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Structural damage detection based on Chaotic Artificial Bee Colony algorithm

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Abstract. A method for structural damage identification based on Chaotic Artificial Bee Colony (CABC) algorithm is presented. ABC is a heuristic algorithm with simple structure, ease of implementation, good robustness but with slow convergence rate. To overcome the shortcoming, the tournament selection mechanism is chosen instead of the roulette mechanism and chaotic search mechanism is also introduced. Residuals of natural frequencies and modal assurance criteria (MAC) are used to establish the objective function, ABC and CABC are utilized to solve the optimization problem. Two numerical examples are studied to investigate the efficiency and correctness of the proposed method. The simulation results show that the CABC algorithm can identify the local damage better compared with ABC and other evolutionary algorithms, even with noise corruption.

Keywords: damage detection; Chaotic Artificial Bee Colony algorithm; modal assurance criteria; coupled double-beam system

1. Introduction

Inspection of the structural components for damage is important for making decision on the maintenance program of the structure. Over the past few decades, vibration-based structural damage identification methods on the basis of the changes in modal parameters (such as natural frequencies, mode shapes, etc.) have been developed (Cawley and Adams 1979, Rizos *et al*. 1990, Pandy *et al*. 1991, Ratcliffe 1997, Hassiotis 1999). Shi and Law (1998) employed the modal strain energy and flexibility to identify damage location and severity. He and Zhu (2015) presented an adaptive-scale damage detection strategy based on a wavelet finite element model for thin plate structure. Li *et al*. (2015) applied vibration measurements and power spectral density to assess damage in shear connectors.

Structural damage identification problem can also be formulated as an optimization problem in which an objective function, for example the error between the actual measured structural response and the estimated response of a model, is defined. The parameters of such models are obtained by optimizing (Usually to maximize or to minimize) the objective function (Franco 2004). Variety intelligence optimization methods were utilized to solve the problem. Wu *et al*. (1992) adopted BP

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Neural network to solve the damage detection of a three-layer shear frame structure. Mares and Surace (1996) used residual force and genetic algorithm to estimate the structural damage, while Wang (2009) developed a hybrid genetic algorithm with the Gauss-Newton method, to identify both linear and nonlinear structural system. Dimou (2010) applied an enhanced particle swarm optimization to the identification of Bouc-Wen hysteretic systems. The works done by Tang *et al*.(2008) exhibit that the differential evolution algorithm performs well in parameter identification of structural systems with and without pollution. Franco *et al*. (2004) also presented a parameter estimation technique based on evolutionary strategy algorithm for parametric identification. All these methods have generally achieved satisfactory results in solving the multi-modal optimization problem in structural damage detection.

Apart from the above mentioned heuristic algorithms, Artificial Bee Colony (ABC) algorithm is another swarm intelligence technique, which was proposed by Karaboga (2005) to solve numerical optimization problems. This algorithm is motivated by the bee colony's behavior of seeking high quality food source. ABC is a population based stochastic algorithm with implementation simplicity because the only common control parameters are the colony size and termination condition. It has the benefits of simple structure, ease of use, and high stability. Meanwhile, compared with genetic algorithm, particle swarm optimization, differential evolution algorithm and particle swarm inspired evolutionary algorithm (PS-EA), the global optimal ability of the ABC is more excellent and competitive (Karaboga and Basturk 2009). Recently, several researchers have extended the application of ABC to the civil engineering. Kang *et al*. (2009) constructed a hybrid algorithm combining Nelder-Mead simplex method and ABC to solve the inverse problems in concrete dam structures. Sonmez (2011) combined ABC with an adaptive penalty function approach to minimize the weight of truss structures with both continuous and discrete variables. Omkar *et al*. (2011) developed a generic model for multi-objective design optimization of laminated composite components based on Vector Evaluated ABC. Sun *et al*. (2013) introduced a non-linear factor for convergence control to the ABC algorithm and used the modified ABC to solve structural parameter identification problem. Ghashochi-Bargh and Sadr (2014) also presented a kind of elitist-ABC algorithm for optimization of smart FML panels.

In this study, the ABC algorithm is employed to deal with the structural damage detection problem based on modal parameters, that is, the residual of frequencies and modal assurance criteria (MAC) are used to form the objective function. However, similar with other swarm intelligence algorithm, the convergence rate of ABC is slow at latter iteration (Gao *et al*. 2013). In order to develop a more powerful optimization technique, some improvements are made on the original ABC algorithm, in which the tournament selection strategy is adopted instead of roulette wheel to enhance global search capability of the algorithm, and the chaotic search mechanism is introduced to the scout bee phase to improve the global search capability further. The performance of the improved algorithm is illustrated in two kinds of structures, i.e., a simple supported beam system and a coupled beam system. Final results show that the proposed ABC can acquire a better identified results compared with ABC and other evolutionary algorithm, even with noise pollution.

2. Mathematical model

2.1 Parameterization of damage

After finite element discretization, modal parameters of a structural system can be obtained

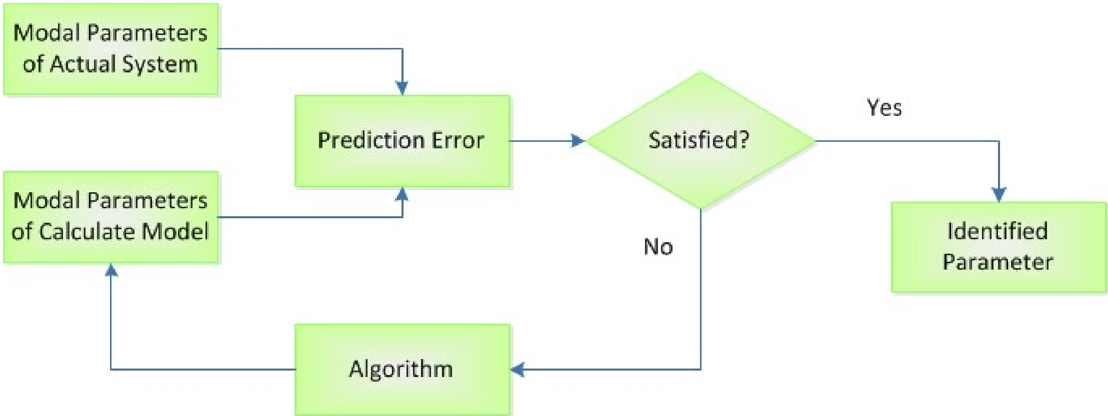

Fig. 1 The process of damage detection as an optimization problem

from the eigenvalue equation

$$(\mathbf{K} - \omega_i^2 \mathbf{M})\mathbf{\Phi}_i = 0 \tag{1}$$

where **K** and **M** are the global stiffness and mass matrices, respectively. ω_i is the i^{th} natural frequency and $\mathbf{\Phi}_i$ is the associated mode shape.

According to continuum damage mechanics, damage can be expressed through a scalar variable α_i with value between **0** and **1** (Perera and Ruiz 2008). α_i=0 represents the i^{th} element is intact while α_i=1 indicates that it is completely damaged. The global stiffness matrix $\mathbf{K}_d$ of the damaged structure can be expressed as

$$\mathbf{K}_d = \sum_{i=1}^{nel} (1-\alpha_i)\mathbf{ke}_i \tag{2}$$

where $\mathbf{ke}_i$ denotes the i^{th} elemental stiffness matrix and *nel* denotes the total number of finite elements.

2.2 Objective function based on the vibration data

Structural damage will lead to changes of natural frequencies and mode shapes of the structure, on the other hand, we can use these modal data to formulate the objective function for damage identification. Usually, the residual of natural frequencies and modal assurance criterion (MAC) are used to establish the objective function

$$f = \sum_{i=1}^{NF} w_{\omega i} \Delta\omega_i^2 + \sum_{i=1}^{NM} w_{\Phi i} (1 - MAC_i) \tag{3}$$

in which

$$\Delta\omega_i = \left| \frac{\omega_i^c - \omega_i^m}{\omega_i^m} \right| \tag{4}$$

$$MAC_i = \frac{(\mathbf{\Phi}_i^C \cdot \mathbf{\Phi}_i^M)^2}{\left\|\mathbf{\Phi}_i^C\right\|^2 \left\|\mathbf{\Phi}_i^M\right\|^2} \tag{5}$$

where $w_{\omega i}$ is a weight factor corresponds to i^{th} natural frequency, while $w_{\Phi i}$ corresponding to i^{th} *MAC*. $\mathbf{\Phi}_i^C$ and $\mathbf{\Phi}_i^M$ are the i^{th} calculated and measured mode shapes. *NF* and *NM* are the numbers of natural frequencies and mode shapes used in calculation, respectively. It should be pointed out that the calculated natural frequency ω_i^C and mode shape $\mathbf{\Phi}_i^C$ are related to damage parameters $[\alpha_1, \alpha_2 ... \alpha_{nel}]$. In the inverse problem, the damage vector is identified to indicate the damage extent of structure. In this study, for simplicity, all the factor values are taken as 1. Meanwhile Fig. 1 presents the process of damage detection as an optimization problem.

3. Algorithm for damage detection

3.1 Artificial Bee Colony algorithm

The bees colony are divided in three groups when they commence to find food. The first group contains employed bees. These bees have a food source position in their mind when they leave from the hive and they share the information (including the quality and quantity about the food resource) on the dancing area in the hive. Some of the bees watch the dances of the employed bees and then decide the food source to exploit. This group of the bees named onlookers. In the algorithm, onlookers select the food sources in a probability that corresponding to the qualities of the food sources. After onlookers choosing the food source, then they will become the employed bees, going to the selected food source and exploiting the better source in the neighborhood around the destination. If they find a better place, they will give up the primary selected place (“greedy selection rule”). The last bee group is called scout bees. Regardless of any information of other bees, a scout finds a new food source and start to consume it, then it continues its work as an employed bee. Hence, while the known resources are consuming, at the same time exploration of the new food sources is provided. At the beginning of the search (initialization phase), all employed bees start with random food sources, in further cycles, when the food sources are abandoned, the employed bee related to the abandoned resource becomes a scout. In the algorithm, a parameter, *limit* is used to control the abandonment problem of the food sources. For every solution, the trial number of improvement is taken, in each cycle of the solution which has the maximum trial number and its trial number is compared with the parameter *limit.* If the *limit* value is reached, this solution is considered fully exploited and continues with a randomly produced new solution.

In ABC algorithm, a food source position is defined as a possible solution and the nectar quality of the food source matches the fitness of the related solution in optimization process. Because each employed bee is associated with only one food source, the number of employed bees is equal to the number of food sources.

The general structure of algorithm is introduced as follows.

Initialization phase

Location of a food source, x_m, is expressed as Eq. (6) in a random way

$$x_{m,i} = l_i + rand(0,1)(u_i - l_i) \tag{6}$$

where m is an arbitrarily solution in the search space and u_i, l_i represent the upper bound and lower bound of the parameter $x_{m,i}$ respectively.

Employed bees phase

The scope of the employed bee is to find a better food source in the neighbor-hood of the food source (x_m). It leaves the hive and finds the target point, beginning the food exploitation. Eq. (7) is used to simulate its behavior

$$V_{m,i} = x_{m,i} + \varphi_{m,i}(x_{m,i} - x_{k,i}) \tag{7}$$

where x_k is a food source, $\varphi_{m,i}$ is a random number in [−1, 1] and i is a randomly chosen dimension. After producing a new candidate source, Eq. (8) is adopted to calculate the fitness of the food source (the solution x_m as an example), given as below

$$fit(x_m) = 1/(1 + f(x_m)) \tag{8}$$

After acquiring the fitness, the "greedy selection rule" is applied between x_m and V_m.

Onlooker bees phase

The employed bees return home and share their food source information with the onlooker bees. They select the food source to exploit relying on the probability value p_m (roulette selection strategy)

$$p_m = fit(x_m) \Big/ \sum_{m=1}^{SN} fit(x_m) \tag{9}$$

where SN denotes the number of employed bees. (The quantity of employed bees is the half of the initial colony size.) After selecting a food source, onlooker bees will fly there to exploit a better food source. In the original ABC algorithm, the behavior is simulated by Eq. (7). Then fitness value is calculated applying the greedy selection to produce better food source.

Scout bees phase

At the end of every cycle, the trial counters of all solutions are examined. Abandonment of the solution is determined as follows. If the solution couldn't improve after *limit* times, the solution is abandoned and Eq. (6) is used to produce a new food source to replace the abandoned one. The *limit* parameter is given as in (Karaboga and Busturk 2009)

$$l = \frac{CS \times D}{2} \tag{10}$$

where D is the dimension of the problems, CS is the initial colony size.

3.2 Chaotic Artificial Bee Colony Algorithm

3.2.1 Tournament selection strategy

The Tournament Selection Strategy is adopted instead of roulette wheel to enhance the global search ability. The Tournament Selection Strategy first makes the two comparisons of the fitness of each solution (including comparing with itself, that is, the worst solution can acquire at least one point), the bigger one will get one point, then finish comparison, each solution x_m will acquire its total point a_m and such total points will be used to calculate the selection probability based on Eq. (14).

$$p_m = a_m \Big/ \sum_{m=1}^{SN} a_m \tag{14}$$

where a_m denotes the total points of a solution x_m, compared with the roulette wheel, this strategy ensures that all solutions have a finite probability of selection, so those solutions with big fitness values do not overwhelm the search strategy. Thus the global search ability of algorithm is enhanced.

3.2.2 Chaotic search mechanism

Chaos is a kind of characteristic of non-linear systems, which is a bounded unstable dynamic behavior that exhibits sensitive dependence on initial conditions and includes infinite unstable periodic motions. It should be distinguished here so-called random and chaotic motions. The former is reserved for problems in which one really does not know the input forces or one only knows some statistical measures of the parameters, while chaotic has its own characteristics, such as randomness, ergodicity (chaos can traverse all states nonreduntant within limit), regularity (chaos comes from some ascertained iteration). Among these characters, ergodicity can be utilized as an effective way to help the algorithm to get rid of trapping local minima (Tavazoei and Haeri 2007). Based on this property, Liu *et al*. (2005) improved the PSO combined with chaos and acquired a more satisfied result, compared with the standard PSO algorithm. Meanwhile, Yuan *et al*. (2002) also incorporated chaos into the GA to construct a hybrid chaotic genetic algorithm, which can overcome premature and increase the convergence speed. In this study, chaotic search mechanism is introduced to the scout bees phase. Because in scout phase, as mentioned above, if the solution couldn't improve after *limit* times, the solution is abandoned. However, for the abandoned solution, also the solution trapped in the local minima use to produce chaotic sequence and the best solution will be replaced the original solution (will be abandoned) in CABC. Via such change, the solution ceased exploitation (will be abandoned) can continue to local search, which can increase the convergence rate and accuracy of the algorithm.

The chaotic sequence can usually be produced by the following well-known one-dimensional logistic map defined by

$$Z_{k+1} = \mu \cdot Z_k + (1 - Z_k), Z_k \in (0,1), k = 0,1,2,... \tag{15}$$

where Z_k is the value of the variable Z at the kth iteration, for certain values of the parameter μ, of which μ=4 is one, the above system exhibits chaotic behavior.

Supposing the ceased solution is $\mathbf{x_k}=(x_{k1}, x_{k2},...x_{kD})$, $x_{k,i}\in[l_i, u_i]$. First, map the $\mathbf{x_k}$ into the domain of Logistic equation and obtain $Z_k^0 = (Z_{k1}^0, Z_{k2}^0 ... Z_{ki}^0 ... Z_{kD}^0)$.

$$Z_{ki}^0 = \frac{x_{ki} - l_i}{u_i - l_i}, i = 1,2...D \tag{16}$$

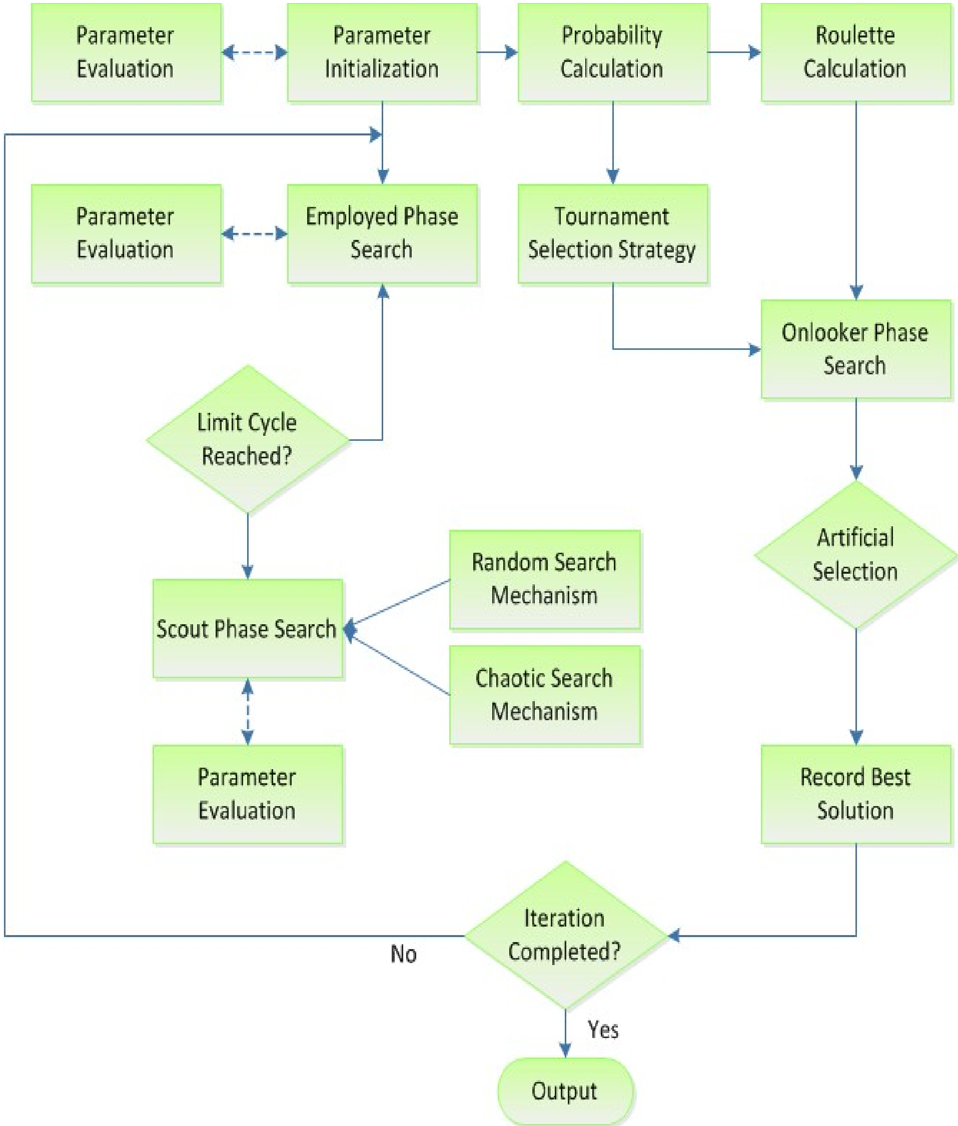

Fig. 2 The flow chat of the ABC and the CABC algorithm

Second, Eq. (15) is utilized to generate chaotic sequence Z_k^n ($n = 1,2,...,C_{\max}$, $C_{\max}$ denotes the maximum cycle number of the chaotic local search). Third, transfer the chaotic sequence into the original search space by inverse map based on Eq. (17), given below

$$x_{ki}^{'} = l_i + (u_i - l_i) \cdot Z_{ki}^n \tag{17}$$

After acquiring $\mathbf{x_k^{'}} = (x_{k1}^{'}, x_{k2}^{'}, ..., x_{kD}^{'})$, calculate its fitness and the "greedy selection rule" is applied between $\mathbf{x_k}$ and $\mathbf{x_k^{'}}$. Finally, repeat the chaotic local search process until meet the $C_{\max}$. The flow chat of the ABC algorithm and the CABC algorithm is shown in Fig. 2.

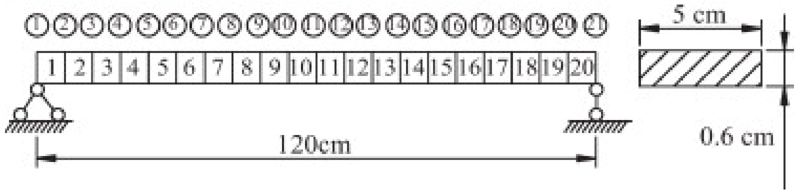

Fig. 3 The simply supported beam (Kang *et al.* 2012)

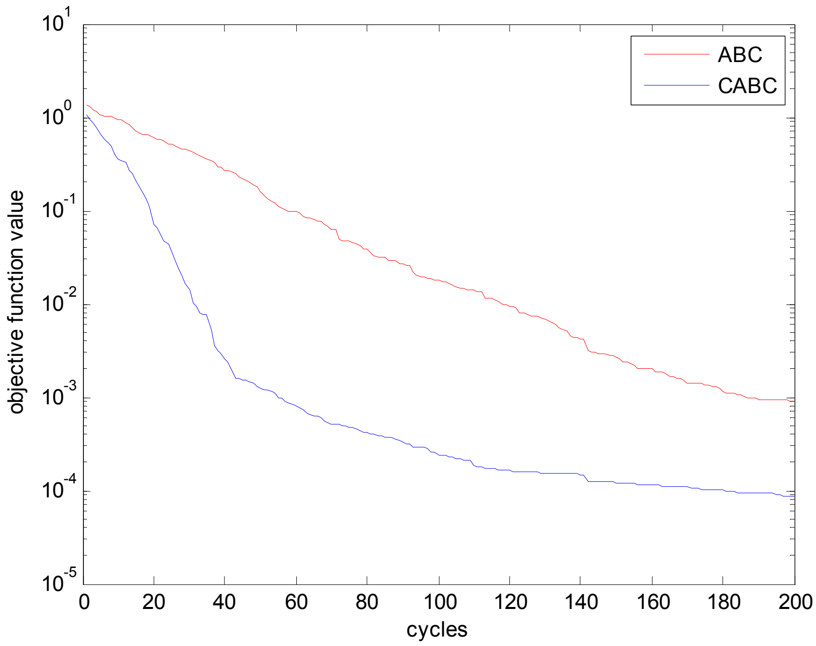

Fig. 4(a) The evolution process of the objective function of the supported beam (Nil)

4. Numerical simulations

4.1 A simply supported beam

In order to make comparison with other methods, the simply supported beam studied by Kang *et al*. (2012), shown in Fig. 3, is adopted to verify the effectiveness of the proposed algorithms. The total numbers of elements and nodes are 20 and 21. The basic material parameters are: Young's modulus E=70 GPa, ρ=2700 kg/m^3, cross section area $A=3\times10^{-4}$ m^2, Poisson's ratio μ=0.3. The same damage case is introduced, assuming that element 2 and 9 has 10% reduction in Young's modulus while element 16 has 15% reduction in Young's modulus. That means α_2=0.1, α_9=0.1 and α_{16}=0.15. For the original ABC and CABC algorithms, the colony size is 40 and maximum cycle number is 200. Meanwhile, for the CABC, the maximum chaotic local search number is taken as 10. The first three frequencies and associated mode shapes are applied in the identification, which are the same as Kang *et al*. (2012). Moreover, to ensure fairness in comparison of the robustness of the examined algorithms, for each problem the analysis is repeated 10 times with a different initial random seed. The averages are presented in graphical form. Fig. 4(a) presents the evolution

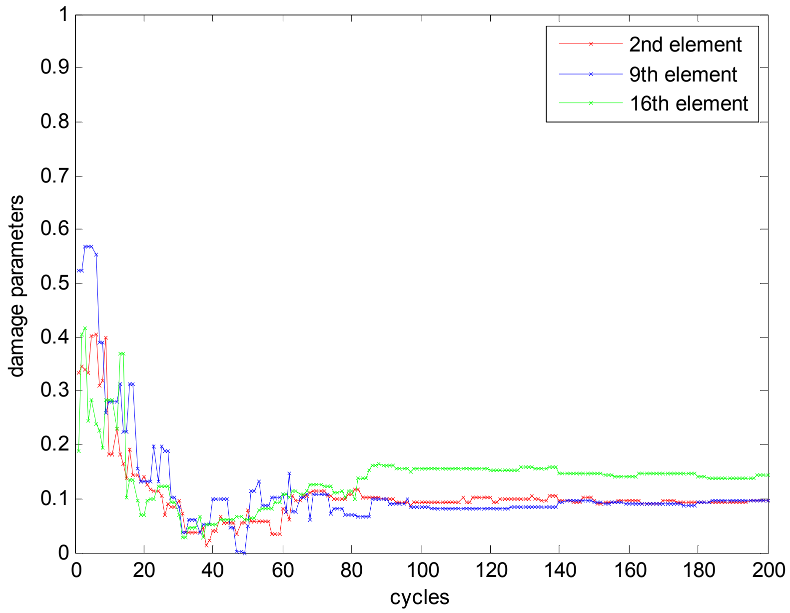

Fig. 4(b) The evolution process of the damage parameters based on CABC (Nil)

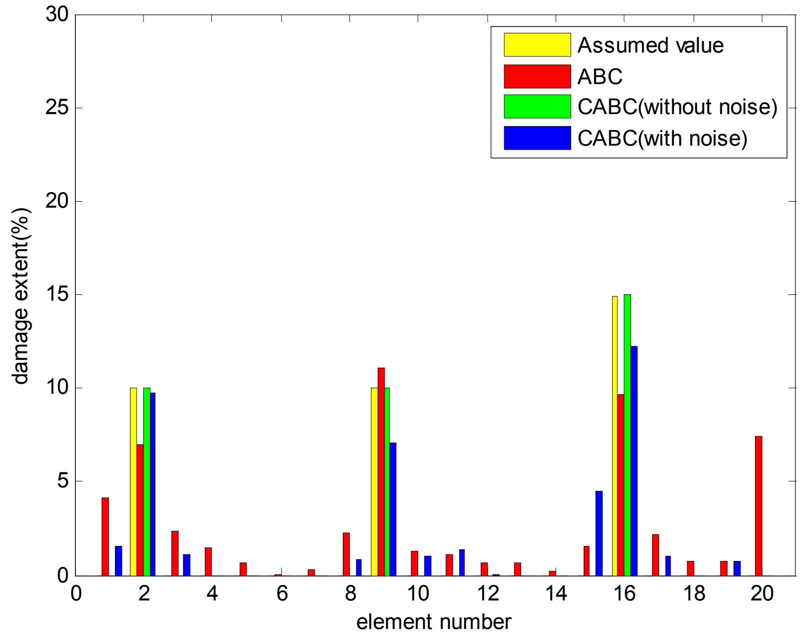

Fig. 4(c) The final results of the simply supported beam case

process of the objective function of the best solution based on the mentioned techniques, it is observed that the objective function value from CABC algorithm is closer to zero, indicating that the identified results from CABC algorithm are closer to the true damage extents. From Fig. 4(b),

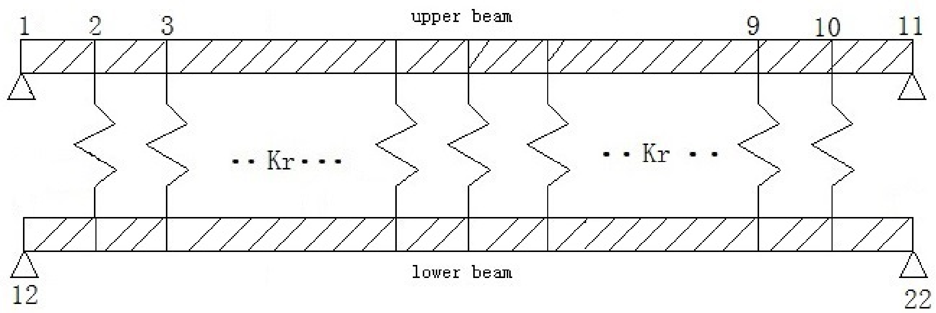

Fig. 5 The coupled-beam system

Table 1 The natural frequencies of the coupled double-beam system (Hz)

Mode Order	Strongly coupled beam	Weakly coupled beam
1st	72.4	72.4
2nd	289.7	88.4
3th	652.2	289.7
4th	1160.7	294.1
5th	1817.7	652.2
6th	2627.9	654.1

it can be seen that the damage parameters of element 2, element 9, element 16 quickly converge to 0.09972, 0.09995 and 0.14897, which is very close to the assumed value and more competitive than those obtained by ABC. Moreover, the result is also better than those acquired by genetic algorithm, differential evolution algorithm, particle swarm optimization, and immunity enhanced particle swarm optimization (0.09958, 0.09989 and 0.14734) (Kang *et al*. 2012). To include the uncertainty in the measured data and to study the sensitivity of proposed method to noise, 1% uniformly distributed random noise is added to the natural frequencies and 10% uniformly distributed random noise is added to the mode shapes (Kang *et al*. 2012). In this scenario, the maximum error acquired by CABC is 4.35%, occurring in 15th element, however, the immunity enhanced particle swarm optimization obtained the maximum error is over 10%, which can sufficiently the better robustness of CABC. Final results are presented in Fig. 4(c).

4.2 A coupled-beam system

The coupled beam system is employed as the second simulation example and the initial geometry of the coupled beam is shown in Fig. 5. The total numbers of elements and nodes are 20 and 22, respectively. The basic material parameters of structures are: Young's modulus E_1=E_2=210 GPa, density ρ_1=ρ_2=7800 kg/m^3 length l_1=l_2=10 m, Cross-section A_1=A_2=1.25×10^{-2} m^2, Poisson's ratio μ_1=μ_2=0.3. The coefficient of the weakly coupling spring is taken as Kr=10^5 N/m while the strongly coupling spring is taken as Kr=10^9 N/m. The damage case is also multiple damage scenario, assuming that element 2 has 15% reduction in Young's modulus, element 3 has 20% reduction in Young's modulus meanwhile element 12 and 17 has 10% reduction in Young's modulus. That means α_2=0.15, α_3=0.2, α_{12}=0.1 and α_{17}=0.1. The first six natural frequencies (as listed in Table 1) and the associated mode shapes are adopted in the damage identification. For the

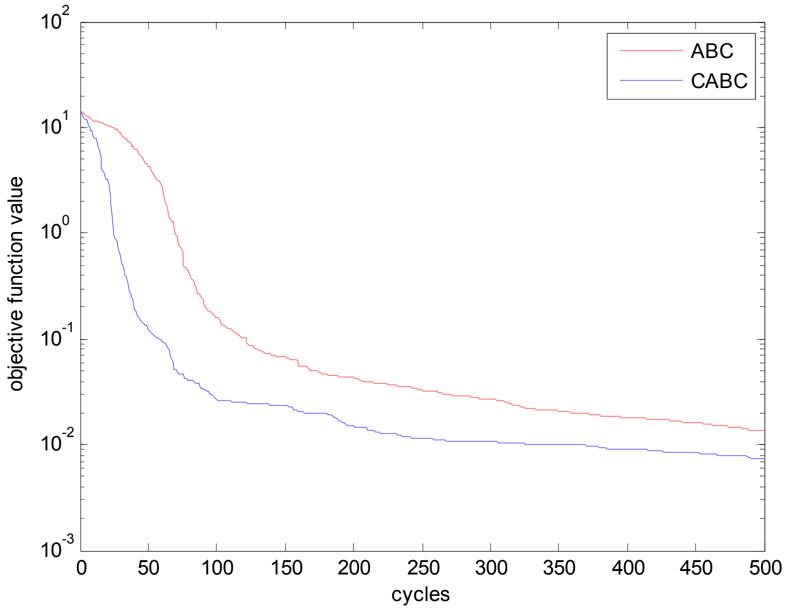

Fig. 6(a) The evolution process of the objective function of the strongly coupled beams

Table 2 Identified damage parameters based on ABC and CABC in coupled beam system

		Element number			
		2nd	3rd	12th	17th
	Assumed value	0.15	0.2	0.1	0.1
Strongly coupled	ABC results	0.1345	0.1646	0.0854	0.035
	ABC std.	0.0292	0.0215	0.0226	0.0339
	CABC results	0.1472	0.1647	0.0921	0.0831
	CABC std.	0.0075	0.0187	0.0122	0.0204
Weakly coupled	ABC results	0.1164	0.1706	0.0472	0.0429
	ABC std.	0.0344	0.037	0.0276	0.0322
	CABC results	0.1307	0.1736	0.0742	0.0795
	CABC std.	0.0158	0.0127	0.0135	0.0207

(std. denotes the standard deviation)

algorithm implemented, the colony size is 50 and the maximum cycle number is 500 and for the CABC, the maximum chaotic local search number is 10. Further, 1% uniformly distributed random noise is added to the natural frequencies and 10% uniformly distributed random noise is added to the mode shapes. Moreover, for each problem the analysis is also repeated 10 times with a different initial random seed.

Strongly coupled beam system

The evolutionary process of the objective function value is presented in Fig. 6(a), one can find

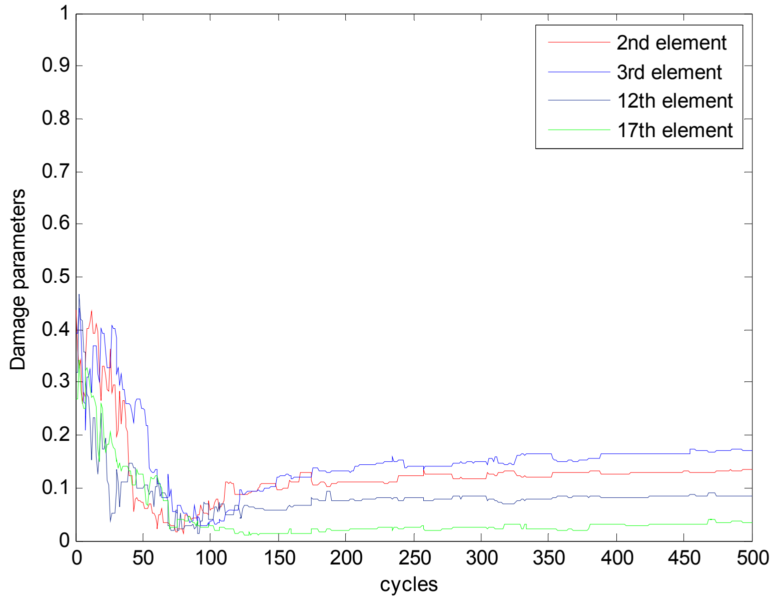

Fig. 6(b) The evolution process of the damage parameters (strongly coupled, ABC)

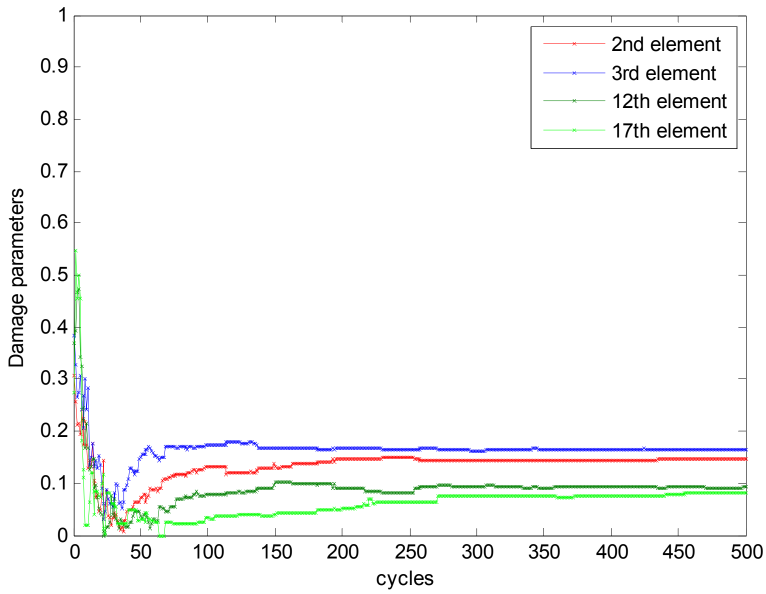

Fig. 6(c) The evolution process of the damage parameters (strongly coupled, CABC)

the results obtained by CABC is closer to zero. Fig. 6(b) and 6(c) provide the evolution process of the damage parameters based on the two methods mentioned, it can be clearly seen that the convergence rate and accuracy based on CABC is better. The CABC algorithm converges in approximately 100 cycles while the original ABC algorithm needs 300 cycles for convergence. Final identified results are presented in Fig. 6(d) and Table 2. For the damaged elements, CABC

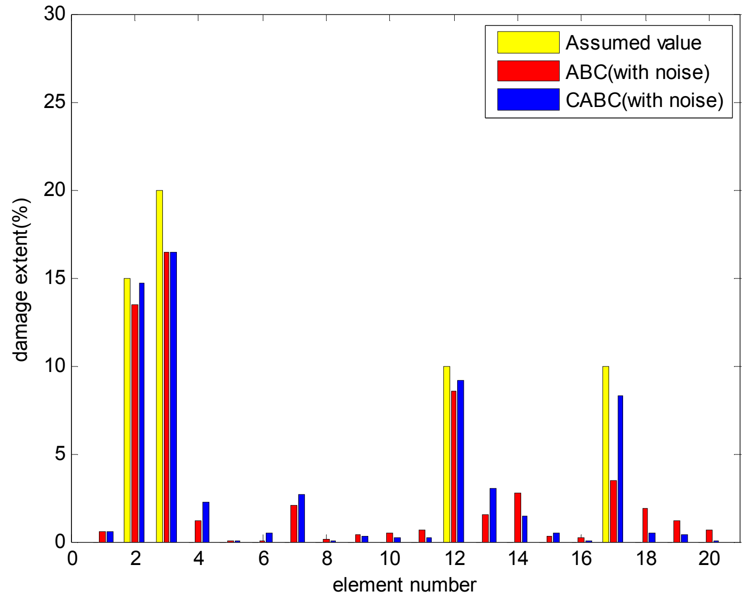

Fig. 6(d) The final results of the strongly coupled beams case

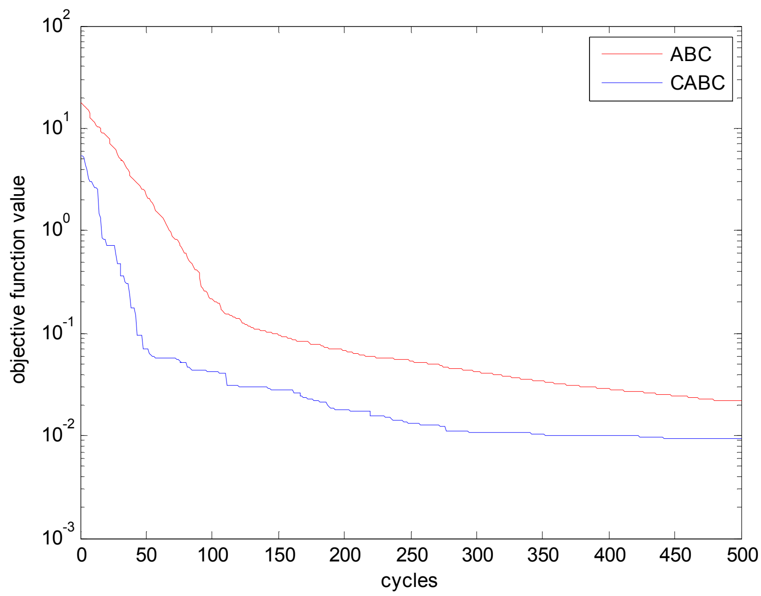

Fig. 7(a) The evolution process of the objective function of the weakly coupled beams

obtained a more accuracy estimated outcome with less standard deviation.

Weekly coupled beam system

The evolutionary process of the logarithmic best objective function value is exhibited Fig. 7(a) and the evolution process of the damage parameters are shown in Fig. 7(b) and 7(c), similar to Fig.

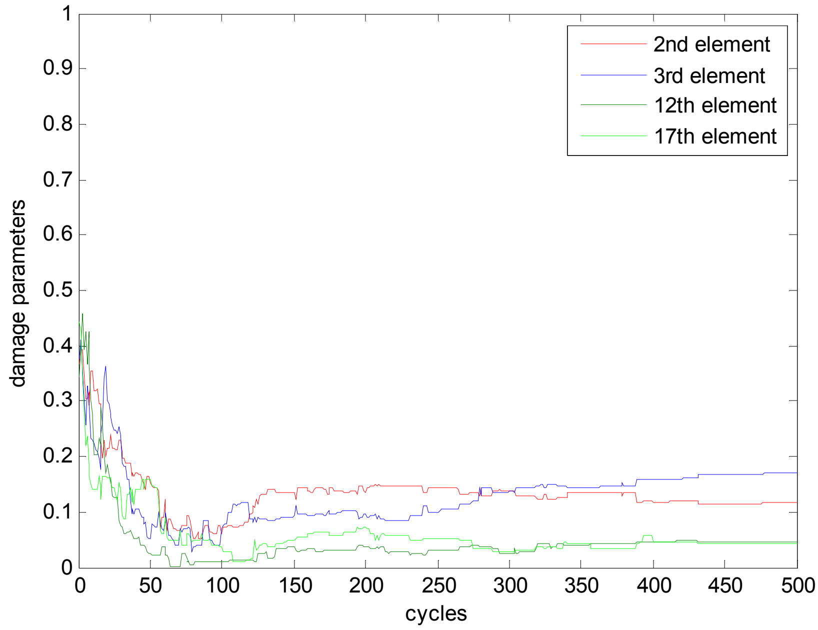

Fig. 7(b) The evolution process of the damage parameters (weakly coupled, ABC)

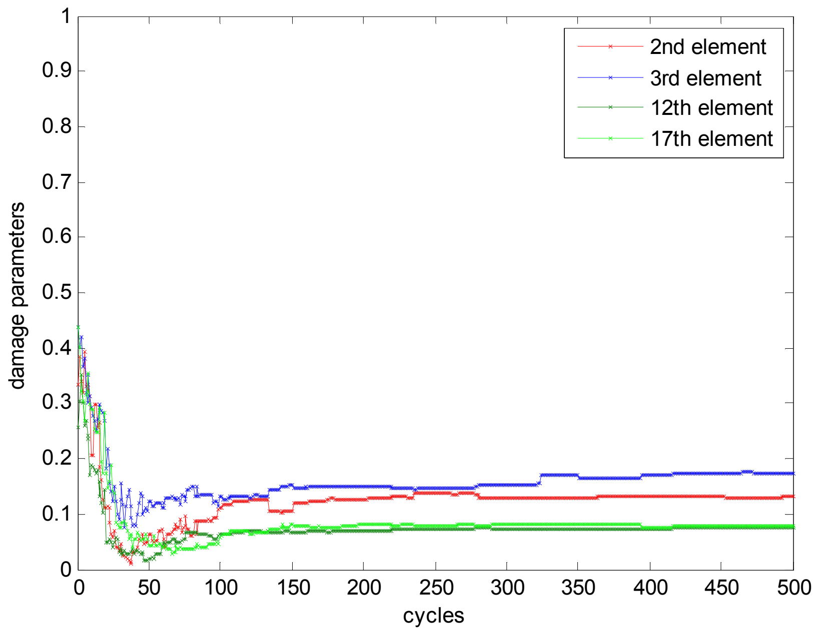

Fig. 7(c) The evolution process of the damage parameters (weakly coupled, CABC)

6(b) and 6(c), CABC can still acquire a better result with faster convergence rate. Fig. 7(d) and Table 2 present the final identification results, which can illustrate the good robustness and excellent global search ability of CABC further.

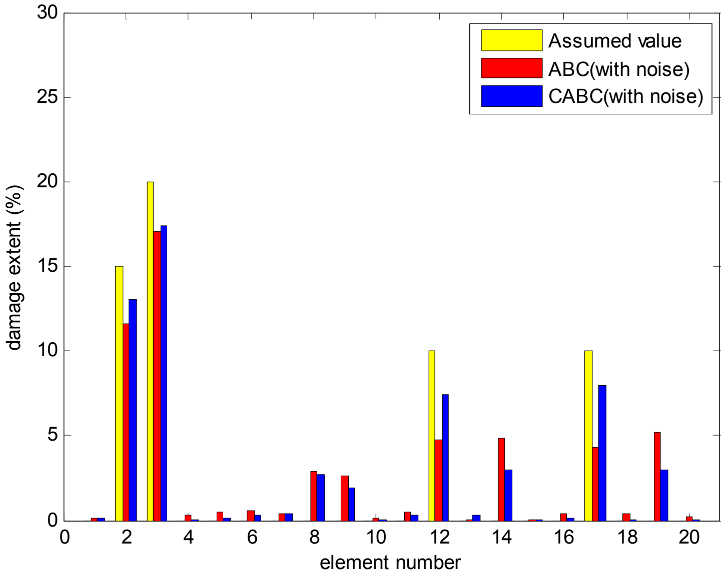

Fig. 7(d) The final results of the weakly coupled beams case

5. Conclusions

A structural damage identification method based on original ABC algorithm and CABC algorithm using vibration data is investigated in this work. In the modified algorithm, the tournament selection mechanism is chosen instead of roulette mechanism, chaotic search mechanism is also introduced to improve the algorithm's convergence rate and accuracy. Two numerical simulations are utilized to investigate the applicability of this proposed technique to damage detection. In the case of supported beam, for the damage element, the maximum errors of CABC are 0.028% better than that acquired by immunity enhanced particle swarm optimization (0.042%), meanwhile the corresponds error obtained by ABC is 5.35%. When the modal data is polluted by the uniform distributed noise, the maximum error from CABC is 4.35%, occurring in element 15, however, the immunity enhanced particle swarm optimization recieved the maximum error over 10%, which can sufficiently the better robustness of CABC. In the case of the strongly coupled beam, the maximum identified errors of CABC is 3.53%, smaller than 6.5% acquired by ABC algorithm. When the beam is weakly coupled, the maximum estimated error of CABC is 2.64% while the ABC is 5.71%. Further, in all cases, the standard deviation of CABC are smaller than those got by ABC, which illustrates that the identified results from CABC are more stable. To sum up, the simulation results show that the proposed CABC algorithm can produce excellent damage estimation with small errors.

Acknowledgments

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