Fault detection in beam structure using adaptive immune based approach

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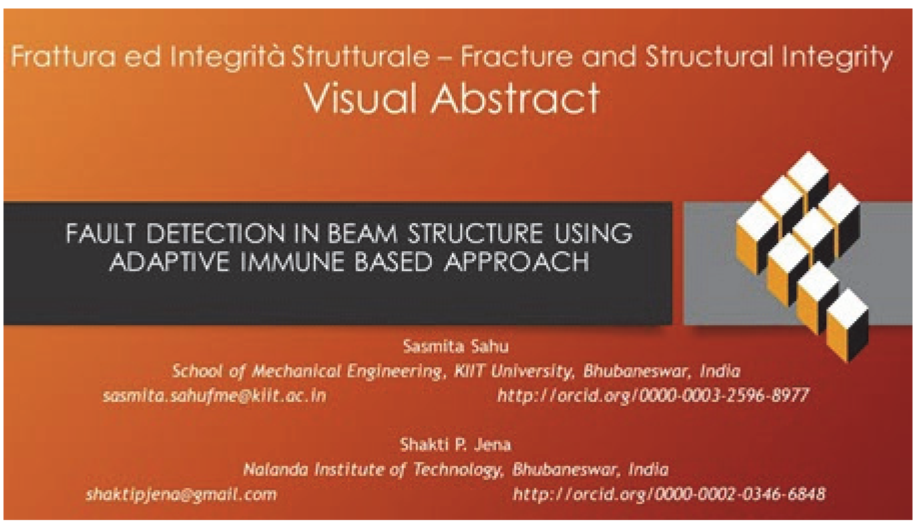

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INTRODUCTION

The appearance of a transverse crack affects the dynamic responses of a structural member. First Irwin in 1975 related local flexibility to the stress intensity factors (SIF) and gave a technique for calculation of SIF based on the local stiffness. It is known to all that the presence of any types of discontinuity will change the dynamic ways of behaving of the structural element. The discontinuity is usually symbolized in the form of a transverse crack. In the past years many efforts have been done by different researchers for the development of new non-destructive techniques (NDT) for the detection and quantification of presence of damage [1-4]. As already discussed, due to the presence of any discontinuity (crack or damage) leads to changes in physical/dynamic responses and the stiffness of structure. Due to this, the vibration features like the natural frequencies and mode shapes are changed. This can be utilized to find the damage parameters (like crack location and crack depth). Due to the difference in the vibration parameters of cracked and uncracked beam, the damages are detected. After this, the next step is to quantify the damage parameter using different natural frequencies and mode shapes. As these factors changes are more dependent on crack geometry. It could be possible to find out the damage location and size by finding the changes in vibration responses [5-7]. Besides [9-10], Parandaman and Jayaraman used Finite Element Analysis of Reinforced Concrete Beam It has already been known that the mass has no role in the detection of structural damage. It is observed that the modal frequencies are effects of changes in physical properties. So, this analysis can be exploited to propose a non-destructive method of testing to find out the damage detection.

In the present scenario Artificial Intelligence (AI) techniques are gaining significance value for designing online devices for various fault detection methods. Various researchers have also added AI techniques in their methods for damage detection [11-13]. But it has also been noticed that the standalone methods sometimes are trapped in local solutions and are not able to give proper optimized solution. Rongshuai et.al [14] implemented hybrid approach for structural health monitoring issues based on immune algorithms and representational time series analysis. So, any two or three AI techniques can be accomplished together to get an optimized solution for the problem.

In real life, any engineering problem needs mathematical modeling, for that dynamic analysis has been done. The slightest change in the system changes the dynamic and physical properties of any structural member. So, to study the changes in the physical properties analytical method is used. Due to the appearance of any minute crack or fault the stiffness or the flexibility of the element changes. These changes directly affect the modal parameters of the structural element. The alteration in the modal parameters like the frequencies and mode-shapes can be utilized for the identification of the presence of any changes in the geometry of the structural element. In this methodology the three modal natural frequencies have been used as input variables for the Clonal Selection Algorithm [15-18]. So, for initialization part of the evolutionary algorithm, a data pool or solution space is made using different data from analytical method. Each data contains of three input and two output variables. The output variables comprise of crack geometry. This is a kind of inverse engineering problem. First, the data pool is generated by directly giving various crack depths and crack locations in analytical method. Then these data pool is trained in Clonal Selection Algorithm get the crack depth and crack location for a particular set of first three modal natural frequencies [19-20]. But it is observed that during the process of collection of data some amount of errors are also collected in the data pool. These errors may put the algorithm in local trap which will reduce the convergence rate of the algorithm also. So, to avoid this gap and to establish a relationship between the input and output variables, a statistical method has been advised. In this paper, Regression Analysis (RA) has been proposed for the statistical method [21-22]. Aleksandar et.al [23] used localized regression concepts for damage detection in great multipart mechanical structures. Zhang et al. [24] have applied the Long Short Term Memory (LSTM) along with the extended version of finite element method to predict the occurrence of cracks in a gravity dam. Jena and Parhi [25] has also developed a crack detection procedure for moving load dynamics problem in the domain of recurrent neural networks.Santonocito and Milone [26] also developed a noble crack assessment approach using deep algorithm approach to identify the damage in material. Mishra et al. [27] explored a computer based algorithm to determine the fracture crack in Oil Hardening Non-shrinking die after the completion of machining process recently.Ming and Zhao [28] applied the artificial immune system approach to identify faults in chemical factory. Yin et al. [29] applied the CSA for exact detection of intrusion.

To the best of author's knowledge, the implementation of Regression Analysis (RA) along with has the Clonal Selection Algorithm (CSA) is quiet scanty. Here, the proposed technique can be used to solve multimodal and multivariable continuous nonlinear problems. An artificial immune (clonal selection algorithm) based technique has been used in combination with Regression Analysis (RA). Many authors have either applied artificial immune system or CSA for fault identification in different factories. But no such author has approached the combination of artificial immune system with CSA with regression analysis mechanism. Again, the application of such method (ACSA) in the field of structural dynamics is also scanty. The use of regression analysis makes more adaptive and the residual error in the collection of vibration data is reduced. The steps followed in the proposed paper are described in the schematic diagram (Fig.1). For discrete values for geometry of the crack are taken to find the natural frequencies of first three modes. Though different evolutionary algorithms use different coding systems and many of them use numerical values also. Here the numerical values are converted into dimensionless values. This is done by comparing the values of cracked structural element and uncracked structural element.

Literature Review

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Dynamic Analysis/FEA

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Data Acquisition/Generation of a data pool

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Training of data in CSA

↓

Training of data in RSA

↓

Training of data ACSA

↓

Laboratory Tests

↓

Result & Discussion

↓

Conclusion

Figure 1: Procedures involved in the proposed analogy.

DYNAMIC ANALYSIS OF CRACKED CANTILEVER BEAM

As discussed earlier, any changes in the structural element changes its dynamic features which depend on the stiffness of the element. So, it is very important to find the stiffness matrix of the element. There are different ways of calculating stiffness matrix. One such method has been depicted in this section. The physical geometry of the cracked beam has been described in Fig 2. Where 'l' is the position of crack, 'L' is the length of the beam, 'd' is the depth of crack and 'D' is the width of the beam.

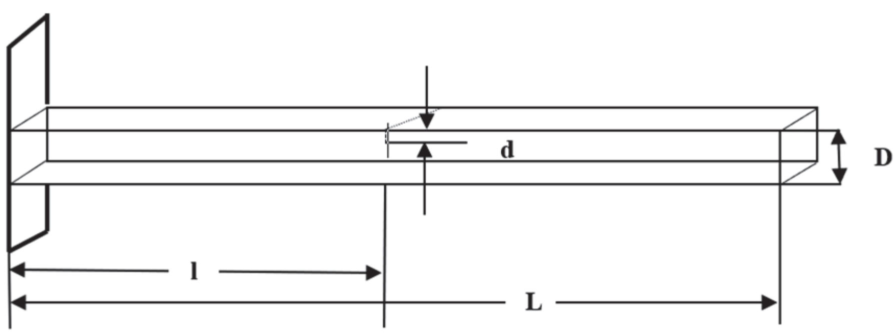

Figure 2: Geometrical view of the cracked cantilever beam.

The equation for the dynamical response of a structural element for 'm' degrees of freedom has been given below.

$$[M_b]\{\ddot{u}(t)\}+[D_b]\{\dot{u}(t)\}+[K_b]\{u(t)\}=F(t) \tag{1}$$

where, M_b, D_b, K_b represent the (m ×m) mass, damping, and stiffness matrices, respectively.
The external force and the displacement are described as below

$$F(t)=\{f(\omega_b)\}e^{j\omega_b t} \tag{2}$$

$$u(t)=\{u(\omega_b)\}e^{j\omega_b t} \tag{3}$$

$$\left(-\omega_b^2\left[M_b\right]+j\omega_b\left[D_b\right]+\left[K_b\right]\right)\left\{U\left(\omega_b\right)\right\}e^{j\omega_b t}=\left\{f\left(\omega_b\right)\right\}e^{j\omega_b t} \tag{4}$$

Shape functions perform an important role in solving the problems of dynamic analysis of cracked or faulty beams. The Shape functions refer to one of the displacements being equal to '1' and all other displacements are taken as '0'. In the current research work Hermitian shape function is used.

$$\left[H_b\left(\omega_b\right)\right]=\left(-\omega_b^2\left[M_b\right]+j\omega_b\left[D_b\right]+\left[K_b\right]\right)^{-1} \tag{5}$$

$$\left\{X_b\left(\omega_b\right)\right\}=\left[H_b\left(\omega_b\right)\right]\left\{f\left(\omega_b\right)\right\} \tag{6}$$

When the damping condition is neglected.

$$\left[H_b\left(\omega_b\right)\right]=-\omega_b^2\left[M_b\right]+\left[K_b\right]^{-1} \tag{7}$$

Here
BC-Before the appearance of crack
AC-After the appearance of crack

$$\left[H_b\left(\omega_b\right)\right]_{BC}=-\omega_b^2\left[M_b\right]_{BC}+\left[K_b\right]_{BC}^{-1} \tag{8}$$

$$\left[H_b\left(\omega_b\right)\right]_{AC}=-\omega_b^2\left[M_b\right]_{AC}+\left[K_b\right]_{AC}^{-1} \tag{9}$$

$$\left[K_b\right]_T=\left[H_b\left(\omega_b\right)\right]_T^{-1}+\omega_b^2\left[M_b\right]_T \tag{10}$$

where the subscription 'T' represents the total stiffness matrix.
We know that the mass matrix does not change during the process of crack generation. So, the change in stiffness can be written as follow,

$$\left[\Delta K\right]=\left[H\right]_{BC}^{-1}-\left[H\right]_{AC}^{-1} \tag{11}$$

APPLICATION OF AN IMMUNE BASED AI APPROACH FOR STRUCTURAL FAULT DETECTION

Structural health monitoring (SHM) consists of different assignments in the damage detection. One of the most important benefits of SHM is the damage identification before any severe catastrophic failure. Practical solution needs a large quantity of sensors and robust system for data analysis. In this case a bio-motivated method has been analyzed and described. The proposed technique includes identification of damage or any discontinuation and use of immune based technique for finding out the location of the damage. As SHM processes require continuous data processing algorithms to make a robust tool for a quick and efficient damage detection process. This work is used to first identify the discontinuation or development of any minute crack, then the use of Artificial Immune System (AIS) based method for designing the algorithm.
Artificial Immune System (AIS) is an emerging field of heuristic evolutionary algorithm. It has been noticed that there is an increasing interest to design and develop of calculative models inspired by immunological principles and theory. Collective name of number of algorithms inspired by an immune system is known as Artificial Immune System (AIS). All the research within AIS in theoretical immunology and numerous parallel streams have also been conducted over the past two decades. This research results in development of distinct sub-streams like the computational immunology. In a disposition of computational and theoretical immunology lies at the core of Artificial Immune System (AIS). Within the

process of mathematical modeling of immunological mechanisms is similar, in principle to the development of immune inspired algorithms. The theoretical models of immune phenomena acted as a foundation for the AIS algorithms like Clonal Selection Algorithm, Negative Selection Algorithm and Immune Network based approaches. One of the above mentioned Artificial Immune System (AIS) approaches, Clonal Selection Algorithm (CSA) has been used for developing the proposed algorithm.

Clonal Selection Algorithm (CSA) is a one type of Artificial Immune System that is based on the immune response to an antigenic stimulus. In this algorithm, only those cells will proliferate which can be aware of the antigen. Clonal Selection Algorithm (CSA) can be treated as an improved Artificial Immune System with a higher mutation rate. It gives an efficient optimization performance and is usually not trapped in local minimums. So, this heuristic algorithm can be used to detect anomaly present in the structural and machine elements. In recent years Clonal Selection Algorithm (CSA) has been widely utilized in every engineering field. Though Clonal Selection Algorithm has been considered as a very efficient Artificial Immune System to be successfully applied in various research fields, it has many loopholes. The loopholes may be less convergence rate and insufficient theoretical support. So, to increase the competence and adaptiveness of the Clonal Selection Algorithm, a sample of data pool collected from the dynamic analysis and experimental analysis is given in Table 1.

Sl. No	Sample Type	rfnf	rsnf	rtnf	rcd	rcl
1	Dynamic analysis	0.9953	0.9991	0.9934	0.28124	0.5623
2	Expt. analysis	0.9962	0.9989	0.9988	0.24	0.26
3	Expt. analysis	0.9964	0.9947	0.9967	0.48	0.377
4	Dynamic analysis	0.99643	0.9995	0.9950	0.331	0.51
5	Dynamic analysis	0.99975	0.9962	0.9997	0.334	0.3123
6	Dynamic analysis	0.9461	0.9463	0.9455	0.365	0.3123
7	Dynamic analysis	0.9554	0.9552	0.9546	0.2832	0.376
8	Expt. analysis	0.962	0.9619	0.9617	0.24	0.4377
9	Dynamic analysis	0.9926	0.9951	0.9945	0.36	0.40626
10	Expt. analysis	0.9989	0.9995	0.9977	0.15624	0.3123

Table 1: Sample of data pool collected from Dynamic Analysis and Experimental Analysis.

Relative crack location (rcl)=l/L, Relative crack depth (rcd)=d/D. The ratio of the natural frequency of cracked beam to that of healthy beam at a particular mode is expressed here as the relative natural frequency. The first relative natural frequency (rfnf) has been determine with the ratio of natural frequency of cracked beam to that of healthy beam at mode-1 only. Simlilary the relative natural frequencies of other modes are determined at shown in Table-1. These relative natural frequencies are calculated from both dynamic and experimental analyses.

DESCRIPTION OF ARTIFICIAL IMMUNE SYSTEM USING CLONAL SELECTION ALGORITHM (CSA):

The steps used in Clonal Selection Algorithm are given below.

1. The first move in the Clonal Selection Algorithm is the identification of the antigen to boost the immune system. This recognition has to satisfy some criteria. The criteria are used to measure affinity of different individuals or antibodies.
2. The receptor when recognizes an antigen, a binding occurs between the cell receptor and the pathogen. The binding strength depends on the affinity. When the affinity value is more than the threshold affinity value, the immune system is activated.
3. There are two types' immune cells known as T-cell and B-cell. In Clonal Selection Algorithm B-cells are used. The above two types of cells are alike but they diverge in antigen recognition.
4. When a B-cell encounters any pathogen, it proliferates into memory and effectors cells which are known as Clonal Selection.
5. The antibodies are selected using Affinity Measurement. Affinity Measurement is a type of natural selection which leads to reproduction.

6. During the reproduction operation which is a type of asexual reproduction, the progenies or offspring are generated by proliferation. This process is known as cloning.
7. After cloning, the progenies undergo hyper mutation. The activated antibodies showing higher affinities towards the antigens and become memory cells. So, that whenever the organism faces these types of antigens, the immune system will be able to produce required antibodies.

CLONAL ALGORITHM FOR THE FAULT DETECTION IN DAMAGED BEAM

The current section describes the algorithm based on Clonal Selection Algorithm.
Different data are generated using dynamic analysis before training in the Clonal Algorithm. As in different evolutionary algorithms, the first step is to initialize the population (P_n) from the available data pool.
Step 1: Initialization: Randomly initialize a population of individuals (P_n)
Step 2: Next step is to find the affinity of the solutions in the population using affinity measurement equation.

$$\text{ObjectiveFunction}=\sqrt{\left(fnf_d-fnf_{x1,j}\right)^2+\left(snf_d-snf_{x1,j}\right)^2+\left(tnf_d-tnf_{x1,j}\right)^2} \tag{12}$$

fnf_d= First natural frequency of the structure.
fnf_x = Relative first natural frequency
snf_d =Second natural frequency of the structure.
snf_x=Relative second natural frequency
tnf_d =Third natural frequency of the structure.
tnf_x = Relative third natural frequency
j =number of iterations

Step3: The affinity measurement considers the Hamming Distance 'H_d' between the antigens and antibodies according to the subsequent equation:

$$H_d=\sum_{r=1}^{L}\delta$$

where

$$\delta=\begin{cases}1,\text{if } ab_i \neq ag_i\\ 0,\text{otherwise}\end{cases}$$

Step4: Select 'n_{s1}' of the best individuals in the search space.
Step5: The selected individuals are proliferated to make copies. The rate of proliferation is proportional to the closeness of the individual towards the antigen.
Step6: Then the proliferated individuals or antibodies are mutated. The mutation rate is inversely comparable to the affinity value.
Step7: The clonal size is taken as a constant integer. In this article the integer is calculated using the subsequent equation:

$$C_n=\sum_{r=1}^{n}\text{Round}\left(\frac{\alpha.Q_n}{R}\right) \tag{13}$$

where,
C_n- Total number of clones generated
n- antibodies selected
α- Multiplying factor [13, by Castro]
Q_n- Total number of antibodies (population size)
R- Rank of the selected antibodies.

Step8: Then the mutated clones are added to the search space or the initial population (P_n) and reselect 'n_{s2}' of the optimized clones. Then these are added to the memory cells (M) of the immunity cells.
Step9: Step 2-8 are repeated till the end conditions are not met.
The termination conditions may vary from problem to problem. In this case, the numbers of iterations (20) are taken as the terminating condition.

APPLICATION OF REGRESSION ANALYSIS FOR STRUCTURAL DAMAGE DETECTION

Data mining is the process of discovering or finding out the potentially useful data or information from the database. This has been successfully applied in many fields other than engineering also. In the proposed methodology, data mining used to make a data base for the proposed algorithm. So, the relation between the variables should be known. So, for the above mentioned reasons Linear Regression Analysis has been used. Regression Analysis describes the relationship between a response (dependent) variable and explanatory (independent) variables. Once the relationship is established that can be used for future assessment of relationship between variables. In general, we can say regression analysis gives the best guess while making a kind of prediction. In real life problems, there may be number of input and output variables. So, simple regression analysis (RA) may not be enough to predict the relationship between the independent and dependent variables. The Fig.3 depicts the classification of Regression Analysis (RA).
This can also be used to predict the future value of the dependent variable using the established relationship. The two main distinct purposes are given below.

1. Regression Analysis (RA) is mainly used for forecasting and prediction.
2. This can be used for inferring a predictable relationship between the dependent and independent variables.

$$y=a+bx+e \tag{14}$$

where, a=Dependent variable, b=Slope, x=Independent variable, e=Residual error

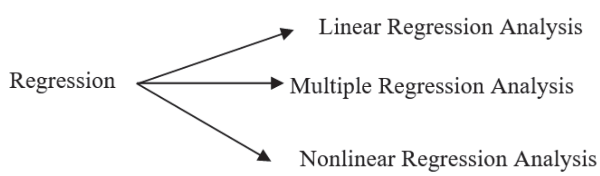

Figure 3: Classification of Regression Analysis

APPLICATION OF HYBRIDIZED CSA AND REGRESSION ANALYSIS

The theory of Clonal Selection Algorithm (CSA) is based on the coping of the immune cells. So, during the application of Clonal Selection Algorithm for optimization with the characteristics of CSA, the conventional CSA method usually suffers premature convergence and trapping of the algorithm in local solutions which will lead to improper solution. To address the concerning the loopholes, a statistical method has been incorporated in the conventional method. Most of optimization methods including CSA are used to train the data from the data acquisition methods. Usually during the collection of data, errors are induced in the data. These errors are also known as residual errors. These errors will lead to trapping of the algorithm in local solutions. So, to avoid this condition a statistical method has been incorporated. Here, Regression Analysis is applied to find the correlation between the dependent and independent variables. Usually, it has been observed that the patterns or methods used for the prediction of the outcome data from the solution space or data pool. As earlier mentioned, the collection of data contains the residual error. It is difficult to establish any relation between the input and output variables. So, to establish the relationship between the input and output variables and to reduce the effect of the residual error on the prediction of solutions, the analyses are done.
Due to the above-mentioned reasons, the data generated from the data acquisition methods are trained in the Regression Analysis. After the training of data in the Regression Analysis, the trained data are trained in Clonal Selection Algorithm.

Experimental arrangement for the validation of results from the adaptive clonal selection algorithm

The experimental arrangement developed of a cantilever beam. Various experiments or tests are done using different crack geometries were taken. From the various tests the first three modal frequencies of the vibration signature were collected. The dimensions of the cantilever beam considered for experimental analysis are 800x38x10. Instruments used in the experimental analysis are given below:

1	Beams	Specifications
2	Vibration Sensor	Type : 4513-001 Make : Bruel & kjaer Sensitivity : 10mv/g-500mv/g
3	Vibration Analyzer	Type : 3560L Product Name : Pocket front end Make : Bruel & kjaer
4	Vibration Indicator	PULSE LabShop Software Version 12
5	Impact Hammer	Range :222N Maximum Force: 890N Frequency Range: 10KHz Overall Length: 122mm
6	Power Distribution	220V power supply, 50Hz

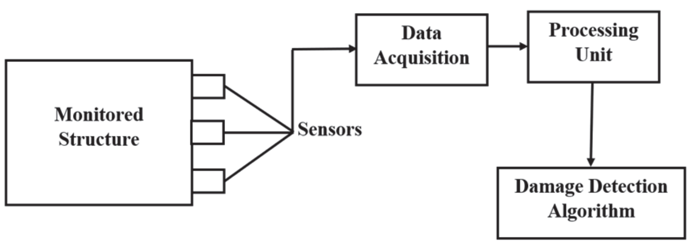

Figure 4:Description of the Experimental Analysis using schematic diagram.

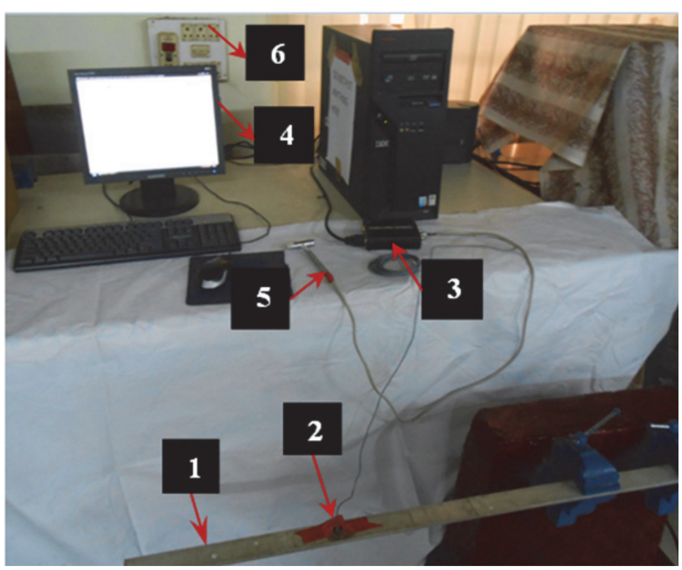

Figure 5: Experimental arrangement for cantilever beam with a single crack.

An impact hammer has been used to excite the beam element. Vibration parameters were taken using accelerometer for the whole length of the beam. Then the vibration parameters are processed in vibration analyzer. The transverse hairline crack in this case is generated using electrical discharge machining (EDM). The vibration indication of the cracked and uncracked beam is obtained from the experiment. The steps used or the arrangement needed for the experimental analysis is described in Fig.4 and the real picture of the experimental analysis is described in Fig.5. The different values for the relative natural frequencies are also obtained at different modes.

RESULT AND DISCUSSIONS

The development of fault detection method along it's validation with other techniques are discussed in this work.In this work, the fault detection (relative crack locations and depth) approach has been developed in an artificial immune based approach. The artificial immune system is here nothing but the Adaptive Clonal Section Algorithm (ACSA). The ACSA approach is the hybridization of CSA and RA. In the initial stage, the dynamic analysis of the beam with single hair line crack was analyzed. The relative natural frequencies for the first three modes of the healthy and unhealthy cracked structure are obtained by experimentation. These relative natural frequencies are the input parameters for the training of the proposed ACSA model. Apart from the ACSA, the individual CA and RA models are also analyzed here. The individual results from CA and RA at first compared with those of ACSA. Later, the results obtained from the ACSA model are compared with those of laboratory tests values. To authenticate and check the accuracy of the proposed ACSA model, a numerical model is exemplified with laboratory test methods. A mild steel beam of size 100×50×0.4 mm has been considered for the analysis. The analyses are conducted at various locations and depth of crack. The relative crack locations (RCL) considered here are 0.4, 0.367, 0.2833, 0.25 and 0.2166 respectively. The corresponding relative crack depths (RCD) to the RCL are 0.25, 0.3125, 0.375, 0.4375 and 0.5 respectively.

Sl. No	RFNF	RSNF	RTNF	RCD (Numerical)	RCL (Numerical)	RCD (CSA)	RCL (CSA)	RCD % Error	RCL % Error
1	0.9212	0.9228	0.9217	0.4	0.25	0.3815	0.2384	4.62	4.64
2	0.9459	0.9462	0.9453	0.367	0.3125	0.3499	0.298	4.65	4.6
3	0.955	0.953	0.958	0.2833	0.375	0.2706	0.358	4.48	4.53
4	0.9622	0.9613	0.9614	0.25	0.4375	0.2380	0.4166	4.8	4.77
5	0.9708	0.9702	0.9705	0.2166	0.5	0.2064	0.4766	4.7	4.68

Table 2: Comparison of results between dynamic analysis and Clonal Selection Algorithm(CSA).

Sl. No	RFNF	RSNF	RTNF	RCD (Numerical)	RCL (Numerical)	RCD (ACSA)	RCL (ACSA)	RCD % Error	RCL % Error
1	0.9212	0.9228	0.9217	0.4	0.25	0.3861	0.2401	3.475	3.96
2	0.9459	0.9462	0.9453	0.367	0.3125	0.3541	0.3017	3.514	3.45
3	0.955	0.953	0.958	0.2833	0.375	0.2732	0.3617	3.565	3.54
4	0.9622	0.9613	0.9614	0.25	0.4375	0.2411	0.4212	3.54	3.72
5	0.9708	0.9702	0.9705	0.2166	0.5	0.2090	0.4815	3.5	3.7

Table 3: Comparison of the results from Dynamic Analysis and Adaptive Clonal Selection Algorithm(ACSA).

Sl. No	RFNF	RSNF	RTNF	RCL (Expt.)	RCL (ACSA)	RCD (Expt.)	RCD (ACSA)	RCD % Error	RCL % Error
1	0.9212	0.9228	0.9217	0.378	0.3678	0.2405	0.2324	3.36	2.69
2	0.9459	0.9462	0.9453	0.3502	0.339	0.3025	0.2931	3.1	3.19
3	0.955	0.953	0.958	0.271	0.2646	0.3685	0.3577	2.93	2.36
4	0.9622	0.9613	0.9614	0.238	0.2301	0.428	0.4144	3.17	3.31
5	0.9708	0.9702	0.9705	0.2057	0.2002	0.496	0.4851	2.19	2.67

Table 4: Comparison of the results from Experiments and Adaptive Clonal Selection Algorithm(ACSA).

The results obtained from different methods are shown in Tables 2-4. The results obtained from the proposed ACSA are compared with those from CSA, dynamics analysis and experimentations separately. The comparisons of results are shown in Tables 2-4 and also in graphical manner in Figs 6-8. The results obtained for various values of experimental and ACSA, RCL values are shown in Fig 9.

The comparison of results between CSA and ACSA for RCD and RCL are shown in Figs 6 and 7 respectively through line charts. The convergence behavior of the results between CSA and ACSA for RCD are shown in Fig 7 with 300 numbers of iterations. .

The numerical model data are compared with the results obtained from CSA and ACSA in table 2 &3 respectively. In case of CSA, the percentage of errors of RCD and RCL with the numerical model is about to 4.6% each, while those of ACSA, the percentage of errors of RCD and RCL are about to 3.51% and 3.67% respectively. It is having clear evidence that the ACSA yield good results than that of CSA. Again a comparison results are done between the experiment and ACSA which are represented in Table 4. The percentage of errors of RCD and RCL between the results of experiment and ACSA are about to 2.95% and 2.84% respectively. So from the analyses, ACSA is a convergent one approach which can be applicable for fault identification in structural member.

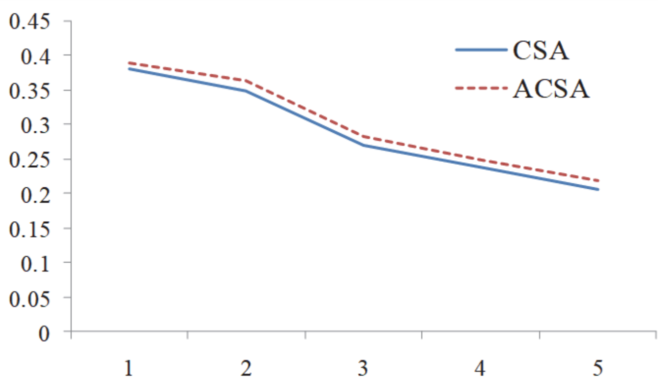

Figure 6: Comparison of results between CSA and ACSA for RCD.

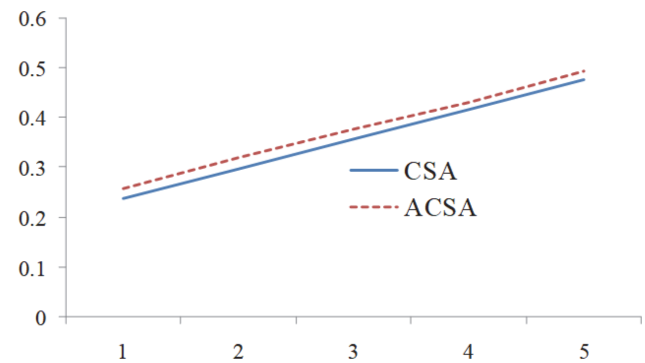

Figure 7: Comparison of results between CSA and ACSA for RCL.

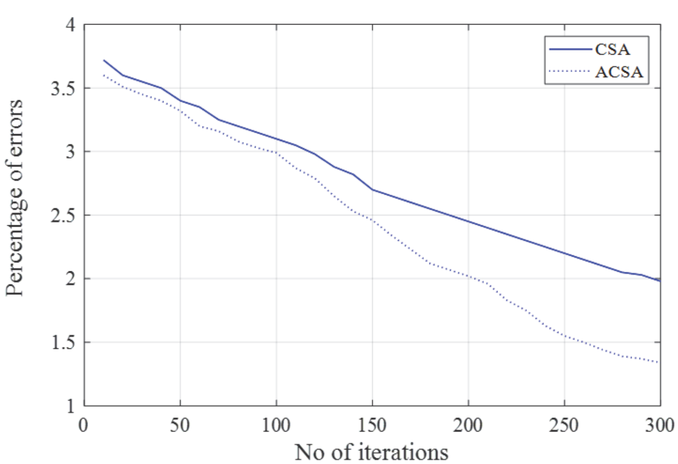

Figure 8: Convergence behavior of results between CSA and ACSA for RCD.

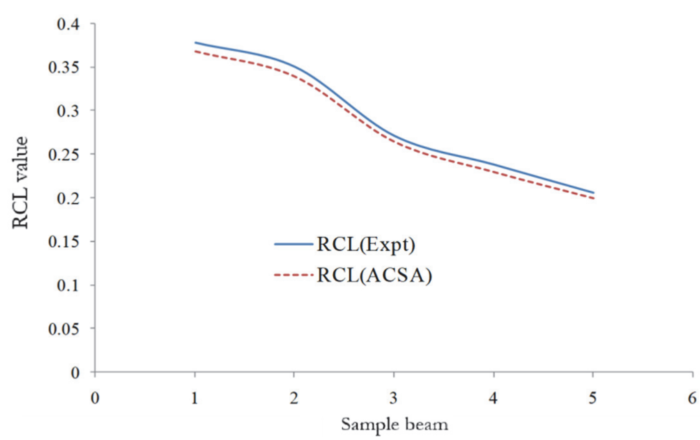

Figure 9: Graphical results for the position of cracks.

CONCLUSION

As described earlier, this article depicts a simple method for identification of structural damage. The crack model is analyzed in a theoretical manner. This analysis includes the mechanism of CSA, RA and ACSA. The ACSA is the hybridization of CSA and RA. The different steps involved in each CSA, RA and ACSA approaches are described in a precise manner. The results obtained from CSA and ACSA are compared with those of the adopted numerical model data. The error percentages of RCD between the results of CSA and ACSA with numerical model data are 4.6% and 3.51% respectively while those of RCL are about 4.6% and 3.67% respectively. To check the correctness and precision of the proposed ACSA, experiment has also done in laboratory. The percentage of errors between ACSA and experiment of RCD and RCL are about 2.95% and 2.84% respectively. So from the above studies, it has been come to an end that ACSA yield good results and also convergent to experimental results. So ACSA approach can be a useful methodology for fault indemnification in vibration structure.

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