DETECTION AND LOCATION OF STRUCTURAL DEGRADATION IN MECHANICAL SYSTEMS

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ABSTRACT

The investigation of a diagnostic method for detecting and locating the source of structural degradation in a mechanical system is described in this paper. The diagnostic method uses a mathematical model of the mechanical system to determine relationships between system parameters and measurable spectral features. These relationships are incorporated into a neural network, which associates measured spectral features with system parameters. Condition diagnosis is performed by presenting the neural network with measured spectral features and comparing the system parameters estimated by the neural network to previously estimated values. Changes in the estimated system parameters indicate the location and severity of degradation in the mechanical system.

I. INTRODUCTION

Traditional monitoring methods can detect from vibration signatures when mechanical degradation has occurred but provide little indication of the location and severity of the degradation. The main advantages of the investigated method are (1) that signature interpretation is based on mathematical model results, allowing a direct association between spectral changes and structural degradation, and (2) that both the location and the magnitude of structural changes are estimated. This approach removes much of the subjectiveness often associated with signature interpretation.

The diagnostic method combines a mathematical model of the monitored system to relate system parameters to measurable spectral phenomena, a technique to extract the significant features from the frequency spectra, and a neural network to match the extracted spectral features with system parameters. The steps comprising the technique are:

1) Develop a mathematical model describing the dynamics of the mechanical system.
2) Use the mathematical model to form a neural network training set. The training set consists of calculated model responses (i.e., spectral features) as input and the corresponding spring and damping constants (i.e., system or model parameters) as output.
3) Design a neural network and train it to simulate the relationship between the model's input and output.
4) Use the trained neural network to estimate the system parameters corresponding to a set of measured spectral features.

The modeling technique is independent of the monitoring method. Thus, for some applications relatively simple lumped-parameter approximations may be suitable, while for others, detailed models employing sophisticated modeling techniques may be needed. The only requirement placed on the mathematical model is that the significant and measurable effects caused by changing system parameters must be simulated.

The training set uses spectral features calculated from the mathematical model as neural network input and uses the corresponding model input parameters as the neural network output. After training, the neural network will effectively contain all of the significant information available from the model and will, in effect, perform the mathematical inverse of the model.

The neural network output estimates the system parameters. Comparison of the latest estimated system parameters with previously estimated values indicates if degradation has occurred and can also indicate the severity of the degradation. The model parameters experiencing changes indicate the degradation location.

II. APPLYING THE DIAGNOSTIC METHOD TO COMPUTER-SIMULATED DATA

The computer simulation was intended to address the following questions:

1) What effect does the training set composition and size have on the accuracy of the model parameter estimates made by the neural network.
2) Is the formation of the training set or the neural network training so computationally intensive that the diagnostic method is impractical.
3) Are eigenvalues and eigenvector components practical choices for forming the neural network training set and is this information sufficient for accurate model parameter prediction.
4) Can the trained neural network solve the "inverse problem", that is, can the neural network accurately estimate the model parameters corresponding to a given set of eigenvalues and eigenvector components (natural frequencies and mode shape components).

When using computer-simulated data, a direct comparison of the estimated and known model parameters can be used to evaluate the accuracy of the neural network interpolation.

A. Mechanical Model Description

A simple lumped-parameter model representing a uniform beam supported by springs was used in this investigation. The beam model is shown in Figure 1. Mass points 2 and 3 each contain one third of the beam's mass and mass points 1 and 4 each contain one sixth of the beam's mass. Linear springs K_{mm} and K_{mp} attach the beam ends to ground. This model was used to calculate the vibrational modes of the beam, which are greatly affected by the mounting springs K_{mm} and K_{mp} . The beam model was used to calculate mode shapes and natural frequencies for various combinations of K_{mm} and K_{mp}. The calculation results were used to form a neural network training set.

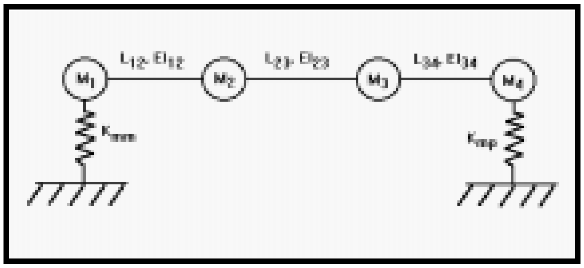


Figure 1. The simple mechanical system model.

B. Formation of the Training Sets, the Neural Network, and Network Training

The training sets were selected so the effects of the training set member increment size and the effects of the number and type of model output values on neural network prediction accuracy could be examined. The number of model output values determines the number of nodes in the neural network input and hidden layers. The model input value increment size affects the neural network prediction accuracy because increment sizes result in neural network interpolation over a narrower range during the recall phase.

Training set input parameters were selected after examining the effect of changing the spring rates on the calculated natural frequencies and mode shapes. Nine different training sets were created and used in network training. Each training set used a different combination of input parameters and input parameter spacing.

The NeuralWorks Professional II/PLUS code, distributed by NeuralWare, Inc. of Pittsburgh, PA., was used in this investigation.[1] Back propagation networks with a single hidden layer were used. Each network had two outputs corresponding to the spring rates K_{mm} and K_{mp}. Nine different training sets were used. Training sets 1, 2, and 3 had four inputs consisting of the first four natural frequencies. Training sets 4, 5, and 6 had 20 inputs consisting of the natural frequencies and mode shape components for the first four natural modes. Training sets 7, 8, and 9 had 45 inputs consisting of the natural frequencies and mode shape components for the first 9 natural modes. Training sets 1, 4, and 7 had 27 members, sets 2, 5, and 8 had 125 members, and sets 3, 6, and 9 had 343 members.

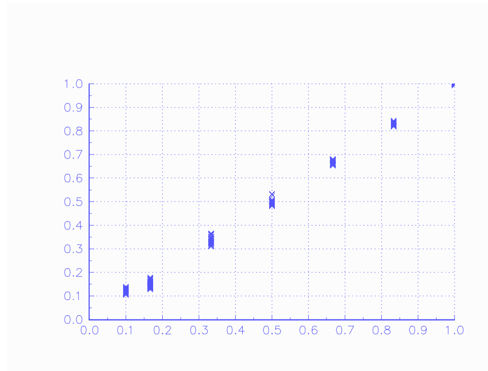
It was found that a suitable number of hidden layer nodes was approximately one-half of the input dimension. Additional factors that must be considered in the development of a back propagation network are the nonlinear transfer function used and the variation of the learning rule incorporated. For our work the hyperbolic tangent function gave better results than the sigmoid function and was used as the nonlinear transfer function in all cases. Network learning was achieved by using the cumulative delta rule, a version of the gradient descent rule.

C. Results Obtained from Applying the Diagnostic Method to Computer-Simulated Data

The ability of the neural network to reproduce the training set output, given the training set input, is shown in Figures 2 and 3. These figures show the most accurate results obtained; the average absolute error and standard deviation of the estimated spring rates are 3.6% and 3.1%.

The ability of the neural network to generalize over the training set (i.e., to interpolate between the spring rate values used in the training set) is shown in Figures 4, and 5. A test set was formed by using calculated results for spring rates between those used in the training set. The overall absolute error is 3.2% and the standard deviation is 2.7%.

The effect of the training set size on the accuracy of the neural network estimate of spring rates not included in the training set is shown in Figure 6. These results show that for each of the training set types, the accuracy of the neural network spring rate estimate improves as the number of training set entries increases. This improvement occurs because the greater number of training set members reduces the range over which the neural network must interpolate to estimate the spring rate values. The improvement decreases as the number of training set members increases.



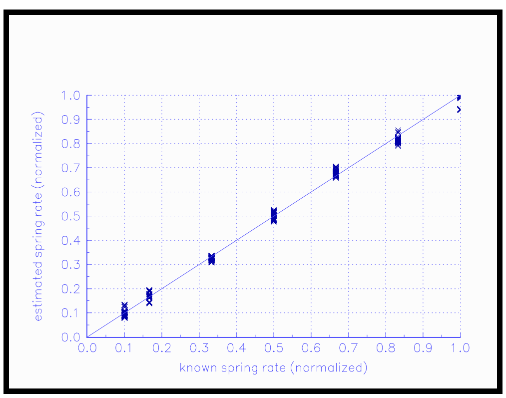


Figure 2. A comparison of the known and estimated spring rates for the values of K_{mm} used in the training set.

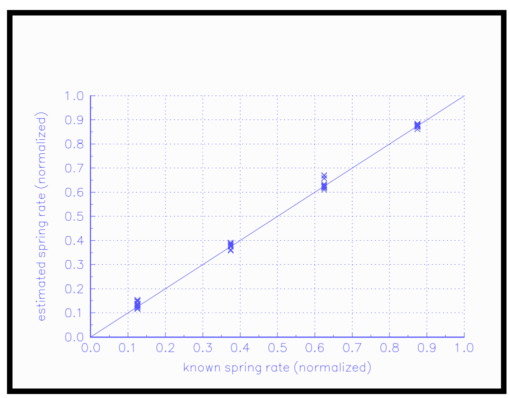
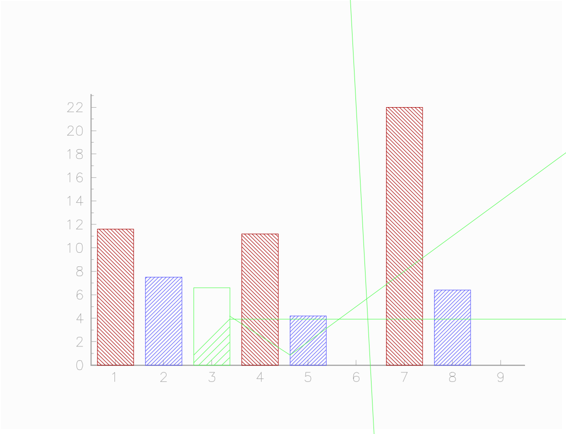


Figure 5. A comparison of the known and estimated spring rates for values of K_{mp} between those used in the training set.



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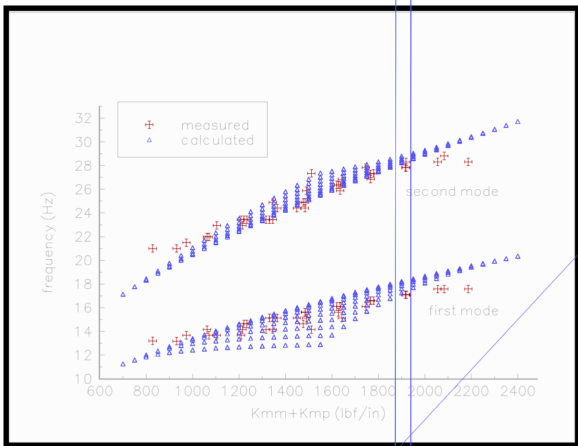
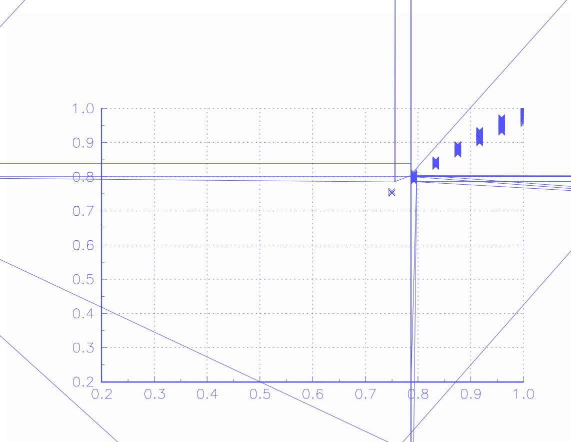


Figure 8. Comparison of the measured and calculated values of natural frequency.



be detected. For example, a 10% change in one of the parameters would result in approximately a 10% change in the estimated value regardless of the initial agreement between the estimated and actual values.

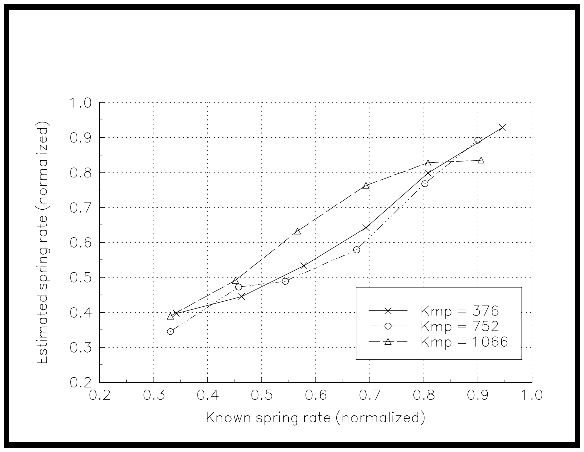


Figure 11. Estimated value of K_{mm} calculated while holding the value of K_{mp} fixed.

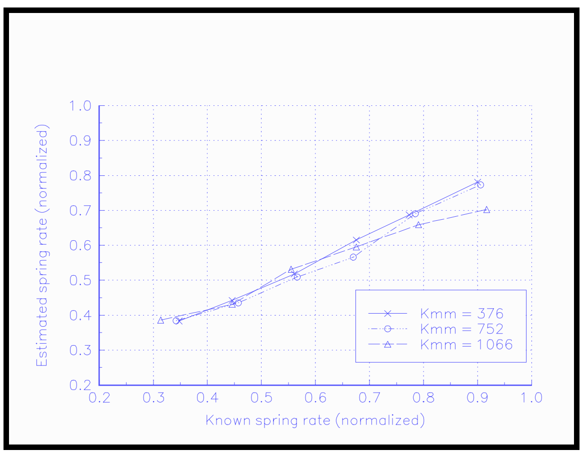


Figure 12. Estimated value of K_{mp} calculated while holding the value of K_{mm} fixed.

IV. SUMMARY AND CONCLUSIONS

Computer simulation results and a demonstration using a bench-top test unit were used to determine that the diagnostic method can be successfully applied to detect and locate structural changes in a mechanical system. In particular, it was shown that a neural network, trained by using eigenvalues and eigenvector components calculated from a mathematical model, can estimate structural condition from measurements of natural frequencies and mode shape components. It is concluded that the diagnostic method can be applied to monitor the structural condition of a mechanical system with the following characteristics:

1) The relationship between the measured parameters (neural network input) and the monitored parameters (neural network output) must be single-valued if the neural network is to train properly.
2) Changes in the monitored parameters must have a significant effect on the values of the measurable parameters.

The simulation results show that the accuracy of the neural network parameter estimation depend heavily on the composition and the increment size of the training set. If the training set composition is such that the relationship between the neural network input and output is not single-valued, the resulting model parameter estimation is poor. An example of this behavior is the relatively high error associated with training sets 1, 2, and 3 (Figure 6). Because these training sets contained only natural frequencies as input, in some cases more than one combination of spring rates resulted in nearly identical natural frequency values. Including mode shape components in training sets 4 through 9 avoids this problem, producing better parameter estimates, as shown by the lower error values obtained by using these training sets.

Figure 6 also shows that the increment size affects the accuracy of the estimated spring rates. Interpolation between training set members performed by the neural network when estimating spring rate values occurs over a smaller interval as the training set member spacing decreases, resulting in more accurate spring rate estimates.

The amount of computation required to form the training set and train the neural network was not prohibitively large in the applications of the diagnostic method used in this work. Although the applicability of this statement is obviously limited by the relatively simple models and the small number of parameters adjusted in this work, there appears to be no reason to expect prohibitively large calculations for significantly larger models. Thus, this question remains open at this time but does not appear to pose a great threat to the practical application of the method.

The results from the computer simulation show that the trained neural network can accurately solve the inverse problem of determining model parameters from the natural frequencies and mode shape components. The computer simulation results indicate that the diagnostic method is applicable to real mechanical systems with a single-valued relationship between the neural network input and output.

The application of the diagnostic method to the bench-top test unit was intended primarily as a demonstration of the method on a simple mechanical system. In addition to demonstrating the method, an indication of the effect of modeling and measurement errors on the method's accuracy was obtained.

The demonstration clearly shows the ability of the diagnostic method to estimate values of the mounting spring rates. Thus, it is concluded that the diagnostic method can be used to detect, locate, and estimate the magnitude of structural changes in mechanical systems that have a single-valued relationship between neural network input and output and that have monitored parameters that significantly affect the measured parameters.

The effect of modeling and measurement errors on the method's accuracy are indicated by the results. The three main error sources are modeling errors, neural network errors, and measurement errors. From the results shown in Section II and in Figure 9, the neural network errors are known to be on the order of 2%. The model error, indicated by the comparison of calculated and measured values shown in Figure 8, is estimated to be on the order of 5%. The measurement errors, although not quantified, are believed to be relatively large, on the order of 5%. This error was due to difficulty with the pressure regulators (which continuously bled air, changing the air spring pressure), stickiness in one of the pressure gauges, and the unavoidable unit-to-unit variability that would introduce errors into the pressure-to- spring rate equation. Both modeling and measurement errors will cause a mismatch between the measurements and the neural network input values contained in the training set, resulting in poor system parameter estimates.

Note that sensitivity to modeling error does not necessarily mean that complicated mathematical models are needed. The required model complexity depends on the dynamic characteristics that need to be measured to detect changes in the monitored system parameters. If parameters such as the mounting spring rates need to be monitored, as was done in this work, the rigid body modes supply all the information needed to detect and locate changes in these spring rates. These modes can be accurately modeled by using a relatively simple model, as shown by the results in Section III. If, on the other hand, system parameters that affect higher modes need to be monitored a more complex model would be needed.

Finally, it should be pointed out that, although the diagnostic method has been presented only in connection with vibration signature interpretation, this is really a specific application of a more general methodology. This methodology has a range of application beyond vibration signature analysis. This technique should be applicable to monitor parameters in any system or process that satisfies the requirements that the relationship between the measured output and the monitored parameters be single-valued, that shows sufficient sensitivity to the parameters being monitored, and that can be accurately modeled. Thus, the results in addition to showing that the diagnostic method can be applied to detect and locate the source of changes in vibration signatures, also serves as a successful demonstration of the more general methodology.

ACKNOWLEDGMENTS

Research sponsored by the Laboratory Directed Research Program of Oak Ridge National Laboratory.

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