AUTOMATED DETECTION AND LOCATION OF STRUCTURAL DEGRADATION

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1. ABSTRACT

The investigation of a diagnostic method for detecting and locating the source of structural degradation in mechanical systems is described in this paper. The diagnostic method uses a mathematical model of the mechanical system to define relationships between system parameters, such as spring rates and damping rates, and measurable spectral features, such as natural frequencies and mode shapes. These model-defined relationships are incorporated into a neural network, which is used to relate measured spectral features to system parameters. The diagnosis of the system's condition 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.

The investigation applied the method by using computer-simulated data and data collected from a bench-top mechanical system. The effects of neural network training set size and composition on the accuracy of the model parameter estimates were investigated by using computer simulated data. The measured data were used to demonstrate that the method can be applied to estimate the parameters of a "real" mechanical system.

The results show that diagnostic method can be applied to successfully locate and estimate the magnitude of structural changes in a mechanical system. The average error in the estimated spring rate values of the bench-top mechanical system was less than 10%. This degree of accuracy is sufficient to permit the use of this method for detecting and locating structural degradation in mechanical systems. It was also shown that the neural network training sets required for this level of estimate accuracy are not impractically large and can consist of natural frequency and mode shape information.

2. INTRODUCTION

Traditional monitoring methods can detect 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 that signature interpretation is based on mathematical model results, allowing a direct association between spectral changes and structural degradation, and that both the location and the magnitude of structural changes can be estimated. This approach removes much of the subjectiveness commonly associated with signature interpretation.

2.1 Overview of the Diagnostic Method

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 to corresponding system parameters. The steps comprising the technique are:

1) Develop a mathematical model describing the vibrations and dynamics of the monitored mechanical system.

2) Use the mathematical model to form a training set for the neural network. The training set will consist of calculated model responses (i.e., spectral features) as a known input and the corresponding spring and damping constants (i.e., system or model parameters) as a known output. Thus, if the relationship between the spectral features and the system parameters is single-valued, the neural network will perform the mathematical inverse of the model.

3) Design a neural network which will be trained to simulate the model.

4) Train the neural network by iteratively adjusting the neural network connection weights to obtain optimum agreement between the neural network and the mathematical model.

5) Use the trained neural network to estimate the system parameters corresponding to a measured set of spectral features.

The modeling technique is independent of the monitoring method. Thus, for some applications relatively coarse lumped-parameter approximations may be suitable, while for others, detailed models employing sophisticated modeling techniques, such as finite element methods, may be needed. The only requirement placed on the mathematical model is that the significant and measurable effects caused by the changing of system parameters must be simulated. The parameters most likely to change in mechanical systems are stiffness or damping and the significant and measurable effects of these changes will be the characteristics of the natural frequencies and mode shapes.

The supervised learning mode of neural network training used in this investigation involves adjusting internal neural network parameters until satisfactory agreement is obtained between the sets of known input and output parameters in the training set. For the neural network to relate spectral features to system parameters, the training set will use spectral features calculated by the mathematical model as neural network input and will use the corresponding model input parameters as 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 implementation of the trained neural network for interpreting vibration signatures is summarized in Figure 1. Sensor signals are conditioned and then transformed into frequency spectra by an FFT algorithm. The spectral data are decomposed, yielding frequency peaks and mode shape components. These spectral features are used as input to the neural network. The neural network output are estimates of the original 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 specific model parameter that experiences a change indicates the location of the degradation because each model parameter represents a specific system component.
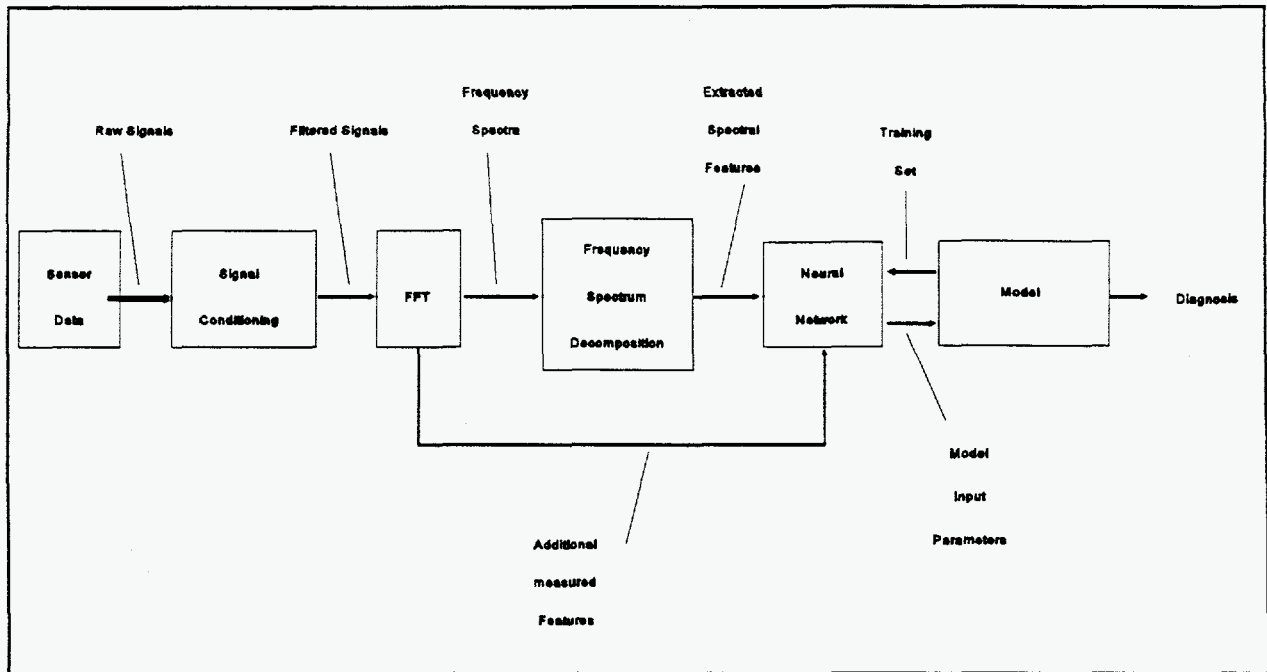
Figure 1. Diagram showing the implementation of the diagnostic method.

3. 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 a practical choice for forming the neural network training set and is the information contained in these values sufficient for the diagnostic method to accurately predict model parameters.

4) Can the trained neural network solve the "inverse problem", that is, can the neural network be used to accurately estimate the model parameters that correspond 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.

3.1 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 2. 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}
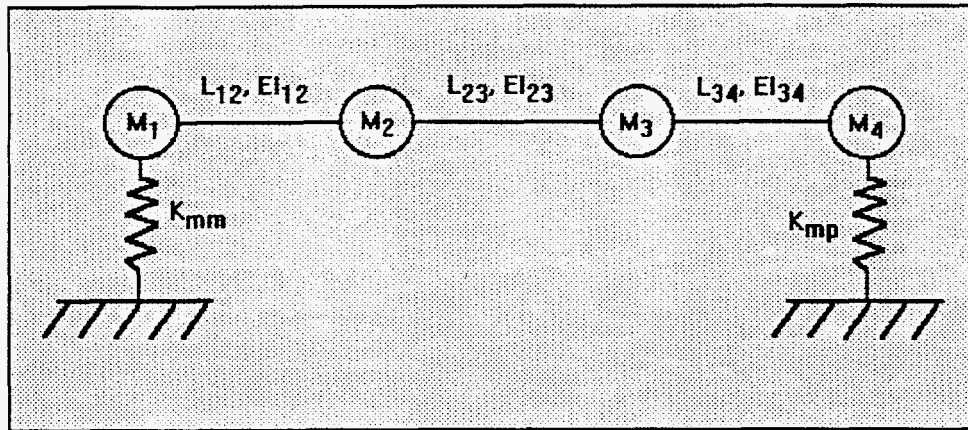
Figure 2. The simple mechanical system model.

attach the beam ends to ground. This model was used to calculate the first two rigid body modes of the beam, both of 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.

3.2 Formation of the Training Sets, the Neural Network, and Network Training

The training sets were selected so the effects of the spacing between the training set members 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 spacing between the model input values affects the neural network prediction accuracy because closer input value spacings 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}. The number of inputs included the natural frequency values and the mode shape components for each natural frequency. Nine different training sets were used. Training sets 1, 2, and 3 had four inputs, sets 4, 5, and 6 had 20 inputs, and sets 7, 8, and 9 had 45 inputs. 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 (provided that number remained greater than the number of output nodes). A larger number complicated the network and did not improve either the convergence rate or the final accuracy; a smaller number in some cases degraded the final results. Additional factors that must be considered in the development of a backpropagation 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.

3.3 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 3 and 4. 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 5, and 6. 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 7. 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.

4. APPLYING THE DIAGNOSTIC METHOD TO MEASURED DATA

The bench-top test unit and the data acquisition system are described in this section. This equipment was used to demonstrate the use of the diagnostic method on a relatively simple mechanical system.

4.1 Description of the bench-top test unit

The bench-top test unit consists of three main structural members, the frame base, the top beam, and the test beam (Figure 8). The structural members were designed to allow deflection primarily in the vertical plane. This constraint is imposed to force consistency between the deflections of the bench-top test unit and the calculated deflections of the mathematical model. The frame base is constructed of 4" × 5.4 steel channel, 72 inches in length. At each end of the base are two horizontal stabilizing members and an 18 inch vertical upright, each constructed of 4" × 5.4 steel channel and welded to the horizontal base. The top beam is constructed of 4" × 5.4 steel channel and is bolted to the uprights at each end. The test beam is constructed of 7" × 9.80 steel channel and is constrained to move only in the vertical plane by four rollers, two on each end of
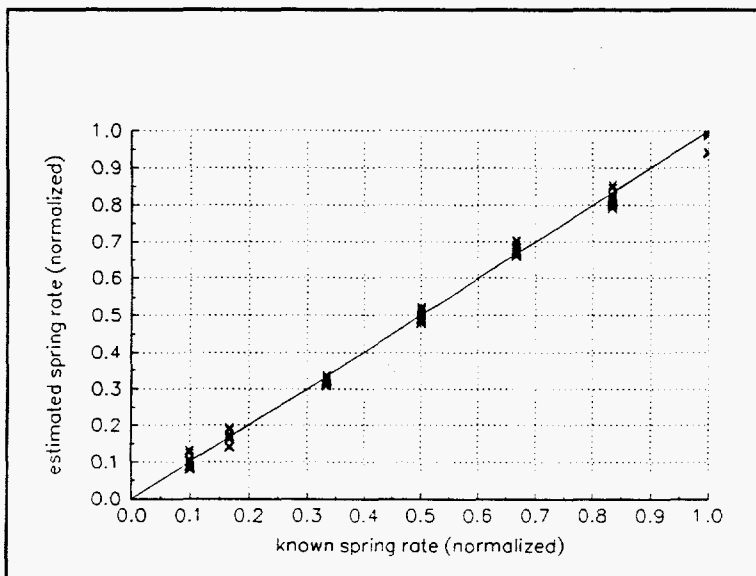
Figure 3. A comparison of the known and estimated spring rates for the values of K_{mm} used in the training set.
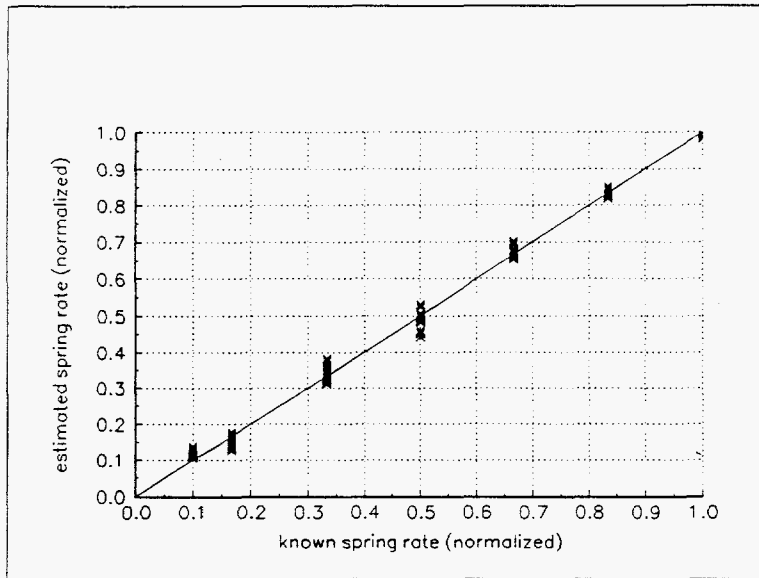
Figure 4 comparison of the known and estimated spring rates for the values of K_{mp} used in the training set.

the beam. These rollers contact the faced outside surface of each upright and also act to prevent twisting of the test beam.

The test beam is mounted to the base and to the top beam by four Firestone model 1M1A air springs that correspond to the mounting springs K_{mm} and K_{mp}. The dependence of the spring rate on air pressure of the 1M1A air springs at the design height of 2.5 inches shown in Figure 9.[2] The nearly linearly relationship between the spring rate and the gauge pressure of the Firestone 1M1A airspring shown in Figure 9 can be approximated by using

$$K \approx 6.9 P_g + 50 . \qquad (1)$$

The pressure in each air spring is controlled with an Norgren model R46-200-RNLA in-line pressure regulator. Individual pressure gauges are used to monitor the pressure in each air spring.

Three Endevco model 2233E accelerometers are used to measure the vibration of the bench-top test unit. The signal from each accelerometer is amplified by an Endevco model 2721A charge amplifier before being supplied to the data acquisition system. Each end of the test beam has one accelerometer stud-mounted on the center line next to the air spring to measure the absolute movement of each end of the test beam.
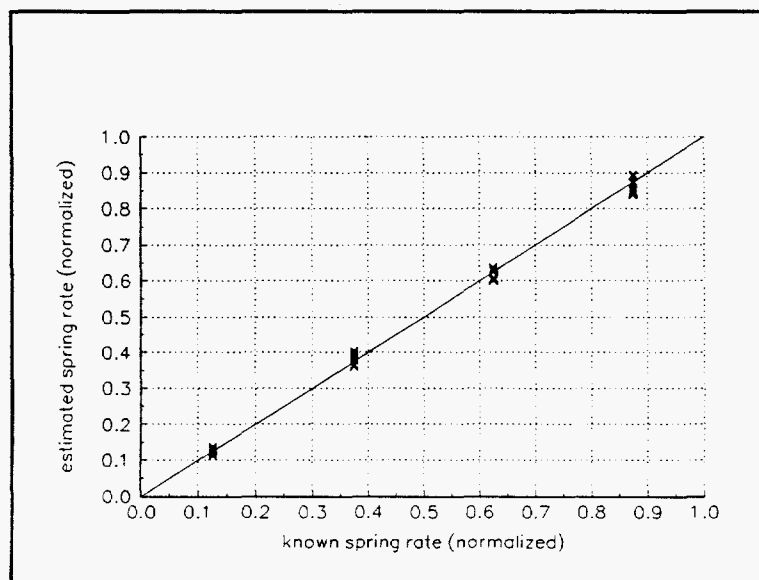

Figure 5. A comparison of the known and estimated spring rates for values of K_{mm} between those used in the training set.

The data acquisition system consisted of an IBM-compatible 486 PC computer equipped with a 16-bit, multiple channel digital data acquisition board (AT-MIO-16X from National Instruments Corporation). The LabVIEW data acquisition package, also from National Instruments Corporation, was used as the software driver.[3] All data was low pass filtered by using a Rockland 852 active filter prior to digitization.

The mechanical system model described in Section 3.1 was used to predict the dynamics of the bench-top test unit. The initial value of the beam bending stiffnesses was calculated by taking the product of the modulus of elasticity and the area moment of inertia of each beam.
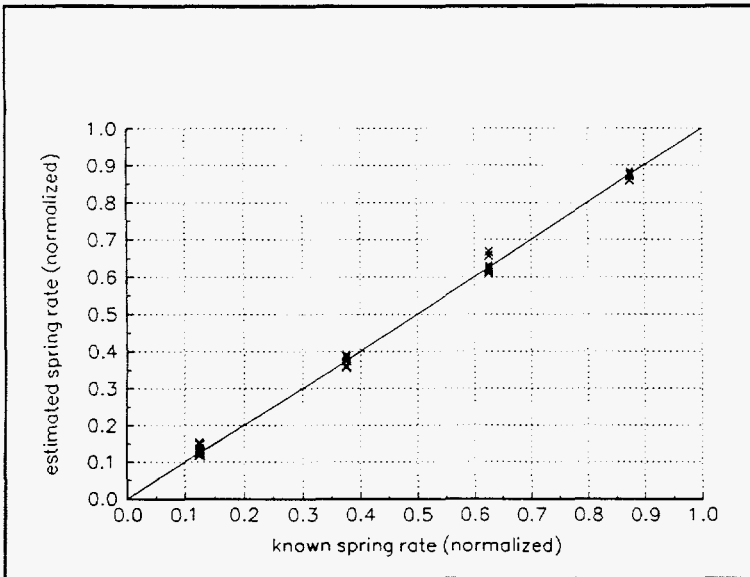
Figure 6. A comparison of the known and estimated spring rates for values of K_{mp} between those used in the training set.

The nominal model parameter values had to be adjusted to obtain satisfactory agreement between the calculated and measured natural frequencies and modes. The mass point values and their locations were held fixed during model tuning because these values are easily and accurately calculated. The beam bending stiffnesses EI was adjusted by trial and error during model tuning. Neglecting to include the rotational inertia at the mass points and the trunnion spring rate of the bearings results in a model that under predicts the stiffness of the bench-top test unit. Thus, the calculated natural frequencies of the flexural modes of the test beam will be lower than the measured natural frequencies. The value of EI was adjusted from it's initial value to a tuned value in which good agreement between the natural frequencies of the flexural modes was obtained. Table 1 lists the measured natural frequencies as well as the natural frequencies calculated by using both the initial and tuned values of EI, K_{mm}, and K_{mp}.
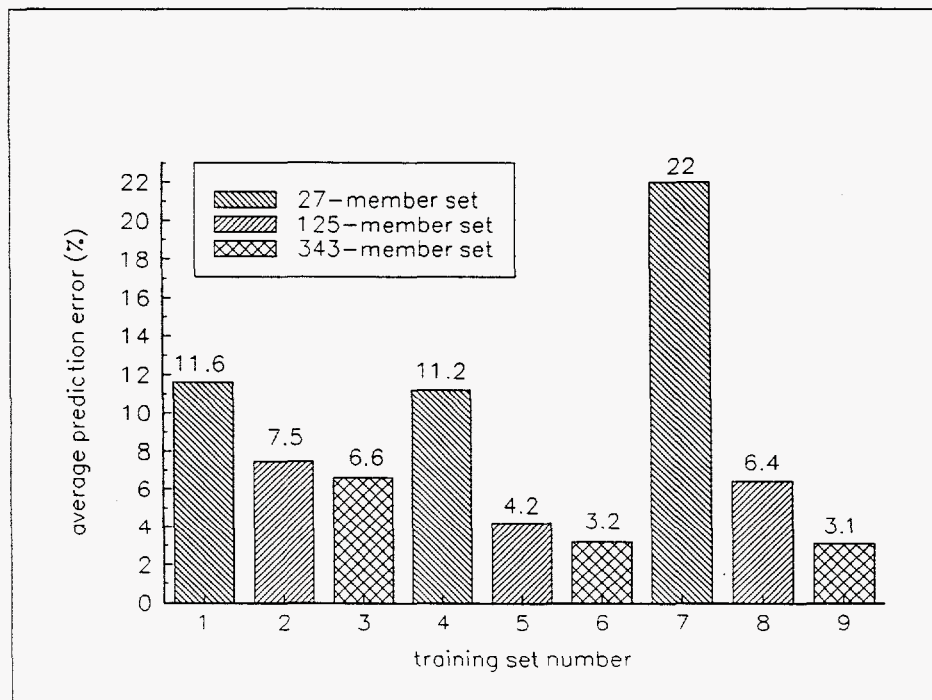

Figure 7. Effect of number of training set entries on neural network estimation accuracy for the three training set types .
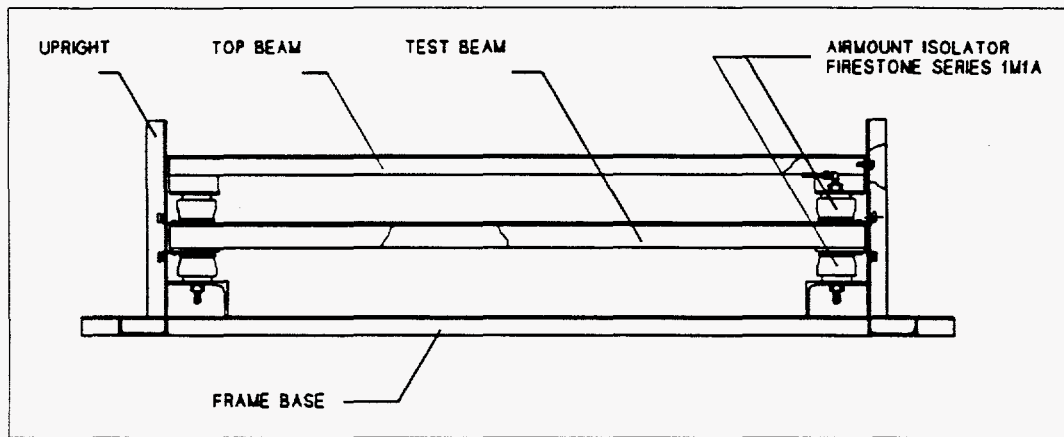
Figure 8. The bench-top test unit.

4.2 Measured data

The data was collected for 36 combinations of air spring pressures ranging from 20 psig to 70 psig in 10 psig increments. For each combination, nine data sets were taken by using a sampling rate of 1000 samples/s and a 1024 sample blocksize. Vibrational modes were excited by impacting the beam on the left and right sides (3 sets each)). Each data set was then Fourier transformed and the auto-power spectral density calculated. The resulting spectrum for each pressure combination is the average of the nine sets of spectra obtained. Natural frequencies corresponding to the first and second rigid body modes were used for diagnostic analysis.

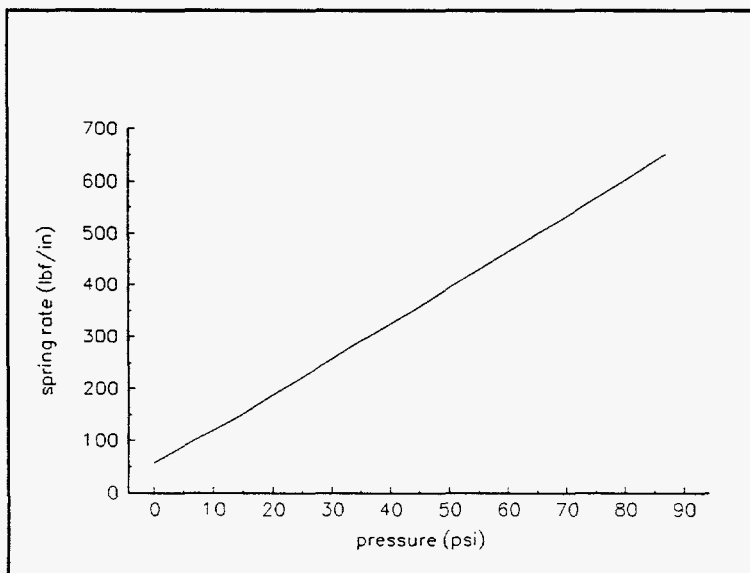## 4.3 Formation of the Training Sets and Training of the Neural Network

Figure 9. Effect of internal pressure on the spring rate of the Firestone 1M1A airspring.

The values of K_{mm} and K_{mp}, contained in the training set were selected so the calculated natural frequencies spanned the range of measured values. Both K_{mm} and K_{mp} ranged from 350 lb$_f$/in to 1200 lb$_f$/in in 50 lb$_f$/in increments. Figure 10 shows a comparison of the measured and calculated frequencies of the first two rigid body modes, calculated by using the values of K_{mm} and K_{mp} in the training set. These results show good, but not perfect, agreement between the measured and calculated natural frequencies. The combination of spring rates used to form the training set resulted in a 972-member training set. The neural network input consisted of the natural frequency and the normalized mode shape components of each end of the test beam for the first two rigid body modes. The neural network output was the values of K_{mm} and K_{mp}.

Table 1
Natural frequencies of the bench-top test unit model

Mode	Tuned (Hz)	Measured (Hz)
First rigid body	18.3	18.5
Second rigid body	25.6	26.0
First test beam flexural	110.4	110.0
Second test beam flexural	251.7	267.0

The neural network for this case required six inputs (two frequencies and two mode shape components per mode). Therefore, for consistency with the previous networks, a single hidden layer of approximately one-half the number of input nodes (i.e. three) was used. Also, as before, the hyperbolic tangent transfer function was used and the cumulative delta learning rule was employed. Best results were obtained for a training total of 70,000 iterations. Figure 11 shows results for the trained network tested with the training set for the two spring rates K_{mm} and K_{mp}. Average errors in this case were 2.04% for K_{mm} and 2.34% for K_{mp} with standard deviations of 1.41% and 1.71% respectively. These results are approximately the same as those obtained during the analysis using computer-simulated data. Note that results obtained for the middle of the output range are somewhat better than those for the high and low extremes.

4.4 Results Obtained from Applying the Diagnostic Method to Measured Data

The 36 sets of experimental results discussed in Section 4.2 were tested by using the network trained from the tuned model of the experimental bench-top unit. Figure 12 shows results for the spring rates K_{mm} and K_{mp}. Average errors are 5.91% for K_{mm} and 10.7% for K_{mp} with standard deviations of 5.30% and 10.1% respectively. It is noted that the K_{mp} values are well grouped but fall beneath the unit line shown in Figure 12; that is, the actual value of the spring rate tends to be larger than the estimated value. It is this difference that accounts for the larger error in K_{mp}. Otherwise, results for the two cases are considered similar. The effects of several sources of uncertainty appear in Figure 12. These include the uncertainties in the mathematical model, uncertainties in the neural network interpolation as discussed previously, and in the data acquisition. Data acquisition errors include difficulty in obtaining a precise pressure reading and some question as to the accuracy of the pressure-to-spring rate conversion equation. This latter concern may explain the increased error in K_{mp}. With these considerations in mind, results in the 5% - 10% range are acceptable.

Figure 13 shows a parametric display of the variation in K_{mm} with K_{mp} held approximately constant. Figure 14 shows a similar display for K_{mp} with K_{mm} approximately constant. In both figures, three plots are shown with the constant parameter at 376, 752, or 1066. These values correspond to pressure values of 20, 40, and 70 psig. These plots show that trends in one of the spring rates can easily be detected. That is, for example, a 10% change in one of the parameters would result in about a 10% change in the estimated value regardless of the initial agreement between the estimated and actual values.
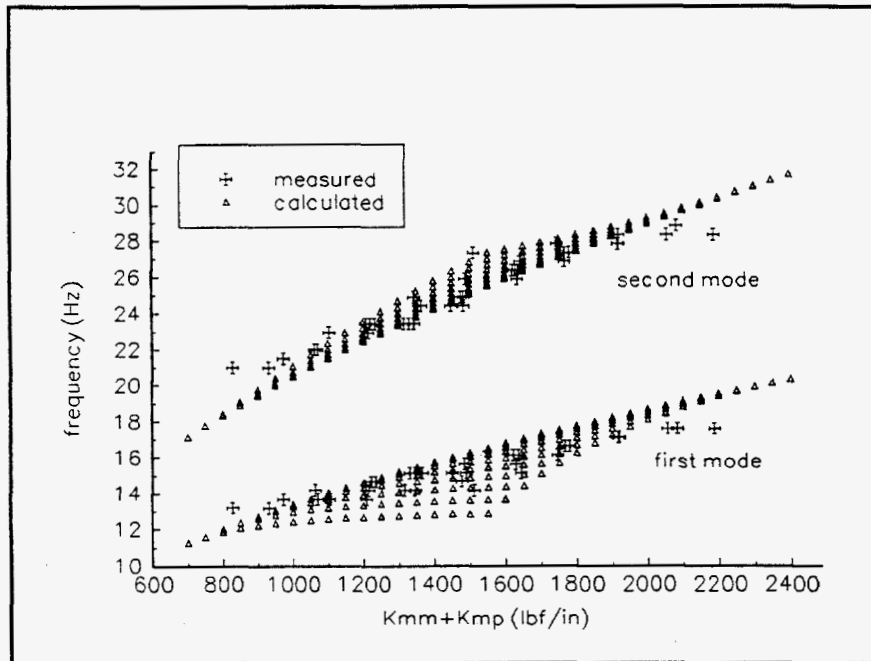
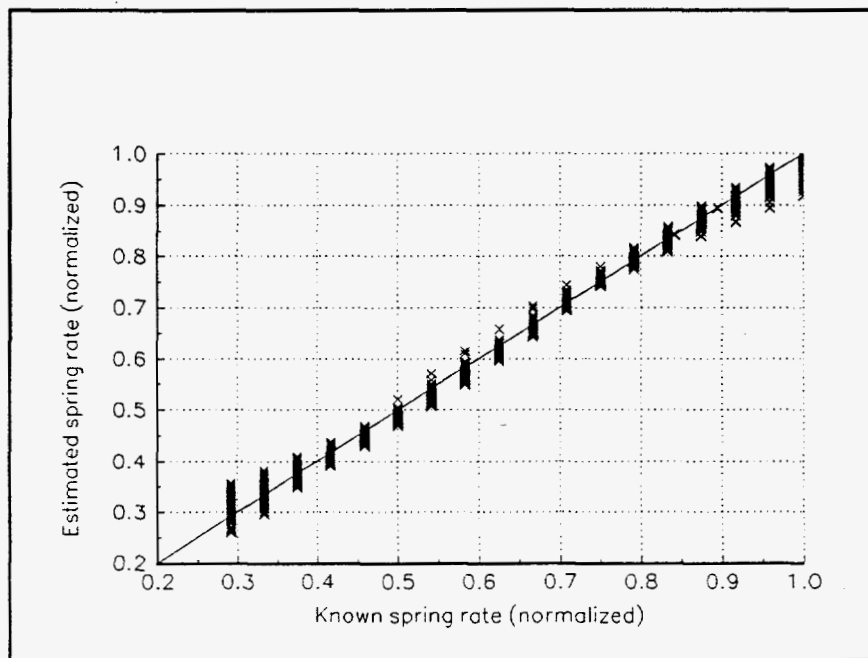**Figure 10. Comparison of the measured and calculated values of natural frequency.**

Figure 11. A comparison of the known and estimated spring rate values for spring rates contained in the training set.
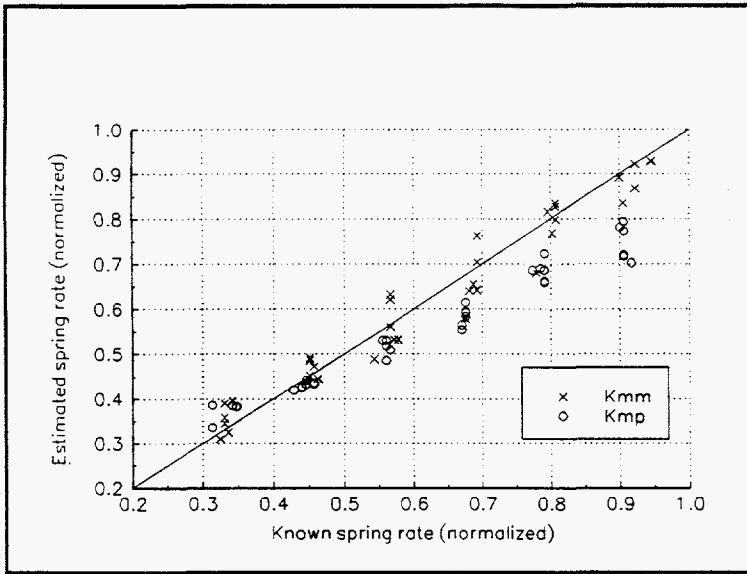
5. SUMMARY AND CONCLUSIONS

Computer simulation results and a demonstration using a bench-top test unit were used to determine that the diagnostic method using frequency spectra to estimate structural parameters 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 by a mathematical model, can be used to estimate the structural condition of the mechanical system using measurements of natural frequencies and mode shape components extracted from vibration spectra. It is concluded that the diagnostic method should be able to be successfully applied to monitor the structural condition of a mechanical system with the following characteristics:

Figure 12. A comparison of the known and estimated spring rate values made by using measured data.

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.

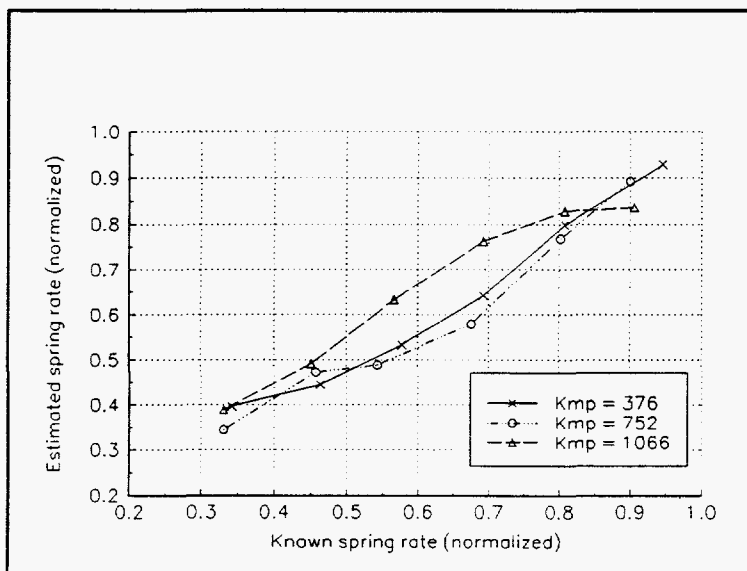2) Changes in the monitored parameters must have a significant effect on the values of the measurable parameters.

Figure 13. Estimated value of K_{mm} calculated while holding the value of K_{mp} fixed.

The simulation results show that the accuracy of the neural network parameter estimation depend heavily on the composition and the "spacing" of the members in 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 7). 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
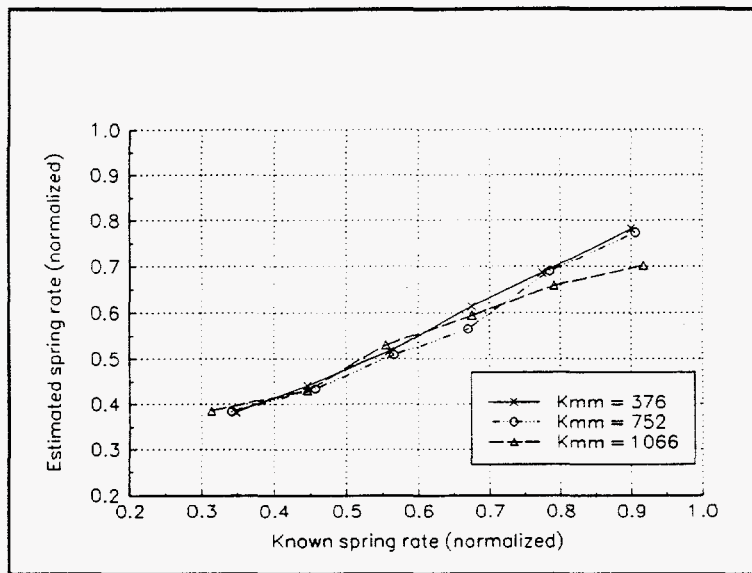
Figure 14. Estimated value of K_{mp} calculated while holding the value of K_{mm} fixed.

values obtained by using these training sets.

Figure 7 also shows that the spacing between members in the training set affects the accuracy of the estimated spring rates. As the number of training set members increases, the spacing between adjacent members decreases because the parameter range remains constant for all training sets. Thus, the 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 diagnostic method.

Finally, the results from the computer simulation, taken together, show that the trained neural network can accurately (to within 3%) solve the inverse problem of determining model parameters from the natural frequencies and mode shape components. The results of the computer simulation indicate that the diagnostic method should be applicable to a real mechanical systems that have a single-valued relationship between the neural network input and output and if the monitored parameters have a significant effect on the measurable quantities.

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 (to within 10%) values of the mounting spring rates. Thus, it is concluded from the demonstration 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, although not specifically investigated, 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 3 and in Figure 11, 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 10, 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 of 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. Thus, it appears that both the system modeling and the measurements must be performed with a considerable level of care if the method is to provide accurate parameter estimates.

Note that this sensitivity to modeling error does not necessarily mean that complicated mathematical models are always needed. The required model complexity will depend on the dynamic characteristics that need to be measured in order 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 4. If, on the other hand, system parameters that affect higher modes, such as shaft flexural 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. The general methodology can be summarized in three steps as follows: 1) form a training set from mathematical simulation results, 2) Train a neural network to estimate model input parameters from model output values, and 3) Use the neural network to monitor the system (simulation model) parameters over time, thus detecting and identifying the source of changes in measured values. 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 presented in this report, 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.

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