Reconstruction of Stress Corrosion Cracking Using Multi-Frequency Eddy Current Testing Signals Based on Genetic Algorithm

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Considering that the multi-frequency eddy current testing (ECT) technique can supply rich information from different positions of the inspection target, relation between multi-frequency ECT signals and stress corrosion cracking (SCC) parameters is investigated through numerical simulation. Numerical results show that features of ECT signals from different excitation frequencies are closely related to the crack profiles and local conductivity distribution. Generally, high-frequency ECT signals can be used to determine the approximate values of the conductivity in the upper layer of the crack zone. Low-frequency ECT signals contain more information from the lower layer conductivity and shape of crack. Consequently, SCC reconstruction using features of multi-frequency ECT signals is proposed. For the multi-parameter and multi-variable optimization problem, an inversion strategy using genetic algorithm is proposed to reconstruct the crack shape and conductivity distribution. The validation of the proposed strategy is verified through results from simulated and measured multi-frequency ECT signals.

***Index Terms*—signal reconstruction, stress corrosion cracking, multi-frequency, eddy current testing, genetic algorithms**

I. INTRODUCTION

IN THE regular nondestructive testing for key structural components of nuclear power plants, quantitative evaluation of stress corrosion cracking (SCC) profiles is necessary to guarantee both the safety and high efficient operation when SCC occurs. However, the conventional single-frequency eddy current testing (ECT) technique often underestimates SCC depth because of its local conductive property and ill-posedness of the inverse problem [1]-[2].

Considering that the multi-frequency ECT technique can supply rich information from different positions of the inspection target, a scheme using multi-frequency ECT signals is proposed to reconstruct SCC profiles. For the high-dimension optimization problem with multiple parameters of the crack shape and conductivity, the validation of an inversion strategy using genetic algorithm is investigated. Reconstruction of several modelled SCC is implemented to verify effectiveness of the proposed strategy.

II. RECONSTRUCTION OF SCC USING FEATURES OF MULTI-FREQUENCY ECT SIGNALS

The problem of SCC reconstruction often appears multiple minimum values due to lack of information from measured ECT signals. In order to fully exploit measured information, the relation between features of multi-frequency ECT signals and SCC parameters is investigated through numerical simulation firstly.

Numerical results show that ECT signals of different excitation frequencies vary differently with the change of crack parameters, especially the change of conductivity distribution in the crack zone. In general, the high-frequency ECT signals embody more information from parameters of the surface crack, especially the local conductivity of crack. Low-frequency ECT signals contain information of the crack shape and conductivity distribution in the whole crack zone. Therefore, in order to alleviate ill-posedness of crack reconstruction, features of multi-frequency ECT signals are used to the minimum problem of mean-square residual

$$min\ \varepsilon(c,\sigma)=\sum_j \alpha_j \sum_i \left|Z_{i,j}(c,\sigma)-Z_{i,j}^{obs}\right|^2, \qquad (1)$$

where $Z_{i,j}(c,\sigma)$ and $Z_{i,j}^{obs}$ respectively are the calculated signals and measured values at the ith scanning point corresponding to the excitation frequency j, which have been normalized; c is parameters of the crack profile, σ is the conductivity distribution, and α_j is a non-negative parameter corresponding to the jth excitation frequency.

A numerical method is usually applied to solve the optimization problem and it can be solved several times successively when the excitation frequency is from high to low. The crack conductivity distribution in the depth direction from the upper to lower is determined step by step, and the results are preserved as a priori information and then used to the next optimization model of SCC reconstruction. For quantitative evaluation of SCC, the method gradually determines the information of conductivity distribution in the depth direction, and thus reduces error of the shape reconstruction resulting from the inaccurate crack conductivity distribution. Therefore, reconstruction precision of the crack shape is expected to be improved by using features of multi-frequency ECT signals.

III. AN INVERSION STRATEGY USING GENETIC ALGORITHM FOR SCC RECONSTRUCTION

A. Genetic algorithm

The genetic algorithm is a high-efficient and globally random search method which inspired by the process of natural selection. In a genetic algorithm, a population of candidate solutions to an optimization problem is evolved toward the better solutions. Each candidate solution has a set of properties called chromosomes or genotype which can be mutated and altered. The evolution usually starts from a population of randomly generated individuals and the population in each iteration is called a generation. In each generation, individuals are stochastically selected from the current population according to the fitness values and then used to crossover and mutation operator to form a new generation [3].

B. Genetic algorithm design for SCC reconstruction

The parameters that need to be reconstructed for the SCC inverse problem include the crack shape parameters and conductivity distribution in the depth direction. This is a high-dimensional optimization problem. Genetic algorithm is suitable for solving this kind of problem of multi-variable and multi-parameter. The basic flows of genetic algorithm for SCC reconstruction are as follows: firstly, the feasible solutions of *N* group are selected randomly; then the forward subroutine is separately called and the fitness value of each candidate solution is calculated; finally, if the terminate condition is satisfied, output the best solution; if not, according to the fitness values and genetic scheme, generate a new population from old ones by means of selection, crossover and mutation operation, and then continue iterating.

Genetic algorithm requires coding, initialization, fitness calculation, and operations of selection, crossover and mutation. The main implementation procedure and method are as follows:

1) Coding: Each potential solution to this problem is represented in binary as a string of 0s and 1s, and the value of a string is known as a chromosome. For a two-dimensional rectangular crack, the crack shape parameters only comprise the crack depth and two crack edges in the length direction. For example, if defining the domains of the crack length is [-6, 6] and the required accuracy is 0.2 mm, the crack edge in the length direction needs a string of 6 bits. For a string of 6 bits, the parameter of one crack edge x can be parameterized as a decimal integer

$$M = \frac{2^6 - 1}{12}(x + 6). \tag{2}$$

Similarly, if defining the domains of the crack depth is [0, 5] and the required accuracy is 0.1 mm, the depth parameter needs a string of 6 bits; if defining the domains of the crack relative conductivity is [0, 1] and the required accuracy is 0.001 of relative conductivity, a conductivity parameter needs a string of 10 bits. If 3 conductivity parameters in the crack depth direction are used for SCC reconstruction, the full length of crack shape and conductivity coding is 48 binary bits.

2) Fitness function: The objective function can be easily converted into the fitness function by the following

$$f_i = C_{\max} - \varepsilon_i, \tag{3}$$

where f_i is the fitness function of the ith individual, ε_i is the mean-square residual corresponding to the ith individual, and $C_{\max}$ is a constant large enough.

3) Genetic operators:

Replication is the basic operation of genetic algorithm and the excellent individuals reproduce to the next generation of new groups, which embodies the natural selection law of survival of the fittest.

To avoid premature convergence, a sequential selection strategy is used rather than the roulette selection in the SCC inversion. For the sequential selection strategy, the individuals are sequenced and the selected probability is defined as

$$p_j = \frac{q(1-q)^{j-1}}{1-(1-q)^{NP}}, \tag{4}$$

where j is the individual location in the sequence, q the selected probability of the maximum fitness value, and NP is the number of population.

An adaptive strategy is used to adjust the crossover probabilit and mutation probability in real time according to the fitness value in the process of evolution. The individual that the fitness value is greater than the average of population is allowed to live and produce offspring in the next generation by setting a smaller crossover probabilit and mutation probability. In constrast, the individual is eliminated as its crossover probabilit and mutation probability is greater. Therefore, the adaptive strategy can improve the evolution speed and prevent the population from premature.

IV. A NUMERICAL RESULT

A rectangle crack of 12 mm length, 3 mm depth and 2% relative conductivity is used as the target of reconstruction. Randomly generate 20 candidate solutions with different shapes and conductivity as the initial individuals of population. Calculate the fitness function values of each individual and generate 20 new crack solutions from old ones by means of selection, crossover and mutation operation according to the fitness values and the genetic scheme. After 200 generations, the reconstructed result is length of 12.0 mm, depth of 2.98 mm and relative conductivity of 1.99%, respectively. After repeated reconstruction process, the errors between the reconstructed crack parameters and the truth are small. Though the genetic algorithm needs much computational time, it is stable and gives better results for the problem of SCC profiles reconstruction.

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