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Cluster analysis of stress corrosion mechanisms for steel wires used in bridge cables through acoustic emission particle swarm optimization

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ABSTRACT

Stress corrosion is the major failure type of bridge cable damage. The acoustic emission (AE) technique was applied to monitor the stress corrosion process of steel wires used in bridge cable structures. The damage evolution of stress corrosion in bridge cables was obtained according to the AE characteristic parameter figure. A particle swarm optimization cluster method was developed to determine the relationship between the AE signal and stress corrosion mechanisms. Results indicate that the main AE sources of stress corrosion in bridge cables included four types: passive film breakdown and detachment of the corrosion product, crack initiation, crack extension, and cable fracture. By analyzing different types of clustering data, the mean value of each damage pattern's AE characteristic parameters was determined. Different corrosion damage source AE waveforms and the peak frequency were extracted. AE particle swarm optimization cluster analysis based on principal component analysis was also proposed. This method can completely distinguish the four types of damage sources and simplifies the determination of the evolution process of corrosion damage and broken wire signals.

1. Introduction

The cable structure is one of the most important load-carrying members of long-span bridges. When positioned in natural environments for a long time, the polyethylene (PE) sheath wrapped on the steel surface of bridge cables, especially those located in damp environments in the sea, presents different levels of cracks. After the emergence of a crack on the PE sheath, the steel strands or high-tensile steel wires inside the sheath are exposed to the external environment; thus, corrosion occurs. Under the effect of stress, the localized corrosion pit on the surface of steels exhibits stress concentration. This stress concentration significantly affects the mechanical property of steels. Rupture failure will occur although the stress is far less than the yield strength of steels [1–3]. Therefore, stress corrosion monitoring of bridge cables plays an important role in ensuring the safety of bridges.

The stress corrosion mechanisms in bridge cables are highly complex. Different damage types involve various damage source signals, such as passive file breakdown, production of hydrogen bubbles, hydrogen embrittlement, corrosive pitting, initialization and extension of cracks, and fracture. Effective methods for the monitoring of bridge cable stress corrosion are scarce. Common existing methods include artificial detection, ultrasonic testing, and magnetic leakage [4–7]. Artificial detection cannot identify internal defects nor quantitatively evaluate the damage state. Thus, its outcome involves many human factors. Ultrasonic testing is the most common means to detect corrosion in bridge cables. The exact location and damage condition of corrosion can be determined with this method. However, experiment results have indicated that although this method can detect the locations of damage near the head of steel wires, effective corrosion damage monitoring of the wires in the distance remains challenging. Magnetic leakage method is also commonly utilized to detect damage in metal materials. However, this method has several apparent disadvantages. When used to detect bridge cables with protection, the monitoring signals are too weak to receive, the monitoring accuracy does not meet the requirements, and different types of defects cannot be distinguished. This study introduces the application of acoustic emission (AE) technology to monitor stress corrosion in bridge cables. AE is a dynamic monitoring method. The monitoring signal originates from the structure itself, and sensor placement is convenient. All-weather monitoring can thus be realized without delaying traffic. Stress corrosion monitoring with AE has been extensively applied, and several research achievements have been attained. Characteristic AE features (e.g., amplitude, energy, duration, rise time, counts, and frequency) are commonly extracted to

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analyze the micro failure mechanisms of different materials. AE waveform features, such as duration and frequency, generally carry information about the mode of the crack. Additionally, the AE amplitude recorded during loading is proportional to the intensity of the damage event and the emission energy that is connected to the intensity of the crack. AE counts characterize the oscillation frequency of the damage signal.

Ramadan [8] investigated high-strength steel stress corrosion cracking with the AE technique. This study produced promising results for the potential in situ use of AE in real-time health monitoring of eutectoid steel cables. AE has been utilized to monitor concrete and steel wire damage and failure in pre-stressed concrete [9–11]. AE can detect corrosion, macro cracks, and crack propagation in representative structures. AE has also been employed as a tool to detect corrosion processes in 304 stainless steel [12–14]. Different damage types (uniform corrosion, pitting, and crevice corrosion) can be identified with typical AE feature signals. However, related studies on the description of stress corrosion mechanisms in bridge cables according to AE signals and identification of the damage source at different stages are relatively scarce. AE is influenced by the signal characteristics and attenuation properties of bridge cables. Uncertainty is also an important issue in damage classification. Uncertainty exists in material properties, sensor characteristics, noise and nucleation, and evolution [15]. Different damage sources are affected by one another. Distinguishing the different stages of damage in a corroding structure is difficult when the traditional AE analysis method is utilized. For the cluster algorithm, the most frequently used methods are k-means, self-organized map combined with k-means, and fuzzy-c means algorithm. The k-means algorithm is the simplest and most effective method for AE signal clustering. Cluster analysis includes three main steps: AE characteristic parameter extraction, clustering algorithm selection, and validation of the defined clusters [16,17]. Calabrese [18] proposed a combination of principal component analysis and self-organizing map algorithms as a new procedure to identify the progression of different damage mechanisms in pre-stressed concrete beams. Johnson [19] developed a new AE uncorrelated feature to solve the dependency of the clustering process on varying parameters. With the AE signal difference, Máthis et al. [18] identified plastic deformation and crack propagation during stress corrosion cracking of stainless steel. Li et al. [21] adopted k-means clustering to study the stress corrosion process of 304 stainless steel for AE signal classification. Several researchers applied the signal process method to identify different corrosion sources. Piotrkowski et al. [22] studied corroded galvanized steel through wavelet and bi-spectrum analyses of AE signals.

In the current study, a stress corrosion experiment was conducted on steel wires used in bridge cables. The AE characteristic signal at different damage stages was obtained. A particle swarm optimization cluster algorithm was proposed to obtain the AE characteristic signal and determine the corrosion mechanisms of different damage sources. Subsequently, to improve the effect of clustering, a particle swarm optimization clustering algorithm based on principal component analysis was introduced.

2. AE particle swarm optimization cluster algorithm

2.1. Basic principle of the particle swarm optimization cluster algorithm

The shortcoming of conventional clustering algorithms is that they easily fall into the local optima. In this paper, a global optimal particle swarm cluster algorithm is presented. Particle swarm optimization can produce collective intelligence to guide the optimal search through cooperation and competition between particles. The solutions of each generation exhibit double excellence: self-learning for individual improvement and learning from others. Thus, the algorithm can obtain the optimal solution after a few iterations only.

Given an n-dimensional space containing m particles $z = \{z_1, z_2, \ldots, z_m\}$, each particle can be considered the solution of one combinational optimization problem, and the position coordinates of each particle are denoted by $z_i = \{z_{i1}, z_{i2}, \ldots, z_{in}\}$. Each particle has a unique direction of motion denoted by $V_i = \{v_{i1}, v_{i2}, \ldots, v_{in}\}$. The entire particle swarm moves in the solution space. The particles adjust their location to search for a new solution through local and global extrema. During the motion, each particle searches and records the optimal solution, which is denoted by P_{id} (local optimal extremum). The best solution identified by all particles is denoted by P_{gd} (global optimal extremum). When these two optimal solutions are found, the updating displacement–velocity formula is obtained as follows:

$$v_{id}(t+1) = w \cdot v_{id}(t) + \eta_1 \cdot rand() \cdot (P_{id} - z_{id}(t)) + \eta_2 \cdot rand() \cdot (P_{gd} - z_{id}(t)), \tag{1}$$

$$z_{id}(t+1) = z_{id}(t) + v_{id}(t+1), \tag{2}$$

where $v_{id}(t+1)$ is the speed of the ith particle in the dth dimension during the $(t+1)$th iteration. To prevent particles from moving too fast, speed limit $V_{\max}$ is necessary. When $v_{id}(t+1) > v_{\max}$, $v_{id}(t+1) = v_{\max}$; when $v_{id}(t+1) < -v_{\max}$, $v_{id}(t+1) = -v_{\max}$. This transformation can be realized with Formula (3).

$$w = w_{\max} - iter \times \frac{w_{\max} - w_{\min}}{iter\max}, \tag{3}$$

where $iter$ denotes the current number of iterations and $iter\max$ denotes the default maximum number of iterations. w represents inertia weight, which can be utilized to help a particle maintain its inertia. If $w = 0$, the speed of a particle will not have memorability. The particle swarm will directly shrink to the current global optimal position and lose the ability to conduct subsequent searches. As a general rule, w is a random number between 0 and 1. η_1 and η_2 are the acceleration constant and the speed regulation parameter. They denote the acceleration weight of particles moving to extreme points P_{id} and P_{gd}, and $rand()$ is a random number between 0 and 1.

The preceding formula shows that velocity updating of particles has three parts. The updating mechanism is shown in Fig. 1. The three parts are as follows:

(1) a particle's original speed, $v_{id}(t)$;
(2) the direction between the particle and the best position it has experienced, P_{id}–$z_{id}(t)$;
(3) the direction between the particle and the best position all the particles have experienced, P_{gd}–$z_{id}(t)$.

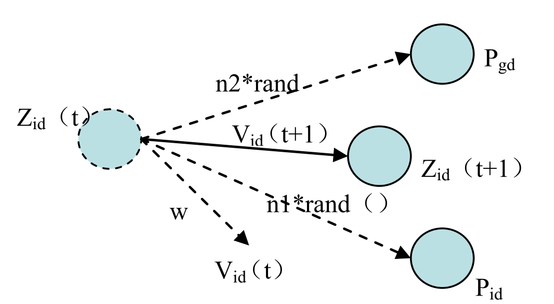

Fig. 1. Schematic of particle update.