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Structural Damage Detection and Identification Using Fuzzy Logic

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Although improved design methodologies have significantly enhanced the reliability and safety of structures in recent years, it is still not possible to build structures that are infallible. There is an increasing interest in the development of smart structures with built-in fault detection systems that would provide damage and/or failure warnings. A general methodology is presented for structural fault detection using fuzzy logic. The methodology is based on monitoring the static, eigenvalue, and dynamic responses to determine the health status of a structure or machine. Fuzzy logic coupled with principles of continuum damage mechanics is used to identify the location and extent of the damage. The proposed methodology represents a unique approach to damage detection that can be applied to a variety of structures used in civil engineering and machine and aerospace applications.

Nomenclature

A, B, C	=	fuzzy sets
a_i	=	firing strength of the ith antecedent
D	=	damage parameter
$\boldsymbol{d}$	=	damage parameter vector
E	=	elastic modulus of damaged element
$\bar{E}$	=	elastic modulus of undamaged element
k	=	number of structural regions or elements
p	=	noise level parameter
$\boldsymbol{u}_i$	=	ith eigenvector of damaged structure
$\bar{\boldsymbol{u}}_i$	=	ith eigenvector of undamaged structure
u_{nx}	=	displacement of nth node in the x direction of damaged structure
$\bar{u}_{nx}$	=	displacement of nth node in the x direction of undamaged structure
w_i	=	weight of the ith antecedent
$\boldsymbol{x}$	=	vector of measured structural responses
x, y, z	=	set elements
Y_j	=	measured response
$\hat{Y}_j$	=	analytically determined response
α	=	strength of evidence inference parameter
ε	=	error norm
μ	=	fuzzy set membership grade
ω_i	=	ith natural frequency of damaged structure
$\bar{\omega}_i$	=	ith natural frequency of undamaged structure

Introduction

IMPROVED design methodologies have significantly increased the reliability and safety of structures. However, due to a wide variety of unforeseen conditions and circumstances, it will never be possible nor practical to design and build a structure that has a zero percent probability of failure. Structural aging, environmental conditions, and reuse are examples of circumstances that could affect the reliability and life of a structure. This realization has led to the concept of smart structures with built-in fault detection systems that will provide failure warnings. The term smart structure is widely used to describe a structure that has integrated sensors, actuators, and control systems that monitor and change the behavior of the structure to produce desirable effects such as active vibration control. The network of sensors could also be used for collecting data for online fault detection. This paper proposes a new methodology for structural damage detection that monitors static and dynamic responses to determine the health status of a structure or machine component. The methodology uses a fuzzy rule base and inference algorithm to locate possible damage sites based on the evidence provided by changes in structural response. The reason for using fuzzy logic is to establish a system that can effectively handle the uncertainties and complexities of real structures.

Structural faults such as cracking, delamination, debonding, misuse, or the loosening of fasteners will change the mechanical properties of a structure. A change in any one of the mechanical properties of stiffness, damping, or mass will result in a change in the dynamic response of the structure. Kim and Bartkowicz[1] and Kam and Lee[2] investigated methods for fault detection based on statistical identification procedures. Identification procedures and signature analysis have been used for a number of years to fine tune finite element models to the actual behavior of existing structures using modal test data. By the use of the same procedure, modal test data from a suspect structure can be used to update the stiffness matrix of the corresponding sound structure. The damage locations are then identified by determining the elements for which the stiffness has changed. Hajela and Soeiro[3] suggested the use of static deflection in addition to modal analysis in an approach to damage detection based on an identification procedure and an iterative method of optimization. The use of neural networks in structural damage detection has been studied by several investigators including Kudva et al.,[4] Chaudhry and Ganino,[5] Elkordy et al.,[6] Manning,[7] Simon,[8] Spillman et al.,[9] Szewczyk and Hajela,[10] Tsou and Shen,[11] and Worden et al.[12] The general approach in these systems involves the unsupervised training of a neural network to associate particular structural responses to damage. Data for the training process is typically provided by finite element models. Once properly trained, the neural network will in theory provide damage information when measured structural responses are provided to the system. Several expert systems for structural fault detection and reliability assessment have been proposed. These systems in general assess structural integrity based on the information generated by visual inspections. Visual inspections generate linguistic expressions that describe the condition of the structure and noticeable damage. Fuzzy expert systems have been developed by Yao[13] and Ross et al.[14] to process this type of information to assess the overall condition of existing structures. The work presented by Yao[13] uses a fuzzy expert system to assess the condition of a structure based on information provided by the

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visual observations made by building inspectors. In the approach presented in the present paper, fuzzy associations between measurable structural responses and damage conditions are generated by finite element simulations and supervised learning and are to be used for online (real-time) damage detection.

Fuzzy Logic

Since it was introduced by Zadeh,[15] the theory of fuzzy sets has found a wide range of applications including consumer electronics, image processing, speech recognition, medical diagnosis, securities trading, and control systems. In a broad scope, fuzzy systems are mathematically based systems that process vague, imprecise, or ambiguous information. Recent developments in the area of fuzzy systems, particularly in the area of fuzzy associative memory systems and adaptive fuzzy systems, have provided a new foundation for machine learning and artificial intelligence.[16]

A fuzzy set is a set where membership is a matter of degree. The degree of membership is determined by a membership function. The fuzzy term about 5 may be represented by a fuzzy set defined by the following membership function:

$$\mu_D(x) = \begin{cases} 0, & \text{for} \quad x < 3 \\ (x-3)/2, & \text{for} \quad 3 \le x \le 5 \\ (7-x)/2, & \text{for} \quad 5 \le x \le 7 \\ 0, & \text{for} \quad x > 7 \end{cases} \tag{1}$$

A membership grade of zero indicates nonmembership, and a grade of one signifies full membership. In this example, the element $x = 4$ has a membership grade of $\mu(4) = 0.5$ in the fuzzy set about 5. Other examples of fuzzy sets are shown in Figs. 1 and 2. The fuzzy sets shown here are defined by linear membership functions. Nonlinear forms, such as bell-shaped curves, may be used as well.

Classical or bivalent logic is based on the assumption that every proposition is true or false. In most situations, the truth states of a proposition are neither completely true nor false, and the dichotomy of classical two-valued logic makes it an inappropriate reasoning process in real-world applications. Fuzzy logic is reasoning with fuzzy or uncertain sets. Fuzzy associations or rules can be expressed in the following form:

$$\text{If } \boldsymbol{X} \text{ is } A_1 \text{ and } \boldsymbol{Y} \text{ is } B_1\text{, then } Z \text{ is } C_1$$

$$\text{If } \boldsymbol{X} \text{ is } A_2 \text{ and } \boldsymbol{Y} \text{ is } B_2\text{, then } Z \text{ is } C_2 \tag{2}$$

In these expressions, A_i, B_i, and C_i are fuzzy terms that are defined by fuzzy sets. Given two input values, x and y, the rules can be evaluated and a conclusion about the value of z is inferred. Many inference procedures have been proposed. The most commonly used method is the correlation-minimum inference procedure shown in Fig. 3 (Ref. 16). Here, the degree of truth in the statement X is A_1 is determined by the membership value of x in A_1. Likewise, the degree of truth in the statement that Y is B_1 is determined by the membership value of y in B_1. In this example, the input values and respective membership grades are

$$x = 3.0 \Rightarrow \mu_{A_1}(3.0) = 0.3 \tag{3}$$

$$y = 2.2 \Rightarrow \mu_{B_1}(2.2) = 0.8 \tag{4}$$

In the rules [Eq. (2)], the two antecedents are connected with an AND operator, thus the overall degree of truth or firing strength of the rule is taken as the minimum of these two values. That is,

$$\min\left[\mu_{A_1}(x), \mu_{B_1}(y)\right] = \min(0.3, 0.8) = 0.3 \tag{5}$$

Thus, the conclusion Z is C_1 is true to a degree of 0.3. The resulting fuzzy set C_1' is obtained by clipping the membership values of C_1 to this degree of truth. Each rule leads to a decision in the form of a fuzzy set. The overall conclusion is the union of the fuzzy sets produced by each individual rule. Some applications may require a final crisp decision. A crisp representation z is determined by locating the centroid of the fuzzy set C'; thus,

$$z = \frac{\int x\mu(x)\,\mathrm{d}x}{\int \mu(x)\,\mathrm{d}x} \tag{6}$$

The location of z in this example is shown in Fig. 3. Figure 4 shows the structure of a general fuzzy logic decision making system. The input vector $\boldsymbol{X}$ consists of fuzzy feature variables, and the output vector $\boldsymbol{Y}$ consists of fuzzy conclusion variables. The fuzzifier part of the system maps the crisp or fuzzy input values to predefined fuzzy sets. The inference engine matches the premises of the rules in the knowledge base with the input data and performs implication. The defuzzifier translates the fuzzy conclusions into crisp values.

The proper selection of the membership functions and rules is essential to successful development of a fuzzy-logic-based decision system. The concept of introducing machine learning capabilities to establish membership functions and rules has received considerable attention. The learning block shown in Fig. 4 represents this function. Here, known inputs and corresponding correct decisions are used to generate the membership functions used by the fuzzifier and to develop the rule base. If the fuzzy sets are predetermined or manually defined, the teaching method is referred to as supervised learning because the fuzzy sets are prescribed. Various other architectures, such as neural networks and adaptive fuzzy associative memory systems,[16] use unsupervised learning. An unsupervised system learns from raw training data that are clustered into like patterns to form classes and fuzzy associations. In general, a large number of training data sets are required for unsupervised learning.

Structural Fault Detection Using Fuzzy Logic

The purpose of a structural health monitoring system is to provide information about the condition of a structure in terms of reliability and safety. A system designed for this purpose will consist of hardware and software that together will measure certain properties of a structure in a given state and, by analyzing any changes in these properties, infer if the structure is damaged. If it is damaged, the

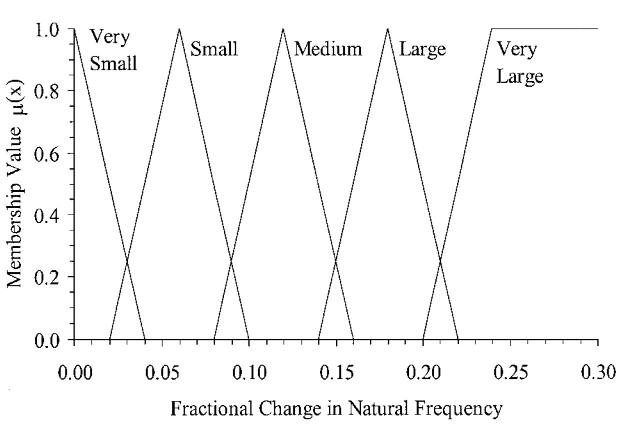

Fig. 1 Membership functions for terms describing changes in natural frequencies.

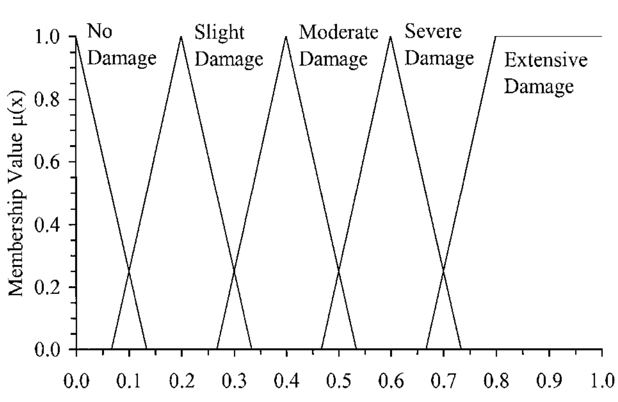

Fig. 2 Damage level membership functions.

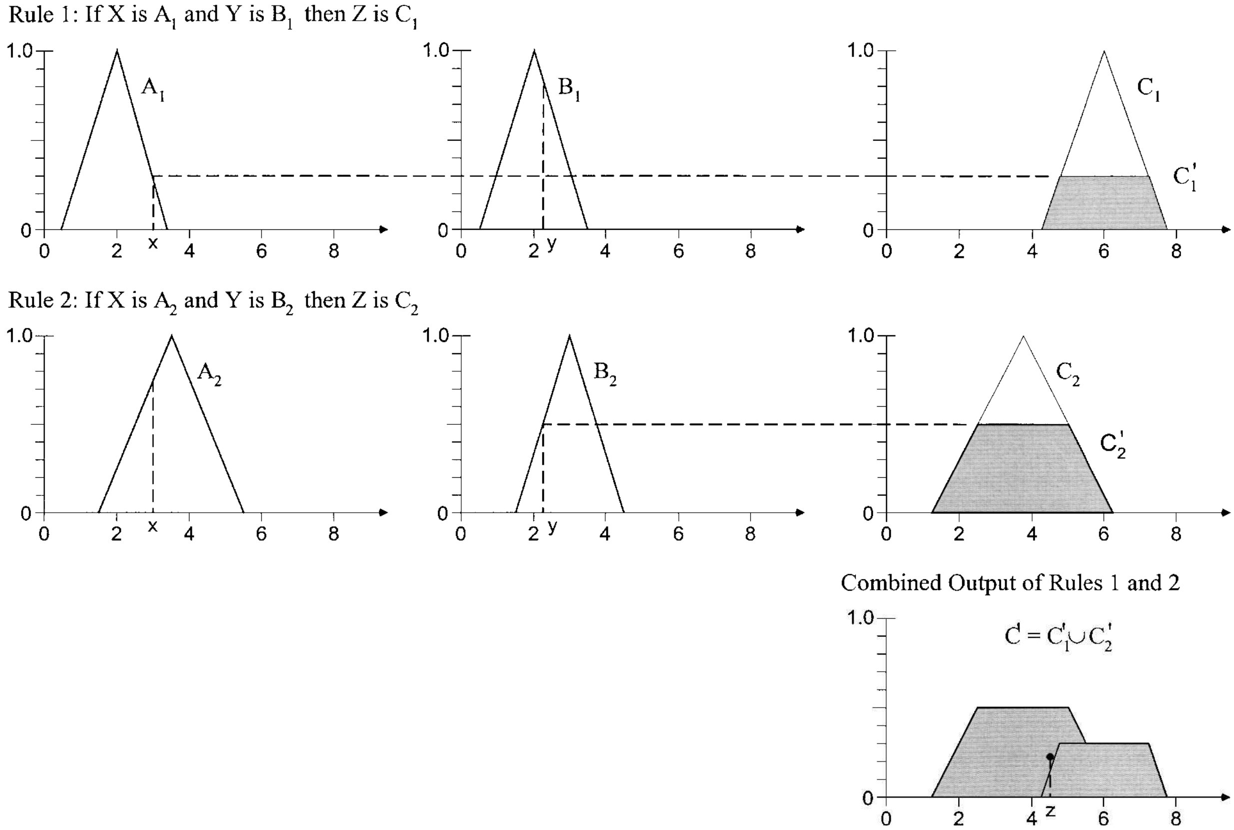

Fig. 3 Correlation-minimum inference procedure.[16]

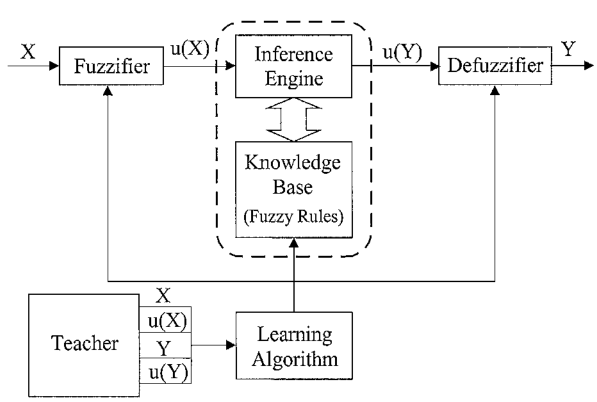

Fig. 4 General fuzzy logic decision system.

structural fault detection system will report possible damage sites and the severity of the damage.

The proposed fuzzy-logic-based structural fault detection system is shown in Fig. 5. The knowledge base consists of fuzzy associations between observed structural responses or properties and particular damage conditions. The system reads a state vector of measured structural properties and then maps these crisp values into the fuzzy sets. The inference engine performs damage implication through evaluation of the rules in the knowledge base and the supplied fuzzy states. The output of this implication procedure is a fuzzy vector that describes possible damage levels of predefined regions throughout the structure. The knowledge base is created by a rule generation algorithm that converts crisp training data into fuzzy rules through supervised learning. The training data are generated by executing damage simulations with a finite element model of the structure.

The input vector $\boldsymbol{x}$ contains measured properties or responses of the structure that is being evaluated. In most cases, these values will be compared to the baseline values of the undamaged structure. For example, if the first natural frequency is used, the corresponding component of the input vector $\boldsymbol{x}$ would be the fractional decrease in this frequency. That is,

$$x_i = (\bar{\omega}_1 - \omega_1)/\bar{\omega}_1 \tag{7}$$

where $\bar{\omega}_1$ and ω_1 are the first natural frequencies of the undamaged and damaged structure, respectively. However, the use of mode shapes in damage detection has been limited due to the relative insensitivity to damage and acquisition difficulties. However, should a particular application favor the use of eigenvectors, a state variable could be defined in terms of a mode shape correlation coefficient or the model assurance criteria (MAC).[17] This coefficient quantifies the difference between two mode shapes with a normalized scalar product. The state variable is defined such that

$$x_i = 1 - \mathrm{MAC}\,(\bar{\boldsymbol{u}}_1, \boldsymbol{u}_1) = 1 - \frac{\left(\bar{\boldsymbol{u}}_1^T \boldsymbol{u}_1\right)^2}{\left(\bar{\boldsymbol{u}}_1^T \bar{\boldsymbol{u}}_1\right)\left(\boldsymbol{u}_1^T \boldsymbol{u}_1\right)} \tag{8}$$

where $\bar{\boldsymbol{u}}_1$ and $\boldsymbol{u}_1$ are the first mode eigenvectors of the undamaged and damaged structure, respectively. This quantity will range from 0 (no change) to 1.0 (orthogonal vectors) as the eigenvector changes due to damage. These modal state variables may be defined for any number of modes deemed appropriate or useful for a particular structure. Static deflections may also be used for damage detection. Here, state variables are defined as a fractional change in displacement due to a given load. That is,

$$x_i = (\bar{u}_{nx} - u_{nx})/\bar{u}_{nx} \tag{9}$$

where $\bar{u}_{nx}$ and u_{nx} are the displacements of the nth node in the x direction of the undamaged and damaged structure, respectively, for a given load condition. These state variables can be expressed in fuzzy terms and sets like those shown in Fig. 1. Any combination of these or other appropriately defined structural state variables may be used for monitoring structural changes.

The fault detection system provides information about the possible damage levels and sites throughout the structure. By the use of predefined regions of a structure, the possible level of damage in

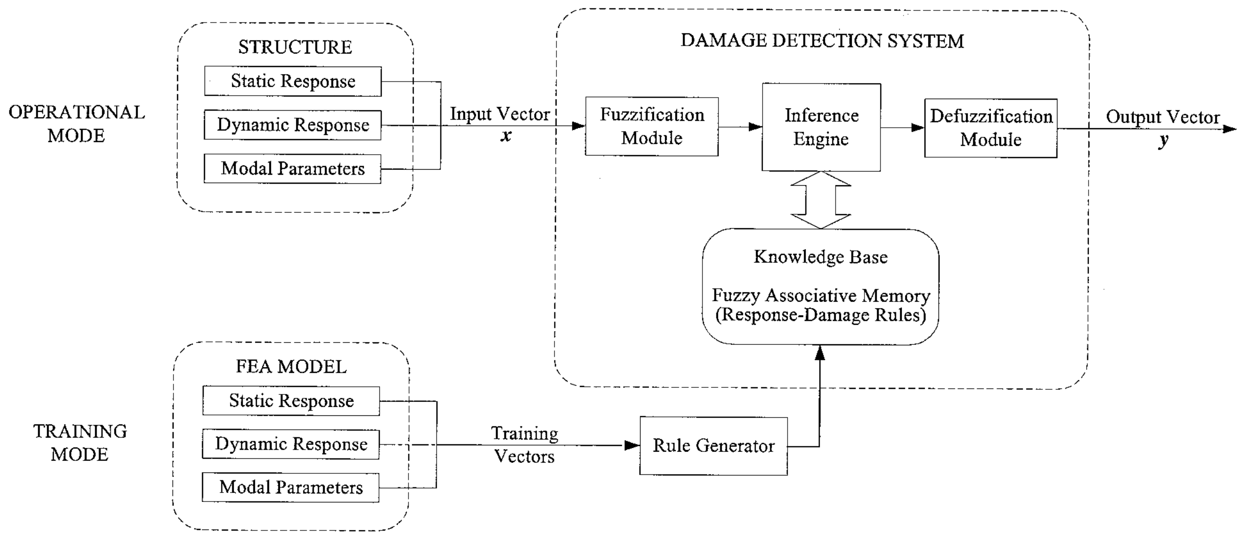

Fig. 5 Structural fault detection system based on fuzzy logic.

each region is determined. Because a finite element model is used to train the system, a logical definition of these regions for moderately sized systems would be the same discretization used in the model. Thus, the output vector $\boldsymbol{y}$ will provide the possible damage level in each element defined in the model. Damage is modeled as a simple reduction in element stiffness. Using principles of continuum damage mechanics, a damage parameter D can be defined such that

$$D = (\bar{E} - E)/\bar{E} \tag{10}$$

where $\bar{E}$ and E represent the elastic modulus of the element in the undamaged and damaged condition, respectively. Examples of fuzzy sets representing damage terms defined over the damage parameter space are shown in Fig. 2.

The rule base contains fuzzy rules that relate the structural states given in the input vector $\boldsymbol{x}$ to possible damage conditions that are then supplied in the output vector $\boldsymbol{y}$. In the complete knowledge base, a rule for each damage level (none, slight, moderate, severe, extensive) in each element is defined. In this system, the rules are encoded in a fuzzy associative memory (FAM) bank.[16] The inference engine in the structural fault detection system executes the FAM inference procedure. The overall firing strength of several antecedents connected with an AND operator, the intersection, is typically determined by taking the minimum value of the individual firing strengths as described in the preceding section. An OR operator, the union, takes the maximum of the firing strengths. In diagnostic applications, such as this, the intersection may be too restrictive, and the union would be too relaxed in evaluating the overall truth of the proposition. For example, if the proposition is based on changes in the first four natural frequencies and if any one of the four measurements is completely erroneous, the overall firing strength would evaluate to zero regardless of the strength of the evidence provided by the other states. The overall conclusion about the health of the structure would be determined to be inconclusive despite the evidence provided by the other measurements. In such cases, the minimum operator should be relaxed to consider the strength of the other antecedents in the overall firing strength of the rule. This can be accomplished by parameterizing the operator such that it can evaluate overall firing strengths in a range from the minimum (intersection) to a maximum (union) of the individual firing strengths. A weighted generalized mean[18]

$$h(a_1, a_2, \ldots, a_n; w_1, w_2, \ldots, w_n) = \left(\sum_{i=1}^{n} w_i a_i^{\alpha}\right)^{\alpha} \tag{11}$$

is used in this application. Here, a_i and w_i are the firing strength and weight of the ith antecedent, respectively, n is the number of antecedents in the rule, and α is a parameter ranging from $-\infty$ to ∞. The inference procedure is initiated with an intersection operator ($\alpha = -\infty$). If a conclusion cannot be drawn from the given set of measurements, α is increased until a conclusion can be drawn. The parameter α is a measure of the strength of the evidence or confidence level associated with the conclusion. The output of the entire inference procedure is a vector of k fuzzy sets, where k is the number of regions or elements in the structure. The kth fuzzy set is defined over the damage parameter space and describes the level of damage in the kth element or region. The defuzzification procedure evaluates the centroid of each fuzzy set to produce a vector of crisp damage parameter values.[19]

Training the structural fault detection system is a procedure wherein the rules in the knowledge base are formulated from structural response data for known damage conditions. These data are supplied by simulating damage with a finite element model. The crisp data generated by the damage simulations are read by a rule generation algorithm that fuzzifies the data and formulates the fuzzy rules. In this system, a rule for each damage level in each element is generated. This supervised learning is accomplished with a finite number of simulations and ensures that all possible damage sites and levels are reflected in the rule base. The weights of the individual antecedents are prescribed based on the sensitivity of the particular state variable to damage.[20]

Damage Detection Examples

The first example involves a cracked fixed–free beam. This simple structural system has been used in experimental tests by Rizo et al.[21] and numerical analysis by Kam and Lee[2] to evaluate damage detection methodologies. The steel beam is 300 mm in length and has a 20×20 mm cross section. The first three natural frequencies are the structural parameters used as input to the fault detection system. The measured values for various damage conditions are listed in Table 1. For training purposes, the system is modeled with 20 beam elements. Damage is simulated in each element with the set of damage parameters $D = \{0.0, 0.2, 0.4, 0.6, 0.8\}$. The resulting rulebase consists of 100 fuzzy rules. A rule for each damage level in each element is generated. This requires $N \times n$ simulations, where N is the number of damage levels simulated and n is the number of elements in the model. During fuzzification, the natural frequencies are mapped into fuzzy sets. A family of six fuzzy sets is used to define the space for each input parameter. Five fuzzy sets are defined over the damage space.

Figure 6 shows the possible damage sites and levels in the cantilever beam with an edge crack near the fixed end. In the first case (Fig. 6a), where the crack depth is only 10% of the section height, the detection system recognized the presence of slight damage, but could not pinpoint the location. The small shift in the natural frequencies produced by this small crack along with measurement uncertainty does not allow for locating the damage with any certainty. As the crack extends to 30 and 50% of the section height, the shift in the natural frequencies becomes more significant and distinct, thus

Table 1 Natural frequency data for damaged fixed–free beams[2]

Crack depth, mm	Natural frequency, Hz ω_1	ω_2	ω_3
Crack position 10			
2	182.7	1149.4	3242.9
6	163.9	1073.4	3097.3
10	129.8	980.6	2954.2
Crack position 140			
2	184.7	1153.1	3258.1
6	181.2	1092.9	3250.1
10	171.5	971.5	3233.6
Undamaged condition	185.2	1160.6	3259.1

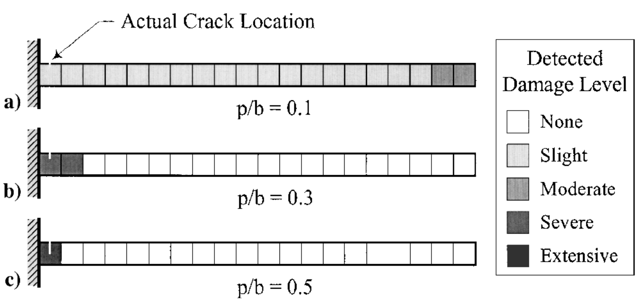

Fig. 6 Fixed–free beam with a crack 10 mm from the fixed end; crack depth indicated as a fraction of the section height (*p/b*). Shaded regions indicate possible damage locations and levels reported by the fault detection system.

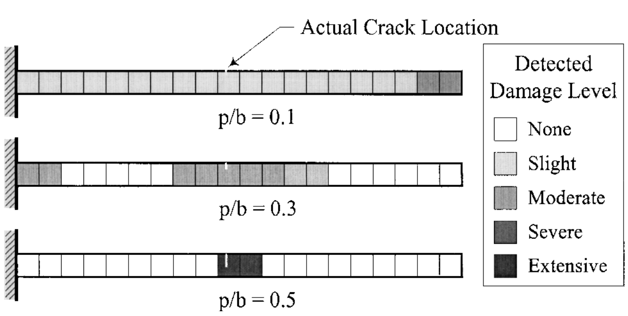

Fig. 7 Fixed–free beam with a crack 140 mm from the fixed end; crack depth indicated as a fraction of the section height (*p/b*). Shaded regions indicate possible damage locations and levels reported by the fault detection system.

increasing the possibility of distinctly locating the damage. Figure 7 shows similar results for the case with a crack located 140 mm from the fixed end. A similar procedure can be used for cracked free-free beams.[22]

To further illustrate the possible advantages of the proposed fuzzy approach in structural damage detection, the following examples are evaluated using the present method and the system identification approach proposed by Hajela and Soeiro.[3] The system identification approach of Hajela and Soeiro consists of formulating an optimization problem that minimizes the difference between the analytical (finite element analysis) and experimental (measured) response of the system. The damage parameters d_i, which describe the reduction of stiffness in the ith element, constitute the design variables for the optimization problem. This optimization problem can be written as follows. Find

$$\boldsymbol{d} = \begin{Bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{Bmatrix}$$

which minimizes

$$f(\boldsymbol{d}) = \sum_{j=1}^{m} (Y_j - \hat{Y}_j)^2 \tag{12}$$

subject to

$$0 \le d_i \le 1, \qquad i = 1, 2, \ldots, n$$

where Y_j and $\hat{Y}_j$ are the measured and analytically determined values of the jth state, respectively, m is the number of states monitored, and n is the number of elements in the finite element model.

This minimization requires that $\hat{\boldsymbol{Y}}$ be obtained from the eigenvalue or static load deflection problem using a stiffness matrix that is a function of the design variables d_i. On convergence to a solution, damage is located through inspection of the element damage parameters d_i. In the following examples, Powell's method was used for function minimization.

The 15-bar and 48-bar trusses shown in Figs. 8 and 9, respectively, are the systems considered. In each case, the measured values were provided by computer simulations with added noise of varying severity. Noise was introduced to represent uncertainty in structural modeling, damage conditions, and measurement systems. Given a computed response value x_0, a random number u in the interval $[-1, 1]$, and a noise level parameter p, the simulated measured value x is generated by the expression

$$x = x_0(1 + up) \tag{13}$$

The parameter p determines the maximum variance between the computed value x_0 and the simulated measured value x. If, for example, $p = 0.2$, the simulated measurement x with random noise may be as much as 20% different than the given value x_0. Thus, p can be used to control the amount of noise added in the simulations. In these simulations, the added noise is uniformly distributed.

In the 15-bar planar truss example, static deflection values in the direction of loading for each of the nodes with point loads (nodes 7 and 8) were monitored. As shown in Fig. 8, three different load conditions were used. Thus, a total of six measurements were used as input to the damage detection procedure. In the 48-bar space truss example, static deflection values in the direction of loading for the 12 free nodes (nodes 5–16), shown in Fig. 9, were monitored. One static

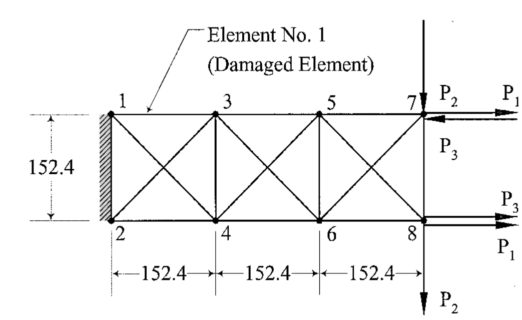

Fig. 8 Example: 15-bar planar truss, dimensions in centimeters.

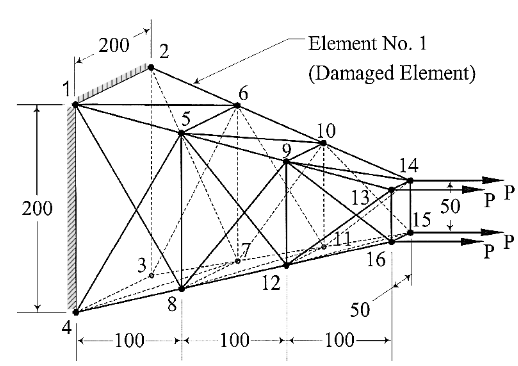

Fig. 9 Example: 48-bar space truss, dimensions in centimeters.

Table 2 Results for 15-bar planar truss example

Element number	Nodes	Actual damage parameter	Damage parameter without system noise: Present method	Damage parameter without system noise: Identification method	Damage parameter with system noise: Present method	Damage parameter with system noise: Identification method
1	1–3	1.000	0.960	0.998	0.950	0.957
2	2–4	0.000	0.000	0.006	0.000	0.000
3	2–3	0.000	0.000	0.014	0.000	0.419
4	1–4	0.000	0.000	0.010	0.000	0.000
5	3–4	0.000	0.000	0.011	0.000	0.000
6	3–5	0.000	0.000	0.004	0.950	0.098
7	4–6	0.000	0.000	0.000	0.000	0.000
8	4–5	0.000	0.000	0.014	0.000	0.001
9	3–6	0.000	0.000	0.000	0.000	0.000
10	5–6	0.000	0.000	0.000	0.000	0.000
11	5–7	0.000	0.000	0.006	0.950	0.700
12	6–8	0.000	0.000	0.000	0.000	0.000
13	6–7	0.000	0.000	0.033	0.000	0.967
14	5–8	0.000	0.000	0.030	0.000	0.000
15	7–8	0.000	0.000	0.013	0.000	0.825
Error norm		——	0.040	0.053	1.350	1.514

Table 3 Results for 48-bar space truss example

Element number	Nodes	Actual damager parameter	Damage parameter without system noise: Present method	Damage parameter without system noise: Identification method	Damage parameter with system noise: Present method	Damage parameter with system noise: Identification method
1	1–5	0.870	0.870	0.869	0.790	0.814
2	1–6	0.000	0.000	0.000	0.000	0.003
3	1–8	0.000	0.000	0.000	0.000	0.001
4	2–5	0.000	0.000	0.010	0.000	0.000
5	2–6	0.000	0.000	0.000	0.000	0.000
6	2–7	0.000	0.000	0.000	0.000	0.003
7	3–6	0.000	0.000	0.001	0.000	0.839
8	3–7	0.000	0.000	0.000	0.000	0.001
9	3–8	0.000	0.000	0.002	0.000	0.009
10	4–5	0.000	0.000	0.014	0.000	0.000
11	4–7	0.000	0.000	0.000	0.000	0.002
12	4–8	0.000	0.000	0.000	0.000	0.000
13	5–6	0.000	0.000	0.000	0.000	0.000
14	5–8	0.000	0.000	0.001	0.000	0.003
15	5–9	0.000	0.000	0.000	0.000	0.588
16	5–10	0.000	0.000	0.001	0.000	0.552
17	5–12	0.000	0.000	0.007	0.000	0.981
18	6–7	0.000	0.000	0.000	0.000	0.000
19	6–9	0.000	0.000	0.001	0.000	0.002
20	6–10	0.000	0.000	0.000	0.000	0.000
21	6–11	0.000	0.000	0.000	0.000	0.000
22	7–8	0.000	0.000	0.000	0.000	0.000
23	7–10	0.000	0.000	0.010	0.000	0.004
24	7–11	0.000	0.000	0.000	0.000	0.000
25	7–12	0.000	0.000	0.003	0.000	0.007
26	8–9	0.000	0.000	0.001	0.000	0.007
27	8–11	0.000	0.000	0.000	0.000	0.000
28	8–12	0.000	0.000	0.001	0.000	0.000
29	9–10	0.000	0.000	0.001	0.000	0.001
30	9–12	0.000	0.000	0.000	0.000	0.003
31	9–13	0.000	0.000	0.000	0.000	0.000
32	9–14	0.000	0.000	0.000	0.000	0.001
33	9–16	0.000	0.000	0.002	0.000	0.857
34	10–11	0.000	0.000	0.002	0.000	0.000
35	10–13	0.000	0.000	0.001	0.000	0.001
36	10–14	0.000	0.000	0.001	0.000	0.000
37	10–15	0.000	0.000	0.000	0.000	0.001
38	11–12	0.000	0.000	0.000	0.000	0.000
39	11–14	0.000	0.000	0.005	0.000	0.000
40	11–15	0.000	0.000	0.000	0.000	0.000
41	11–16	0.000	0.000	0.000	0.000	0.039
42	12–13	0.000	0.000	0.000	0.000	0.000
43	12–15	0.000	0.000	0.001	0.000	0.001
44	12–16	0.000	0.000	0.003	0.000	0.013
45	13–14	0.000	0.000	0.016	0.000	0.007
46	13–16	0.000	0.000	0.010	0.000	0.017
47	14–15	0.000	0.000	0.001	0.000	0.000
48	15–16	0.000	0.000	0.000	0.000	0.000
Error norm		——	0.000	0.030	0.080	1.748

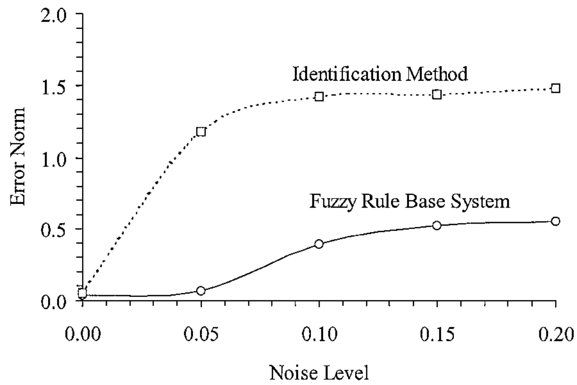

Fig. 10 Comparison of error in reported damage for the 15-bar planar truss example.

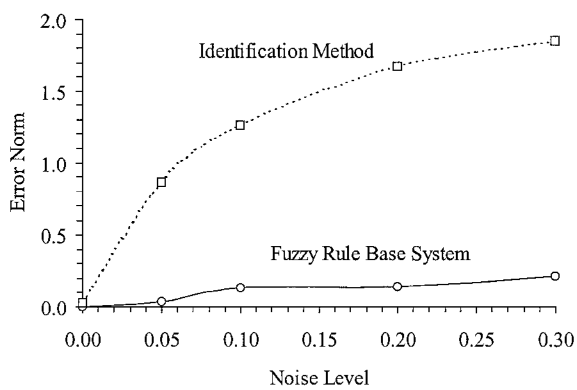

Fig. 11 Comparison of error in reported damage for the 48-bar space truss example.

load condition was used, which gave 12 deflection measurements as the monitored values.

In the 15-bar planar truss example, the actual damage was located in element number one with a damage parameter of $d_1 = 1.0$ (zero stiffness). In the 48-bar space truss, the actual damage is located in element number one with a damage parameter of $d_1 = 0.87$. The damage parameters as determined by both the fuzzy rulebase and the identification methods for representative noise conditions are listed in Tables 2 and 3. By the use of an error norm

$$\varepsilon = \sqrt{\sum_{i=1}^{n}(d_i - \hat{d}_i)^2} \tag{14}$$

to quantify the difference between the vectors of actual damage parameters $\boldsymbol{d}$ and the parameters returned by the damage detection system $\hat{\boldsymbol{d}}$, performance trends for each method under the varying noise conditions can be analyzed. For these examples, the trends are plotted in Figs. 10 and 11. Note that, in the case of 15-bar truss (Table 2), although the method shows artificial damage in members 6 and 11 (along with the actual damage of member 1), these are still longerons near where the actual damage occurred. The method appears to be trying to capture the physics of the damage. Perhaps the smearing of the damage is caused by the introduction of system noise. These results clearly indicate that the fuzzy approach can better tolerate noise and uncertainty in these systems. The identification approach theoretically can detect multiple damage sites, wherein the present fuzzy rulebase is only setup to evaluate single damage site conditions. However, the ability to locate multiple sites also means that there are a number of possible solutions and local minima that make it difficult for the optimization method to converge to the actual damage condition.

Conclusions

This paper presents a new procedure for structural fault detection based on fuzzy logic. Fuzzy logic and continuum damage mechanics are used to process and analyze the uncertainties and complexities of damaged structures. Fuzzy associations between observable structural responses and damage conditions are generated by finite element simulations and supervised learning. The fuzzy associations or rules are encoded in a fuzzy associative memory bank to form a knowledge base. This knowledge base is referenced by a fuzzy inference algorithm that infers possible damage locations and levels based on the evidence provided by changes in the structural states. The numerical examples demonstrate performance advantages of the fuzzy-logic-based system in noisy or uncertain conditions.

In the present method, the possible damage sites are reported on an element-by-element basis. In the analysis of a large or complex structure, an extremely large number of elements may be required to model the system adequately. This would lead to a large number of rules if damage detection is done on an element-by-element basis. In such cases it would be more practical to define regions (or substructures) in the structure for reporting damage. The rules in the knowledge base would then be established to determine the possibility of damage in each region (or substructure). The present procedure is structured for single site damage conditions. Rules for multiple damage sites could be constructed in a similar fashion. However, attempting to cover a large number of possible damage conditions would require a large number of rules. It may be more practical to preselect the possible damage sites of concern and generate rules based on these situations. The method and examples presented focus on the monitoring of global responses to damage detection and are not well suited for multiple-site (simultaneous) damage cases. The reason for this is that it would be necessary to simulate the combinations of multiple-site damage and damage levels to generate the associated rules. Further research into the use of local responses (local strain measurements) in a fuzzy logic damage detection approach has been conducted. In this approach, the rules are constructed and evaluated based only on local effects, thus damage detection at various sites could be done independently.

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