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Structural Damage Recognition Based on the Finite Element Method and Quantum Particle Swarm Optimization Algorithm

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ABSTRACT Structural damage recognition is always the concerned focus in many fields like aerospace, petroleum and petrochemical industry, industrial production and civil life. For damage recognition in complex structure or structural interior, especially somewhere sensors can't go, minor damage is often hard identified by not only traditional nondestructive testing methods like ultrasonic testing, radiographic testing, magnetic particle testing, penetrant testing, eddy current testing, but also the current popular ultrasonic guided wave based on the piezoelectric wafer, electromagnetic acoustic transducer or magnetostrictive sensor, which is mainly because the response signals are always affected by many structural features. In this article, the advanced global search algorithm, quantum particle swarm optimization algorithm is first combined with the finite element method to accurately recognize the structural damage based on the conductance-frequency spectrum resulted from electromechanical impedance method. Meanwhile, the objective function is designed to compare the difference of peak frequency variations in the experiment and finite element calculation respectively. By adopting the stiffness reduction method of the elements near the structural damage, the identification efficiency is largely improved for no need to repeatedly partition the model grid. And after multiple iteration optimization of the artificial intelligence algorithm - quantum particle swarm optimization algorithm, the identification error of damage parameters including location and degree can be reduced to below 4 percent. Therefore, the combination of finite element method and quantum particle swarm optimization algorithm is quite effective for guaranteeing high accuracy and efficiency for damage parameters' recognition in complex structures.

INDEX TERMS Quantum particle swarm optimization algorithm, finite element simulation, electromechanical impedance, structural damage identification, conductance signal.

I. INTRODUCTION

Glaser *et al.* [1] as the experts and leaders of bridge structural health monitoring and control point out that in the last thirty years, there are quite many large-scale bridges, railways and highways are built, so in the next thirty years, the primary task is maintenance and management to prevent catastrophic accidents, i.e. failure prognostics and health management will be of great concern in future. Now, there are many SHM (structural health monitoring, SHM) [2]–[7] and NDT (nondestructive testing, NDT) [8], [9] researches based on various sensors such as displacement sensor, acceleration sensor, strain sensor, temperature sensor, piezoelectric sensor, etc., but for some complex structures or structural state affected by many factors, it is not easy to fast identify the structural damage degree and location, so usually, there are two or more methods combined to perform qualitative and quantitative analysis. Adegboye *et al.* [10] realized the discrimination of two types of damages by combining the Lamb method with support vector machine but compared to the EMI (electromechanical impedance, EMI) method, the Lamb technology needs to combine relatively complex circuit

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system because of its high excitation voltage, severe energy dissipation, and multiple signal reflections, etc. Therefore, the author of [11] combined the EMI technology and ANN (artificial neural network, ANN) to recognize changes in the structural surface, in which a large number of training samples are required. For damage parameters identification, there are many feature selection methods like firefly algorithm [12], PSO (particle swarm optimization, PSO) [13], differential evolution [14], and genetic algorithm [15], but in this article, the EMI method sensitive to a structural state change, combined with the AI optimization algorithm based on the concept of PSO is first proposed to recognize minor structural damages, which is mainly because that the PSO algorithm has the characteristics of fewer parameters, simple implementation, fast computing speed, etc. [16]

Although many advantages are mentioned above, however, in the standard PSO algorithm, the particles converge in the form of orbits, and the search space of the particles is limited and cannot cover the entire space. What's more, when the number of iterations is infinite, the PSO algorithm cannot converge to the global optimal solution with probability 1 and is easy to fall into the local optimal solution [17]. In 2004, Sun Jun *et al*. proposed a global optimization algorithm - QPSO (quantum particle swarm optimization, QPSO) algorithm [18], [19] from the perspective of quantum mechanics. And after that, the QPSO algorithm is used in many fields like robotic vehicle path planning [20], bacteria detection, and classification [21]. In this new algorithm, the definition of particles has the characteristics of quantum behavior, there is no certain flight trajectory, and the position is updated with a certain probability. In theory, it can reach any point of the feasible solution space, so compared with the standard PSO algorithm, the global search ability of the QPSO algorithm is stronger, the search range is wider, and the damage recognition accuracy is more accurate. There are also many other PSO algorithms used in different areas. For example, PSO with compression factor for the optimization of mine-laying strategy, the variable-size cooperative co-evolutionary particle swarm optimization for feature selection on high-dimensional data, a filter-based bare-bone particle swarm optimization algorithm for unsupervised feature selection, and a bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch. In this article, only a few geometrical parameters for local structure damage need to be obtained fast and accurately, so only employing the ordinary QPSO is enough and appropriate.

In the remaining part of the study, the basic principle of the EMI, FEM (finite element method, FEM) and QPSO method are first presented, together with establishment of objective function in the subsection D of Section II. Subsequently, quantitative damage identification method for complex structures is discussed. Then, damage detections of porous plate and L-shaped thin plate are performed in Subsections A and B respectively of Section IV, and simultaneously results are described and discussed. Finally, the study conclusions are discussed in the last section of the body.

II. THE BASIC PRINCIPLE OF STRUCTURAL DAMAGE IDENTIFICATION BY FINITE ELEMENT METHOD AND QUANTUM PARTICLE SWARM OPTIMIZATION ALGORITHM

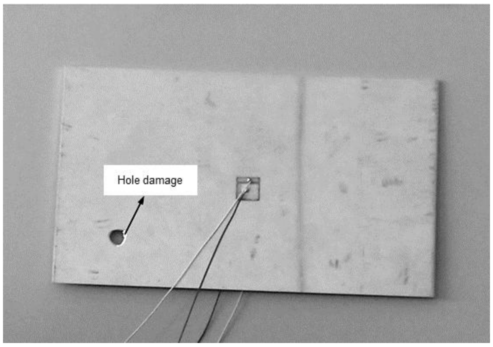
Accurately and quickly identify structural damage is based on not only the effective damage response identification method but also rapid damage parameter analysis algorithm. In this article, the EMI method is used to sense the slight structural state changes caused by minor damage, and then the QPSO combined with FEM is introduced to identify the structural damage parameter information.

A. ELECTROMECHANICAL IMPEDANCE THEORY

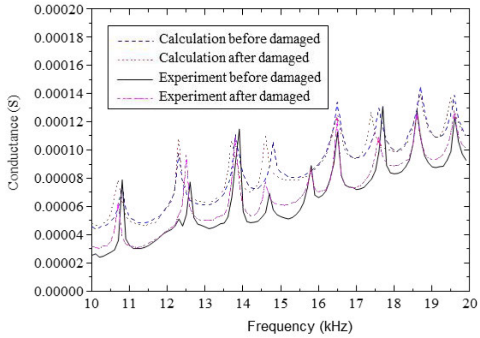
Based on the piezoelectric effect and its inverse effect, the EMI method is used to identify the change of structural state by impedance/admittance or their real and imaginary parts. It, via global vibration to recognize local damage, principally transforms electric energy to mechanical energy to produce excitation and on the contrary, transforms mechanical energy to electric energy in the form of voltage to sense structural response. Then by analyzing, contrasting between baseline and experiment, and synthesizing all the sensors' receipt signals, the damage existence, location, and degree can all be obtained to further predict residual structure or system lifetime.

The local damage like hole and crack refers to damage in the local position, which only affects the performance or lifetime of the local structure; and the global damage like extensive corrosion and large deformation of the whole usually refers to damage affecting the overall performance of the structure or system. Although the limit detection area, the EMI method is applicable to both local and global damage. And offline inspection and online monitoring are both feasible, because of the flexible detection manners of EMI method. Combined with various damage evaluation method, the EMI method can be used to quantitatively recognize and assess structural damage conveniently. In the last few years, the damage index representation method based on statistical analysis is mainly adopted in the structural damage degree identification based on EMI technology, which generally includes RMSD (root mean square deviation, RMSD), MAPD (mean absolute percentage deviation, MAPD), covariance and CCD (correlation coefficient deviation, CCD). This approach is simple and easy to operate, and can quickly determine structural damage. However, due to the complexity of the influence of structural damage on the piezoelectric impedance/admittance signals, the specific physical parameters of the damage cannot be obtained.

Previous researches like [22] has shown that the real part of the electrical admittance is more sensitive to the structural state changes than the imaginary part or magnitude, so hereinafter only the real part of admittance - electrical

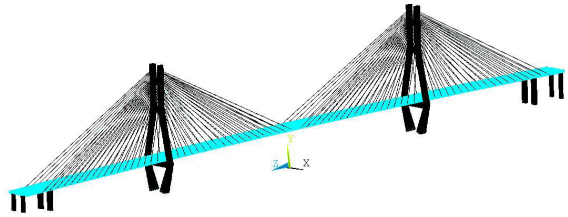


(a) a thin aluminum plate specimen

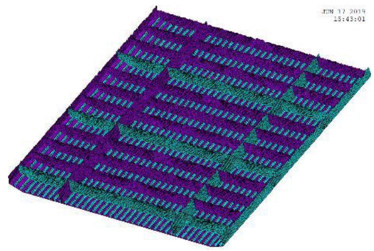


(b) conductance-frequency spectrum

FIGURE 1. A thin plate is tested by EMI method before and after the hole damage is manufactured.



(a) finite element model of full bridge



(b) partial steel bridge deck

FIGURE 2. FEM of a certain Yangtze River Bridge with the internal structure of its steel bridge deck.

conductance is extracted to demonstrate the signal difference before and after structural damage based on EMI. Although conductance results from the theoretical calculation, full-size simulation and experiment are often quite different for a certain working condition, the peak frequency offset before and after the damage is almost the same, so the location and size of the damage can be judged by the difference of peak frequency offset, which can be seen from Figure 1 that the peak frequencies' offset by calculation and experiment is almost uniform at the given frequency domain.

B. FINITE ELEMENT METHOD

FEM as a tool of simulating real structure is mainly by discretizing a system into a lot of elements and then perform element analysis and element synthesis to solve the characteristic equation. With the development of a GPU (graphic processing unit, GPU), the high performance parallel computing power becomes stronger and stronger, which makes the finite element simulating of many complex structures become easy, i.e. with sufficient calculation capacity and quite a high efficiency for simulating infrastructures, constructions, and bridges. For example, the main bridge of a certain Yangtze River bridge presented in Figure 2 is wholly simulated by FEM software for fatigue crack growth analysis at various parts, which length and width are respectively near to 1000 m and 40 m. Nowadays, FEM simulating computation has been applied in many fields like not only civil engineering but also machinery, aerospace, water conservancy, and others for structural damage propagation calculation, system safety evaluation, flow field, and wind field simulation, etc.

The FEM tool can be used to analyze the structural health status, determine the damage propagation process and extract all kinds of response signals, to lay a solid foundation for structural health monitoring (SHM) and NDT&E in reality.

C. QUANTUM PARTICLE SWARM OPTIMIZATION ALGORITHM

Let the particle size scale be N and the particle dimension be D. The current position of the i-th particle is $\mathrm{S}_i = (\mathrm{S}_{i1}, \cdots, \mathrm{S}_{iD})$, and the position with the best fitness value that the i-th particle can find is $\mathrm{Pbest}_i = (\mathrm{Pbest}_{i1}, \cdots, \mathrm{Pbest}_{iD})$, which is called the optimal position experienced by the particle i (i.e., the local best point). Among them, the best one in Pbest_i $(i = 1, 2, \cdots, N)$ is recorded as *Gbest*, the optimal position that all the particles in the population have experienced (or called the global best point). Since the position and velocity of particles cannot be determined simultaneously in quantum space, [18] uses the wave function $\varphi(x, t)$ to describe the state of the particle, obtains the probability uses the wave function $\varphi(x, t)$ to describe the state of the particle, and obtains the probability density function of the particle reaching a certain point in space by solving the solution of the Schrödinger equation. Then by the reverse Monte Carlo transformation, the update formula for the position in the d-th dimension of the i-th particle is as follows:

$$S_{id}(t+1) = p_{id}(t+1) \pm \frac{L_{id}(t+1)}{2} \ln \frac{1}{u_{id}(t+1)} \tag{1}$$

where, the symbol "±" is determined by a random number between 0 and 1 which is uniformly distributed. In other words, when the generated random number is greater than 0.5, "-" is taken, otherwise "+" is taken. In the above formula, the random point position p_{id} in the d-th dimension can be expressed as:

$$p_{id}(t+1) = \frac{m_{id}(t+1)Pbest_{id}(t) + n_{id}(t+1)Gbest(t)}{m_{id}(t+1) + n_{id}(t+1)} \tag{2}$$

Among which, $m_{id}(t+1)$, $n_{id}(t+1)$, and $u_{id}(t+1)$ are random numbers that are independent of each other and are uniformly distributed in section [0, 1]. In [4], the $L_{id}(t+1)$ is defined as:

$$L_{id}(t+1) = 2b(t+1)\left|mbest_d(t+1) - S_{id}(t)\right| \tag{3}$$

where, $mbest_d(t+1) = \frac{1}{N}\sum_{i=1}^{N} Pbest_{id}(t)$ is the data in the d-th dimension of the average optimal position of the particle population; $b(t)$ is called the contraction and expansion coefficient, which is an important parameter that affects the convergence of the QPSO algorithm, and is also the only parameter that needs to be customized. It can be a value according to the actual situation, namely, it can be a constant and also can be dynamically changed, which is usually defined as follows:

$$b(t) = b_1 - (b_1 - b_2)\frac{t}{Maxiter} \tag{4}$$

Among which, b_1 and b_2 are respectively the initial and ending values of the coefficient $b(t)$, $Maxiter$ represents the maximum number of iterations. Equation (4) shows that as the iteration progresses, $b(t)$ decreases linearly from b_1 to b_2. Under normal circumstances, better convergence can be achieved when $b_1 = 1$ and $b_2 = 0.5$.

Substitute Equations (2) and (3) into (1) can result in:

$$\begin{aligned} S_{id}(t+1) = p_{id}(t+1) \pm b(t+1)\,|mbest_d(t+1) \\ -S_{id}(t)\frac{L_{id}(t+1)/2}{2}\ln\left(\frac{1}{u_{id}(t+1)}\right) \end{aligned} \tag{5}$$

It can be seen from the above analysis that the QPSO algorithm is a global optimization algorithm, and the specific steps are as follows:

(1) Set initial parameters to generate an initial population;
(2) Calculate the current fitness value of each particle and compare it with the value of the previous iteration. If the current fitness value is smaller than the previous one, update the current position of the particle, that is $p_i(t+1) = x_i(t+1)$, if $f(x_i(t+1)) < f(p_i(t))$.
(3) Calculate the average optimal position $mbest$.
(4) Calculate the current global optimal position of the population and compare it with the global optimal position of the previous iteration. If the current global optimal position is better, the global optimal position of the population is updated.
(5) For each dimension of the particle, calculate the random point position p_i according to Equation (2) and calculate the new position S_i of the particle according to Equation (1). If a particle flies out of the search space (i.e., violates the constraint), the position of the particle is equal to its boundary value, and its velocity is multiplied by -1 to cause the particle to search in the opposite direction.
(6) Verify that the end condition is met: If the iteration stop condition is reached (the current iteration number reaches the maximum number of iterations or the optimal solution reaches the minimum error requirement), the algorithm ends, returning the current optimal individual $Gbest$ as the solution output; otherwise, the process is transferred Step (2).

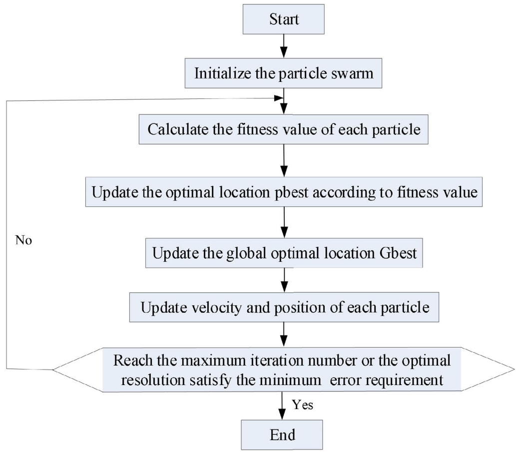


FIGURE 3. QPSO algorithm flow chart.

D. OBJECTIVE FUNCTION OF DAMAGE IDENTIFICATION

In this article, the quantitative identification of damage parameters is transformed into the optimal solution of the objective function using the QPSO algorithm. Therefore, the objective function of the PSO algorithm firstly need to be determined. Through the predecessors' researches in [23]–[26], it can be found that the calculation results of the EMI response model established are close to the experimental results, but there are always some differences, which reason is that theoretical modeling is impossible to accurately determine all the factors in the experiment. Considering it, there is always a difference between the theoretical modeling analysis and the actual measurement results, and usually, this difference will affect the accuracy of damage identification. But at the same time, the research in [27], [28] shows that the peak frequency variation of the conductance curve calculated by the model before and after the structural damage is very close to peak frequency variation in experiment. Therefore, in order to reduce the impact of the difference between theoretical modeling and experiment on the accuracy of damage recognition, the objective function is designed as follows:

$$f(\mathbf{D}) = \sum_i \left[(P_i^{tu} - P_i^{td}(\mathbf{D})) - (P_i^{eu} - P_i^{ed})\right]^2 \tag{6}$$

In the above formula, P represents the corresponding frequencies of main peaks among the conductance signal of the piezoelectric smart structure, i represents the peak number of the conductance signal, $\mathbf{D}$ represents the vector composed of the damage parameters, and the superscripts t and e respectively represent the results of theoretical analysis and experimental measurement, at meanwhile the superscripts u and d indicate that there is no damage and some damage in the structure to be tested, respectively. For cracked beam structures, the damage parameter vector $\mathbf{D}$ can be expressed as $\mathbf{D} = (h, x)$, h and x respectively represent the depth and position of the crack from its end, and for the boundary loosening, $\mathbf{D} = (k, K)$, in which k and K respectively represent the boundary linear elasticity coefficient and torsional elasticity coefficient. It should be noted that he peak frequency used is not the maximum peak frequency, but all the peak frequencies in the electrical impedance/admittance-frequency spectra.

III. QUANTITATIVE DAMAGE IDENTIFICATION METHOD FOR COMPLEX STRUCTURES

Based on EMI detection method, the traditional manner is mainly to adopt kinds of damage indexes based on a statistical analysis of impedance/admittance - frequency spectra, which can describe the damage existence and development. Then various intelligent algorithms like an artificial neural network [11], [29], support vector machine [10], and genetic algorithm [30] are all introduced to improve the damage identification accuracy, which all can approximately quantitative characterize damage status but cannot calculate exactly the damage parameters. To solve some structural damage parameters is a typical inverse problem, and it is usually a nonlinear problem, which is difficult to be solved by solving equations. Therefore in this article, QPSO algorithm combined with FEM is used to solve this inverse problem.

When the QPSO algorithm is used for damage identification, multiple iterative operations are required. Each iteration means that the damage needs to be re-assumed, so it is necessary to re-mesh the mesh. In order to avoid repeated meshing and ensure certain recognition accuracy, when the structure is slightly damaged, only the stiffness of the structure near the center of the damage changes in this article, and the properties of the rest of the structure are unchanged. Therefore, only the stiffness of the elements near the structural damage can be approximately considered to be decreased. Supposed that the element stiffness matrix before and after damaged is respectively K_{0i}^e and K_i^e the relationship of the element stiffness matrix between the conditions before and after damaged can be expressed:

$$K_i^e = K_{0i}^e(1-\varepsilon_i) \qquad 0 \leq \varepsilon_i \leq 1 \tag{7}$$

The above formula actually considers the stiffness matrix of the damage element as the perturbation of the undamaged element stiffness matrix, and the parameter ε_i is the variation of the element stiffness matrix, reflecting the degree of structural damage. The reduction of the element stiffness usually adopts a relatively coarse (mean sense) quantization process, and it can be considered that the damage is the reduction of the common factor - elastic modulus in the structural element

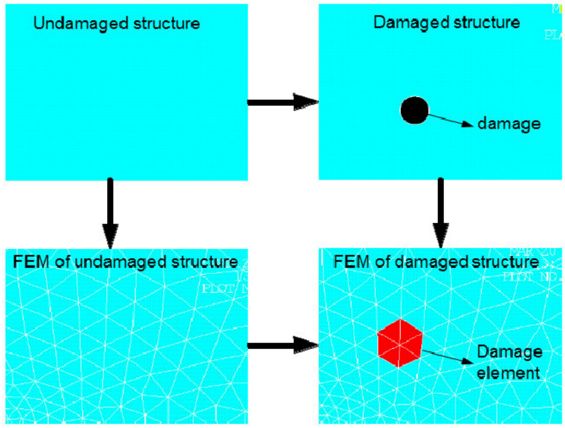


FIGURE 4. FEM processing diagram of damaged structure.

TABLE 1. Physical parameters of thin plate structure.

elastic modulus E(GPa)	density ρ(kg/m^3)	Poisson's ratio μ	damping ratio η
67	2700	0.33	0.01

stiffness matrix. Therefore, the average relative change value of the elastic modulus of the structural discretization elements is used as the damage identification parameter, which doesn't lose its general meaning, because there is the common factor in all kinds of element elastic stiffness matrix, and for the torsion term it is only need to convert the shear modulus into the elastic modulus by formula $G = E/2(1+\mu)$, which thus establishes a quantitative relationship between structural element damage and structural parameters at some average meaning.

In this article, the finite element modeling of the piezoelectric smart structure is firstly carried out. After the model is established, it is assumed that the damage is located at a certain node in the finite element model, and the properties (i.e. the elastic modulus) of several units sharing the mutual node in the finite element model are changed. The method achieves the purpose of simulating structural damage, as shown in Figure 4 below.

IV. DAMAGE IDENTIFICATION TEST

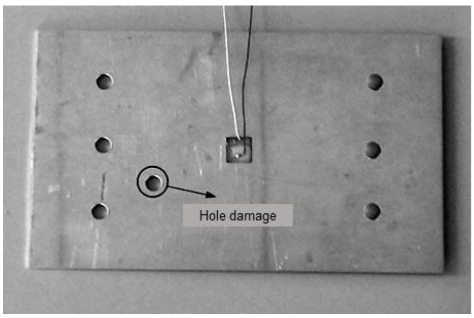
In this section, the hole damage on different complex structures like the perforated plate and L-shaped plate structure is detected by the method of the above section, and the specific material parameters of the aluminum plate are shown in Table 1. The size of the piezoelectric wafer is PZT-5A with dimensions of $a_p \times b_p \times c_p = 15$ mm $\times$ 15 mm $\times$ 0.5 mm and its specific physical parameters are displayed in Table 2.

A. DAMAGE DETECTION OF POROUS PLATE

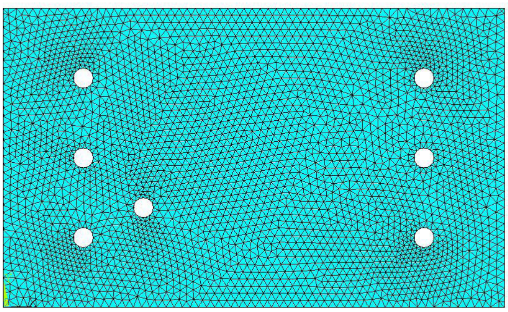
A hole damage was made on the perforated plate structure with dimensions of 250 mm $\times$ 150 mm $\times$ 2.7 mm by electric drill. The diameter of the hole was 10 mm, and the center coordinate of the hole was (70mm, 50mm) from the left bottom, i.e. the hypothetical origin of coordinates, as shown

TABLE 2. Physical parameters of piezoelectric ceramic wafer.

flexibility coefficients **S**(m^2/N)	piezoelectric coefficients **d**(C/N)	permittivity ε(F/m)	density ρ(kg/m^3)	mechanical loss η	dielectric loss δ
$S_{11}=S_{22}=16.4\times10^{-12}$	$d_{31}=-171\times10^{-12}$	$\varepsilon_{11}=1.53\times10^{-8}$	7450	0.01	0.01
$S_{12}=-5.74\times10^{-12}$	$d_{32}=-171\times10^{-12}$	$\varepsilon_{22}=1.53\times10^{-8}$			
$S_{13}=S_{23}=-7.2\times10^{-12}$	$d_{33}=374\times10^{-12}$	$\varepsilon_{33}=1.50\times10^{-8}$			
$S_{33}=18.8\times10^{-12}$	$d_{42}=584\times10^{-12}$				
$S_{44}=S_{55}=47.5\times10^{-12}$	$d_{52}=584\times10^{-12}$				
$S_{66}=44.3\times10^{-12}$					



(a) test specimen



(b)finite element mesh

FIGURE 5. Porous thin plate structure specimen and its FEM.

in Figure 5(a). The excitation frequency used in this experiment is 10 kHz - 20 kHz. When the mechanical impedance of the structure is analyzed by finite element model analysis software, the element size of the finite element model is less than 5mm to ensure sufficient calculation accuracy. The structure is divided by SOLID45 unit, and the total number of units is 12316. The finite element mesh is shown in Figure 5(b). The AC (alternating current, AC) excitation is applied to the piezoelectric wafer, and the EMI response signal of the porous plate structure before and after the damage is shown in Figure 6.

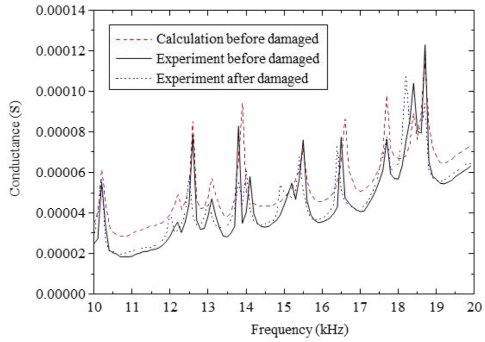


FIGURE 6. Conductance signals of porous plate structure before and after damaged.

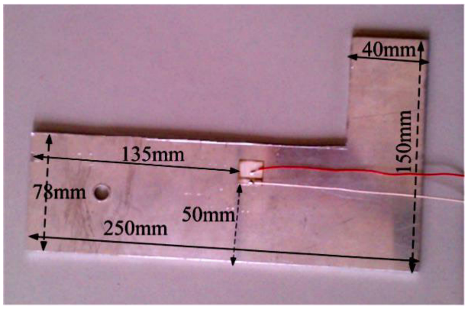
TABLE 3. Damage identification result of porous plate structure.

damage parameter	real value	recognition result	error
x_d	70mm	72.3mm	3.3%
y_d	50mm	51.4mm	2.8%
r_d	5mm	4.62mm	3.8%

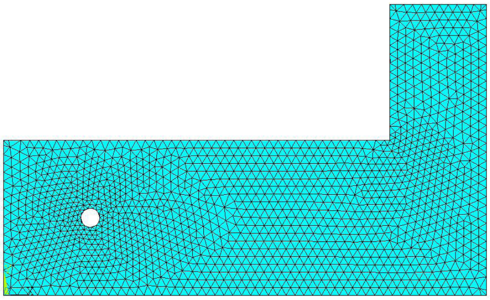
In order to effectively identify the structural damage radius r_d, the elastic modulus of the elements at the damage position is set as follows: $E_d = E_b(1 - 0.5 \times r_d/ l_e)$, where E_b is the elastic modulus before the structure is damaged, i.e. at the healthy status, and l_e is the maximum size of the element, which is taken as 5 mm. The QPSO algorithm is used to identify the structural damage. The identification parameter is selected as x_d, y_d, r_d, so the dimension of the particle is 3. The upper limit of the iteration number is set to 200, or the iteration is terminated when the objective function f is less than 0.005. The size of the particle group is 20. After many tests, it generally tends to be stable after about 130 iterations and to reach the optimal solution. The damage parameter identification results are shown in Table 3. It can be seen from the table that the method identification error is within 4%, which indicates that the damage identification method is effective and feasible. What's more, the identification accuracy is higher in many large-scale structures because compared to the big detection range, the near-field effects of piezoelectric wafer (like PZT and PMNPT) can be ignored. However, during the damage identification process, the temperature change and environmental noise are in reality not considered, which influence can be easily eliminated by one of many temperature compensation methods and signal filtering methods respectively.

B. DAMAGE IDENTIFICATION OF L-SHAPED PLATE

Compared with rectangle or square plate, L-shape and T-shape plates are more complex and more general, and these structures can be found in some recent papers based on UGW (ultrasonic guided wave, UGW) because there are



(a) specimen with dimensions marked



(b)FEM

FIGURE 7. L-shaped piezoelectric smart plate structure specimen and its FEM.

TABLE 4. Damage identification result of L-shaped plate structure.

damage parameter	real value	recognition result	error
x_d	45mm	46.6mm	3.6%
y_d	40mm	38.6mm	3.5%
r_d	5mm	5.15mm	3.0%

more boundaries and structural features to influence the complexity of response signal. Therefore, in this subsection the damage detection of the L-shaped plate structure is also carried out by the method of the above section. The piezoelectric wafer used is same as before. Some specific geometrical parameters are as shown in Figure 7(a), and the thickness of the L-shaped plate structure is 2.7 mm. The diameter of the hole used to simulate the damage is 10 mm, and the center coordinates of the hole are (45mm, 40mm) from the lower left corner. The specific material parameters of the L-shaped plate structure are shown in Table 1, and also the excitation frequency used in this experiment is 10 kHz - 20 kHz. When the mechanical impedance of the structure is analyzed by ANSYS, the element size of the finite element model is less than 5 mm to ensure sufficient calculation accuracy and efficiency. SOLID45 element is adopted in this structure, which contains a total of 8565 SOLID45 elements. The finite element meshing is shown in Figure 7(b). The AC excitation is applied to the piezoelectric wafer, and the EMI response signal of the L-shaped plate structure before and after damaged is shown in Figure 8. From the identification result in Table 4, it is obvious that the error is less than 4%, satisfying the realistic needs.

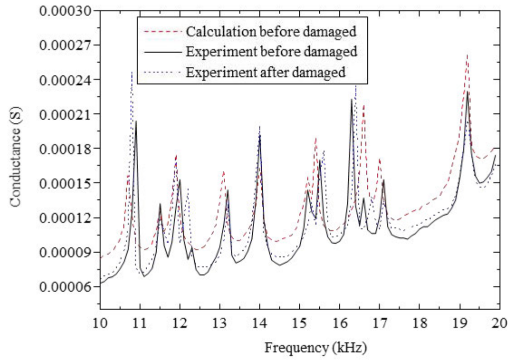


FIGURE 8. Conductance signals of L-shaped plate structure before and after damaged.

Through the above two examples of hole detection, it can be concluded that the error of hole size is only less than 0.4 mm, and that the location error is below 3 mm less than the damage radius, which both far exceed the detection accuracy of the previous researches-References [29], [31], [32]. In this article, the sensitive range of a minor piezoelectric wafer is large enough to cover the area of 250 mm × 250 mm at least. However, for the EMI method in practice, the sensitive range of a single piezoelectric wafer can be reach to 2000 mm × 2000 mm in many metal structures and at least 500 mm ×500 mm in composite structures. Although compared to structures like aerospace weapons and equipment, the structure used in this article is relatively small and simple, the application objects of EMI detection method and the QPSO-FEM algorithm are still wide enough to contain many mechanical structures, because the main principle of them two is the comparative law, i.e. the response change of current measurement relative to its baseline. Also, the time used for the computation of the proposed QPSO-FEM is only a few minutes, especially for a Core i7 computer with a solid state disk, 32 GB of memory, 64-bit operation system and dual CPUs whose core number and main frequency are respectively 8 and 3.4 GHz. And the experiment time is also a few minutes including the preparation process. Therefore, it can be concluded that after reasonable optimization, QPSO and FEM based structural damage recognition in big, complex structure or precise instruments can be used to identify damage like hole, crack and corrosion which affects structural local stiffness. However, it should be noted that there are indeed a few disadvantages for the method used in this article. First, the QPSO-FEM method is applicable to only mechanical damage detection, and not electrical devices which consist of many components and parts, seriously affecting the test results of EMI response due to the modelling difference. Secondly, the EMI method is mainly used to typical structures and micro structures, not appropriate for large-scale structures like long-distance pipeline because of the detection scope of EMI. Next, the QPSO-FEM method adopts the explorative manner to search the whole feasible solution space, so multiple iterations consuming a large amount of time are needed to find the optimal solution.

V. CONCLUSION

From the above experimental analysis and result discussion, it can be concluded that the structural damage recognition based on the first combination of FEM and QPSO is quite effective, which can guarantee high accuracy and efficiency for damage parameters' recognition in complex structures. Next, the stiffness reduction method of the finite elements near the structural damage is proposed and applied in local damage simulation to reduce the fine mesh division process and raise the identification efficiency. And then the established objective function for comparing the difference of peak frequency variation between two experiment results and peak frequency variation between two finite element calculations respectively, largely improves the identification precision, and reduces the influence of the difference between theoretical modeling and experiment on damage identification accuracy. Hence, the study provides a new method for the rapid identification of damage parameters of mechanical structures.

In the next step, this method will be used in some large and complex structures, or structures which are made of many small structural parts, making the EMI response complicated usually. And in meanwhile, the SAFE (semi-analytic finite element, SAFE) for replacing FEM will be adopted to combine with QPSO so as to improve the computation efficiency. More importantly, the QPSO algorithm for damage characterization should be introduced into the different types of multi-site damage parameters' identification rather than the qualitative and quantitative recognition of single common damage.

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