Estimation of Wooden Cross-Arm Integrity Using Artificial Neural Networks and Laser Vibrometry

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***Abstract*—A significant problem faced by utility operators is the degradation and failure of wooden cross-arms on transmission line support structures. In this paper, a nondestructive, noncontact, reliable method is proposed, which can quickly and cost-effectively evaluate the structural integrity of these cross-arms. This method utilizes a helicopter-based laser vibrometer to measure vibrations induced in a cross-arm by the helicopter's rotors and engine. An artificial neural network (ANN) then uses these vibration spectra to estimate cross-arm breaking strength. The first type of ANN employed is the feed-forward artificial neural network (FFANN). After proper training, the FFANN can reliably discern healthy cross-arms from those that are in need of replacement based on vibration spectra. Next, a self-organizing map is applied to this same problem, and its advantages are discussed. Finally, a FFANN-based data compression scheme is presented for use as a preprocessor for the vibration spectra.**

***Index Terms*—Data compression, laser measurements, neural networks, nondestructive testing, self-organizing feature maps, transmission lines.**

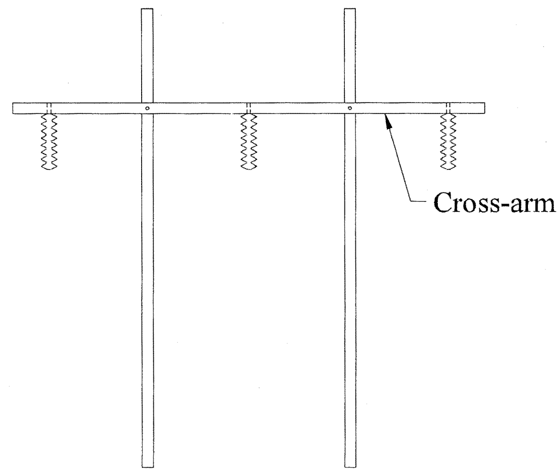

Fig. 1. H-frame transmission line support structure.

I. Introduction

ELECTRIC power is transmitted throughout the world by high voltage transmission lines many of which are suspended by wooden H-frame support structures. Illustrated in Fig. 1, the cross-arm is typically the first part of a support structure to fail. These wooden cross-arms rot, become weak, and eventually break. This type of failure leads to power outages, high repair costs, and is potentially very dangerous.

Utility operators must perform regular inspections of these cross-arms to ensure reliability and safety. Due to the enormous number of cross-arms in service, a method for testing the integrity of these arms should be quick, inexpensive, accurate, and nondestructive. Among the more commonly used inspection techniques is the climbing inspection, which involves climbing the structure, striking the cross-arm with a hammer, and judging the strength of the arm based on the resulting sound. This technique is obviously time consuming and subjective. Another common inspection technique is the visual inspection, which is often performed from a helicopter. This method is also subjective and it only gauges the outside appearance of the wood. Despite these serious shortcomings, these two techniques remain widely used because they are relatively quick, inexpensive, and nondestructive. Therefore, there is a strong need for a more reliable, commercially feasible method for predicting the strength of these wooden cross-arms.

There are alternate evaluation techniques that promise more reliable results. Some of these techniques include: drilling or chipping, stress wave, sonic or ultrasonic, electrical resistivity, infrared, radar, and tomography [1]–[7]. However, all of these techniques are either destructive, require a sensor to make contact with the cross-arm, require a relatively long time to obtain measurement data, and/or only test a local area of the arm—rather than evaluate the entire length of the arm. These disadvantages make the above evaluation techniques either exceedingly costly or too slow to be utilized in applications involving many thousands of transmission support structures. In this paper, a nondestructive, noncontact, reliable, cost-effective method for evaluating the structural integrity of wooden cross-arms is introduced and experimentally validated.

II. Vibration Analysis of Wood

It can be shown that ultrasonic wave velocities are able to indicate changes in structural properties of wood caused by fungal attack [1], [2], [5]. Other studies successfully analyze sonic/ultrasonic pulses or stress wave measurements in the frequency domain in an effort to obtain acoustic signatures of specimens

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and consequentially evaluate integrity [1], [4]. Thus, a reasonable correlation between acoustic wave propagation in wood and structural integrity is established. In this research, it is the acoustically induced vibration of the cross-arm itself that is analyzed and used to predict strength.

When a mechanical bar is excited by acoustical energy, the bar will vibrate. The resulting frequencies of vibration are a function of the bar's length and mass (for a given cross section). Degradation of wood, which is primarily due to fungus (rot), insects, or marine borers, causes a reduction of mass. Therefore, as a sample of wood degrades, its frequencies of vibration should change for a given type of excitation. The method investigated in this research uses broadband acoustical excitation to induce vibration in the cross-arms. The vibration is measured, converted to the frequency domain, and the analysis of the data is performed using artificial neural networks (ANNs) [8].

III. Field Measurements

Due to the often-remote location of most transmission line support structures, the measurement platform is helicopter based. Vibration of the cross-arms is induced by the broadband acoustical energy emitted from the helicopter's rotors and engine. The vibration measurement device is a field hardened, commercially available laser vibrometer with a typical range of only a few feet. In field trials, the helicopter is able to hover approximately 16 ft from the arms; therefore, the laser's range must be extended by one of two methods: 1) application of retro-reflective tape to the cross-arm face producing a range well in excess of 50 ft, 2) physically extending the laser vibrometer from the helicopter via an 18 ft boom. The boom-mounted laser vibrometer option is preferred since placing tape on every cross-arm is not practical in a commercial application.

While the helicopter is in flight, the vibrometer data are acquired, converted to the frequency domain, and stored on a laptop computer. In addition to measuring cross-arm vibration, the data acquisition system also records the GPS (latitude/longitude) coordinates so the spectra can be matched to the proper structure. A typical measurement (vibration and GPS coordinates) requires the helicopter to hover at each structure for only 1 to 2 s.

In January 2000, field trails were conducted near Beaumont, TX. A helicopter and crew, equipped with the laser vibrometer, flew along approximately 10 miles of a 115-kV transmission line, suspended by H-frame support structures. The helicopter paused over each support structure while a visual inspection and vibration measurement were obtained for each cross-arm. At the time, the boom-mounted laser was not ready for deployment; thus, data were acquired with a hand-held laser shooting retro-reflective tape targets, which had been previously placed on each cross-arm.

A. Breaking Strength Measurements

In all, data were collected for 95 cross-arms. Of these 95 arms, 24 were then removed from service or "harvested" for testing. These 24 arms were selected such that their condition ranged from poor to new. Each decommissioned arm was transported to a laboratory and strength tested by anchoring it at the same boltholes that attached the arm to the pole as illustrated in Fig. 2. A cable was attached to the arm at the same points where the two outermost phase wires were attached while a winch slowly pulled the cable until the arm broke. One-half of the maximum force recorded during this process was deemed that arm's breaking strength.

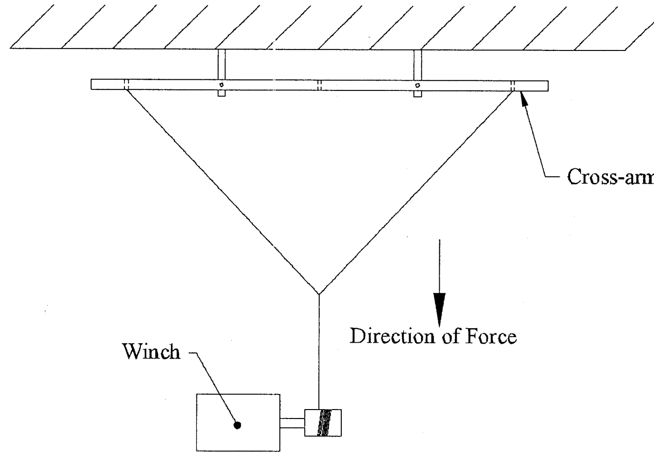

Fig. 2. Method of strength testing each cross-arm.

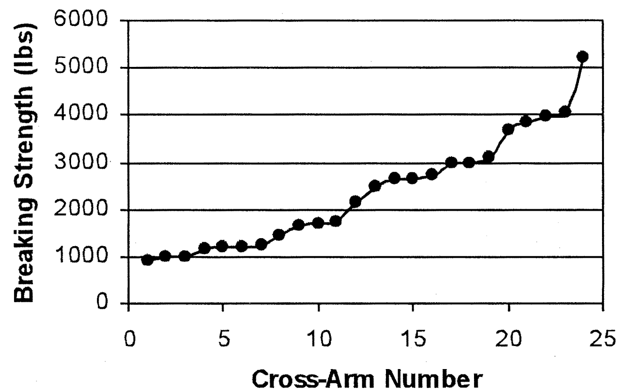

Fig. 3. Distribution of breaking strength among the 24 samples.

The final data set from this field trial is comprised of 95 frequency spectra, 95 visual inspection results, and breaking strength for 24 of the 95 arms. As Fig. 3 illustrates, the distribution in breaking strength among the 24 arms is approximately linear. Notable differences found among the arms include: species of wood, cross-section of arm (round or rectangular), solid or laminated construction, and time in service.

B. Vibration Spectra

The purpose of this research is to estimate the breaking strength of a wooden cross-arm based on its vibration characteristics. Fig. 4(a) shows a portion of the vibration *spectra* of three typical cross-arms excited by a broadband source. From this figure, the need for a tool such as an ANN is obvious: there is no way to visually inspect the spectra and "see" the strength of the cross-arm. The ANNs used in this research perform the best when the natural logarithm operation is applied to the vibration spectra before presentation to the networks. Nevertheless, Fig. 4(b) shows that breaking strength still cannot be "seen" in a visual inspection of this type of spectra either.

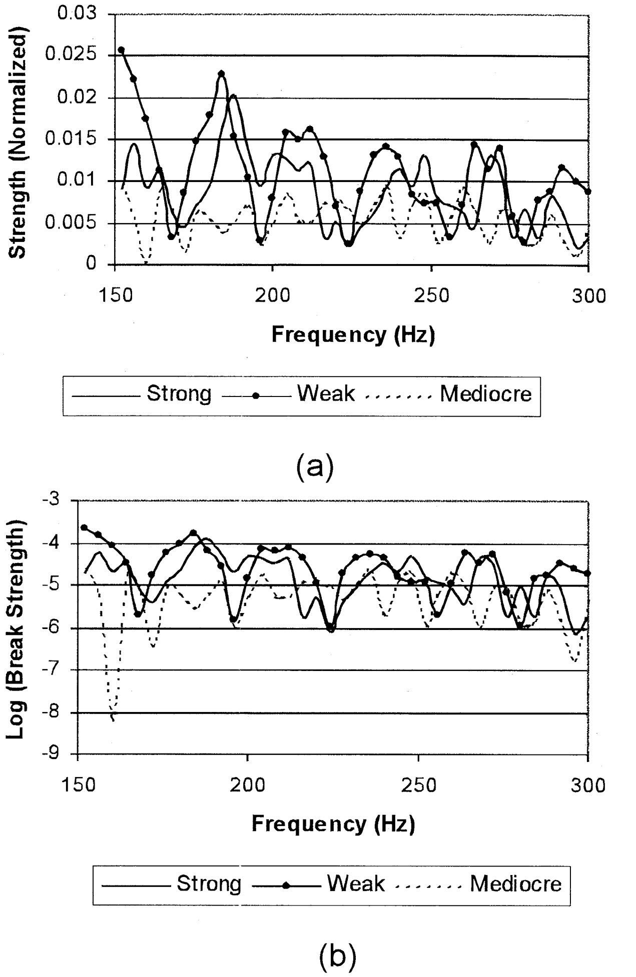

Fig. 4. Typical cross-arm vibration spectra. (a) Normalized breaking strength versus frequency for a strong, weak, and mediocre strength cross-arm. This illustrates the futility in attempting to predict breaking strength based on the visual appearance of a spectrum. (b) The natural logarithm applied to the amplitudes of the three spectra in (a); it is still impossible to "see" the breaking strength from the spectra.

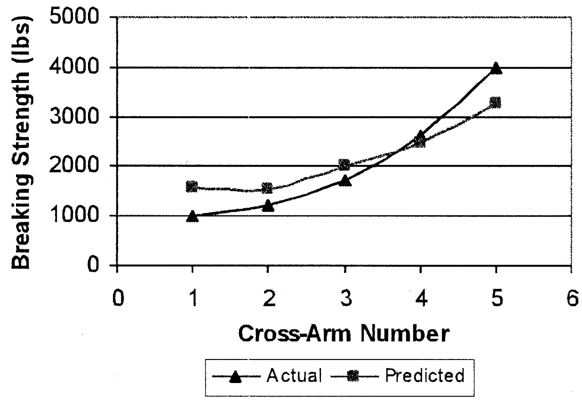

Fig. 5. Topology of the feed forward ANN.

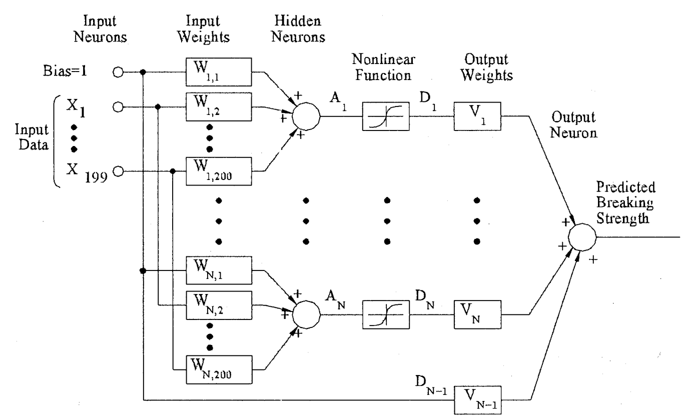

Fig. 6. Typical prediction results for feed forward ANN.

In addition, the manner in which rot affects the vibration of wood and the strength of wood is extremely complex; this makes the derivation of a credible model highly unlikely. These circumstances make this research an ideal application for an ANN, which can learn the complex, nonlinear relationship between breaking strength and spectral content.

IV. Data Analysis Using Feed-Forward Artificial Neural Networks

Feed forward ANNs (FFANNs) operate under the principle of supervised learning, which means that the desired output must be known for all inputs used in training the network. In this application, the inputs are the vibration frequency spectra and the output is the breaking strength. Therefore, only the 24 arms with known breaking strengths are used to train and test the FFANN.

The topology of the FFANN is illustrated in Fig. 5. Since the input vector is a frequency spectrum, the resolution at which the spectra are sampled determines the number of input nodes. Thus, an unfortunate tradeoff exists between spectral resolution and FFANN size. The optimum resolution is experimentally determined, and the spectra are sampled from 0 to 792 Hz in 4-Hz increments requiring 200 input nodes (199 for the spectral magnitudes and 1 for the bias input). Increasing the spectral resolution (e.g., sampling at 2-Hz increments) or including frequencies above 792 Hz, does not improve FFANN performance.

Two preprocessing steps are performed to the data before presentation to the FFANN. First, the breaking strengths and spectral magnitudes are each normalized to have values between 0 and 1. Then, the natural logarithm operation is applied to each spectrum. Once the preprocessing is complete, five arms are set aside and used as a "test set." The arms within the test set are chosen to adequately represent the full range of cross-arm strengths. The remaining 19 arms comprise the "training set." It is important to ensure that the arms in the training set linearly represent all breaking strengths that the FFANN will be expected to characterize. This prevents the network from becoming biased during the learning process.

During the training process, arms are randomly (and exhaustively) selected from the training set of 19 cross-arms, presented to the network, and the network weights are adjusted according to the back-propagation algorithm. Presentation of all 19 arms in the training set completes one epoch, and the FFANN is trained for 10 000 epochs.

Fig. 6 shows a typical set of results when the trained FFANN is used to predict the breaking strength of the five cross-arms in the test set. In these results, the RMS error is only 9%; however, the maximum individual cross-arm error is 58% with the largest errors occurring at either extreme of breaking strength. Varying parameters of the back-propagation algorithm, such as the learning gain or momentum, change the predicted strengths only slightly. To ensure the network is learning and the results are not accidental, the number of samples in the training set is decreased and then increased again. As the number of samples in the training set is decreased, the network performance degrades (and vice/versa). Also, the training and testing sets are rebuilt with different cross-arms, the network is retrained, and similar results are obtained. This is done in an attempt to assure the validity of the results.

These results suggest that the FFANN is able to predict breaking strength based on the vibration spectra. Therefore, a relationship exists between the vibration of a cross-arm and its structural integrity. Certainly, a larger data set must be obtained to improve the prediction accuracy and ensure the robustness of this method. At this point in the research, the minimum number of cross-arms required to achieve a level of performance suitable for commercial use is still under investigation.

Although these results obtained with the FFANN topology are encouraging, this approach has two main disadvantages. In addition to removing weak arms from service, equally large numbers of mediocre and new arms must also be removed and broken to construct the training sets. The cost associated with removing new arms from service detracts slightly from the economic feasibility that would make this new method promising in widespread commercial use. Second, only the arms with breaking strength data can be used for training. Therefore, all of the arms with valid spectra but without breaking strength (the majority of the data set) are of no use for the training process of a FFANN. For these reasons, the use of the self-organizing map (SOM) is investigated in the next section.

V. Data Analysis Using the SOM

The SOM is an ANN that falls under the category of unsupervised learning because it is trained with unclassified data (i.e., the breaking strength is not needed for training). The SOM simply groups or "clusters" the N-dimensional input data within a two-dimensional (2-D) output space (Kohonen layer) according to statistical properties of the input data. Fig. 7 depicts the basic topology of the SOM where the number of neurons in the Kohonen layer is varied to optimize clustering accuracy. In this approach, the frequency spectra are again used as the input data. Since no breaking strength data are required, all 95 cross-arm spectra can now be used to train the SOM.

A. Training the SOM With Frequency Data

Training a SOM is fundamentally different from training a FFANN. When an input vector (frequency spectrum) is presented to the SOM a "winning neuron" is found by determining which Kohonen layer neuron's connection weights most closely match the input vector. Then the weights of that neuron are adjusted to make them even closer to the input vector. Typically,

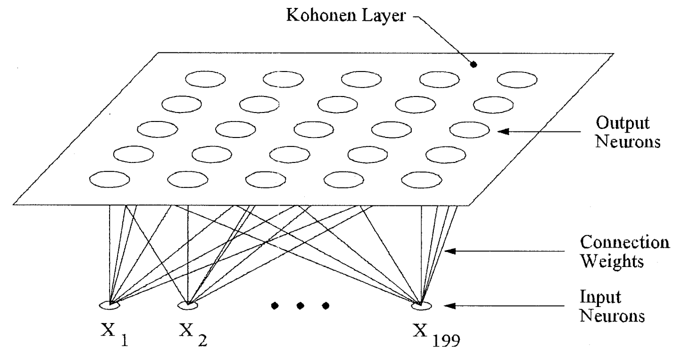

Fig. 7. Topology of the self-organizing map.

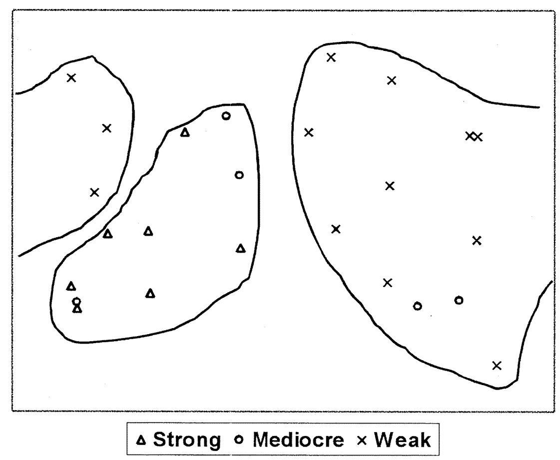

Fig. 8. Results of SOM trained on frequency spectra.

not only are the weights of the winning neuron adjusted but the weights of neurons in the neighborhood of the winner are also adjusted. A "neighborhood function" is defined that causes the weight changes to decrease as the distance from the winning neuron increases. It is this neighborhood function that causes the topological grouping or clustering found in the Kohonen layer [9].

Once the network is trained with the vibration spectra of all 95 arms, the connection weights are frozen and the clusters must be identified. A cross-arm with known breaking strength is then presented to the SOM. The winning neuron is found, marked, and the process repeated for all 24 arms with known strengths. For a correctly trained network, the "strong" arms will form one cluster in the Kohonen layer, and the "weak" arms will form another cluster. Fig. 8 shows the winning neurons in a 5 by 5 Kohonen layer after all 24 arms with known strengths are presented. In this figure, "weak" arms have breaking strengths less than 1700 lbs. while "strong" arms have strengths greater than 3100 lbs. It is important to note that in this research, the SOM is trained using "wrap around" in the Kohonen layer. This means the Kohonen layer in Fig. 8 can be visualized as the surface of a sphere that has been unfolded onto a flat surface. Consequentially, the results in Fig. 8 depict only two clusters (indicated by the dotted lines). The cluster in the middle of the Kohonen layer is comprised of strong and mediocre arms (triangles and circles), and the cluster that wraps around the sides of the Kohonen layer is comprised of mediocre and weak arms (circles and Xs).

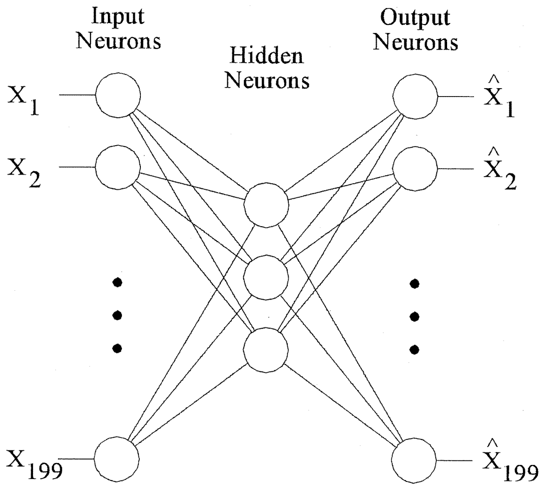

Fig. 9. Typical auto-associative FFANN used for data compression.

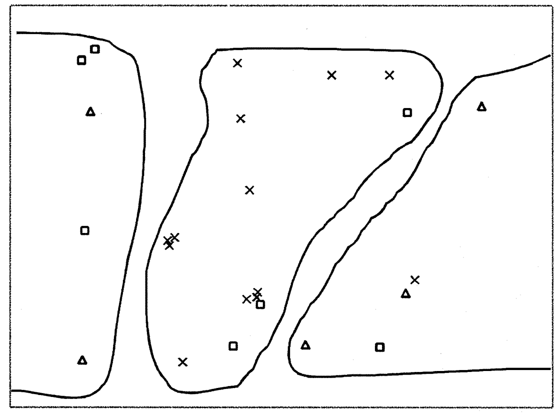

Fig. 10. Results of SOM trained on compressed frequency data.

Normally, tightly grouped, clearly defined clusters would be expected; however, due to the small data set, the clusters obtained are not grouped as tightly as would be preferred.

Presentation of arms with known strengths is only to identify the location of the clusters. Once the clusters are located, the remaining 71 arms with unknown strengths can be presented and their structural integrity estimated by observing where each arm falls on the map.

While the results in Fig. 8 suggest the SOM clustering is favorable, presentation of the arms with unknown strengths reveals that not all of these arms fall nicely within the outlined clusters. This is most likely caused by one or both of the following: 1) there are not enough arms with known strengths to properly identify the clusters, 2) there is not enough training data to properly form the clusters. To alleviate the first problem, more field trials must be completed. While waiting to complete more field measurements, a resolution for the second problem is attempted by reducing the number of required training vectors. One way this can be accomplished is by reducing the number of weights that must be trained in the SOM. Compression of the input vectors (spectra) from 199 points to a smaller dimensionality significantly reduces the number of weights in the network.

B. Training the SOM With Compressed Frequency Data

While control of the number of neurons in the Kohonen layer must be reserved to optimize clustering accuracy, compressing the input data can drastically reduce the number of input neurons. This will lead to a significant reduction in the overall size (number of weights) of the SOM. A FFANN arranged in the basic auto-associative configuration of Fig. 9 is used to achieve this data compression. The network has 199 input neurons and 199 output neurons, and the number of hidden neurons is varied to achieve the desired compression.

Each normalized vibration spectrum is presented as the input vector as well as the vector of desired values. In this data compression scheme, the output vector of estimated values produced by the network should be identical to the input vector. However, the information in the input vector is compressed as it passes through the network (e.g., from 199 in the input to 20 in the hidden layer and then expanded back to 199 at the output). Therefore, the values produced at the output are only approximations of the values presented at the input, and the difference is the training error. This error is used along with the back-propagation algorithm to train the network. Once adequate convergence is attained, the weights are frozen and the output layer is deleted. Then each frequency spectrum is again presented, and the output of the hidden layer (which is now the new output layer) is taken as the compressed form of that spectrum. Fig. 10 shows the clustering in a 5 by 5 Kohonen layer of a SOM trained on spectra that have been compressed down to a dimensionality of 20.

The results presented in Fig. 10 using data compression are encouraging. Compared to the results of Fig. 8, the SOM trained with compressed data performs almost as well, and it does so with a ten times reduction in the number of neurons. With a decrease in network complexity comes an increase in performance due to shorter training and testing times.

In general, the results achieved through the use of the SOM are not as impressive as the performance of the FFANN. Since a SOM is learning in an unsupervised fashion, it typically requires more training data than a FFANN in the same application. Therefore, it is not expected that the SOM will perform as well as the FFANN given the size of the data set presented in this paper. However, continued experimentation with the SOM in this application is important for the significant advantages it poses when used in widespread commercial deployment.

VI. Future Research

Thus far, this research is demonstrating some exciting possibilities in the realm of nondestructive, noncontact evaluation of wooden cross-arms. However, as is common in most applications of ANNs, much more data are needed. While this technique remains in the prototype phase of development, early results show that the concept is valid. More field trials are planned and their completion will greatly expand the training base and move this research closer to commercial deployment.

VII. Conclusions

The purpose of this research is to demonstrate that laser vibrometry and ANNs can be combined to form a reliable, commercially viable method for estimating the structural integrity of wooden cross-arms. Based on results achieved from the data collected to date, the following conclusions are made.

1) There is a correlation between the breaking strength and frequency spectrum of a wooden cross-arm excited by broadband acoustical energy.
2) Wooden cross-arm can be successfully categorized according to breaking strength by ANNs—provided adequate size and distribution of training data.
3) Nondestructive, noncontact measurements can be obtained in a reliable, cost-effective manner from a helicopter mounted, laser vibrometer-based measurement platform.
4) The system for acquiring these cross-arm spectra can be constructed entirely from commercially available, "off-the-shelf" hardware.

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