The Particle Swarm Optimization (PSO) algorithm in Structural Health Monitoring (SHM) application

Le Thanh Cuong[1*], To Thanh Sang[1]

[1]Faculty of Civil Engineering, Ho Chi Minh City Open University, Vietnam
[*]Corresponding author: cuong.lt@ou.edu.vn

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ABSTRACT

In the paper, a method of determining the structural damage using the Particle Swarm Optimization (PSO) algorithm is presented. PSO is a famous algorithm to search optimization. Damaged structural system members are detected by the PSO through the frequency change before and after the damage.

1. Introduction

With the strong development of science and technology, many new methods in structural health monitoring (SHM) have developed strongly in recent decades. One of these is to apply an optimal algorithm to predict the damage for structure (Capozucca, 2009; Cha & Buyukozturk, 2015). There are many powerful optimization algorithms and some of them are Ant Colony Optimization (ACO) (Colorni, Dorigo, & Maniezzo, 1992; Dorigo, Caro, & Gambardella, 1999), Artificial Bee Colony (ABC) (Karaboga, 2005), Cuckoo Search (CS) (Yang & Deb, 2009), Jaya Algorithm (Mirjalili, 2016). In the present work, the Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995) lgorithm is applied for damage forecasting of the 2-dimensional truss problems.

PSO algorithm

PSO is a famous optimization algorithm that is widely used in almost every field from economics to engineering, from agriculture to industry, from politics to daily life. Inspired by swarm intelligence, Kennedy and Eberhart proposed the PSO algorithm as follows:

$$Vx_j^d(i) = \omega Vx_j^d(i-1) + c_1 \times rand \times \left(p_j^d(i-1) - X_j^d(i-1)\right) + c_2 \times rand \times \left(g_j^d(i-1) - X_j^d(i-1)\right) \quad (1)$$

$$X_j^d(i) = X_j^d(i-1) + Vx_j^d(i-1) \quad (2)$$

Where:

$X_j^d(i)$ *d*th parameter in the location vector of the *j*th member in the ith iteration

$Vx_j^d(i)$ *d*th parameter in the velocity vector of the *j*th member in the ith iteration

g	The best location of swarm at current
p	The best location of the member at current
$c_1; c_2$	=2
$rand$	[0 ,1]
ω	The inertia weight base on iteration and calculated as follows (3)

$$\omega = 0.9 - \frac{i \times (0.9 - 0.4)}{Max\_iteration} \tag{3}$$

Figure 1 illustrates the operative process of the PSO algorithm.

Initialize the swarm Xi (i = 1, 2, ..., n)
Initialize the velocity of swarm Vi (i = 1, 2, ..., n)
while *(t < Max number of iterations)*
  Calculate ω, c_1, c_2
  Calculate the fitness of each search agent
  Update the best location ***g*** *of swarm at the current*
  Update the best location ***p*** *of each member at the current*
  Update the velocityof the current member by equation (1)
  Update the position of the current member by equation (2)
  t=t+1
end while
return ***g***

Figure 1. Pseudocode of the PSO algorithm

2. Damage indicator

As mentioned, we use PSO as an efficient method for searching the location as well as forecasting the severity of the structure. In which, the objective function (Obj) of the problem is the value of the natural frequency of the structure.

$$Obj = \sqrt{\sum_{i=1}^{n} \frac{\left(f_i^c - f_i^m\right)^2}{\left(f_i^m\right)^2}} \qquad i = 1, \cdots, n \tag{4}$$

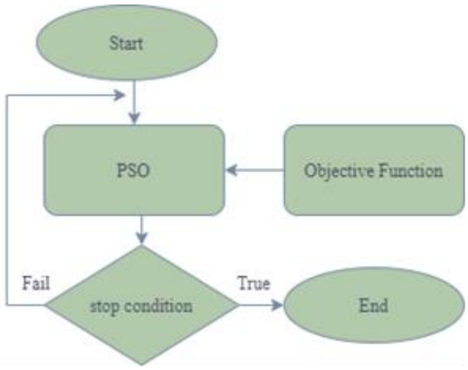

Figure 2. The flowchart of the PSO algorithm for SHM

3. Current status and some plans for Hill tribe languages

3.1. Steel frame structure

A two-dimensional truss system with 3 bars is considered here shown in Figure 3, and the properties of the truss structure are indicated in Table 1.

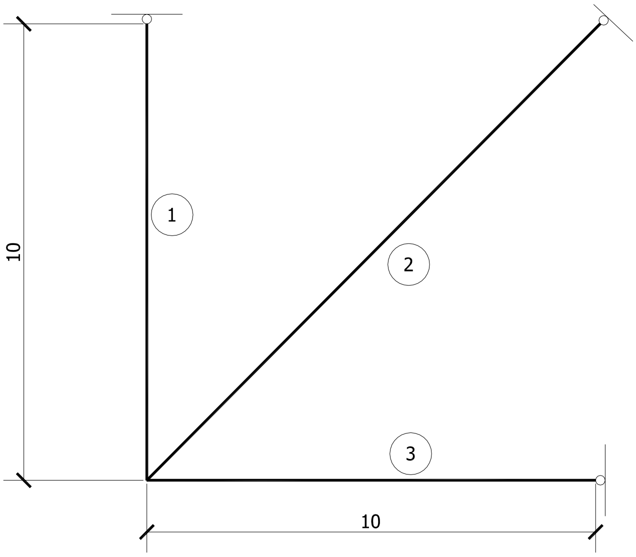

Figure 3. Truss system

As you know that the dynamics equation as follows:

$$[M]\ddot{x}+[K]x=\vec{0} \tag{5}$$

$[M]$: Mass matrix

$[K]$: Stiffness matrix

In which

$$x=\psi\sin(\omega\mathrm{t}+\varphi) \tag{6}$$

$$\ddot{x}=-\omega^2\psi\sin(\omega\mathrm{t}+\varphi) \tag{7}$$

In other words,

$$\left([K]-\omega^2[M]\right)\vec{\psi}=\vec{0} \tag{8}$$

Solve (8) we can find out, and the frequency is found using equation (9)

$$f_i=\frac{\omega_i}{2\pi} \tag{9}$$

Table 1

The properties of the truss system

Ply property	Mean value
E - Young modulus - (N/cm2)	30E6
A - Area - (cm2)	2
ρ - Density - (kg/cm3)	0.0078

Source: The researcher's data analysis

3.2. Results and discussion

In this paper, we present a scenario for structural health monitoring is shown in Table 2.

Table 2

The scenario for the damage

Damaged Element(s)	Damage rate %
Element 1	0
Element 2	0.35
Element 3	0.15

Source: The researcher's data analysis

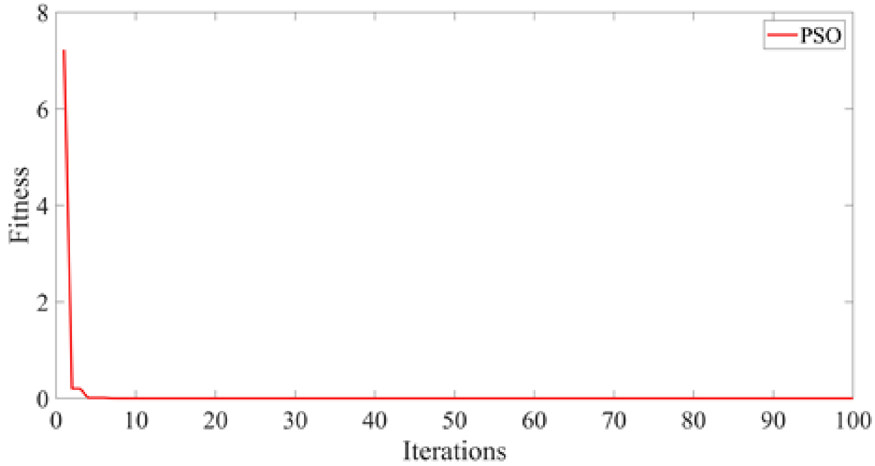

Figure 4. Convergence of fitness damaged elements

We can see from **Error! Reference source not found.**, PSO is demonstrated that the convergence of obtained results in the first iterations. Whereas **Error! Reference source not found.** illustrates the damage rate (%) of each member over iterations very accurately in comparison to the scenario given in **Error! Reference source not found.**, **Error! Reference source not found.** shows the high accuracy of using PSO in forecasting structural health monitoring.

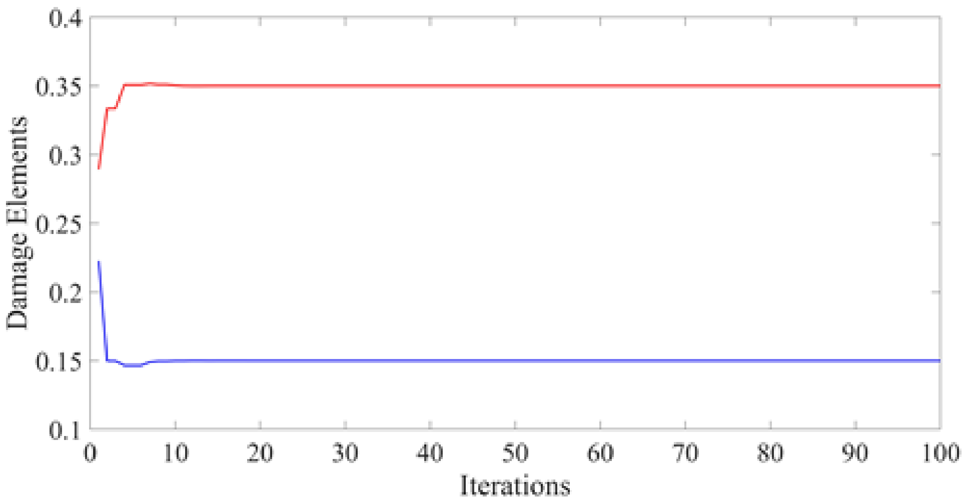

Figure 5. Convergence of damaged elements

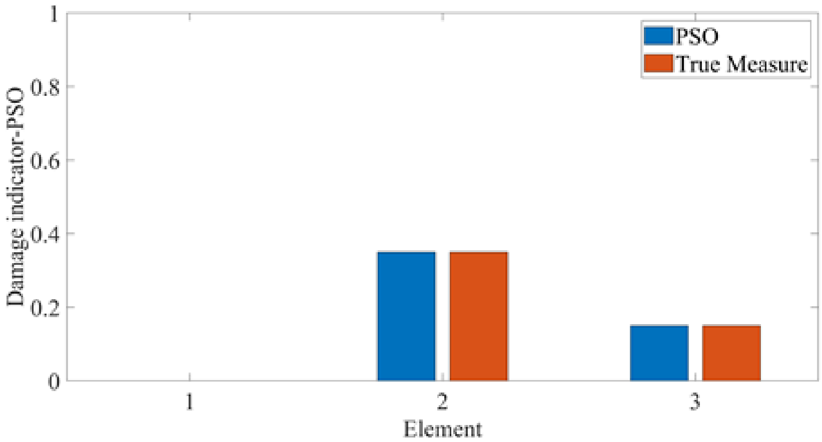

Figure 6. Damaged identification of location and severity

4. Conclusions

In the study, we present an approach for forecasting structural damage. PSO is a powerful tool to search for the best solution for the vast search space. The combination of PSO into the structure will, therefore, create a superior method to evaluate structural health monitoring. The two-dimensional truss system was proved the effectiveness of this method.

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