A Fuzzy Logic System for Ground Based Structural Health Monitoring of a Helicopter Rotor using Modal Data

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ABSTRACT: A fuzzy logic system (FLS) is developed for ground based health monitoring of a helicopter rotor blade. Structural damage is modeled as a loss of stiffness at the damaged location that can result from delamination. Composite materials, which are widely used for fabricating rotor blades, are susceptible to such delaminations from barely visible impact damage. The rotor blade is modeled as an elastic beam undergoing transverse (flap) and in-plane (lag) bending, axial and torsion deformations. A finite element model of the rotor blade is used to calculate the change in blade frequencies (both rotating and nonrotating) because of structural damage. The measurements used for health monitoring are the first four flap (transverse bending) frequencies of the rotor blade. The measurement deviations due to damage are then fuzzified and mapped to a set of faults using a fuzzy logic system. The output faults of the fuzzy logic system are four levels of damage (undamaged, slight, moderate and severe) at five locations along the blade (root, inboard, center, outboard, tip). Numerical results with noisy data show that the FLS detects damage with an accuracy of 100% for noise levels below 15% when nonrotating frequencies are used. The FLS also correctly classifies the "undamaged" condition up to noise levels of 30% thereby reducing the possibility of false alarms, a key problem for diagnostics systems. The fuzzy logic approach is thus able to extract maximum information from very limited and uncertain data. Using rotating frequencies lowers the success rate for small damage because the centrifugal stiffening caused by rotation counters the stiffness reduction caused by structural damage. The fuzzy logic system in this study is proposed as an information-processing tool to help the maintenance engineer by locating the damage area roughly but accurately for further nondestructive inspections.

INTRODUCTION

HELICOPTER blades are susceptible to structural damage because of high dynamic stresses caused by highly flexible rotating blades and an unsteady aerodynamic environment. In addition, structural aging, environment conditions and reuse can also affect the life and reliability of rotor blades. Since rotor blades are crucial elements of a helicopter, their health needs to be monitored on a regular basis to prevent catastrophic failure of the helicopter.

There are two broad approaches for health monitoring of a helicopter rotor. These two methods can be called online and ground based health monitoring. Online health monitoring involves monitoring selected system in-flight response parameters such as vibration and blade response and comparing them to a baseline reference value for the undamaged parameter to detect and identify damage. Ground based health monitoring involves using nondestructive testing methods such as modal analysis, strain analysis, photoelastic techniques, ultrasound and acoustic emission on the rotor blades when the helicopter is on the ground (Haas and Schaefer, 1996).

A few studies have been conducted on development of online health monitoring methods for helicopter rotors. Azzam and Andrew (1992), and Ganguli et al. (1996) used mathematical models of a helicopter rotor to study the impact of blade damage on rotor system behavior in forward flight. The damages were modeled using changes in blade stiffness, inertial and damping properties. The basic idea in these studies was that the response of the damaged blade becomes different from that of the undamaged blade. In addition, an undamaged rotor only transmits $N\Omega$ vibrations to the rotor hub, while a rotor with one damaged blade transmits many other harmonics also. Using the change in blade response and hub loads, Ganguli et al. (1998) developed a neural network for online health monitoring of a helicopter rotor. Besides the above model based studies, health and usage monitoring systems (HUMS) have also been developed by the helicopter industry (Cleveland and Trammel, 1996). These HUMS systems typically use

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vibration signatures to detect damage in the gearing system and rotor track and balance problems.

Online health monitoring of helicopter rotors using a model-based approach is complicated because of difficulties in accurately predicting rotor system behavior. For example, helicopter vibration is very difficult to predict accurately even when using sophisticated aerodynamic and dynamic models, as found in a study comparing various analysis predictions with flight test data (Hansford and Vorwald, 1998). This has prompted some researchers to work on ground based *approach* for health monitoring that can be used by a maintenance engineer to find structural damage in a rotor blade before it becomes catastrophic. These ground based approaches can be based on system parameters that can be measured and predicted accurately, when compared to loads. The key components of such ground based systems are properly placed sensors on the rotor blade and a good information processing system to extract information from the sensor measurements for making diagnostic and prognostic decisions.

Modal analysis is one of a few NDT (nondestructive testing) methods that are technically mature enough to be used as a structure integrated damage-monitoring system (Boller, 2000). The other mature methods identified by Boller are strain analysis, acoustic emission, lamb waves and acoustic ultrasound. Modal analysis is quite sensitive when the size of the damage is more that 10% of the surface area being monitored by the sensor. Such damage can occur in delamination of composite materials that are extensively used to fabricate rotor blades. Acoustic emission is another well-established method for locating cracks in metals and can also be used for detecting damage in polymer-based composites (Schoess et al., 1996). Piezoelectric sensors are traditionally used for monitoring vibrations both for modal analysis and acoustic emissions. If embedded on the structure, they constitute an automated health monitoring system.

As mentioned by Boller in a recent paper (Boller, 2000), there is no need for a health monitoring system to locate damage to within a few millimeters. The cost and effort involved in predicting damage to a high level of accuracy can be prohibitive. In addition, because of measurement, model and signal processing inaccuracies, a health monitoring system that claims to predict damage with great accuracy is likely to give false alarms and lose the faith of maintenance personnel using it. A better idea is to roughly locate the damage to within about one meter using a health monitoring system, and then use standard NDE methods for a closer analysis of the damaged area (Boller, 2000). Modal analysis based methods are good at locating the damaged area approximately, and were used for helicopter rotors in the two studies discussed below.

Kiddy and Pines (1998) used an eigenstructure assignment method based on measured test data and a finite element model of a rotor blade to detect and identify the extent of damage. The damage was modeled as a reduction in the mass and stiffness of 10% at the third of six approximately uniform finite elements used to model the damaged blade. The first four damaged mode shapes and their frequencies were used for damage detection. The authors found that the effect of rotation was to enhance the sensitivity of mass damage and to lower the sensitivity to structural stiffness changes. While the damage detection approach worked well with noise free data, it started deteriorating as the noise level in the data increased.

In a recent paper, Cattarius and Inman (2000) showed that helicopter blade structural damage could be detected using a beat phenomenon approach. Damage was modeled as a mass increase (locally added weight) and mass decrease (drilled holes in the structure). No analytical models were used in this study. The beat phenomenon is derived from frequencies but magnifies changes in frequencies due to damage. The authors suggested that the response data on the ground be measured between flights and compared with a set of undamaged data. They also mention that frequency shifts are a function of both magnitude and location of damage.

Changes in frequency shifts have been suggested as a way to locate damage in structures by several researchers (Kam and Lee, 1992; Chondros et al., 2001) and a review paper on this subject has recently been published (Salawu, 1997). Though frequencies are sensitive indicators of structural damage, they cannot distinguish damage at symmetric locations in a symmetric structure, and small cracks may not affect frequencies to an extent that can be useful to damage detection. The symmetry issue is important for many civil engineering structures such as bridges that are symmetric about the midsection. For helicopter rotors, which are slender beams, fixed (hingeless rotors) or simply supported (articulated rotors) at one end, the symmetric issue does not arise. Furthermore, helicopter rotor blades are designed to tolerate a substantial amount of damage before failure (Cattarius and Inman, 2000). This damage is not always visible through surface inspections even when the damage becomes large. In addition, helicopter blades are routinely made from composite materials that are much more susceptible to delamination than cracks. Therefore, a frequency-based approach to ground based structural damage detection in helicopter rotors appears attractive.

Most studies on structural damage detection model the damage as a decrease in stiffness at the damaged section. In some cases, formulas have been developed that link crack size with the stiffness reduction based on fracture mechanics method (Kam and Lee, 1992). Such analyses are also available for delaminated beams

(Lee, 2000). Delamination can develop as a result of manufacturing defects such as incomplete wetting and trapped air packets between the ply layers. Delamination can also result from in-service factors such as low velocity impact by foreign objects such as dropped tools or bird strikes. While such impact damage can cause a number of delaminations, it may not leave any external indication and is often called "barely visible impact damage" (BVID) (Lee, 2000). However, such damage causes degradation in stiffness and changes vibration characteristics. In general, the stiffness reduction approach can model a large class of structural damages, including cracks and delamination.

For successful damage detection and estimation, we need to solve the inverse problem relating the change in measurements between the damaged and undamaged structure to the location and size of the structural damage. The inverse problem is complicated by incomplete information (not all states of the system are available) and uncertainty in modeling, measurement and signal processing. Researchers have often used neural networks for this purpose. Neural networks have the reputation of being black boxes that are difficult to understand. Fuzzy systems allow for easier understanding because they are expressed in terms of linguistic variables (Zadeh, 1996). Fuzzy systems have a built-in fuzzification process at the front end that accounts for uncertainty and does not need to be trained on several cycles of noisy data like neural networks to account for uncertainty. Fuzzy systems are finding increasing use in mechanical engineering diagnostics. It is well known that feedforward neural networks are universal function approximators (Hornik et al., 1989). Recently, it has been proved that classical feedforward neural networks can be approximated to an arbitrary degree of accuracy by a fuzzy logic system, without having to go through the laborious training process needed by a neural network (Hong and Chen, 2000). Therefore, fuzzy systems share the universal approximation characteristics with neural networks.

In this study, we use a fuzzy logic system for ground based helicopter rotor structural damage detection using natural frequencies. Both nonrotating and rotating frequencies are used for the numerical results.

FORMULATION

The hingeless rotor blade is modeled as an Euler–Bernoulli cantilever beam undergoing transverse (flap) and in-plane (lag) bending, torsion and axial deformation (Hodges and Dowell, 1974). A finite element approach is used to calculate the natural frequencies of the beam. Each beam finite element has fifteen degrees of freedom corresponding to cubic variation in axial and bending deflections (flap and lag), and quadratic deflection in elastic torsion. Damage is modeled as a reduction in element stiffness and a percentage damage parameter D is defined such that

$$D = 100\frac{E^{\text{undamaged}} - E^{\text{damaged}}}{E^{\text{undamaged}}}$$

where E is the Young's modulus of the material. The blade is divided into five uniform segments of equal lengths. These segments are labeled as "root", "inboard", "center", "outboard" and "tip", as shown in Figure 1. The structural damage in each segment is modeled by stiffness reductions (D) of 5, 15 and 25% respectively. These damage sizes are classified as "slight damage", "moderate damage" and "severe damage", respectively. Damage sizes below "slight damage" are classified as undamaged. Damage sizes greater than "severe damage" are classified as "catastrophic damage". From a practical implementation viewpoint, given a slight damage, the warning issued by the diagnostic system is classified as a 'Level I advisory". For moderate damage, the warning issued is a "Level II advisory" and for severe damage the maintenance action is an "Alert". No warning is issued for an undamaged blade. This form of classification of the structural damage along location of the blade allows for development of a user-friendly decision system that can be deployed in a handheld electronic device or field computer.

The measurement suite consists of the first four transverse bending (flap) natural frequencies of the cantilever beam. The torsion, lag and axial frequencies are not used for damage detection. In general, the higher frequencies of these modes are quite high and difficult to measure. At least a few higher modes are needed to locate damage away from the root of the blade. The first four flap frequencies are often measured for helicopter blades (Hansford and Vorwald, 1998). Using flap modes beyond the fourth may increase the accuracy of damage detection while resulting in increasing measurement complexity.

The difference between the frequency of the damaged and undamaged blade is used as the system indicator for damage and is referred to as a "measurement delta" and is positive for structural damage since the reduction in stiffness for a damaged blade decreases the frequency. The measurement delta is expressed as a percentage change

$$\Delta\omega = 100\frac{\omega_{\text{undamaged}} - \omega_{\text{damaged}}}{\omega_{\text{undamaged}}}$$

There is always some difference between predictions by models and test results. This difference is called modeling uncertainty. Hansford and Vorwald (1996) showed that predictions by eight different helicopter

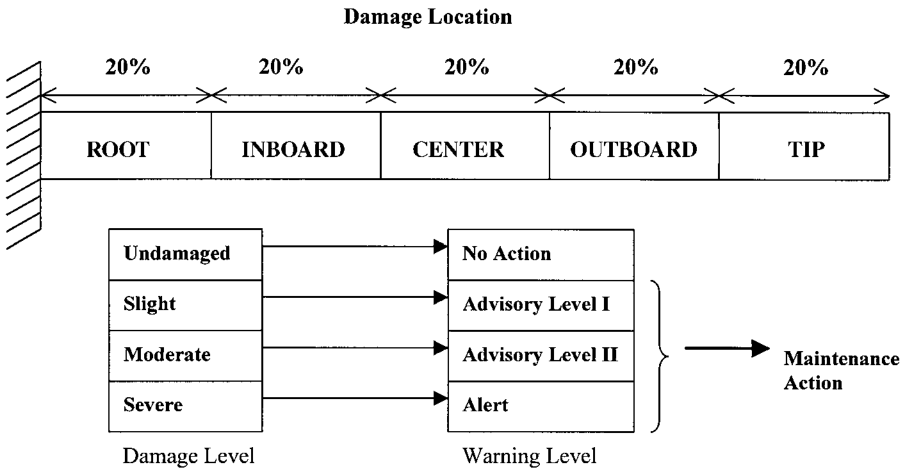

Figure 1. *Schematic representation of rotor blade and ground based health monitoring system.*

blade analysis codes for rotating natural frequencies were within 4% of the experimental measurements for the Lynx helicopter rotor. In this study, all participants used the same structural and inertial properties of the blade to calculate the in vacuum rotating mode frequencies. The test data were obtained from spectral analysis of strain gage measurements. Modeling uncertainty can result from uncertainties in material properties and assumptions made during model development.

In addition to modeling uncertainty, noise may be present in the measured data. This measurement uncertainty can originate from sensor noise and measurement errors. Though the use of modern instruments has reduced measurement uncertainty, it can never be eliminated, especially in the field setting.

It can therefore be expected that uncertainty is present in the frequency measurement deltas ($\Delta\omega$'s). We shall assume noise of about 10–15% is present in the measurement delta, originating from a combination of model and measurement uncertainty. Fuzzy logic based decision systems give an effective way to make health monitoring decisions from such uncertain data.

INTRODUCTION TO FUZZY LOGIC SYSTEM

A fuzzy logic system (FLS) is a nonlinear mapping of an input feature vector into a scalar output (Kosko, 1997). Fuzzy set theory and fuzzy logic provide the framework for the nonlinear mapping. Fuzzy logic systems have been widely used in engineering applications because of the flexibility they offer designers and their ability to handle uncertainty. An FLS can be expressed as a linear combination of fuzzy basis functions and is a universal function approximater. Further information on fuzzy logic systems is available from textbooks (Kosko, 1997).

A typical multi-input single-output (MISO) FLS performs a mapping from $V \in R^m$ to $W \in R$ using four basic components: rules, fuzzifier, inference engine, and defuzzifier. Here

$$f : V \in R^m \rightarrow W \in R$$

where $V = V_1 \times V_2 \times \cdots \times V_n \in R^m$ is the input space and $V \in R$ is the output space.

A typical FLS maps crisp inputs to crisp outputs using four basic components: rules, fuzzifier, inference engine, and defuzzifier, as shown in Figure 2. Once the rules driving the FLS have been fixed, the FLS can be expressed as a mapping of inputs to outputs.

Rules can come from experts or can be obtained from numerical data. In either case, engineering rules are expressed as a collection of IF–THEN statements such as "IF u_1 is HIGH, and u_2 is LOW, THEN v is LOW". To formulate such a rule we need an understanding of

1. Linguistic variables versus numerical values of a variable (eg. HIGH versus 3.5%)
2. Quantifying linguistic variables (eg. u_1 may have a finite number of linguistic terms associated with it, ranging from NEGLIGIBLE to VERY HIGH), which is done using fuzzy membership functions
3. Logical connections between linguistic variables (eg. AND, OR etc.) and
4. Implications such as "IF A THEN B". We also need to understand how to combine more than one rule.

The fuzzifier maps crisp input numbers into fuzzy sets. It is needed to activate rules that are expressed in terms of linguistic variables. An inference engine of the FLS maps fuzzy sets to fuzzy sets and determines the way in which the fuzzy sets are combined. In several applications, crisp numbers are needed as an output of the FLS. In those cases, a defuzzifier is used to calculate crisp values from fuzzy values.

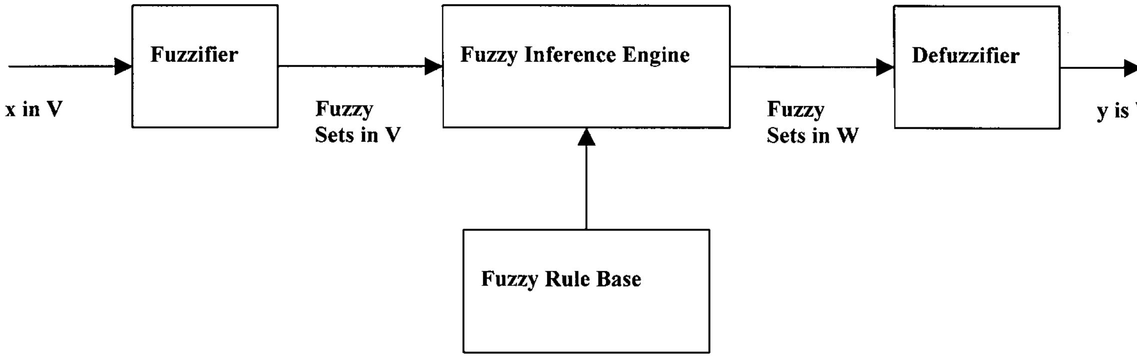

Figure 2. *Schematic representation of a fuzzy logic system.*

Fuzzy Sets

A fuzzy set F is defined on a universe of discourse U and is characterized by a degree of membership $\mu(x)$, which can take on values between 0 and 1. A fuzzy set generalizes the concept of an ordinary set whose membership function only takes two values, zero and unity.

Linguistic Variables

A linguistic variable u is used to represent the numerical value x, where x is an element of U. A linguistic variable is usually decomposed into a set of terms $T(u)$, which cover its universe of discourse.

Membership Functions

The most commonly used shapes for membership functions $\mu(x)$ are triangular, trapezoidal, piecewise linear or Gaussian. The designer selects the type of membership function used. The Gaussian functions overlap to some degree across all fuzzy sets and therefore allow all fuzzy rules to fire simultaneously. Therefore, they smooth out the output signal (Mengali, 2000). There is no requirement that membership functions overlap. However, one of the major strengths of fuzzy logic is that membership functions can overlap. FLS systems are robust because decisions are distributed over more than one input class. For convenience, membership functions are normalized to one so they take values between 0 and 1, and thus define the fuzzy set.

Inference Engine

Rules for the fuzzy system can be expressed as:

$$R_i\text{:}\quad \text{IF } x_1 \text{ is } F_1 \quad \text{AND} \quad x_2 \text{ is } F_2 \quad \text{AND} \ldots x_m \text{ is } F_m$$
$$\text{THEN } y = C_i \quad i = 1, 2, 3, \ldots, M$$

where m and M are the number of input variables and rules, x_i and y are the input and output variables, and $F_i \in V_i$ and $C_i \in W$ are fuzzy sets characterized by membership functions $\mu_{F_i}(x)$ and $\mu_{C_i}(x)$, respectively. Each rule can be viewed as a fuzzy implication $F_{12\cdots m} = F_1 \times F_2 \times \cdots F_m \rightarrow C_i$, which is a fuzzy set in $V \times W = V_1 \times V_2 \times \cdots V_m \times W$ with membership function given by

$$\mu_{R_i}(x, y) = \mu_{F_i}(x_1) * \mu_{F_2}(x_2) * \cdots * \mu_{F_m}(x_m) * \mu_{C_i}(y)$$

where $*$ is the T-norm with $x = [x_1 x_2 \cdots x_m] \in V$ and $y \in W$. This sort of rule covers many applications. The algebraic product is one of the most widely used T-norms in applications, and leads to a product inference engine.

Defuzzification

Popular defuzzification methods include maximum matching and centroid defuzzification (Chi et al., 1998). While centroid defuzzification is widely used for fuzzy control problems where a crisp output value is needed, maximum matching is often used for pattern matching problems where we need to know the output class only. Suppose there are K fuzzy rules and among them, K_j rules ($j = 1,2,\ldots,L$ and L is the number of classes) produce class C_j. Let D_p^i be the measurements of how the pth pattern matched the antecedent conditions (IF part) of the ith rule, which is given by the product of membership grades of the pattern in the regions which the ith rule occupies

$$D_p^i = \prod_{i=1}^{m} \mu_{li}$$

where m is the number of inputs and μ_{li} is the degree of membership of measurement l in the fuzzy regions that the ith rule occupies. Let $D_p^{\max}(C_j)$ be the maximum matching degree of the rules (rules $j_l, l = 1, 2, \ldots, K_j$) generating class C_j

$$D_p^{\max}(C_j) = \max_{l=1}^{K_j} D_p^{j_l}$$

then the system will output class C_{j*} provided that

$$D_p^{\max}(C_{j*}) = \max_j D_p^{\max}(C_j)$$

If there are two or more classes that achieve the maximum matching degree, we will select the class that has the largest number of fired fuzzy rules (a fired rule has a matching degree of greater than zero) (Chi and Yan, 1996).

FORMULATION OF FUZZY LOGIC SYSTEM

Input and Output

Inputs to the FLS are measurement deltas and outputs are structural damage faults. We have four measurements represented by $\mathbf{z}$ and five fault locations represented by $\mathbf{x}$. The objective is to find a functional mapping between $\mathbf{z}$ and $\mathbf{x}$. Mathematically this can be represented as

$$\mathbf{x} = F(\mathbf{z})$$

where $\mathbf{x} = \{\text{Root, Inboard, Center, Outboard, Tip}\}^T$ and $\mathbf{z} = \{\Delta\omega_1,\ \Delta\omega_2,\ \Delta\omega_3,\ \Delta\omega_4\}^T$. Each measurement delta has uncertainty.

Fuzzification

Here the structural damages are crisp numbers. For example, "root" ranges from 0 to 20% of the blade, "inboard" from 20 to 40%, "center" from 40 to 60%, "outboard" from 60 to 80%, and "tip" from 80 to 100%, as shown in Figure 1. To get a degree of resolution of the extent of damage, each of these damage locations is allowed several levels of damage and split into linguistic variables. For example, consider "root" as a linguistic variable. Then it can be decomposed into a set of terms

$$T(\text{root}) = \{\text{Undamaged, Slight Damage, Moderate Damage, Severe Damage, Catastrophic Damage}\}$$

where each term in $T(\text{root})$ is characterized by a fuzzy set in the universe of discourse $U(\text{root}) = \{0, 30\}$.

The other structural damage variables are fuzzified in a similar manner.

The measurement deltas $\Delta\omega_1$, $\Delta\omega_2$, $\Delta\omega_3$ and $\Delta\omega_4$ are also treated as fuzzy variables. To get a high degree of resolution, they are further split into linguistic variables. For example, consider $\Delta\omega_1$ as a linguistic variable. It can be decomposed into a set of terms

$$T(\Delta\omega_1) = \{\text{Negligible, Very Low, Low, Low Medium, Medium, Medium High, High, Very High, Very Very High}\}$$

where each term in $T(\Delta\omega_1)$ is characterized by a fuzzy set in the universe of discourse $U(\Delta\omega_1) = \{0, 9\}$. The other three measurement deltas are defined using the same set of terms as $\Delta\omega_1$. Measurement deltas larger than covered by the universe of discourse will represent an extensive structural damage indicative of a catastrophic failure.

Fuzzy sets with Gaussian membership functions are used for the input variables. These fuzzy sets can be defined using the following Equation

$$\mu(x) = e^{-0.5(x-m/\sigma)^2}$$

where m is the midpoint of the fuzzy set and σ is the uncertainty (standard deviation) associated with the variable. Table 1 gives the linguistic measure associated with each fuzzy set and the midpoint of the set for each measurement delta. The midpoints are selected to span the region ranging from an undamaged rotor blade (all measurement deltas are zero) to one with significant damage.

The standard deviations for $\Delta\omega$ are 0.35%, and are selected to provide for enough intersection between the fuzzy sets so as to optimize accuracy of detection. Figure 3 shows the membership functions for each of the nine input fuzzy sets.

Table 1. Gaussian fuzzy sets.

Linguistic Measure	Symbol	Midpoints $\Delta\omega$
Negligible	N	0
Very Low	VL	1
Low	L	2
Low-Medium	LM	3
Medium	M	4
Medium-High	MH	5
High	H	6
Very High	VH	7
Very Very High	VVH	8

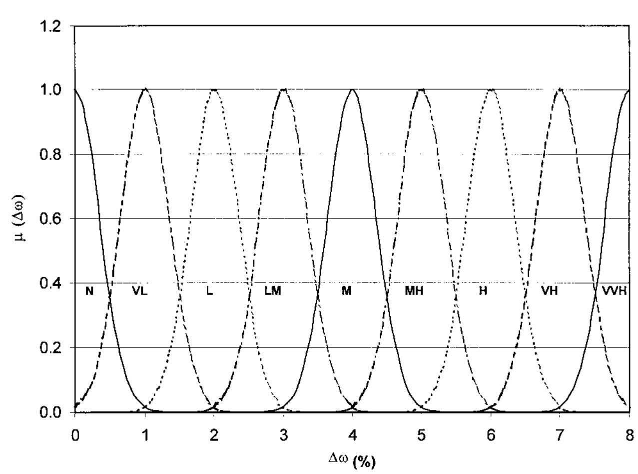

Figure 3. *Fuzzy sets representing measurements deltas over universe of discourse (0–8%).*

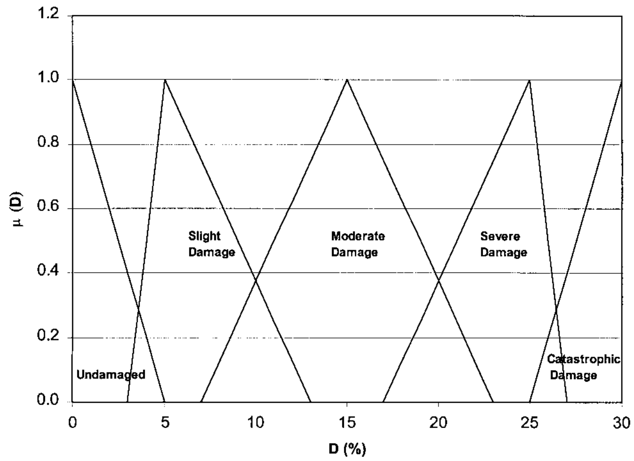

Figure 4. *Fuzzy sets representing damage levels over universe of discourse (0–30%).*

The five output fuzzy sets for structural damage are expressed in terms of triangular membership functions spanning a universe of discourse of D from 0 to 30%, as shown in Figure 4. Levels beyond $D=30$ represent very large and potentially catastrophic damage and are excluded.

Rules and Fault Isolation

Rules for the fuzzy system are obtained by fuzzification of the numerical values obtained from the finite element analysis using the following procedure (Wang and Mendel, 1992; Abe and Lin, 1995):

1. A set of four measurement deltas corresponding to a given structural fault is input to the FLS and the degree of membership of the elements of $\Delta\omega_1$, $\Delta\omega_2$, $\Delta\omega_3$ and $\Delta\omega_4$ are obtained. Therefore, each measurement has nine degree of memberships based on the linguistic measures in Table 1.
2. Each measurement delta is then assigned to the fuzzy set with the maximum degree of membership.
3. One rule is obtained for each fault by relating the measurement deltas with maximum degree of membership to a fault.

These rules are tabulated in Table 2 for nonrotating frequencies and Table 3 for rotating frequencies. The linguistic symbols used in this table are defined in Table 1. These rules can be read as follows for the "Moderate Damage at Root" fault:

IF
$\Delta\omega_1$ is Medium High AND
$\Delta\omega_2$ is Low AND
$\Delta\omega_3$ is Very Low AND
$\Delta\omega_4$ is Low
THEN
Moderate Damage at Root

Table 2. Rules for fuzzy system (nonrotating frequencies).

	Measurement Deltas			
Faults	$\Delta\omega_1$	$\Delta\omega_2$	$\Delta\omega_3$	$\Delta\omega_4$
Undamaged	N	N	N	N
Slight Damage at Root	VL	VL	N	N
Slight Damage at Inboard	VL	N	VL	N
Slight Damage at Center	N	VL	N	VL
Slight Damage at Outboard	N	VL	VL	N
Slight Damage at Tip	N	N	N	VL
Moderate Damage at Root	MH	L	VL	L
Moderate Damage at Inboard	LM	VL	L	VL
Moderate Damage at Center	VL	LM	VL	L
Moderate Damage at Outboard	N	L	LM	L
Moderate Damage at Tip	N	N	VL	L
Severe Damage at Root	VVH	M	LM	LM
Severe Damage at Inboard	MH	VL	M	LM
Severe Damage at Center	L	H	VL	M
Severe Damage at Outboard	N	M	MH	LM
Severe Damage at Tip	N	N	VL	LM

Table 3. Rules for fuzzy system (rotating frequencies).

	Measurement Deltas			
Faults	$\Delta\omega_1$	$\Delta\omega_2$	$\Delta\omega_3$	$\Delta\omega_4$
Undamaged	N	N	N	N
Slight Damage at Root	N	N	N	N
Slight Damage at Inboard	N	N	VL	N
Slight Damage at Center	N	VL	N	VL
Slight Damage at Outboard	N	N	VL	N
Slight Damage at Tip	N	N	N	N
Moderate Damage at Root	VL	VL	VL	VL
Moderate Damage at Inboard	N	N	L	VL
Moderate Damage at Center	N	L	VL	L
Moderate Damage at Outboard	N	VL	LM	VL
Moderate Damage at Tip	N	N	VL	L
Severe Damage at Root	L	L	L	L
Severe Damage at Inboard	N	VL	LM	L
Severe Damage at Center	N	LM	VL	LM
Severe Damage at Outboard	N	L	M	LM
Severe Damage at Tip	N	N	VL	LM

The rules for the other faults can be similarly interpreted. These rules provide a knowledge base and represent how a human engineer would interpret data to isolate structural damage using frequency shifts. For any given input set of measurement deltas, the fuzzy rules are applied using product implication. Once the fuzzy rules are applied for a given measurement, we have degree of memberships for each fault. For fault isolation, we are interested in the most likely fault. The fault with the highest degree of membership is selected as the most likely fault.

NUMERICAL RESULTS

Numerical results are obtained using a helicopter blade with rotating frequencies close to that of the

BO-105 helicopter. Relevant properties of the blade are shown in Table 4 and the baseline rotating and nonrotating frequencies are shown in Table 5. The blade is modeled as a beam and divided into twenty five finite elements of equal length. Each segment spanning 20% of the blade in Figure 1 is therefore divided into five finite elements. The high level of discretization assures that the mesh does not have to be refined as the damage (stiffness reduction) is increased from 5% (slight damage) to 15% (moderate damage) and 25% (severe damage) at each of the five segments from the root to the tip.

The fuzzy logic system is tested using noise contaminated simulated data. The added noise in the data simulates the uncertainty present in experimental measurements and the modeling process. Given a computed frequency measurement delta $\Delta\omega$, a random number u in the interval $[-1, 1]$, and a noise level parameter α, the noisy simulated measurement delta is given as

$$\Delta\omega_{noisy} = \Delta\omega(1 + u\alpha)$$

The parameter α defines the maximum variance between the computed value $\Delta\omega$ and the simulated measured value $\Delta\omega_{noisy}$. For example, if $\alpha = 0.20$, then the simulated measurement delta can be different by as much as 20% from the ideal value predicted by the simulations. Thus α can be used to control the noise levels in the simulated data used for testing the fuzzy logic system. For the results in this study, the added noise is uniformly distributed. Adding noise to $\Delta\omega$'s accounts for both model uncertainties in the FEM model and measurement uncertainty. The fuzzy systems defined by rules for nonrotating frequencies (Table 2) and rotating frequencies (Table 3) are tested separately.

The simulated measurement deltas with added noise are used for testing the fuzzy logic system. In each case, five thousand noisy data points are generated for each seeded fault and the percentage success rate for the fuzzy system in isolating a fault calculated.

Table 4. Rotor blade properties.

Radius, R, m	4.94
Hover tip speed, ΩR, m/s	198.12
m_0 (kg/m)	6.46
$EI_y/m_0\Omega^2R^4$	0.0168
$EI_z/m_0\Omega^2R^4$	0.0268
$GJ/m_0\Omega^2R^4$	0.00615

Table 5. First four flap (transverse bending) frequencies for undamaged rotor blade.

	Nonrotating	Rotating
First Mode	3.03 Hz	7.57 Hz
Second Mode	18.98 Hz	25.12 Hz
Third Mode	53.33 Hz	59.89 Hz
Fourth Mode	105.38 Hz	112.26 Hz

Nonrotating Frequency Results

First, the test is performed for undamaged data. In the case of an undamaged blade, the simulated $\Delta\omega$ are zero. However, when noise is added to the simulations, the measurement deltas have some nonzero values. The fuzzy logic system results in 100% correct detection of the undamaged blade until noise levels of 30% that are considered in this study. The fuzzy logic system is therefore unlikely to give false alarms for noise levels below 30% in measurement data.

Results for increasing noise levels using nonrotating frequencies are shown in Figures 5, 6 and 7 respectively, for "slight", "moderate", and "severe" damage. The fuzzy logic system has an accuracy rate of 100% in damage detection for noise levels below 15%. For damage levels greater than 15%, there is a gradual

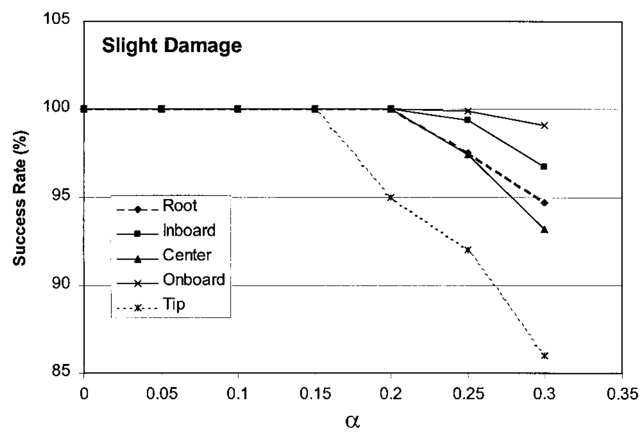

Figure 5. Accuracy of damage detection using fuzzy logic system based on nonrotating frequencies for "slight" damage at different locations along the blade and increasing noise levels.

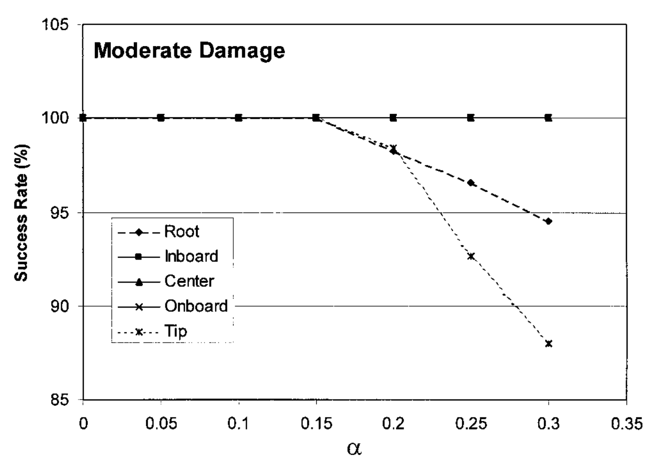

Figure 6. Accuracy of damage detection using fuzzy logic system based on nonrotating frequencies for "moderate" damage at different locations along the blade and increasing noise levels.

decline in accuracy of detection with increasing noise levels, especially for a damage located in the tip region. However, the damage detection accuracy level remains above 85% even for the damage located at tip at noise levels as high as 30%. We can therefore conclude that the fuzzy logic system is able to handle considerable uncertainty in the measurement data.

Table 6 lists the success rate and also shows the average success rate for increasing noise levels. The average rate is obtained by summing the success rates over all the five damage locations, for a fixed damage level. It is clear that the damage detection accuracy is 100% until noise levels of 15% in the data. Most applications will have uncertainty much less than 15%; therefore the fuzzy system proposed can be used in a practical setting.

Rotating Frequency Results

Results for rotating frequencies are shown in Figures 8 and 9 respectively, for "moderate" and "severe" damage respectively. Table 7 shows the average success rate in damage detection as noise levels in the data increases. The fuzzy system based on rotating frequencies is unable to distinguish between undamaged and slight damage. The reason for this can be seen from Table 5 where the fuzzy rules for undamaged are the same as those for "slight damage at root" and "slight damage at tip". In addition, the rules for "slight damage at outboard" and "slight damage at inboard" are the same, resulting in difficulty in differentiation. Thus the only fault in the "slight" damage category that can be detected by the fuzzy logic system is the "slight damage at center".

The "moderate" and "severe" categories show much better results than the "slight' categories. In fact, only "moderate" and "severe" damages can be detected with

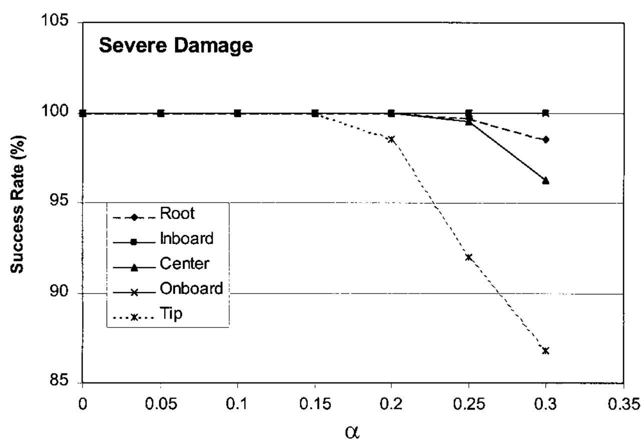

Figure 7. Accuracy of damage detection using fuzzy logic system based on nonrotating frequencies for "severe" damage at different locations along the blade and increasing noise levels.

Table 6. Average percent success rate in fault detection using nonrotating frequencies.

Damage Level	$\alpha=0$	$\alpha=0.05$	$\alpha=0.1$	$\alpha=0.15$	$\alpha=0.2$	$\alpha=0.25$	$\alpha=0.3$
Undamaged	100	100	100	100	100	100	100
Slight	100	100	100	100	99	97.24	93.94
Moderate	100	100	100	100	99.33	97.84	96.51
Severe	100	100	100	100	99.7	98.24	96.32

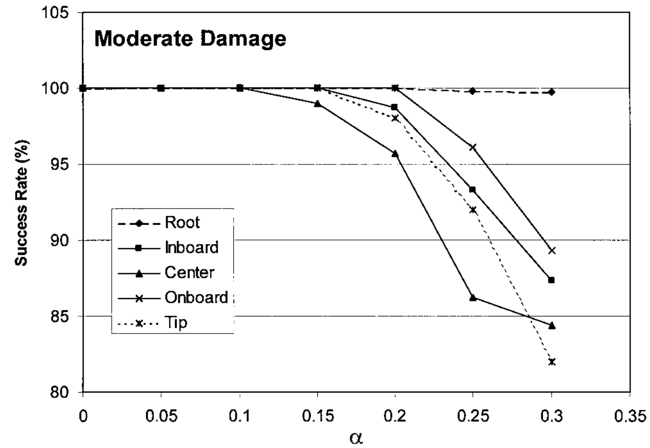

Figure 8. Accuracy of damage detection using fuzzy logic system based on rotating frequencies for "moderate" damage at different locations along the blade and increasing noise.

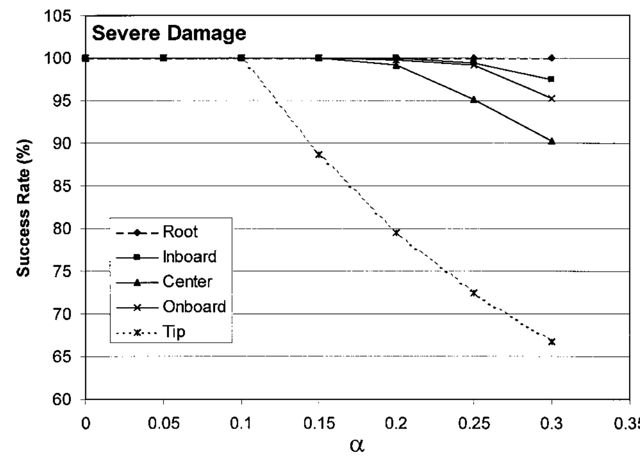

Figure 9. Accuracy of Damage Detection Using Fuzzy Logic System Based on Rotating Frequencies for "Severe" Damage at Different Locations along the Blade and Increasing Noise.

Table 7. Average percent success rate in fault detection using rotating frequencies.

Damage Level	$\alpha=0$	$\alpha=0.05$	$\alpha=0.1$	$\alpha=0.15$	$\alpha=0.2$	$\alpha=0.25$	$\alpha=0.3$
Undamaged	0	0	0	0	0	0	0
Slight	20	20	20	19.26	17.74	16.7	15.98
Moderate	100	100	100	99.8	98.48	93.48	88.54
Severe	100	100	100	97.72	95.68	93.24	89.9

100% accuracy from rotating frequencies provided the noise level is less than 10%. It is clear that rotating frequencies are much less sensitive to structural damage than nonrotating frequencies. This is because the centrifugal stiffening of the rotor blades counters the effect of reduction in stiffness caused by structural damage.

Earlier work (Ganguli et al., 1998) showed that local structural damage such as cracks was difficult to detect from global system behavior such as helicopter vibration and blade tip response. In the current study we have shown that such local faults can be detected at a gross level from the first four flap frequencies. For practical application, periodic frequency measurements of the first four flap frequencies could be done and the fuzzy logic system developed in this study be used to isolate the location and the size of the damage. Depending on the size or level of the damage, further analysis using nondestructive methods could be used to closely locate and then repair the damage. In addition, the predicted level of the damage could be used to identify the blade for continuing use or overhaul, and to generate advisories and alarms for the maintenance personnel. The approach in the current study complements the earlier approaches. Together, they can form part of a comprehensive rotor health monitoring system.

CONCLUSIONS

A ground based health monitoring system for detecting structural damage in a helicopter rotor blade from measured nonrotating and rotating frequencies in vacuum is proposed. The first four flap (transverse bending) modes of the structure are used. Fuzzy logic is used to account for the uncertainty that is typically present in measurements and modeling processes. The rotor blade is divided into five uniform segments having four damage levels. Numerical simulations from a finite element model are used to create a fuzzy rule base for the nonrotating and rotating frequencies. Test results are obtained after adding noise in the data to simulate uncertainty in the measurements and model. The following conclusions are drawn from this study:

1. Nonrotating frequencies are more sensitive indicators of structural damage than rotating frequencies. Rotation in helicopter blades caused centrifugal stiffening that counters reduction in stiffness caused by structural damage. However, since measuring nonrotating frequencies is easier than measuring rotating frequencies, this may not pose a problem.
2. The fuzzy logic system for nonrotating frequencies detects damage with an accuracy of 100% for noise levels below 15% in the measurements. It also classifies an undamaged rotor accurately for noise levels below 30%, thereby preventing the possibility of false alarms. False alarms are a key issue in diagnostics systems since their occurrence can quickly result in a loss of credibility of the system and abort its further usage. Even for noise levels greater than 15% and up to 30%, the fuzzy logic system shows only a small degradation in performance and gives detection results with an accuracy of 93–96%.

NOMENCLATURE

D = percent reduction in stiffness at damage location
EI_y = flap or transverse bending stiffness
EI_z = lag or inplane bending stiffness
GJ = torsion stiffness
m = midpoint of fuzzy sets
m_0 = mass per unit length
N = number of rotor blades
R = rotor radius
T = set of terms for fuzzy variable
U = universe of discourse for fuzzy variable
x = element of fuzzy set
$\mathbf{x}$ = rotor blade damage locations
$\mathbf{z}$ = measurement deltas
Δ = difference between healthy and damaged quantity
μ = fuzzy degree of membership
$\mu_A(x)$ = degree of membership of x in fuzzy set A
σ = standard deviation
ω = blade natural frequency
$\Delta\omega$ = percent reduction in frequency due to damage
Ω = rotation speed

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