# Hybrid Artificial Intelligence Approach to Continuous Bridge Monitoring

DAVID MARTINELLI, SAMIR N. SHOUKRY, AND S. T. VARADARAJAN

A framework for an intelligent fusion of outputs from a combination of the state of the art nondestructive testing techniques of highway bridges and parking garages is described. A hybrid artificial intelligence system that automates the decision-making process is employed for the examination of the results obtained from various nondestructive testing methods. Neural networks, fuzzy logic, as well as other computational paradigms are employed for a preliminary pattern recognition and sensor data reduction from individual nondestructive testing techniques. An expert system is used for providing a user interface, selecting alternative paradigms for data analysis guided by the user input, as well as the information obtained from the system's knowledge base. The final decision-making process is performed via the expert system through the interpretation of the numerical results based on heuristic and knowledge-based reasoning. The system is divided into many independent modules that interact with each other. Any of the modules can be individually modified, retrained or replaced altogether without affecting any of the other modules.

The U.S. Department of Transportation classifies more than 40% of the U.S. bridges as structurally inefficient or functionally obsolete. Therefore, minimization if not prevention of bridge deterioration is a critically important task in avoiding unsafe conditions and in reducing repair cost. Recent attempts on bridge maintenance and rehabilitation are shifting toward early diagnosis and repair of flaws in bridges using nondestructive testing (NDT) techniques. The emphasis is to have a continuous bridge monitoring system in order to obtain quantitative information from in situ measurements (*1*) and use reliable data analysis techniques to arrive at rational and objective maintenance decisions.

NDT techniques have become an integral part of continuous bridge monitoring systems. NDT techniques such as ultrasonics, acoustic emission, ground penetrating radar, impact-echo, and infrared thermography are being increasingly used, and often a combination of various NDT methods is necessary for a complete and effective monitoring system (*2*). Each NDT technique has its own advantages and limitations, especially when used to detect defects in concrete (*3*). Ultrasonic testing of concrete is characterized by the inevitable presence of secondary reflections due to the heterogeneous nature of concrete. Acoustic emission (AE) signals are often contaminated with extraneous noise that makes interpretation extremely difficult and may mask the emission from the defect. Impact-echo is a point testing technique in the sense that its capability to detect a vertical crack or a crack which does not fall exactly below the sensor location is limited. Although radar is capable of testing large areas in a short time, radar signals suffer from multiple reflections and scatters which arise because of the presence of rebars close to the defects. In addition, possible variations in material properties and thickness of the asphalt overlay complicates the process of signal interpretation. The results obtained using infrared thermography are affected by the presence of oil on the road surface. In addition, the depth of an internal void or crack cannot be evaluated. Both radar and thermography results are also influenced by the environmental conditions. It can be observed that data collection and analysis techniques that allow the simultaneous use of information from two or more NDT techniques would be very useful in effective bridge monitoring.

Extraction of useful information from data obtained by the use of NDT techniques requires complex signal analysis and interpretation. The data from the sensors are often obscure and noise prone. Artificial intelligence (AI) techniques such as artificial neural networks (ANN) and expert systems are very useful in pattern recognition, classification, and qualitative interpretation of data obtained from NDT methods. In addition, they also help in synthesizing facts and heuristic knowledge to provide useful tools for problem solving and decision making.

In this study, we propose a hybrid AI system that automates analysis and interpretation of data from different NDT techniques. Neural networks and other computational paradigms are used for complex numerical pattern recognition and data classification tasks. An expert system is used for providing a user interface, selecting alternative paradigms for data analysis [guided by a knowledge base (KB) and the user input], and interpretation of the numerical results based on heuristic and knowledge-based reasoning. The system is divided into many independent modules that interact with each other; these modules can be modified or new modules added without affecting the rest of the system.

## NEURAL NETS VERSUS KB SYSTEMS

Neural networks offer a high potential alternative to the traditional data processing and interpretation techniques. Neural networks are useful for mapping problems which are tolerant of high error rates and for problems to which mathematical relationships cannot be easily derived. Most often this is the case with sensor data obtained from bridges using NDT techniques which are affected to a great degree by environmental conditions such as weather and traffic. In most of the cases there are no mathematical relationships that relate NDT data to physical parameters, and therefore a data analyst normally uses some type of empirical modeling with neural networks or other paradigms. The ability to learn from ambiguous or contradictory information is also another important advantage of using neural networks in processing data obtained from NDT techniques.

D. Martinelli and S. T. Varadarajan, Department of Civil and Environmental Engineering, West Virginia University, Engineering Sciences Bldg., Room 651, P.O. Box 6103, Morgantown, W.Va. 26505-6103. S. N. Shoukry, Department of Mechanical and Aerospace Engineering, West Virginia University, Engineering Sciences Bldg., Room 505, P.O. Box 6106, Morgantown, W.Va. 26505-6106.

In addition, neural networks have great potential for parallelism since the computations of each component are independent of each other. The inherent parallelism allows rapid parallel search and best-match computations. Therefore, much of the computational overhead can be alleviated when applying the new techniques to data interpretation problems. However, a neural network requires a large number of example data from which it can learn and generalize.

In contrast to neural networks, rule-based expert systems use a symbolic computational approach to encoding intelligence. A rule-based system consists of three key parts: an inference engine, a knowledge base, and a collection of known facts and knowledge about the problem to be solved. Rule-based systems are useful when expert knowledge is available and when there is a need for an interactive system that provides explanation for answers and decisions made.

## HYBRID SYSTEMS

A hybrid system, which is a combination of expert systems and neural networks, has the capabilities of both systems while minimizing the problems of each (*4, 5*). Rule-based systems alone cannot always handle large applications requiring complex numerical computations, such as the Continuous Bridge Monitoring system. Their reasoning is not adaptive and their performance does not increase with experience. In addition, they sometimes require too much human input and long experience development. But these hurdles can be overcome by coupling knowledge-based systems with complementary AI approaches like neural networks. Thus, by combining two complementary systems we can obtain effective and complete solutions to difficult problems. Hybrid systems can enhance performance as follows:

1. Neural networks provide pattern-recognition functionality and KBs perform analysis and interpretation of data.
2. Hybrid systems improve user-system interaction by explaining to users how a neural network arrived at a solution to a problem. This is a result of the ability to store within the KB, system data related to environment, traffic load, design properties, maintenance history, and so forth.
3. The rule-based systems can help train neural networks by providing intelligence to create the training and test sets. An important step in training neural nets, is a decision on the type of signal preprocessing applied to the row signal before it can be effectively used for training a neural net. A large number of signal processing approaches are available. Based on the accumulated knowledge regarding the performance of different preprocessing techniques and the achieved consistency of the correct recognition rate of the neural network, the system may suggest a retraining of the network or the use of a particular preprocessing technique for a specific application.
4. The neural network can develop implicit knowledge that supplements the knowledge-based system's explicit rule-based knowledge.

## HYBRID SYSTEM ARCHITECTURE

The hybrid system architecture, shown in Figure 1, was developed as a part of the research undertaken at West Virginia University to develop a continuous bridge-monitoring system. One of the objectives of this research is to develop and implement a system for interpretation and synthesis of acquired NDT data toward the development of an effective system for bridge management. The work was divided into two primary research components:

1. Interpretation and synthesis of acquired sensory data.
2. Integration of NDT data with field conditions (e.g., traffic and weather) and maintenance and repair policies.

The acquisition of accurate information about the physical characteristics of materials and the condition state of the structural members is key to maintenance and repair of bridges. The NDT techniques are sensitive to normal variations in environmental and traffic conditions. Therefore, the use of multiple NDT techniques will enhance the reliability of information obtained and result in a more comprehensive assessment of the state of bridge elements. For example, traffic activities on a bridge may obscure the signal obtained from AE sensors, whereas ground penetrating radar used for crack detection in bridge decks under the same condition could provide more reliable information. Thus, the architecture of the proposed Hybrid AI System is guided by the following considerations:

1. The system is to be interactive with the user being able to decide the course and progress of data analysis.
2. The system is to be equipped with the capability of pattern recognition, and computational and numerical tasks that an expert system alone cannot perform.
3. The system should incorporate methods for integrating context dependent data like temperature, humidity, traffic condition, and so forth, in order to provide a robust and comprehensive method of data analysis and interpretation.
4. The determination of the critical physical parameters of the structural elements of the bridge is to be done based on data acquired from different NDT techniques.
5. Based on the physical conditions of different bridge elements, a safety factor for the members and for the whole bridge is to be developed. Using heuristic and expert knowledge guided by maintenance and repair policies, suitable maintenance and repair priorities and decision alternatives are to be made available to the user.

An overall view of the hybrid system architecture with the main functional modules is shown in Figure 1. The sensor data from different NDT methods serve as inputs to the data analysis and preprocessing module. Environmental data such as temperature and humidity are also measured simultaneously and stored so that their effects can be considered during preprocessing of the sensor data. The expert system data analysis and interpretation module performs data interpretation using the numerical results obtained from the AI-based preprocessor module. It also predicts the condition state and feasible action based on the interpreted results and the database that provides information about the facility that is being inspected for defects.

## DATA ANALYSIS AND PREPROCESSING MODULE

This module shown in Figure 2, consists of various routines which perform specific tasks in processing NDT data that has been acquired and stored. An ANN that performs classification or pattern

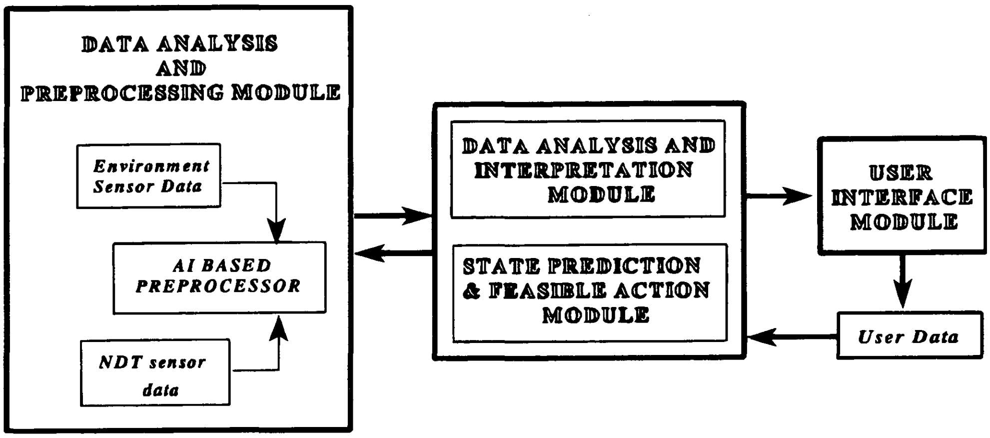


**FIGURE 1 Hybrid system overview.**

recognition of data obtained using a particular NDT technique, may be one of those routines. Other methods of analysis such as time or frequency domain techniques, fuzzy sets, and so forth, may also be used. The use of neural nets to interpret NDT signals provide a better alternative to the expert system approach. A neural network would perform pattern recognition of signals much more easily and more efficiently than an expert system. The expert system requires the formulation of a set of questions that are applied to a pattern, and a set of rules in order to work out answers to questions (*6*). There is enormous difficulty in both the formation of the questions and the rules. Moreover, provided that such problems are successfully solved, the resulting system might not be flexible to changes as new data and information become available. Neural nets not only can be retrained easily; but also retraining could be embodied in their structures. A brief description of each of the preprocessing modules is described below.

### Acoustic Emission (AE)

An ANN network that uses a back propagation algorithm was employed in processing the AE parameters (*7*). It gives estimates of fracture parameters such as the stress intensity factor from which the presence, strength, and intensity of active cracks can be determined. The network architecture is shown in Figure 3. It is trained with AE signal sample wave forms acquired by conducting fatigue and bending tests on steel beams. The AE parameters of interest are the amplitude distribution, energy rate, event rate, deviation, ringdown counts, and rise time. The network is trained to detect signals that result from active propagation of cracks by differentiating it from the noise that is present in the signal.

### Ground Penetrating Radar (GPR)

An algorithmic radar signal processing scheme (*8*) was used to interpret data obtained from simulated concrete blocks. The specimens consisted of a set of 15 laboratory-cast concrete bridge deck specimens with and without different types of internal defects (internal cracks) and with and without reinforcement.

The data obtained from the above set of specimens were used to develop a neural network for the interpretation of radar signals (*9*). The data obtained from only 11 specimens were used to train a learning vector quantization neural network. The data from the remaining four specimens were used to test the recognition performance of the trained network. The test set consisted of specimens with and without defects. The trained network was able to correctly classify three out of the four test specimens. This level of recognition was considered satisfactory in view of the small number of examples (*11*) used for training the network.

### Ultrasonic and Impact-Echo

A considerable potential for the application of various AI techniques exists in ultrasonic or impact-echo testing. A neural net which automates the signal interpretation from impact-echo tests has been developed (*10*). The network receives the normalized spectrum of the time domain signal as an input. The output is the depth of the crack whenever one exists.

Ultrasonic testing is a knowledge-based activity highly dependent on the expertise of the testing personnel. The inspection process includes the selection of an appropriate testing method, testing procedures, and the interpretation of the measured response for the detection of internal defect and/or material deterioration. The correct choice of testing arrangement, procedures, and the interpretation of the received signal requires a high level of expertise. A rule-based expert system was used (*11*) to answer the following questions:

"Which ultrasonic testing arrangement is most suitable?" and

"What are the most appropriate testing procedures?"

Fuzzy sets have been applied for the evaluation of concrete quality using a set of measured ultrasonic parameters. The pulse velocity, attenuation, and main frequency of the reflected ultrasonic signal were modeled using fuzzy mathematics and multivariate mathematical statistics were employed in determining the concrete strength or flow estimation (*12*).

The mechanism of ultrasonic wave propagation in concrete is very complicated and the ultrasonic reflections are a mixture of coupled responses from longitudinal, shear, and surface waves. The received signal amplitude is also dependent on the amount of coupling between the ultrasonic transducers and the surface of concrete. This makes the signal interpretation, in either time or frequency domain, highly difficult and it would appear plausible to employ

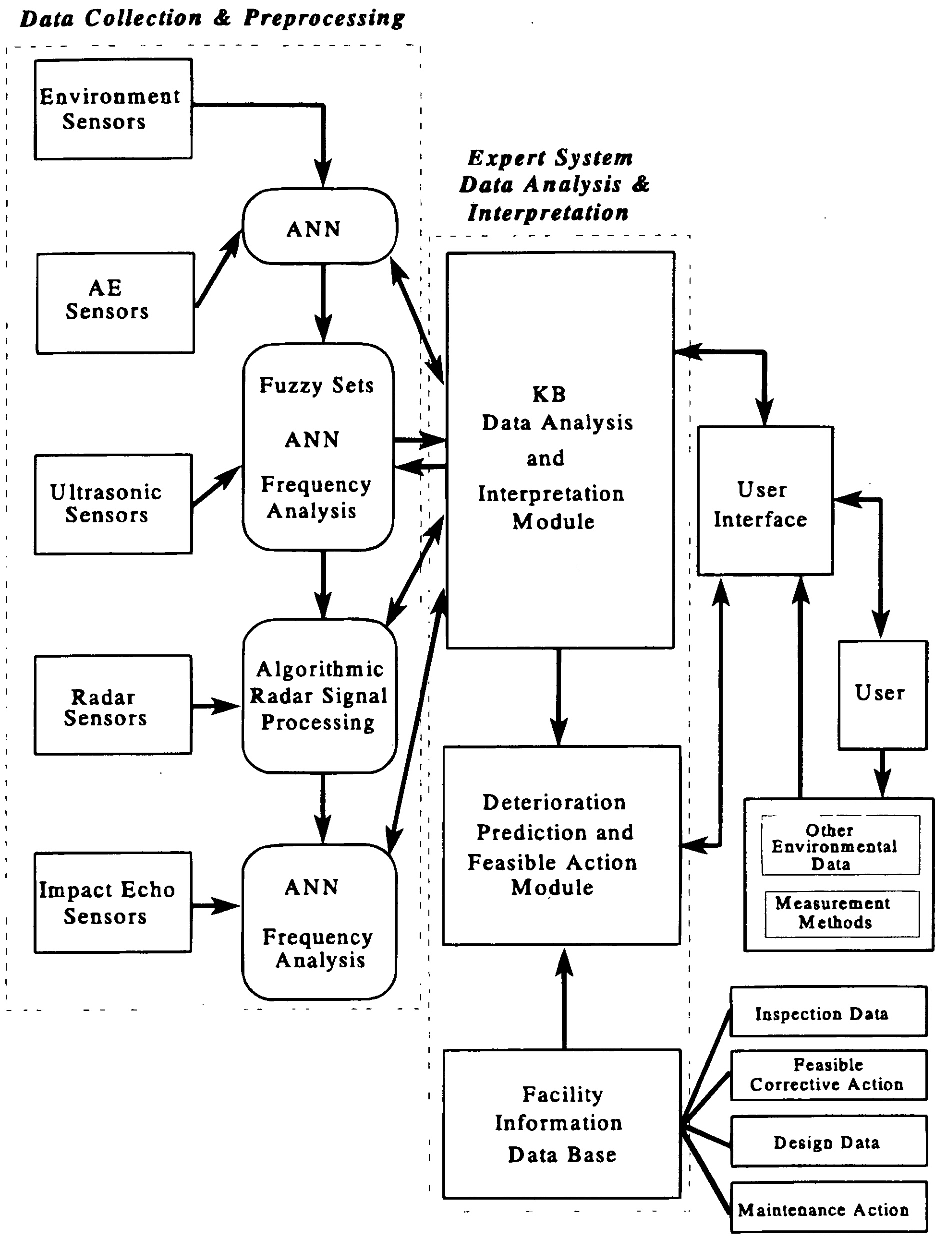


**FIGURE 2 Hybrid system components.**

neural nets for the interpretation process. A backpropagation neural net for the interpretation of ultrasonic signals obtained from simulated concrete bridge deck specimens has been developed (S. N. Shoukry and D. Martinelli, unpublished work). In this work the same set of 15 concrete specimens used in radar testing was again tested using the ultrasonic pitch and catch method (both the ultrasonic transmitter and receiver are laid on the same side of the specimen). Two 125 kHz transducers, each 2.5 cm in diameter, were used. Nine measurements were taken from each specimen at different distances of separations between the transmitter and receiver. The time domain signals were processed using time dependent Fourier transformation before presentation to the network. After training the network using data from only 11 specimens, it was presented with 9 measurements obtained from a single new specimen that was not used in training. The network was able to correctly classify at least 7 out of the 9 signals obtained from any of the 4 specimens used as test sets. The best performing network architecture consisted of 125 nodes in the input layer, 30 nodes at the hidden layer and 2 nodes for the output layer. The network results were interpreted as 100 percent correct recognition rate, because it was successful in correctly classifying a majority (7 out of 9) of the signals obtained for any concrete specimen within the test set.

## DATA ANALYSIS AND INTERPRETATION MODULE

This module uses embedded hybrid system architecture. It is a rule-based system that uses a trained neural network or an algorithmic

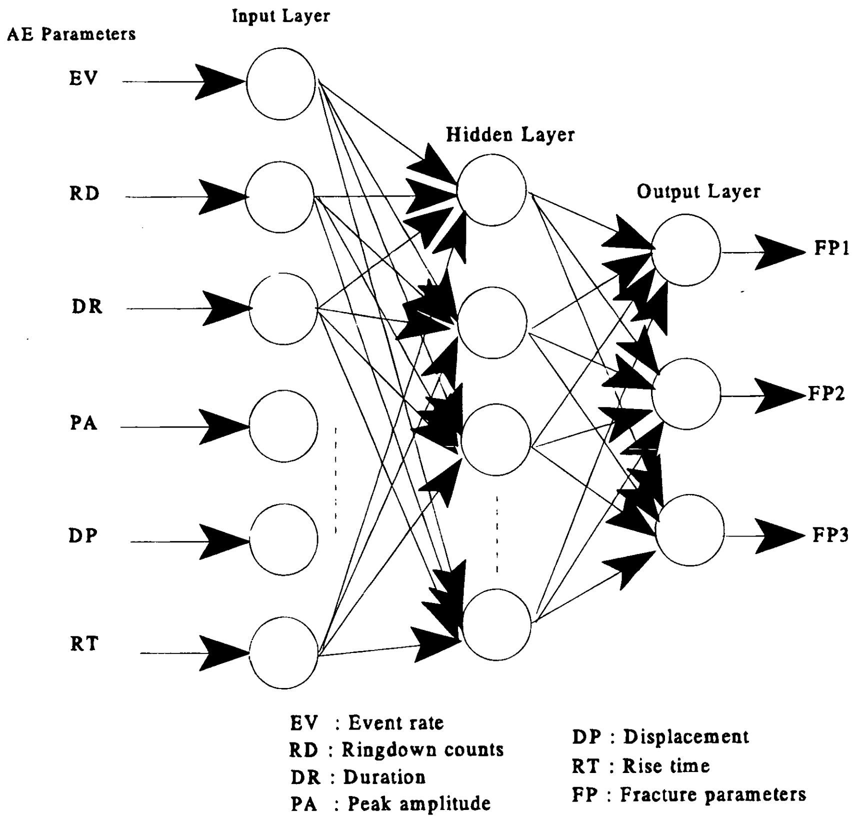


**FIGURE 3 Architecture of neural network for AE analysis. EV, event rate; RD, ring-down counts; DP, displacement; DR, duration; RT, rise time; PA, peak amplitude; FP, fracture parameters.**

signal processing routine as a subroutine to the "THEN" clause of some rules. The network is called to perform some specific action whenever the rule fires. The action can be a classification, a pattern matching or a regression fit of the data. The network passes the response back to the rule-based system. This module also makes corrections to the quantitative results based on the measurement environment information provided by the user and also attaches degrees of uncertainty to the results depending on the NDT technique that was used to acquire the data and the environmental condition during the acquisition of the data in the field. If conflicting results arise from different NDT techniques, this module would be responsible for their resolution. It provides reasoning for why such a conflict has occurred. The output is quantitative in terms of the location coordinates, size, and type of defect.

## STATE PREDICTION AND FEASIBLE ACTION MODULE

This module defines the possible conditions for each unit of the bridge based on the synthesized results and interpretations obtained from the Data Analysis and Interpretation module. Although arriving at this conclusion, the uncertainties attached to the predicted physical parameters are taken into account. Based on the expert knowledge and heuristic reasoning, the degree of safety for each bridge element is determined and the remaining life is predicted. Based on the critical nature of the bridge elements and the condition that they are in, a degree of safety for the bridge as a whole is also determined. All of these results are conveyed to the user, thus the Interface module. Based on maintenance and repair policies, a feasibility action for timely repair and maintenance of the bridge is suggested.

## USER INTERFACE MODULE

The User Interface module is a rule-based expert system shell that guides the user through a session of qualitative reasoning and condition state assessment of the bridge components and the bridge for which data was collected. Continuous bridge monitoring involves periodic assessment of bridge condition over fixed intervals. The data for different critical bridge elements, as chosen by the inspector, is stored in a specific file format corresponding to the NDT technique used. These data are later used by the data-processing routines which are invoked by the Data Analysis and Interpretation module. The interface module provides the flexibility to the user to request for the condition state assessment for only certain bridge components and not necessarily for the bridge as a whole. This module also provides the user with a convenient way to input data related to measurement methods and measurement conditions. It also performs consistency checks on the user input data. The other important function of this module is to present the results of the computation and heuristic reasoning of the other modules to the user in an understandable form, and provide explanations for the results and conclusions when queried by the user.

## CONCLUSIONS

A comprehensive and effective system for continuous bridge monitoring involves several tasks ranging from computational, heuristic, qualitative, and quantitative analysis. Moreover, the interpretation and synthesis of acquired data from multiple NDT techniques involve complex signal processing that cannot be done in only one way. The expert system alone lacks the capability of supporting computation and performing pattern recognition and classification tasks. This limitation is overcome in the hybrid system by providing an environment that supports a combined numerical and symbolic processing. Relative weighing of different sources of information from different NDT techniques helps in obtaining an accurate prediction of the state and remaining life of bridge structures. This information is integrated with the context information such as temperature, moisture, and traffic conditions that are provided by the user to make more reliable predictions. Periodic acquisition and analysis of data using the proposed hybrid system will enable the bridge engineer to know the maintenance and repair priorities well in advance, undertake timely repair that will prevent bridges from being in an unsafe condition, and reduce the cost of repairs undertaken.

## ACKNOWLEDGMENT

The authors acknowledge the financial support received from FHWA.

## REFERENCES

1. Maser, K. R. Automated Interpretation of Sensor Data for Evaluating In-Situ Conditions. *ASCE Journal of Computing in Civil Engineering*, Vol. 2, No. 3, 1988, pp. 215–238.
2. Manning, D. G., and F. B. Halt. Development of Deck Assessment by Radar and Thermography. In *Transportation Research Record 1083*, TRB, National Research Council, Washington, D.C., 1987, pp. 13–20.
3. Malhotra, V. A., and N. J. Carino. *CRC Handbook on Nondestructive Testing of Concrete*. CRC Press, Boca Raton, Fla., 1990.
4. Cardill, M. Expert Networks. *BYTE Magazine*, Vol.16, No. 10, Oct. 1991, pp. 108–116.
5. Martinelli, D. R., and U. B. Halabe. Bridge Monitoring through Sensor Data Synthesis and Interpretation. Presented at ASCE Specialty Conference on Infrastructure Management and Planning, Jun. 1993, pp. 61–65.
6. Roddis, W. M. K., and J. L. Martin. CRACK: Qualitative Reasoning about Fatigue Fracture in Steel Bridges. *IEEE Expert*, Vol. 16, No. 10, Aug. 1992, pp. 41–48.
7. Chen, H. L., and C. L. Chen. Applying Neural Network to Acoustic Emission Signal Processing. Presented at Fourth International Symposium on Acoustic Emission from Composites Materials, Seattle, Wash., Jul. 1992, pp. 273–281.
8. Chen, R. H. L., U. B. Halabe, V. Bhandarkar, and Z. Sami. *Radar Signal Processing and Analysis for In Situ Evaluation of Reinforced Concrete Bridge Decks.* Report No. CFC-93-167 submitted to WVDOH under Contract No. WVDOH RP#90, Phase I. Constructed Facilities Center, West Virginia University, Morgantown, Oct. 1993.
9. Shoukry, S. N., D. Martinelli, S. T. Varadarajan, and U. D. Halabe. *Journal of Material Evaluation*. In press.
10. Sansalone, M., and D. Pratt. Impact-Echo Signal Interpretation Using Artificial Intelligence. *ACI Materials Journal*, Vol. 89, No. 2, Mar.–Apr. 1992, pp. 178–87.
11. McNab, A., and H. S. Young. Knowledge-Based Approach to the Formulation of Ultrasonic Nondestructive Testing Procedures. *IEEE Proceedings*, Vol. 136, Part A, No. 3, May 1989, pp. 134–140.
12. Han Ji-hong, and L. Wei-du. Fuzzy Cluster Analysis and Comprehensive Evaluation of Concrete Quality with Ultrasonic Multi Parameters. Presented at International Conference on Nondestructive Testing of Structural Materials, 1993, pp. 267–276.

*Publication of this paper sponsored by Committee on Artificial Intelligence.*