Uncertainty analysis of sensitivity of MEMS microphone based on artificial neural network

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Abstract Due to the uncertainties from manufacturing processes and material properties, MEMS (micro-electro-mechanical system) microphone may exhibit significant variations in their performance compared to the nominal design. The published analytical methods have obvious shortcomings, which cannot meet the needs of both accuracy and efficiency. In order to improve efficiency, the MC (Monte Carlo) simulation based on ANN (artificial neural network) is presented to analyze the uncertainty of sensitivity of polysilicon circular clamped diaphragm microphone. Using the PDS (probabilistic design system) of Ansys software and MC simulation to predict the qualified rate of microphone, the simulated results are 91.2% and 91.4% respectively. The qualified rate of manufactured microphones is 91.5%. In addition, the time-consuming of these two simulations are 10 minutes and about 3000 minutes. This paper also analyzes the change of sensitivity probability densities with the variety of nominal parameters of diaphragm. The results show that the presented MC simulation with accuracy and high efficiency is an alternative to the traditional methods.

key words: uncertainty analysis, sensitivity, MEMS microphone, artificial neural network, Monte Carlo simulation.

Classification: Micro- or nano-electromechanical systems

1. Introduction

MEMS condenser microphone is a micro sensor for converting sound pressure into electrical signal. Sensitivity of which is the mechanical or electronic response of microphone under standard sound pressure. In reality, the significant uncertainties on the geometry and material properties are unavoidable due to low-precision manufacturing processes of MEMS devices [1, 2, 3, 4, 5]. In the past, Monte Carlo method based on FEM (finite element method) was used to consider the uncertainty associated with the various input parameters during the design of electrostatic MEMS devices [6, 7, 8]. Recently, several improved approaches based on MC simulation, such as lumped parameter model [9,10], Reduced order model [11, 12], Sparse-grid stochastich collocation method [13] and Latin hypercube sampling [14], have been proposed for the reliability-based optimal design. Other stochastic analysis methods, including polynomial chaos expansion [15,16,17], uncertainty quantification [18] and first-order reliability method [19], also have been used to solve these uncertainty problems of MEMS devices. However, these methods mentioned above have obvious shortcomings, which cannot meet the needs of both accuracy and efficiency. ANN is nonlinear so that it has the ability to solve the curse of dimensionality problem. Recently, ANN models have been widely used to simulate electrical or mechanical characteristics of different MEMS devices. They have been applied mostly to the models of pull-in voltage [20, 21, 22] and S parameter [23, 24, 25, 26, 27, 28] of RF-MEMS (radio frequency MEMS) switches, to resonant frequency [29] and spurious modes [30] of RF-MEMS resonator, and to S parameter [31, 32, 33] of RF-MEMS phase shifter. Uncertainty analysis is the key technique and research focus in the MEMS optimization. This paper uses the improved MC simulation based on artificial neural network to predict the probabilistic density of microphone sensitivity due to the uncertainty of diaphragm parameters such as radius, thickness and young modulus. The results show that the MC Simulation based on ANN is extremely effective in uncertainty analysis of MEMS condenser microphone.

2. Device structure and operation

MEMS condenser microphone consists of diaphragm, air-gap, substrate, cavity, clamped backplane and acoustic holes on backplane, depicted in figure 1. The capacitance changes are transformed into voltage signal. Measuring this voltage signal, the value of external sound pressure can be obtained.

Fig. 1. Side-view of typical MEMS condenser microphone.
Let diaphragm thickness be denoted as $h$ and radius be represented as $R$. Young modulus and Poisson ratio are represented as $E$ and $\nu$ respectively. $d$ and $g$ stand for the cavity depth and air-gap height.

This paper designs polysilicon circular clamped diaphragm microphone. The physical dimensions and material parameters of diaphragm are listed in table 1.

| Table I. Design summary of the proposed MEMS microphone. |
|---|---|---|---|
| Parameters | Value Range | Increment | Unit |
| Radius | [0.5,1] | 0.01 | mm |
| Thickness | [8,12] | 1 | µm |
| Air-gap height | 30 | | µm |
| Cavity depth | 1 | | mm |
| Young modulus | [171,209] | 9.5 | GPa |
| Poisson ratio | 0.23 | | |

3. Monte Carlo simulation based on ANN

3.1 ANN model for MEMS microphone

This paper uses BP (back propagation) neural network to find the relationship between the essential parameters of diaphragm and microphone sensitivity. ANN usually consists of three main layers: input layer, hidden layer and output layer. The BP model designed in this paper has three input neurons, corresponding to the dimensions $R$, $h$ and young modulus $E$, one output neuron, corresponding to the sensitivity, and one hidden layers with 5 hidden neurons. Figure 2 illustrates the ANN architecture of MEMS condenser microphone. Tan-Sigmoid is chosen as the transfer function of hidden layer. Because of the characteristics that have fast convergence and less error, LM (Levenberg-Marquardt) algorithm is adopted as the training method. ANN model building, training and testing are all completed in Matlab software.

![Fig. 2. ANN architecture with input and output parameters.](image)

In this work, the training data set simulated by Ansys software includes 1275 data. The 1020 data are chosen for training ANN while the rest are used to test the model quality. The MSE (mean square error) between output vectors and desired values is used to verify the model. If the MSE of trained ANN is more than 0.001, the next steps are adjusting network structure and retraining. The final MSE of ANN model is 0.00083, which is less than 0.001 and meets the design requirement.

3.2 Monte Carlo simulation

MC simulation is a traditional technique used to analyze the uncertainty that cannot easily be predicted due to the interaction of random variables. This paper represents a new MC simulation based on ANN, computing efficiency of which improves significantly. The program flow chart under Matlab software environment is as shown in figure 3. It consists of two subprograms: MC simulation and ANN model establishment. Firstly, the design values and distributions of diaphragm parameters are set in MC simulation subprogram. Next is setting sampling number of MC simulation. The main steps of program are adjusting the sampling number until the simulation convergence. The computation of this process is based on ANN model. Finally, the probability density of sensitivity are calculated by MC simulation.

![Fig. 3. Program flow charts of MC simulation and ANN model establishment.](image)

4. Numerical results and discussion

4.1 Qualified rate of MEMS microphone

This paper designs and produces the polysilicon circular clamped diaphragm microphone, the microstructure photograph of which is as shown in figure 4.

![Fig. 4. Microstructure photograph of the manufactured MEMS microphone.](image)

The probability distributes of diaphragm parameters due to low-precision manufacture process can be effectively fitted by normal distribution. Table 2 shows the nominal values and deviation of diaphragm parameters.

| Table II. Nominal values and deviations of diaphragm parameters. |
|---|---|---|
| Diaphragm parameter | Nominal value | Deviation |
| Radius | 1mm | 1% |
| Thickness | 10µm | 1% |
| Young modulus | 190GPa | 3% |

When the nominal values of diaphragm parameters are
selected, the sensitivity of MEMS microphone is 0.937nm/Pa. In this paper, the standard of qualified rate is that the relative error of microphone sensitivity is less than 10%. If the testing value of sensitivity is within the range [0.84, 1.03], MEMS microphone meet the requirement of sensitivity quality standard. A total of 10000 microphones have been fabricated in this study. The sensitivities of 9152 microphones among them are within the [0.84, 1.03]. The qualified rate of MEMS microphones is 91.5%. The distribution of the measured data fits better into normal distribution, the mean value \( \mu = 0.933 \) and the deviation \( \delta = 0.058 \). Using the MC simulation based on ANN to predict the qualified rates of sensitivities, the variation curve of qualified rate with the sampling number is as shown in figure 5.

![Fig. 5. Qualified rates versus the sampling numbers of MC simulation. The results of MC simulation converge gradually with the increase of sampling number. As sampling number is greater than \( 10^6 \), the simulation result converge to 91.4%. PDS module of Ansys, which combines FEM with probability design, is common tool for uncertainty analysis of MEMS devices. The simulation process includes three steps: generating analysis files, probability design and simulation results output. In this study, normal distribution data is transferred to PDS module, in which the finite element computations are completed. The calculation results are returned to Matlab for distribution fitting. The qualified rate of microphone sensitivity simulated by PDS of Ansys software is 91.2%. Table 3 shows the comparison of distribution between the measured data and the predicted values.

| Range of the sensitivity (nm/Pa) | Practical measured data (%) | Predicted values of MC simulation (%) | Predicted values of PDS (%) |
|---------------------------------|-----------------------------|--------------------------------------|-----------------------------|
| (0.46, 0.65)                    | 0.7                         | 0                                    | 0                           |
| (0.65, 0.84)                    | 7.1                         | 5                                    | 3.9                         |
| (0.84, 1.03)                    | 91.5                        | 91.4                                 | 91.2                        |
| (1.03, 1.22)                    | 0.7                         | 3.6                                  | 4.9                         |
| (1.22, 1.41)                    | 0                           | 0                                    | 0                           |

Table III. Comparison of the distribution between the measured data and the predicted values.

The qualified rate predicted by MC simulation agrees well with the measured data, the relative error is less than 1%. Therefore, the MC simulation based on ANN is effective to calculate the distribution of sensitivity.

In this study, the sampling number of MC simulation and PDS are set to \( 10^6 \) and 1000 respectively. Correspondingly, the time-consuming of two different methods are 10 minutes and about 3000 minutes. the efficiency of MC simulation based on ANN is far more than that of PDS based on FEM.

4.2 Probability density of microphone sensitivity

Using MC simulation and PDS, this paper calculates the Probability density of microphone sensitivity, the comparison of simulation results is as shown in figure 6.

![Fig. 6. Comparison of Probability densities between simulated data and measured data.](image)

The distribution parameters simulated by PDS are \( \mu = 0.939 \) and \( \delta = 0.054 \). Obviously, the results of MC simulation coincides well with that from PDS.

![Fig. 7. Comparison of probability densities between MC simulated data and measured data.](image)

The qualified rate predicted by MC simulation agrees well with the measured data, the relative error is less than 1%. Therefore, the MC simulation based on ANN is effective to calculate the distribution of sensitivity.

In brief, the new MC simulation with accuracy and high efficiency is an alternative to the traditional methods.

In this paper, the MC simulation based on ANN is used to analyze the change of sensitivity distributions with the varieties of diaphragm parameters. The results are as
shown in figure 8. Obviously, the diaphragm parameters have a great effect on the sensitivity distributions. Figure 8(a) shows the means and deviations of distributions keep a increasing tendency as the radius increases. The decreasing tendency of the means and deviations with the increase of thickness is illustrated in figure 8(b). Comparing with figure 8(a) and 8(b), the changing trend shown in figure 8(c) is clearly different. With the increase of young modulus, the means decrease but the deviations maintain.

Using normal distribution to fit the sensitivity distributions shown in figure 8, the fitting results are displayed in table 4.

![Fig. 8. (a) As the thickness and young modulus are set to 10µm and 190GPa, the Probability density of Sensitivity versus radius.](image)

### Table IV. Mean values and deviations versus diaphragm parameters

| Diaphragm parameters | Mean value | Deviation |
|----------------------|------------|-----------|
| $h = 10\mu m$ $E = 190GPa$ | | |
| $R (mm)$ | Mean value | Deviation |
| 0.6 | 0.12 | 0.007 |
| 0.7 | 0.22 | 0.013 |
| 0.8 | 0.36 | 0.023 |
| 0.9 | 0.61 | 0.037 |
| 1 | 0.94 | 0.057 |
| $h (\mu m)$ | Mean value | Deviation |
| 8 | 1.81 | 0.108 |
| 9 | 1.28 | 0.075 |
| 10 | 0.94 | 0.057 |
| 11 | 0.7 | 0.042 |
| 12 | 0.54 | 0.032 |
| $R = 1mm$ $E=190GPa$ | | |
| $h = 10\mu m$ | Mean value | Deviation |
| 171 | 1.03 | 0.058 |
| 180.5 | 0.98 | 0.057 |
| 190 | 0.94 | 0.057 |
| 199.5 | 0.89 | 0.054 |
| 209 | 0.84 | 0.055 |

5. Conclusion

In the period of MEMS microphone design, the most frequently method for improving the sensitivity is enlarging the radius of diaphragm or reducing thickness. As shown in table 4, the varieties of diaphragm parameters influence the sensitivity distributions. Improving microphone sensitivity only by changing geometric parameters of diaphragm will usually cause the decline in the qualified rate. The change of young modulus only affects the mean values of sensitivity distribution but has no influence on the deviations. In order to both improve the sensitivity and remain the qualified rate stable, reducing the young modulus of diaphragm is a effective way.
microphone sensitivity. The radius and thickness of diaphragm affects both mean value and deviation of sensitivity distribution. Different from this, young modulus only influence mean value. Therefore, reducing young modulus of diaphragm is a effective method for optimizing probability density of sensitivity.

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