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Health Monitoring of a Helicopter Rotor in Forward Flight Using Fuzzy Logic

Ranjan Ganguli*
Indian Institute of Science, Bangalore 560 012, India

A fuzzy logic system is developed for helicopter rotor system fault isolation. Inputs to the fuzzy logic system are measurement deviations of blade bending and torsion response and vibration from a "good" undamaged helicopter rotor. The rotor system measurements used are flap and lag bending tip deflections, elastic twist deflection at the tip, and three forces and three moments at the rotor hub. The fuzzy logic system uses rules developed from an aeroelastic model of the helicopter rotor with implanted faults to isolate the fault while accounting for uncertainty in the measurements. The faults modeled include moisture absorption, loss of trim mass, damaged lag damper, damaged pitch control system, misadjusted pitch link, and damaged flap. Tests with simulated data show that the fuzzy system isolates rotor system faults with an accuracy of about 90–100%. Furthermore, the fuzzy system is robust and gives excellent results, even when some measurements are not available. A rule-based expert system based on similar rules from the aeroelastic model performs much more poorly than the fuzzy system in the presence of high levels of uncertainty.

Nomenclature

C_d	=	blade section drag coefficient
C_L	=	blade section lift coefficient
C_m	=	blade section moment coefficient
C_T	=	thrust coefficient
F	=	hub forces
F_x	=	longitudinal hub force
F_y	=	lateral hub force
F_z	=	vertical hub force
M	=	hub moments
M_x	=	rolling hub moment
M_y	=	pitching hub moment
M_z	=	yawing hub moment
m	=	midpoint of fuzzy sets
N	=	number of spatial finite elements
N_b	=	number of blades
R	=	rotor radius
T	=	kinetic energy, set of terms for fuzzy variable
U	=	strain energy, universe of discourse for fuzzy variable
v	=	lag bending deflection of blade
W	=	virtual work
w	=	flap bending deflection of blade
x	=	element of fuzzy set
$\mathbf{x}$	=	rotor system faults
z	=	measurement deltas
α	=	angle of attack
Δ	=	difference between healthy and damaged quantity
δ	=	variation
θ	=	systematic noise
μ	=	advance ratio, fuzzy degree of membership
$\mu_A(x)$	=	degree of membership of x in fuzzy set A
σ	=	solidity ratio, standard deviation
ϕ	=	torsion deformation of blade
ψ	=	azimuth angle, time
Ω	=	rotation speed
$()_{ic}$	=	ith cosine component
$()_{is}$	=	ith sine component
$()_n$	=	noise contaminated quantity
$()_0$	=	zeroth harmonic, steady quantity

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*Assistant Professor, Department of Aerospace Engineering; ganguli@aero.iisc.ernet.in. Senior Member AIAA.

Introduction

HELICOPTER rotors are subject to high vibratory forces caused by time-varying aerodynamic loads. These vibratory loads often cause fatigue damage in flight-critical components such as blade pushrods, control arms, attachment fittings, etc., and contribute to wear in bearings, dampers, and various mechanical joints. Because of this, helicopter rotors require frequent inspections for component damage and rotor track and balance problems. In fact, maintenance costs account for about one-quarter of the direct operating costs of rotorcraft.[1,2] Typically, a rotor track and balance system measures fuselage vibration and blade response to detect track and balance faults and determines the necessary adjustments needed to correct them.[3–7] Most commercial health and usage monitoring systems (HUMS) provide very limited rotor system coverage. Typically, they provide automatic track and balance and seek primarily to reduce 1/revolution fuselage vibration by compensating for the dissimilarities between blades. If adjustments to the rotor track and balance do not bring the vibration levels and blade response to within acceptable limits, a faulty component may be the cause. Thus, rotor system response data can provide a useful basis for fault detection and health monitoring.

The rotor fault detection methods can be classified into two types: local fault detection and global fault detection. Global faults are those that can be detected using remote measurements of global system parameter such as fuselage vibration and blade deflection. The theoretical basis of global fault detection is that, for an undamaged rotor, all blades will have an identical response and only N_b/revolution loads will be transmitted to the hub by an N_b-bladed rotor. However, if one blade is dissimilar to other blades due to a fault, then all harmonics of the rotor loads are transmitted to the hub. In addition, the response of the damaged blade will be different from the undamaged blades. In addition to global faults, there are local faults that are difficult to detect from global system behavior, such as fuselage vibration and rotor response. Localized structural damage such as blade cracks and delamination are examples of local faults. Undetected blade cracks can lead to catastrophic failures depending on flight conditions, crack location, and load severity. Local fault detection methods have evolved to detect such faults and include the use of a robust laser interferometer, photoelastic techniques, ultrasonic techniques, modal analysis, wave propagation, and acoustic emission sensors.[8–11] Such local fault detection methods complement global fault detection methods discussed in this paper. When combined, they can form a comprehensive approach to rotor system health monitoring.

The first step in model-based global fault detection is development of a mathematical model of the faulty system. Some work on modeling a damaged helicopter rotor has been reported. Azzam and Andrew[12] simulated rotor system faults for a five-bladed articulated rotor, similar to the S-61 rotor, using a mathematical model. Faults modeled included blade cracks, chordwise mass imbalance, and defective lag damper. Ganguli et al.[13,14] used a comprehensive aeroelastic analysis based on finite elements in space and time to simulate a damaged helicopter rotor. Numerical results were obtained in hover and forward flight for an articulated four-bladed rotor similar to the SH-60 rotor. Selected predictions of rotor component loads were validated with flight-test data. Fault models included were moisture absorption, loss of trim mass, damaged pitch-control system, defective lag damper, damaged trim tab, structural damage, and misadjusted pitch link. The influence of simulated rotor faults on blade response and hub loads was analyzed and summarized in the form of diagnostic charts. It was concluded that, whereas most rotor faults can be detected by monitoring blade response and vibratory hub loads, blade cracks are difficult to detect from global system behavior. Although the authors did mention in these studies that the diagnostic charts could be used to develop algorithms for detecting faults from system behavior, they did not address this issue in their papers. More recently, Stevens[15] has proposed additional fault models (most notably for cracks) that are appropriate for rotorcraft damage detection systems.

The aforementioned studies did not have comparisons with flight-test data. Addressing this issue, Yang et al.[16] developed a coupled rotor–fuselage–bifilar vibration analysis to study the effects of rotor system faults on fuselage vibrations in hover and forward-flight conditions. Both single and multiple faults were simulated. The airframe vibration results were compared with SH-60 flight-test data with the embedded faults. The faults considered were unbalanced mass, misadjusted pitch control rod, and trim tab fault. The mass imbalance fault resulted in more 1/revolution fuselage rolling vibration than vertical vibration, whereas, for trim tab and pitch-control rod faults, the 1/revolution fuselage vertical vibration was greater than the rolling vibration. Results indicated that vibration amplitude trends were predicted reasonably well, but phasing was not accurately predicted.

The studies just discussed focused on calculation of system response of a helicopter rotor with implanted faults. However, to develop a health monitoring system, we need to solve the inverse problem of predicting the rotor faults from the measured system data. Addressing the inverse problem in rotor health monitoring, Ganguli et al.[17,18] used neural networks for fault detection. The neural networks are trained from a numerically generated rotor system fault database. One drawback of a neural network trained with ideal data is that it classifies ideal test data exactly, but gives significant errors when noise is added to the test data. This problem was overcome by adding noise to the analytical simulation during training. A fault-detection system based on noisy simulated data was found to be more accurate than one trained with ideal data because it accounts for inherent uncertainties in the real system. Testing of the neural network showed that it could detect and identify damage in the rotor system from simulated blade response and vibration data.

Haas and Schaefer[19] applied neural network technology and advanced sensor concepts for onboard real-time diagnostics to warn of incipient catastrophic failure. Using ground and flight testing on an SH-60 and two CH-46 helicopters, they showed that artificial neural networks are a powerful tool that can be used with existing diagnostic techniques to enhance the capabilities of currently fielded helicopter HUMS significantly.

Alkahe et al.[20] used a detailed model of a coupled rotor–fuselage for rotor analysis in forward flight. Several rotor component faults such as moisture absorption, pitch-link damage, lag damper damage, pitch friction increase, and stiffness defects were considered. A bank of Kalman filters, each tailored to a specific fault was used and the statistically best-fitting Kalman filter was selected as the most likely fault. The numerical study used two sets of noisy measurements. The first set was based on the blade tip sensors and the second was based on the fixed frame hub loads. The noisy rotor environment was handled by the Kalman filter using measurement and process noise. The authors mention that their method avoids the cumbersome training needed by the neural network based fault isolation methods.

Stevens and Smith[21] adopted a different and innovative approach for rotor system health monitoring by using trailing-edge flaps to interrogate the rotor system for faults actively. The rotor blade was excited by a low-amplitude trailing-edge flap oscillation at selected discrete frequencies. The blade response was measured using embedded sensors. The health of the rotor system was determined using a frequency-domain damage identification algorithm. An aeroelastic analysis was used to design and test the system using physically modeled faults.

Returning to the issue of the solution of inverse health monitoring problems, we find that neural networks are being increasingly used in helicopter health monitoring applications.[3–5,17,18] Rotor track and balance related problems have found their way from research settings to an industry environment.[5] However, neural networks have the reputation for being black boxes that are difficult to understand. Unlike neural networks that are black boxes, fuzzy systems give a clear view of the real system because they are expressed in terms of linguistic variables.[22–24] In addition, whereas neural networks take an enormous amount of time for training due to the cumbersome gradient-based back-propagation algorithm, fuzzy systems can be built rapidly using a set of rules. Fuzzy systems are increasingly being used for diagnostics of mechanical systems.[25] It is well known that the power of feedforward neural networks comes from their being mathematically proven to be universal function approximators.[26] Recently, it has been proven 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.[27] Therefore, fuzzy systems share the universal approximation characteristics with neural networks. In this study, we use a fuzzy logic system for helicopter rotor fault detection, using a rotor aeroelastic model followed earlier in Refs. 13 and 14.

Formulation

A comprehensive and accurate mathematical model is necessary for model-based diagnostics. Such a model for a helicopter should include accurate modeling of the structural dynamics of highly flexible rotating blades undergoing flap and lag bending, elastic twist and axial deformations, and the aeroelastic interactions between these deformations and the unsteady aerodynamics and nonuniform wake geometry of a helicopter rotor. The UMARC formulation includes the features just mentioned and is used in this study.[28]

Mathematical Model of Rotor System

The helicopter is represented by a nonlinear model of elastic rotor blades dynamically coupled to a six-degree-of-freedom rigid fuselage. Each blade undergoes flap bending, lag bending, elastic twist, and axial displacement. Governing equations are derived using a generalized Hamilton's principle applicable to nonconservative systems:

$$\int_{\psi_1}^{\psi_2} (\delta U - \delta T - \delta W)\,\mathrm{d}\psi = 0$$

The δU, δT, and δW are virtual strain energy, kinetic energy, and virtual work, respectively. The δU and δT include energy contributions from components that are attached to the blade, for example, pitch link, lag damper, etc. External aerodynamic forces on the rotor blade contribute to the virtual work variational δW. The aerodynamic forces and moments are calculated using an inflow distribution from the Scully–Johnson free wake model (see Ref. 29) and unsteady effects are accounted for using the Leishman–Beddoes model (see Ref. 30).

A finite element method is used to discretize the governing equations of motion and allows for the accurate representation of complex hub kinematics and nonuniform blade properties. After the finite element discretization, Hamilton's principle is written as

$$\int_{\psi_i}^{\psi_f} \sum_{i=1}^{N} (\delta U_i - \delta T_i - \delta W_i)\,\mathrm{d}\psi = 0$$

Table 1 Thresholds for system behavior

Variation	Tip flap, lag, m	Tip torsion, deg	Force, N	Moment, N · m	Symbol
Negligible	<0.00635	<0.25	<756.2	<282.46	N
Moderate	0.00635–0.0127	0.25–0.50	756.2–1512.39	282.46–564.92	M
Significant	>0.0127	>0.50	>1512.39	>564.92	S

Each beam finite element has 15 degrees of freedom. These degrees of freedom correspond to cubic variations in axial elastic and (flap and lag) bending deflections, as well as quadratic variation in elastic torsion.

The first step in the aeroelastic analysis procedure is to trim the vehicle for the specified operating condition. The finite element equations representing each rotor blade are transformed to normal mode space for the efficient solution of the blade response. The nonlinear, periodic, normal mode equations are then solved for blade steady response using the finite element in time method. Because the blades are assumed to be dissimilar for the damaged rotor analysis, each blade response is obtained separately. Steady and vibratory components of the rotating frame blade loads, that is, shear forces and bending/torsion moments, are calculated using the force summation method. In this approach, blade inertia and aerodynamic forces are integrated directly over the length of the blade. Fixed frame hub loads are calculated by summing the individual contributions of individual blades. A coupled trim procedure is carried out to solve the blade response, pilot input trim controls, and vehicle orientation, simultaneously. The coupled trim procedure is essential for elastically coupled blades because elastic deflections play an important role in the steady net forces and moments generated by the rotor. Additional details of the aeroelastic analysis are given in Ref. 28.

Modeling of Rotor Faults

In this study, six faults on the SH-60 helicopter are analyzed in detail. Moisture absorption is modeled by increasing the mass of the damaged blade by 2.74%, equivalent to about 0.75 gal (0.002839m^3) of water. The loss of trim mass is modeled by a reduction in mass by 25% at a small damage element of length 1% of blade length and located at 94% of the blade span. This amounts to about 1% of the blade total mass. The misadjusted pitch link is modeled by a reduction in the rigid pitch angle of the damaged blade by 1 deg. The damaged pitch-control system is modeled by a reduction in the pitch-link stiffness of the damaged blade, such that the torsion frequency is reduced by 6.75%. The lag damper is modeled by setting the damping coefficient of the lag damper of the damaged blade equal to zero. The damaged flap is modeled by a static shift in the defection of the flap of the damaged blade of 5 deg. The flap spans the tip of the damaged blade and has a length of about 6% of the damaged blade and a chord of 10% of the blade chord. Details about modeling these faults are given in Ref. 13. The sizes of the faults in Ref. 13 were obtained by consultations with major operators of the SH-60 helicopter and maintenance reports.

Indicators of System Damage

It is assumed that one blade is damaged and the other blades are undamaged. For the undamaged rotor (assuming perfectly tracked blades), all four blades will have the same tip response (magnitude and phase). In addition, for a perfectly tracked rotor, the undamaged rotor transmits only the 4/revolution and 8/revolution forces and moments to the fuselage. Therefore, any deviation of the measurements of a real rotor from an undamaged rotor is an indication of damage. These measurement deltas are used as indicators of system damage.

In practice, there is always some level of fuselage response at 1/revolution and at higher harmonics due to the inability to balance and track a rotor perfectly. Typically, a 1/revolution fuselage response of 0.00381 m/s, equivalent to about 756.2 N vibratory hub force for the helicopter analyzed in this study, is representative of a well-balanced rotor.[13] Vibrations in excess of 0.00762 m/s are considered significant and indicate the need to track and balance the rotor. Approximate thresholds for the moments transmitted to the fuselage can be similarly obtained. Vibratory hub moments below 282.46 N · m are representative of a well-tracked and balanced rotor.

Most real rotors have some degree of variation between the tip displacements of blades, even when the rotor is considered to be in "tracked" condition. One approach to account for these "out of track" blades and uncertainty in the measurements and model is to define linguistic thresholds for system behavior. These measures for system response are defined in Table 1 (from Ref. 13).

Expert System

Expert systems are intelligent computer programs that emulate the reasoning processes of human experts to solve difficult problems.[31] For example, a pilot could use the information in Table 1 to determine the type of rotor fault. However, humans are not well suited to processing large amounts of data rapidly, and a computational approach to decision making needs to be taken for online diagnostics problems. The formulation in Table 1 can be viewed as hard limits or crisp sets because there is no intersection between the definitions of negligible, moderate, and significant. Such definitions can be used to create decision rules R that drive a expert system of the form

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

where m and M are the number of input variables and rules, x_i and y are the input and output variables, and true and false represent binary values. Several such rules can be accumulated to form the knowledge base of an expert system. Decision rules work well when the input data are accurate. However, their performance degrades when input data are uncertain or noisy. In such cases, fuzzy rules can be used to improve classification performance. For decision rules, antecedent conditions are true (1) or false (0). To fuzzify these rules, we have to choose or derive membership functions from the training data and use the membership grades instead of a binary value, 0 or 1, to measure the matching degree.

Hard limits have problems in handling uncertainty. For example, using the thresholds in Table 1 leads to a hub force of 755 N being classified as negligible and 757 N being classified as moderate. There is measurement uncertainty due to sensors, as well as model uncertainty due to approximations in the mathematical model. Therefore, such hard limit thresholds do not account for uncertainty accurately. One approach to account for the uncertainty is using fuzzy logic. Again, the measures defined in Table 1 can be fuzzified and used to develop a fuzzy logic system.

Fuzzy Logic System

A fuzzy logic system (FLS) is a nonlinear mapping of an input feature vector into a scalar output.[23] Fuzzy set theory and fuzzy logic provide the framework for the nonlinear mapping. FLSs have been widely used in engineering applications because of the flexibility they offer designers and because of 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 FLSs is available from textbooks.[23] A brief introduction to fuzzy systems is given hereafter.

A typical multi-input/single-output FLS performs a mapping from $V \in R^m$ to $W \in R$ using four basic components: rules, fuzzifier, inference engine, and defuzzifier, as shown in Fig. 1. 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. Rules for the FLS 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 vs numerical values of a variable (e.g., HIGH vs 3.5%); 2) quantifying linguistic variables (e.g., u_1 may have a finite number of linguistic terms associated with it, ranging from NEGLIGIBLE

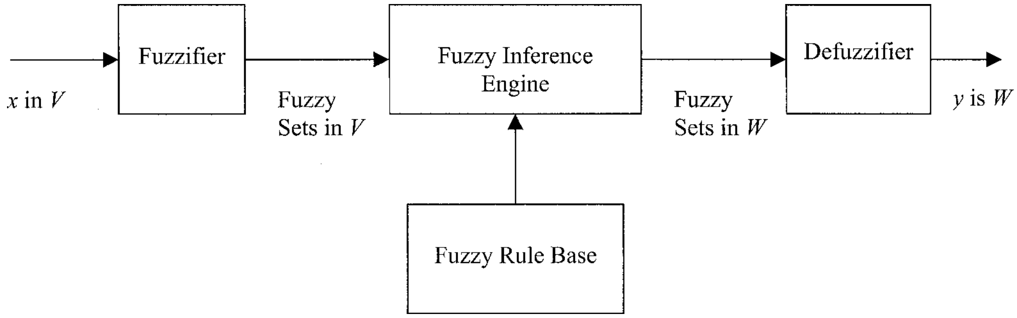

Fig. 1 Schematic representation of components of fuzzy logic system.

to VERY HIGH), which is done using fuzzy membership functions; 3) logical connections between linguistic variables (e.g., 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 necessary 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 or classes are needed as an output of the FLS. In those cases, a defuzzifier is used to calculate crisp values from fuzzy values.

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 generalized 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. For example, x can be a number "3.5" or the linguistic variable u named "displacement." A linguistic variable is usually decomposed into a set of terms $T(u)$ that cover its universe of discourse. Thus, displacement u could be "low," "medium," and "high."

Membership Functions

The most commonly used shapes for membership functions $\mu(x)$ are triangular, trapezoidal, piecewise linear, or Gaussian. The designer of the fuzzy system selects the type of membership function used. There is no requirement that membership functions overlap. However, one of the major strengths of fuzzy logic is that membership functions can overlap. FLS are robust because decisions are distributed over more than one input class. For convenience, membership functions are normalized to one so that they take values between 0 and 1 and, thus, define the fuzzy set.

Inference Engine

Rules for the fuzzy system can be expressed as

$$R_i\text{: IF } x_1 \text{ is } F_1 \text{ AND } x_2 \text{ is } F_2 \text{ AND } \ldots \text{ AND } x_m \text{ is } F_m \text{ THEN } y = C_i$$

$$i = 1, 2, 3, \ldots, M$$

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 $F_{12,\ldots,m} = F_1 \times F_2 \times \cdots \times F_m \rightarrow C_i$, which is a fuzzy set in $V \times W = V_1 \times V_2 \times \cdots \times V_m \times W$ 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 $x = [x_1 x_2, \ldots, x_m] \in V$ 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. In pattern recognition problems, the outputs are often crisp sets, and $\mu_{C_i}(y) = 1$ is often used for the product inference formula.

Defuzzification

Popular defuzzification methods include maximum matching and centroid defuzzification.[32] Whereas centroid defuzzification is widely used for fuzzy control problems where a crisp output is needed, maximum matching is often used for pattern matching problems where we need to know the output class. Suppose there are K fuzzy rules and, among them, K_j rules ($j = 1, 2, \ldots, L$, where 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 that 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.)

Fault Isolation Problem

Having defined the basics of an FLS, we now formulate its use for the helicopter rotor system fault isolation problem. A schematic representation of the process of developing the fuzzy logic damage detection algorithm is shown in Fig. 2.

Measurements

The vibration and blade response measurement deltas are assembled into the following vector form:

$$z = \lfloor \Delta v \quad \Delta w \quad \Delta \varphi \quad \Delta F \quad \Delta M \rfloor^T$$

where the rotor hub forces have three components corresponding to the longitudinal, lateral, and vertical directions:

$$\Delta F = \lfloor \Delta F_x \quad \Delta F_y \quad \Delta F_z \rfloor^T$$

The rotor hub moments have three components corresponding to rolling, pitching, and yawing directions:

$$\Delta M = \lfloor \Delta M_x \quad \Delta M_y \quad \Delta M_z \rfloor^T$$

The measurement deltas represent the difference in measurements between a damaged and undamaged rotor. Because the blade response and hub loads are periodic about the rotor azimuth (period $= 2\pi$), a Fourier series representation is used to break the response and hub loads into harmonic components. The first five harmonics are found to be sufficient to represent the blade response.

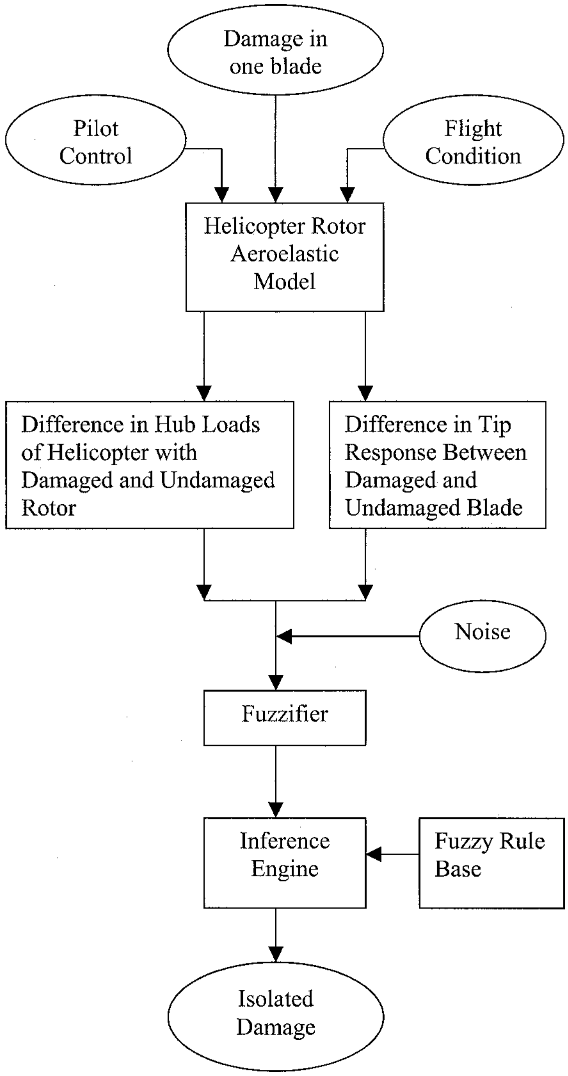

Fig. 2 Schematic representation of fuzzy logic damage detection algorithm design process.

The first 10 harmonics are used to represent the hub loads to account for higher harmonic content created by the faulty rotor. For example, the measurement deltas for lag deflection can be written as follows:

$$\Delta v = \lfloor \Delta v_0 \quad \Delta v_{1c} \quad \Delta v_{1s} \quad \Delta v_{2c} \quad \Delta v_{2s} \quad \Delta v_{3c} \quad \Delta v_{3s} \quad \Delta v_{4c} \quad \Delta v_{4s} \quad \Delta v_{5c} \quad \Delta v_{5s} \rfloor^T$$

Therefore, harmonics of measurement deltas constitute the measurement vector z and contain the needed information about the damage condition of the rotor system in mathematical form.

Note that the hub loads ΔF and ΔM are not directly measured on rotorcraft. Instead, vibration levels can be measured and ΔF and ΔM estimated from the vibration measurement. Recently, some studies have been done on predicting oscillatory loads in the rotor system from fixed system information. Cabell et al.[33] developed a neural network to predict oscillatory loads in the rotor system from fixed system loads. For example, the pitch-link load is estimated by the neural network from roll, pitch, and yaw rates; airspeed; and other fixed system information measured by a flight-control computer on the helicopter. Actual flight loads data from an AH-64A helicopter were used to demonstrate the process. The predicted loads agreed well with measured data. Azzam[34] developed a learning network to predict damage in helicopter rotor from flight parameters. The network predicted the fatigue damage of two rotating components indirectly from the flight parameters with accuracy better than a strain gauge system and with a measurement error of 5%.

Measurements in rotating structures are inherently more difficult than those of nonrotating ones.[35] However, optical blade tracking devices with day and night capability that are part of some commercial HUMS can measure relative height and lead-lag deflection differences between the blades.[2] The blade trackers can be mounted on a helicopter nose or fuselage, oriented upward toward the underside of the rotating hub. The optical tracker views the blade through a window of discrete time and operates on the principle that a higher flying blade will remain in the field of view longer than a lower flying blade. Such track measurements are averaged over a series of measurements to account for variations in blade movements related to wind gusts, control movements, etc.

Measuring rotational degrees of freedom such as tip torsion response is difficult. However, motivated by the fact that measuring rotational degrees of freedom can help machinery diagnostics, some work using laser Doppler vibrometer (LDV) has been done.[36–39] LDV has been developed for noncontact measurement of the torsion oscillation of rotating shafts.

Input and Output

Inputs to the FLS are measurement deltas, and outputs are rotor system faults. We have measurement deltas represented by vector z and six rotor system faults represented by vector $\boldsymbol{x}$. The objective is to find a functional mapping between z and $\boldsymbol{x}$, so that we can find $\boldsymbol{x}$ if z is given. Mathematically, this can be represented as a nonlinear function

$$\boldsymbol{x} = \Psi(z)$$

where $\boldsymbol{x} = \{$moisture absorption, loss of trim mass, damaged lag damper, damaged flap, damaged pitch-control system, misadjusted pitch link$\}^T$ and $z = \{\Delta v, \Delta w, \Delta\phi, \Delta F, \Delta M\}^T$. Each measurement delta component is composed of several harmonics and has uncertainty.

Fuzzification

Here, moisture absorption, loss of trim mass, damaged lag damper, damaged flap, damaged pitch-control system, and misadjusted pitch link are fuzzy sets denoting the six rotor system faults considered in this study. Each fuzzy set has degrees of membership ranging from zero to one. In this paper, we are only interested in the most likely fault class and not in its magnitude. Therefore, we do not further decompose the fault fuzzy sets using linguistic variables.

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

$$T(\Delta v) = \{\text{significant}-, \text{moderate}-, \text{negligible}, \text{moderate}+, \text{significant}+\}$$

where each term in $T(\Delta v)$ is characterized by a fuzzy set in the universe of discourse $U(\Delta v) = \{-0.0254\text{ m}, 0.0254\text{ m}\}$, which is selected to include values in the vicinity of the simulated results.

The other five measurement deltas are defined using the same set of terms as Δv, spanning the following universes of discourse: $U(\Delta w) = \{-0.0254\text{ m}, 0.0254\text{ m}\}$; $U(\Delta\phi) = \{-1\text{ deg}, 1\text{ deg}\}$; $U(\Delta F) = \{-2224.11\text{ N}, 2224.11\text{ N}\}$, $U(\Delta M) = \{-903.88\text{ N}\cdot\text{m}, 903.88\text{ N}\cdot\text{m}\}$. The universe of discourse is sufficiently large to account for most faults, but leaves out catastrophic faults.

Fuzzy sets with Gaussian membership functions are used. These fuzzy sets can be defined using the following equation:

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

Table 2 Gaussian fuzzy sets for measurement deltas

	Midpoint			
Variation	v, w, m	ϕ, deg	F, N	M, N · m
Significant− (S$^-$)	−0.01588	−0.625	−1890.49	−734.40
Moderate− (M$^-$)	−0.00953	−0.375	−1134.30	−423.69
Negligible (N)	0	0	0	0
Moderate+ (M$^+$)	0.00953	0.375	1134.30	423.69
Significant+ (S$^+$)	0.01588	0.625	1890.49	734.40

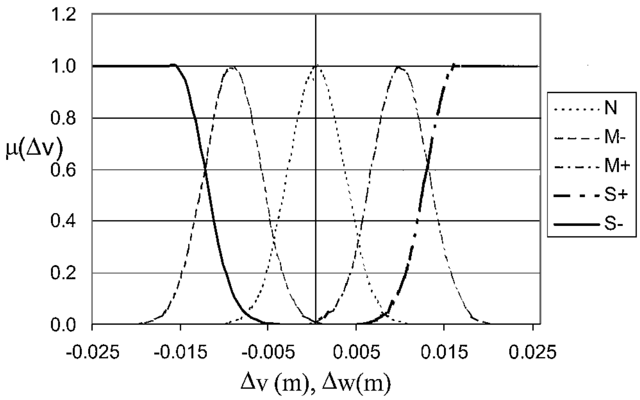

Fig. 3 Fuzzy sets representing changes in tip flap and lag response between undamaged and damaged blade as N, negligible; M, moderate; and S, significant.

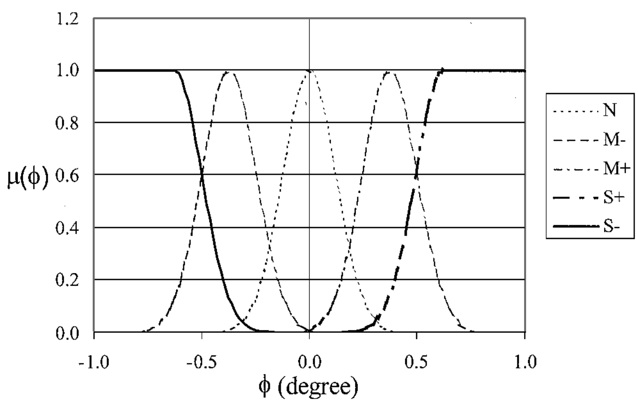

Fig. 4 Fuzzy sets representing changes in tip torsion response between undamaged and damaged blade as N, negligible; M, moderate; and S, significant.

where m is the midpoint of the fuzzy set and σ is the uncertainty (standard deviation) associated with the variable. Table 2 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 a healthy helicopter rotor (all measurement deltas are zero) to one with significant damage. The fuzzy sets closely follow the hard limits for rotor system response shown in Table 1 and represent fuzzified equivalents of the measures in Table 1.

The fuzzy set corresponding to significant is defined slightly differently to account for the open-ended nature of the linguistic variable:

$$\mu(x) = \exp\{-0.5[(x - m)/\sigma]^2\} \qquad m_{VH-} < x \text{ OR } x < m_{VH+}$$

$$\mu(x) = 1 \qquad m_{VH+} < x \text{ OR } x < m_{VH-}$$

Here m_{VH+} represents the midpoint corresponding to fuzzy set $VH+$. The standard deviations for Δv, Δw, $\Delta\phi$, ΔF, and ΔM are 0.003175 m, 0.003175 m, 0.125 deg, 378.1 N, and 169.48 N · m, respectively. These standard deviations are obtained by numerical experimentation and allow sufficient overlap between the fuzzy sets. They are also sufficiently large to allow for high levels of uncertainty. Figures 3–6 show the membership functions for each of the five fuzzy sets for blade response, hub forces, and hub moments, respectively.

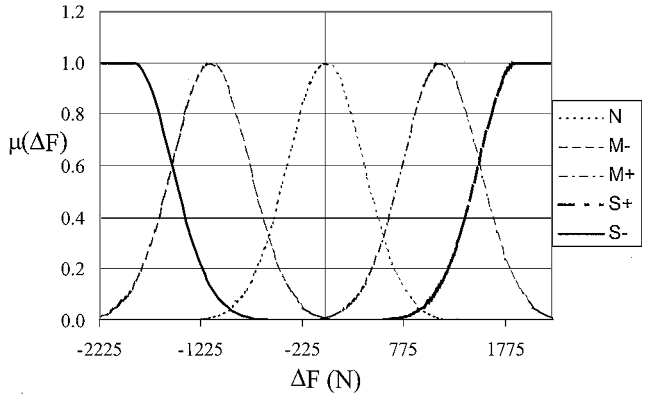

Fig. 5 Fuzzy sets representing changes in hub forces between undamaged and damaged rotor as N, negligible; M, moderate; and S, significant.

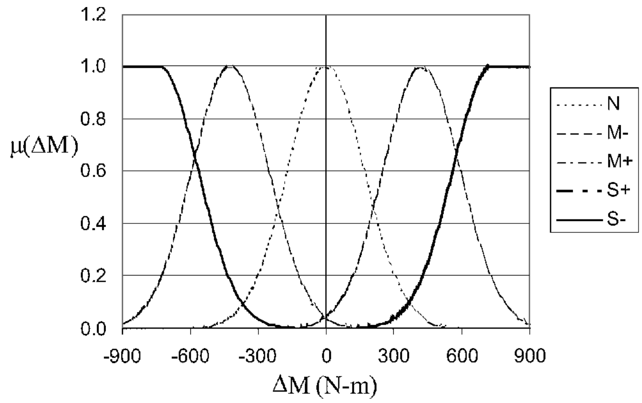

Fig. 6 Fuzzy sets representing changes in hub moments between undamaged and damaged rotor as N, negligible; M, moderate; and S, significant.

Rules and Fault Isolation

Automatically acquiring knowledge from numerical data for fuzzy systems has been the focus of much interest in recent years and is used for this study.[40,41] Rules for the fuzzy system are obtained by fuzzification of the numerical values obtained from the mathematical model of the rotor system using the following procedure:

1) A set of measurement deltas corresponding to a given rotor system fault is input to the FLS, and the degree of membership of the elements of Δv, Δw, $\Delta\phi$, ΔF, and ΔM in each fuzzy set are obtained. Therefore, each measurement component has five degrees of memberships based on the linguistic measures in Table 2.

2) Each measurement delta is then assigned to the fuzzy set with the maximum degree of membership.

3) One rule is obtained for each rotor system fault by relating the measurement deltas with maximum degree of membership to a fault.

The fuzzy rules are tabulated in Table 3 for a helicopter rotor with properties shown in Table 4. The results are obtained in steady, level flight for a normalized rotor thrust coefficient $C_T/\sigma = 0.0726$ and a rotor forward speed of $\mu = 0.3$. The numbers in the Table 3 stand for the harmonic component of the measurement delta. For example, moisture absorption causes a significant decrease in the steady flap deflection harmonic (0-S−) and a moderate decrease in the first flap deflection harmonic (1-M−). As another example, the damaged pitch-control system causes a significant increase in the first harmonic of the vertical hub force (1-S+) and a moderate increase in the second and third harmonic of the vertical hub force. The rules shown in Table 3 are used to construct an expert system and a fuzzy system. It is found that, for this particular application, the rules for the expert system and the fuzzy system are the same

Table 3 Rules for fuzzy system and expert system

Fault	Δv	Δw	$\Delta \phi$	ΔF_x	ΔF_y	ΔF_z	ΔM_x	ΔM_y	ΔM_z
Moisture	0-S+	0-S−	N	1-S+	1-S+	1-M+	N	N	5-M+
absorption	——	1-M-	——	——	——	——	——	——	——
Loss of trim mass	N	N	N	1-S+	1-S+	N	N	N	N
Misadjusted	0-M+	0-S−	N	4-M−	N	1-M+	0-S+	1-M+	0-S+
pitch link	——	1-M+	——	——	——	——	1-M+	4-L+	4-S+
Damaged flap	N	0-S−	3-M+	N	N	1-M+	0-S+	4-S+	0-S+
	——	1-S+	——	——	——	——	——	——	4-S+
Damaged	0-M+	0-S−	3-M+	1-S+	1-S+	1-S+	1-S+	1-S+	5-S+
pitch-control	1-M+	——	——	5-6-M+	5-6-M+	2-3-M+	0-2-6−	6-M+	0-6-M+
system	3-M+	——	——	——	——	——	M+	——	——
Damaged	N	0-M−	3-M+	1-S+	1-S+	1-2-M+	4-M−	N	5-S+
lag damper	——	1-3−	——	——	5-M+	——	——	——	——
	——	M+	——	——	——	——	——	——	——

Table 4 Helicopter properties

Property	Value
Rotor radius, m	8.17
Flap and lag hinge offset, m	0.381
Number of blades	4
Blade chord, m	0.5273
Linear aerodynamic twist, deg	−18
C_L	6.0α
C_D	$0.002 + 0.2\,\alpha^2$
C_M	0.0
Lock number	8
Solidity	0.0826
Blade attachment point, m	1.0541
Rotor tip speed, m/s	220.98
Helicopter weight, kg	7484.27
Blade mass, kg	106.59

because of the close relationship between the two. The expert system is a variation of the fuzzy system with the fuzzy sets replaced by crisp sets defined in Table 1. Results for the fuzzy system and the expert system are compared and discussed later in the paper.

For any given input set of measurement deltas, the fuzzy rules are applied using the product inference engine. The output sets are crisp sets representing the six rotor system faults. Once the fuzzy rules are applied, we have degrees of membership for each fault. For fault isolation, we are interested in the most likely fault, which is obtained by maximum matching defuzzification.

Results and Discussion

For numerical results, a four-bladed nonuniform articulated rotor with properties similar to an SH-60 helicopter is selected (Table 4). The rotor is modeled using 13 spatial finite elements along the bladespan. Six time finite elements with fourth-order shape functions are used along the azimuth to calculate the blade response. Selected validation of rotor component loads using this simulation for a baseline configuration is provided in Ref. 13.

Effect of Random Noise

For testing the FLS, numerical data are obtained from the mathematical model and contaminated with noise. Uncertainty is introduced using the standard deviation σ. The noisy data are generated as follows:

$$z_{\text{noisy}} = z_{\text{ideal}} + \sigma(\text{rand} - 0.5)$$

where rand is a random number between 0 and 1 and z_{ideal} is the ideal input measurement vector obtained from the mathematical model. The baseline standard deviations σ_0 for Δv, Δw, $\Delta\phi$, ΔF, and ΔM are 0.003175 m, 0.003175 m, 0.125 deg, 378.1 N, and 169.48 N · m, respectively. Here, σ_0 represents the baseline uncertainty used to define the fuzzy sets and create noisy data. These standard deviations are selected to be relatively high to account for the high degree of uncertainty in rotor system measurements and models. The simulated noisy measurement deltas are, therefore, representative of a real rotor.

Noisy data are obtained for 1000 points for each of the six implanted faults. In each case, when the FLS is presented with the noisy data, it gives the most likely fault as output. The success rate is 100% for all of the six faults considered in this study, as shown in Table 5. This 100% success rate comes with fairly high levels of uncertainty in the data ($\sigma = \sigma_0$). To test the robustness of the FLS, the uncertainty in the data is further increased beyond σ_0. As the noise level in the data is increased beyond σ_0, the fault isolation success rate gradually falls. However, even with a 40% increase in the uncertainty, the fault isolation accuracy is about 90%. The ability of the FLS to give good results under high levels of uncertainty in the data comes from the generalizing capability of fuzzy systems obtained by the overlap in the fuzzy sets for the measurements (Figs. 3–6). In addition, the fuzzy system have a fuzzifier at the front end that acts as a noise filter, whereas neural networks have to learn about the noise statistics of the data from extensive training.[23]

In sharp contrast, the rule-based expert system (ES) performs very poorly with noisy data. As shown in Table 6, the ES has a zero success rate with noisy data ($\sigma = \sigma_0$). If the noise in the data is decreased, the fault isolation accuracy of the ES increases. At very low noise levels and with noise-free data, the ES gives a fault isolation success rate of 100%. It can be concluded that the FLS is far superior to the ES for noisy data that are representative of a real helicopter rotor.

Effect of Systematic Noise and Random Noise

The preceding results used additive random noise. Besides random noise, there is the problem of systematic noise that can occur because of errors in the mathematical model. We thus define the noisy signal as

$$z_{\text{noisy}} = z_{\text{ideal}} + \sigma(\text{rand} - 0.5) + \theta$$

For numerical results, we assume that the blade tip response delta and the rotor hub load delta are under predicted by 10%, implying that $\theta_0 = -0.10\,z_{\text{ideal}}$. The results for this case are shown in Table 7. The average success rate with systematic noise added to random noise has fallen to 89%. However, we see that the fuzzy system is still quite robust and shows graded degradation in the presence of systematic noise.

Subsets of Measurement Deltas

The measurement deltas include blade response, hub forces, and hub moments. To test the robustness of the fault detection approach, the FLS is tested using information about 1) only blade tip response 2) only hub forces, and 3) only hub moments. In each of these three cases, the fuzzy rules remain the same as shown in Table 3, except that a smaller subset of rules corresponding to the available measurement deltas is used. Results show a high success rate for the FLS, even with the limited measurements, as shown in Table 8. The average success rate of fault isolation with only blade response measurements is 93%, with only hub forces is 89%, and with only hub moments is 90%. Thus, the FLS could compensate for limited sensor failure in case all of the response and load measurements are used for health monitoring. However, it is clear that blade tip response is the best measurement choice for rotor fault detection,

Table 5 Fuzzy system fault isolation success rate (percent) with increasing level of random noise

Fault	$\sigma = \sigma_0$	$\sigma = 1.1\sigma_0$	$\sigma = 1.2\sigma_0$	$\sigma = 1.3\sigma_0$	$\sigma = 1.4\sigma_0$
Moisture absorption	100	98	97	94	89
Loss of trim mass	100	97	95	92	90
Misadjusted pitch link	100	99	97	95	92
Damaged flap	100	98	97	95	93
Damaged pitch-control system	100	100	97	95	91
Damaged lag damper	100	98	97	93	88
Average success rate	100	98	97	94	90

Table 6 Expert system fault isolation success rate (percent) with increasing level of random noise

Fault	$\sigma = 0$	$\sigma = 0.2\sigma_0$	$\sigma = 0.4\sigma_0$	$\sigma = 0.6\sigma_0$	$\sigma = 0.8\sigma_0$
Moisture absorption	100	100	47	20	0
Loss of trim mass	100	100	92	40	0
Misadjusted pitch-link	100	71	46	12	0
Damaged flap	100	100	67	16	0
Damaged pitch-control system	100	68	54	15	0
Damaged lag damper	100	100	45	15	0
Average success rate	100	90	59	20	0

Table 7 Fuzzy system fault isolation success rate (percent) with systematic and random noise ($\sigma = \sigma_0$)

Fault	$\theta = \theta_0$
Moisture absorption	90
Loss of trim mass	88
Misadjusted pitch link	87
Damaged flap	91
Damaged pitch-control system	91
Damaged lag damper	86
Average success rate	89

Table 8 Fuzzy system fault isolation success rate (percent) with reduced measurements ($\sigma = \sigma_0$)

Fault	All	Response only	Hub forces only	Hub moments only
Moisture absorption	100	96	91	90
Loss of trim mass	100	94	89	92
Misadjusted pitch link	100	93	88	91
Damaged flap	100	92	91	88
Damaged pitch-control system	100	92	90	87
Damaged lag damper	100	94	88	90
Average success rate	100	93	89	90

followed by hub forces and hub moments. Using all measurements gives the best fault detection results.

Off-Design Condition

Table 9 shows test results with noisy simulated data for faults that are 25% larger and 25% smaller than those used to derive the rules of the FLS. The average success rate of the FLS falls from 100 to about 93% in both of these cases. Because this result is obtained with noisy data, it can be said that the FLS is robust with respect to changes in fault size. If the fault models selected in this study are representative of real rotor faults, then the FLS developed in this study can give accurate results for highly noisy data. Faults much smaller than the seeded faults may be too small to detect from changes in global system behavior. Faults much larger than the seeded faults may result in catastrophic failure.

Closing Remarks

The preceding results clearly show that the FLS performs very well for rotor system fault detection in the highly noisy environment of the helicopter rotor. Also note that neural networks share the universal approximation capability with fuzzy systems[27] and, therefore, a properly designed and trained neural network would have given good results for the preceding cases also, as shown in Refs. 17 and 18. However, the fuzzy system offers the following advantages over the neural networks: 1) easy-to-interpret rules, 2) built-in noise filtering through the fuzzifier, and 3) low training time. Fuzzy systems are also able to give linguistic outputs rather than numbers that can be directly shown to a human engineer or pilot. Therefore, fuzzy systems are a powerful tool for diagnostics applications.

Table 9 Fuzzy system fault isolation success rate (percent) at off-design conditions ($\sigma = \sigma_0$)

Fault	Baseline	−25% from baseline	+25% from baseline
Moisture absorption	100	93	95
Loss of trim mass	100	92	91
Misadjusted pitch link	100	93	95
Damaged flap	100	97	90
Damaged pitch-control system	100	93	93
Damaged lag damper	100	91	97
Average success rate	100	93	93

Some approximations were made in this study that need to be addressed in future work. One is the issue of isolating faults that do not form a part of the training set for the FLS. Another is a comparison of the FLS and neural network for the same test bed, that is, with the same faults, measurements, and noise levels in data.

Conclusions

An FLS is developed for helicopter rotor system diagnostics. It takes measurement deviations from a baseline model of a good undamaged rotor and isolates the rotor system fault. The FLS operates with five basic measurements (blade tip flap bending, lag bending, torsion response, hub forces, and hub moments) and analyzes six faults (moisture absorption, loss of trim mass, misadjusted pitch link, damaged pitch-control system, damaged flap, and damaged lag damper). Each measurement is split into harmonic components. The rules for the FLS are obtained from an aeroelastic analysis of the damaged helicopter rotor with dissimilar blades and are based on finite elements in space and time.

Noise is added to the numerical output of the mathematical model to generate realistic test data to simulate the highly noisy rotor environment. The following conclusions are drawn from this study:

1) Numerical results show that the FLS has a success rate of 90–100% in isolating the rotor faults, even under very high levels of uncertainty.

2) The FLS also yields good results, with an 85–95% success rate, with a limited suite of measurements involving monitoring only the blade tip response, or the hub forces, or the hub moments. The FLS is, therefore, robust in the case of selected sensor failure. It is found

that blade tip response is a better measurement suite than hub forces or hub moments for fault isolation. The best results, however, are obtained when all measurements are used.

3) Even when the test fault sizes deviate considerably from the seeded faults used to develop the fuzzy rules, the FLS is able to give accurate results with fault isolation accuracy of over 90%.

4) An ES based on decision rules performs much more poorly than the FLS in fault detection in the presence of noise, with almost zero success rates at high noise levels. In contrast, the FLS was able to give 100% isolation accuracy.

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A. Berman
Associate Editor