2: Statistic analysis of algorithm reliability

40 random number seeds	Stop at converge		Best ever solution	
	MDP (%)	Function evaluation	MDP (%)	Function evaluation
Mean	27.25	2596	27.25	2536
Standard deviation	0.0113	379	0.0106	381

Although the optimized fitness value is very close for all the 40 runs, the optimized sensor placement configuration are not always the same. Besides the one that is shown in Figure 6, the sensor distribution configuration obtained in another run is shown in Figure 7. There are also some other configurations observed. The ultimate reason for this multiple solution is that the damage probability distribution shown in Figure 4 is fairly smooth and flat at the center region. Therefore, the MDP values of slightly different sensor configurations are very close. In the context of genetic and evolutionary algorithm, it is because of the extremely small gradient in the searching landscape toward the global optima. The stop criteria setting used here terminates the evolution process when the maximum standard deviation of the decision variables is smaller than 0.25. Further study with refined stop criterion and increased population size could be used to validate the reason for this multi solution result. From another point of view, different configurations with close performance actually provided the designer with more choices in a real application.

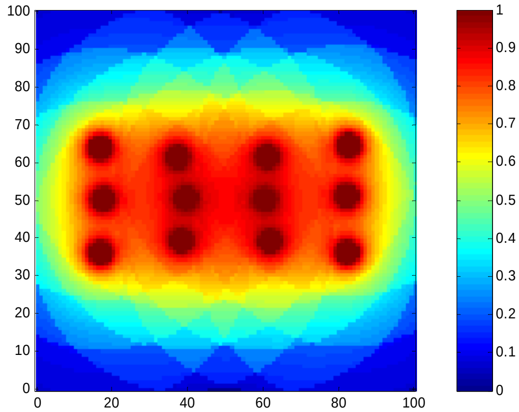

Figure 7: Another example of optimized sensor configuration

3.3.3 Exploration of Sweet Spots: Algorithm Parametric Study

An exploration of the algorithm sweet spot is performed by tuning the population size and parent number.

In the first experiment, the population size sequence used are [8 10 12 14 16 18 20 22 24 26], which covers the default setting of 13. The parent number is also derived from Equation (18). Some typical searching histories are shown in Figure 8. Different population size lead to very close optimized MDP value. The mean and standard deviation are 27.24% and 0.015% respectively. Slight decreasing of the MDP values is observed when the population size increases. This fits into the scenario of evolutionary search that larger population size lead to better global optima search. However, since the deviation is within the range of the algorithm reliability, there is still no conclusive assertion for this.

The number of function evaluation for small population size is significantly smaller than those values for larger population size. When the population size increased from 10 to 26, the number of function evaluation increases from 2000 to 5000. This shows the effectiveness of CMAES algorithm in quick search by using a satisfactory small population size. In addition, extremely smaller population size will not help the process of searching. When population size is 8, the convergence of the algorithm is found to be slower than population size 10. Again, more runs are needed to validate this conclusion from the stochastic behavior of evolutionary search.

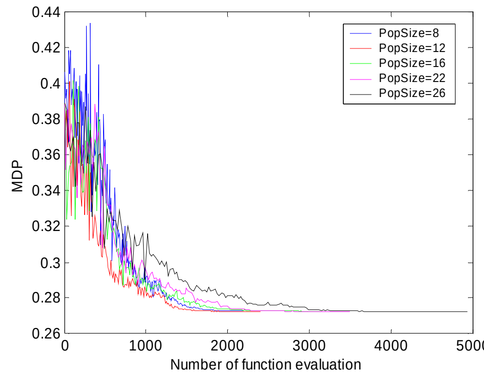

Figure 8: Searching history using different population size.

The parent number analysis is also carried out when the population size is fixed at 13. Six parent numbers [2,4,6,8,10, 12] are used for testing. The result shows that the final optimum of MDP slightly improves with the increase of population size in the range of 0.05%. The number of function evaluation is very close for these runs. However, the best fitness value for each generation along the searching history improves quicker for larger parent number. This is reasonable, because larger parent number ensures steady convergence while the small parent number introduces too much selective pressure and larger oscillation steps in the searching process. Therefore, the fitness value improves in a comparably larger oscillation manner. Because the evolution path, historic covariance information, and step size control are used in CMAES, no obvious premature convergence that ends up with a significantly poor result is observed in these runs.

3.3.4 Comparison with other Evolutionary Strategy Algorithms

To assess the performance of CMAES, the same problem is solved with an ordinary (λ +μ) evolutionary strategy. The same stop criterion used is also when the standard deviations of the decision variables are all less than 0.25. The maximum generation number is set to 200. The selective pressure for the ranking based search is set to 2, which ensures most greedy selection. Firstly, eight population sizes ([20 22 24 26 28 30 32 40]) are experimented. These values are set according to the theoretical guidelines for binary GA drift prediction. $\lambda \sim 1.4\times(2\times SN)=34$ All of the runs terminate at the maximum number of generation. The value of the final evolution results are [0.2733 0.2727 0.2747 0.2729 0.2737 0.2729 0.2724 0.27309]. The mean and standard deviations are 27.32% and 0.0702% respectively. Secondly, the population size is set to 32, which gives the best solution in the eight runs. The results of 30 random seed runs shows the mean value and deviation of the MDP are 27.3% and 0.051% respectively. Comparing these results with the results listed in Table 2, CMAES is found to be better in both searching quality and efficiency.

3.4 SAFETY VERSUS COST

The previous result shows that when the sensor number is 12, the optimized MDP is 27.25%. This is not a satisfactory monitoring design if one damage event may cause significant deterioration or even catastrophic failure of the structure. A multi-objective optimization problem is naturally brought up to find a balance point between the safety and cost. In the decision variable domain it is expressed as putting an optimized number of sensors in its right position

In this study, the performance is evaluated by the MDP value of a sensor network configuration, and the number of sensors represents the cost. A group of single objective optimization problems is solved to approximate the Pareto optimum set. The result of MDP versus sensor number is shown in Figure 9. MDP decreases monotonically with the increasing of number of sensors. When R_1=3, the miss-detection probability decreases to 10% when the number of sensors used is 24.

In addition to get the optimized sensor placement, the improvement of individual sensor performance is also a very important issue. The optimized MDP when the confident monitoring radius of the sensor is 5 is also shown in Figure 9. As was expected, the overall performance increased significantly.

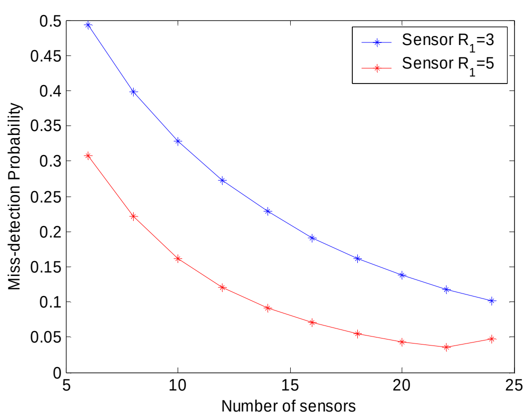

Figure 9: Relation between Miss-detection probability and the number of sensors

4 CONCLUSIONS AND DISCUSIONS

A probabilistic damage detection model is developed in this paper to evaluate the performance of a passive ultrasonic sensor network in structural health monitoring. CMAES is used to optimize sensor distribution on the structure. For the sample network with 12 sensors, CMAES results achieved 11% damage detection probability improvement compared with random sensor network configuration. An algorithm parametric study is also performed including the algorithm reliability, quality, and efficiency test. The result shows that the CMAES algorithm is comparably reliable with the default algorithm parameter settings. Reasonably small population size can be used to find the optimized fitness value quickly. The CMAES over performs the comparing evolutionary algorithm in both the searching converging speed and solution quality in the test runs performed in this research. An approximate Pareto optimum set solution illustrating the tradeoff between safety and cost is obtained by solving single objective optimization problem with different number of sensors.

For future research, the sensor network design problem is essentially a multi-objective optimization problem. NSGA-II, ε -NSGA-II, SPEA-II and other multi-objective genetic and evolutionary algorithms are appropriate tools to get a set of solutions more efficiently. When a multi-metric sensor network quality evaluation are used, a higher order multi-objective optimization problem formulation is in great demand. Application of genetic and evolutionary algorithms in real monitoring structures with material attenuation and anisotropy are some of the future research directions.

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