Utilizing Neural Networks to Interpret Data Acquired from Automated Test Systems

Patrick J. Sincebaugh
U.S. Army Research Laboratory
Materials Directorate
Aberdeen Proving Ground, MD 21005
psinceb@arl.mil
(410) 278-0320

William H. Green
U.S. Army Research Laboratory
Materials Directorate
Aberdeen Proving Ground, MD 21005
wgreen@arl.mil
(410) 278-0317

Abstract

Innovative diagnostic testing techniques must be developed and applied in order to meet the increasing challenges associated with testing complex systems in an era of budget and personnel reductions. Research in testing and evaluation systems in manufacturing at the U.S. Army Research Laboratory Materials Directorate has focused on automating conventional test systems via the development of Intelligent Testing Systems (ITS). An ITS can be defined as a computer based system that utilizes state-of-the-art classification or decision making technology, often artificial intelligence (AI) techniques, to enable the system to make decisions or perform functions previously made by human operators. This paper begins by discussing the defining characteristics and advantages of automated test systems. This is followed by a discussion of the advantages of applying neural networks to data pattern analysis and classification. The reasons for using the backpropagation neural network algorithm in the case study A Smart Shock Absorber Test Stand (SSATS) are then given. The motivation for and the development of the SSATS system is described. Finally, this paper describes the benefits of utilizing the SSATS system and of implementing the methods used to develop it to other Intelligent Testing Systems.

Introduction

New and powerful diagnostic testing techniques must be developed and applied in order to meet the increasing challenges associated with testing complex systems in an era of significant budget and personnel reductions. Test and evaluation systems research at the U.S. Army Research Laboratory Materials Directorate has focused on automating conventional test and evaluation systems by the development of Intelligent Testing Systems (ITS). An ITS can be defined as a computer based system that utilizes state-of-the-art classification and/or decision making technology, often artificial intelligence (AI) techniques, to enable the system to make decisions and perform functions previously made by competent human operators. Advancements in computers, data acquisition and analysis, and AI technology have made these types of systems possible at reasonable cost. The development and implementation of Intelligent Testing Systems have shown high Returns on Investment in a wide variety of industries, including airlines, aerospace, banking, real estate, and government agencies.

The case study, A Smart Shock Absorber Test Stand (SSATS), will be discussed in this paper. This automated ITS utilizes a hydraulic test stand to oscillate a shock absorber under test. A data acquisition system collects data from sensors located on the test stand and attached to the shock absorber. The data is then analyzed to determine if the shock absorber meets predetermined load specifications. If the shock absorber does not meet the specifications the data is processed for input to a neural network classification scheme, which then classifies the shock absorber as one of four fault types. If the shock absorber meets the specifications it is considered nominal (not faulted). The process of acquiring data and determining the condition of the shock absorber under test occurs in real-time.

Neural Networks in Automated Test Systems

An important goal of both the manufacturing industry and the government is the automation of test and evaluation procedures and systems in order to minimize or eliminate entirely functions performed by human operators. Characteristics of automated test systems include simplicity of use, data acquisition and analysis speed, data accuracy, data representation and the user interface, and decision making capability. Automated test systems generally consist of a computer based control unit, often a PC, testing equipment, sensors from which to acquire data, data acquisition hardware and software, and data analysis hardware and software. It is critical that data acquisition and analysis in an automated test system be properly matched to the system to minimize the introduction of error when acquiring sensor data. Basic parameters of analog inputs that must be considered include number of channels, sampling rate, resolution, and input range. Sampling rate determines how often conversions can take place. A faster sampling rate acquires more points in a given time, therefore often forming a better representation of the original signal. Resolution is the number of bits that the analog-to-digital converter (ADC) uses to represent the analog signal. The higher the resolution, the higher the number of divisions the signal range is broken into, and therefore, the smaller the detectable voltage change. Range refers to the minimum and maximum voltage levels that the ADC can quantize. The multifunction data acquisition boards offer selectable ranges so that the signal range can be matched to that of the ADC to take best advantage of the resolution available to accurately measure the signal. The range, resolution, and gain available on a data acquisition board determine the smallest detectable change in voltage. This change in voltage represents 1 Least Significant Bit (LSB) of the digital value, often called the code width. Other parameters of analog inputs that must be considered include the DNL, relative accuracy, settling time of the instrumentation amplifier, and noise. The DNL is a measure in LSB of the worst-case deviation of code widths from their ideal value of 1 LSB.

Well constructed automated test systems utilize an integrated user interface, most often a graphical interface, that is capable of controlling testing and displaying acquired data in real-time in an efficient and easily understood format. Secondly, a well constructed system will acquire accurate data and process and analyze the data in real-time. Finally, a well constructed system will make a decision on what the data infers about the item being tested in real-time. Automated test systems significantly decrease testing, analysis, and decision making or classification time, thereby minimizing labor and increasing Return on Investment. Implementation of automated test systems in high volume applications can result in very significant positive changes in these areas.

Many testing applications rely on the ability of the test to recognize and subsequently classify data patterns. For instance, fault diagnosis can be cast as a pattern-recognition problem, in which patterns of input data representing the behavior of a physical system are associated or mapped to patterns interpretable as normal (nominal) or abnormal (faulted) operation. It is also true that operational state behavior of many complex systems can be accurately represented by only a few critical variables and that these variables form unique data patterns for different operational fault conditions. In SSATS the critical variables which determine the condition of a shock absorber are load (force) applied to the shock absorber and the associated displacement (position). The load vs. displacement plot or phase diagram has different shapes for different fault conditions. In general, application of neural networks to pattern recognition and classification problems requires far less restrictive assumptions about the structure of the input data than existing pattern recognition and signal processing techniques. In addition, the inherent parallelism of these networks allows very rapid parallel search and best-match computations, alleviating much of the computational overhead incurred when applying traditional non-parallel techniques to signal interpretation problems (Gorman & Sejnowski 1988). Secondly, neural networks are resistant to noisy sensor data and they are capable of producing accurate results even with incomplete sensor data. Automated testing systems that utilize neural network methodologies in data processing/analysis and decision making processes offer the promise of exceedingly fast and robust implementations that can conveniently and flexibly be trained to respond to a set of given data patterns representative of a set of unique operational faults. These systems can yield great benefits in terms of system speed, robustness, and knowledge acquisition (Dietz, Kiech, & Ali 1989). The number of previously developed systems exemplifying this are too numerous to note here. However, they do include a real-time jet and rocket engine fault diagnosis system developed at the University of Tennessee Space Institute (Dietz, Kiech, & Ali 1989) and a real-time sonar target classification system developed by Allied-Signal Aerospace Technology Center and Johns Hopkins University (Gorman & Sejnowski 1988).

The Back Propagation Neural Network Paradigm

In the case study discussed in this paper the backpropagation neural network paradigm was utilized. The backpropagation paradigm and several variants have been independently derived by numerous people from varying backgrounds. Rumelhart, Hinton, and Williams presented a description of the backpropagation paradigm in 1986 (Rumelhart, Hinton, & Williams 1986). This paper refocused the attention of the scientific community on the backpropagation paradigm by exploiting the power of the paradigm and also answered many of the questions regarding the limitations of neural networks that had been discussed in a critique published by Minsky and Papert (Minsky & Papert 1969). Later it was found that Werbos had discovered the backpropagation algorithm while working on his doctoral thesis in statistics at Harvard University (Werbos 1974). Parker rediscovered the backpropagation algorithm while conducting graduate work at Stanford (Parker 1982). Although Rumelhart et al created a renewed excitement in the scientific community with their work, there were still critics of the backpropagation algorithm. The convergence proof that Rumelhart et al presented was based on a calculus limit theory, therefore requiring infinitesimal weight adjustments. This would theoretically require infinite training times to solve real world problems. Although the backpropagation algorithm is not the solution to all classification problems, it can be a powerful tool if the appropriate learning coefficient is selected. Care must be taken not to select a value that is too large, preventing the network from converging, or too small, requiring large training times. Experience in implementing the backpropagation paradigm is still the best guide. Another criticism of the algorithm is that complex problems require long training times. This problem can be minimized by intelligently preprocessing the data and by exploiting technological advances, such as utilizing a coprocessor board for network calculations. Rumelhart, Hinton, and Williams have developed a method to reduce training times by adding a momentum term to the delta rule (Rumelhart, Hinton, & Williams 1986). Hush and Salas have also reduced training times by reusing the gradient several times in succession (Hush & Salas 1988). Several other research efforts focused on reducing training times have shown promise, including (Dahl 1987), (Jacobs 1988), and (Cater 1987).

Another criticism of the algorithm is that the network can converge to a local error minimum rather the global error minimum. This results in weight oscillation, which causes the network to stop training. However, independent studies have determined that the backpropagation algorithm can be implemented to solve a wide range of pattern recognition and classification problems to any desired degree of accuracy (Le Cunn 1987, Moore & Poggio 1988). Unfortunately, these studies state that the backpropagation algorithm can find the correct mapping, but they do not state how the mapping is determined. The key to solving this problem is to properly select the network parameters, including the number of nodes, number of layers, learning rate, data mapping, etc. Research efforts have been conducted to assist with the proper selection of these parameters (Surkan & Chen 1988). Improvements to the backpropagation paradigm have made it a popular choice to solve pattern recognition and classification problems. Many successful applications have been developed in the areas of diagnostics, including (Dietz, Kiech, & Ali 1989) and (Baum & Wilczek 1988), and signal processing (Gorman & Sejnowski 1988, Rosenberg & Sejnowski 1987). For these reasons, a backpropagation paradigm was chosen to solve the shock absorber classification problem.

Case Study: A Smart Shock Absorber Test Stand (SSATS)

Motivation for the SSATS System

The need to develop an improved testing methodology for armored vehicle shock absorbers was identified at the Red River Army Depot (RRAD). Armored Fighting Vehicles (AFV), including the Bradley Armored Vehicle (BAV), are brought to RRAD for scheduled maintenance and overhaul procedures. The vehicles are completely disassembled upon arrival. Diagnostic testing is performed on individual components, such as the track and engine. The vehicles are then reassembled using nominal components and subsequently performance tested by driving them around a test track for a predetermined amount of time and distance. If a vehicle meets or exceeds all of the performance criteria it is released back into the field. As previously stated, there are various diagnostic tests performed on individual components during the disassembly phase. However, until the development of SSATS, there was no diagnostic functional test for the AFV shock absorbers. The shock absorbers were being reinstalled or discarded based upon the results of a visual inspection and a unscientific "touch test". This testing methodology led to a high percentage of faulted shock absorbers being reinstalled and entering the field, as well as numerous nominal shock absorbers being discarded. Failure rates as high as 78% occurred in the field. The resulting rise in expense and vehicle downtime created the demand for a diagnostic testing capability for AFV shock absorbers

Development of the SSATS System

Testing Equipment and Hardware Development. An existing hydraulic test stand manufactured in the mid 80's was acquired from RRAD. The test stand was in poor physical and mechanical condition. The capability of the test stand was returned to the high performance level required to develop and implement a diagnostic testing capability for AFV shock absorbers. The test stand consists of an electronic control console interfaced with a hydraulic power supply. Hydraulic fluid is supplied to a servo cylinder mounted on a load frame. A shock absorber is mounted vertically into the load frame and is subjected to a sinusoidal motion of 38 cycles per minute (CPM) (adjustable to 50 CPM, 100 CPM, 150 CPM, and 290 CPM) through a 2 to 3 inch stroke. Sensors are mounted to the test stand and the shock absorber under test in order to acquire data relating to the force (load) on the shock absorber, the resulting displacement (position), the temperature of the shock absorber, and the cycle rate. A PC-based system was developed to automate the acquisition and analysis of data provided by the test stand. Analog voltage signals representing the force applied to the shock absorber under test, the resulting displacement, the temperature of the shock absorber, and the cycle rate are input to an ADC board plugged into an expansion slot of an 80486 PC. The data signals are connected to the ADC board in a Referenced Single Ended (RSE) configuration. The data acquisition (DAQ) system was designed to acquire data at the five testing cycle rates (frequencies) previously mentioned. The DAQ system also calculates velocity data using acquired displacement data and time data based on the system scan rate. The analog input parameters discussed previously, including sampling rate, resolution, input range, relative accuracy, settling time, and noise were properly taken into account in the DAQ system. Parameters derived from the DAQ scan rate (500 scans per second) and the test frequency were coded into the DAQ software routine to assure accurate data measurements.

Data Analysis, Preprocessing, and Representation. Testing procedures for Bradley Armored Vehicle (BAV) shock absorbers were developed with the assistance of the shock absorber original equipment manufacturer (OEM) and the quality assurance team at RRAD. The first test requirement specifies that the shock absorber under test must be at a temperature within an acceptable range. The DAQ software automatically determines if the temperature is within the required range. Next, force values representing the compressive load at midstroke (displacement = 0), rebound load at midstroke, load at 10% into the compressive stroke, and load at 10% into the rebound stroke are acquired from load cell sensors and then compared by the DAQ software to predetermined force requirements. If the shock absorber fails to meet any of the force requirements it is considered to be a faulted shock absorber and is further analyzed by a neural network classification scheme. Based on shock absorber theory (Harris & Crede 1988), it was concluded that the condition of a Bradley Armored Vehicle shock absorber (and AFV shock absorbers in general) could best be evaluated by analyzing the load (force) vs. displacement (position) plot or phase diagram of the shock absorber. A standard testing procedure was developed which specifies that data is acquired as the shock absorber is vertically oscillated at 38 CPM. Preliminary analysis of data acquired from BAV shock absorbers showed that the condition could best be classified into one of four fault categories. These categories are named Fault Type 1, Fault Type 2, Fault Type 3, and Fault Type 4, respectively. These shock absorber fault types are the result of the presence of anomalies such as a bent rod, leaky seal, damaged casing, etc. Figure 1 shows the force vs. displacement phase diagram for a nominal (not faulted) shock absorber. Figures 2, 3, and 4 are typical phase diagrams for Fault Types 1, 2, and 3, respectively. The Fault Type 4 category was defined to account for unique types of faults and for shock absorbers with some combination of Fault Types 1, 2, or 3.

The raw force and displacement data were processed in three distinct steps to produce a representation that would maximize performance of the neural network. First, for each test, five cycles of raw force and displacement data were acquired from the hydraulic test stand. These values were averaged (evenly weighted), resulting in one representative cycle of data. The averaged cycle of data was then statistically analyzed to determine the midstroke position during the compression stroke. The averaged cycle of data was then shifted such that it always began at the compression midstroke point in time. Second, after experimentation with various data representations, it was decided to normalize the averaged/shifted data. The force data was normalized to values ranging from -1.0 to 1.0. The displacement data was normalized to values ranging from 0.0 to 1.0. The input data for the neural network was derived from the normalized data. The normalized phase diagram was broken into one set of four 1/4 cycle intervals and one set of sixteen 1/16 cycle intervals for purposes of analysis. In the first case, the first quarter interval represents the compression stroke and the third quarter interval represents the rebound stroke, respectively. The second and fourth quarter intervals represent intermediate strokes occurring between the compression and rebound strokes. In the second case, the first 1/16 cycle interval is centered around the compression midstroke position and the other intervals are evenly spaced about it. The first and third input node to the neural network is the mean square error (MSE) of the normalized force data in the first and third quarter intervals, respectively. The second and fourth input node to the neural network is the MSE of the normalized displacement data in the second and fourth quarter intervals, respectively. Inputs for nodes 5 - 20 were determined by calculating the averages of the force data within the set of 16 specified intervals.

Training and Testing the Neural Network. A fully connected feed forward backpropagation neural network was developed to classify the faulted condition of used BAV shock absorbers. The network architecture consists of an input layer, one hidden layer, and an output layer (see Figure 5). The input layer comprises 20 input nodes. Their values were discussed in the previous section. The hidden layer comprises eight nodes. The output layer comprises three nodes. Table 1 summarizes the output values associated with each fault classification. If the network output does not meet any

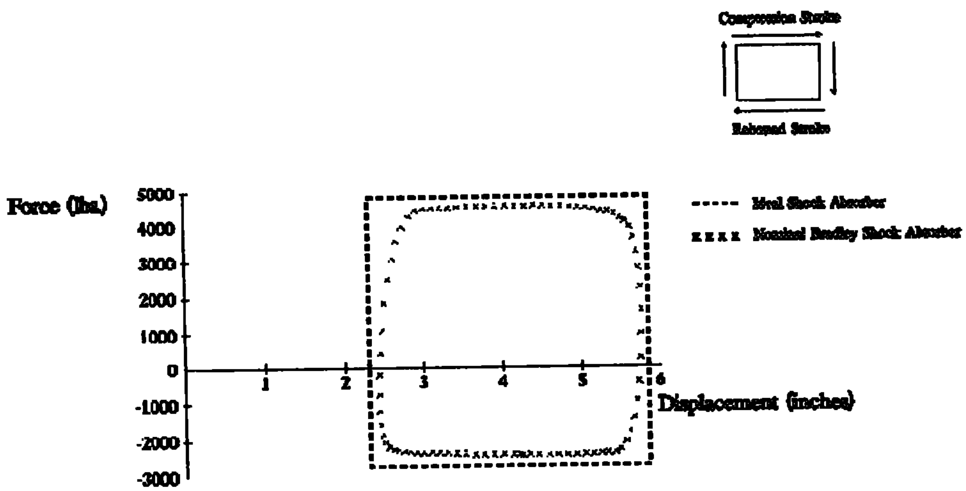


Figure 1. Force vs. Displacement Plots for an Ideal and Nominal Bradley Armored Vehicle Shock Absorber

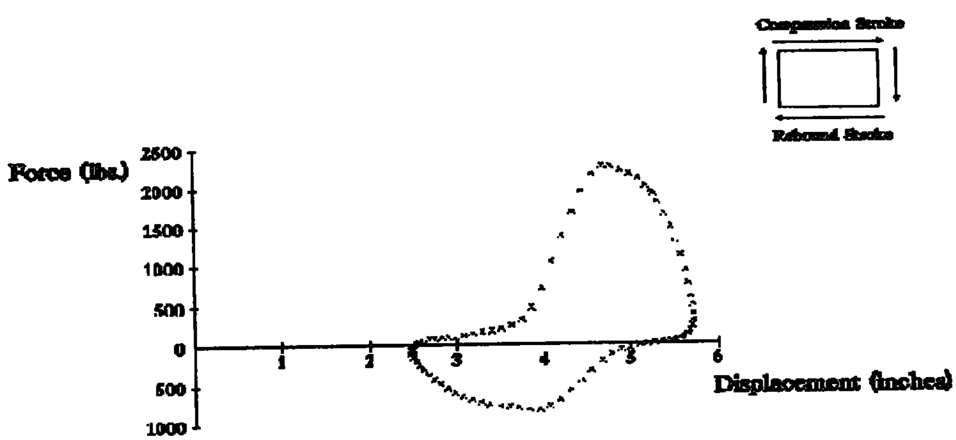


Figure 2. Force vs. Displacement Plot for a Type 1 Faulted Bradley Armored Vehicle Shock Absorber

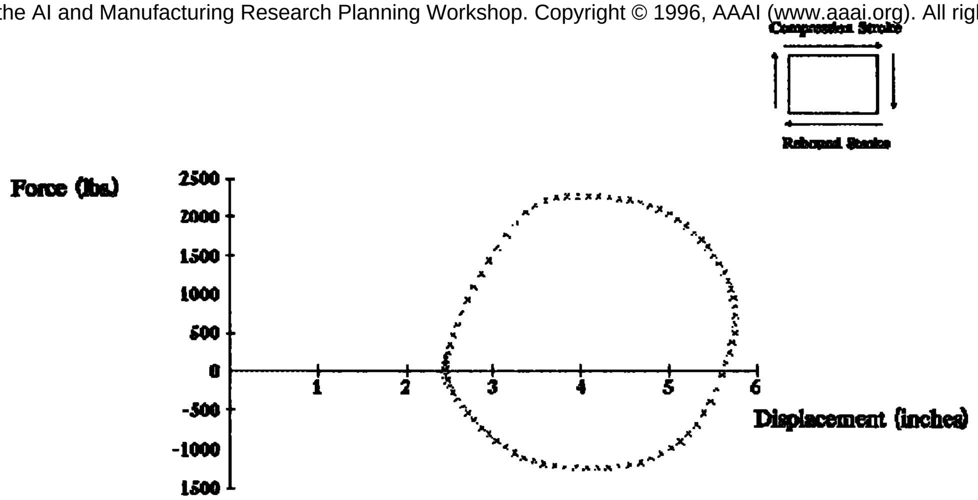


Figure 3. Force vs. Displacement Plot for a Type 2 Faulted Bradley Armored Vehicle Shock Absorber

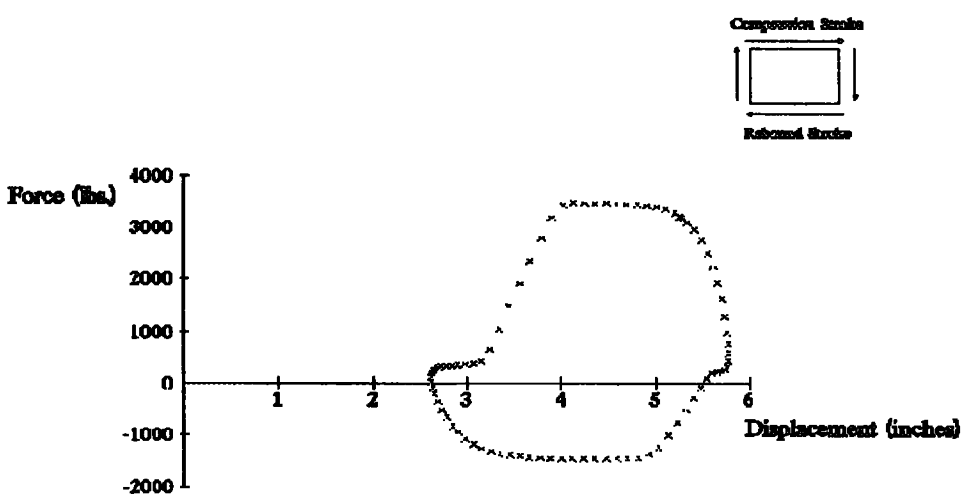
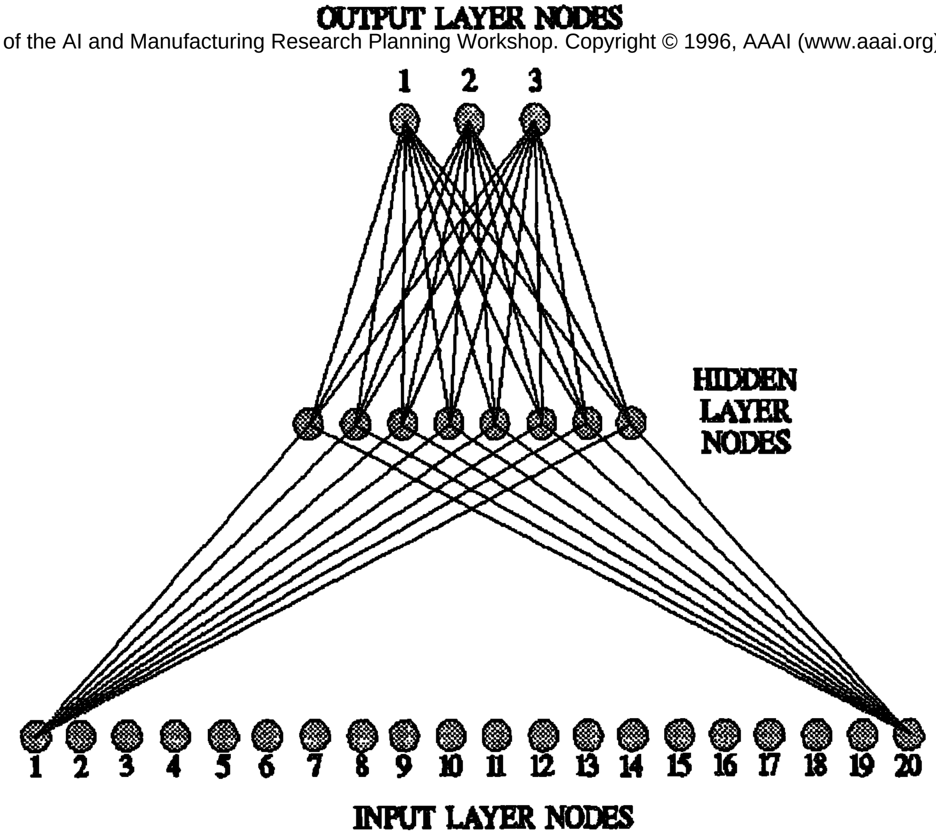


Figure 4. Force vs. Displacement Plot for a Type 3 Faulted Bradley Armored Vehicle Shock Absorber



** The network connections from each of the INPUT LAYER NODES (2-19) to each of the HIDDEN LAYER NODES are not shown for purposes of visual clarity.

Figure 5. Backpropagation Architecture Used to Classify Faulted Shock Absorbers

Fault Type	Node 1	Node 2	Node 3
1	>0.85	<0.35	<0.35
2	<0.35	>0.85	<0.35
3	<0.35	<0.35	>0.85

Table 1. Neural Network Output Nodes Classification

of the criteria outlined in Table 1, then the shock absorber is classified as Fault Type 4. Fault Type 4 can be a unique type of fault for which the network was not trained to recognize, or it could be any combination of Fault Types 1, 2, or 3. There is no corresponding output for a nominal shock absorber since the network is only implemented once the preliminary data analysis determines that the shock absorber is faulted. A total of 84 BAV shock absorbers were acquired from RRAD to train the neural network. Eight of the shock absorbers were new and the other 76 had previously been determined to be faulted by RRAD. Data was then acquired and stored for each individual shock absorber. This data was then manipulated into the format described in the previous section in order to train the backpropagation network using Fault Types 1, 2, and 3. After experimenting with various parameters including learning rate, number of hidden layer nodes, etc. the network was successfully trained to classify the faulted BAV shock absorbers. Once the network was adequately trained, it was tested using shock absorbers of known condition. The network successfully classified 100% of the shock absorbers used. The neural network was then converted to C code and integrated with the previously written DAQ software.

Conclusions and Future Work

Automated test systems significantly decrease testing, analysis, and decision making or classification time, thereby minimizing labor and increasing Return on Investment. Automated testing systems that utilize neural network methodologies in data processing/analysis and decision making processes offer the promise of exceedingly fast and robust implementations that can conveniently and flexibly be trained to respond to a set of given data patterns representative of a set of unique operational faults. These systems can yield great benefits in terms of system speed, robustness, and knowledge acquisition (Dietz, Kiech, & Ali 1989).

The U.S. Army Research Laboratory Materials Directorate (ARL/MD) has successfully developed and implemented a Smart Shock Absorber Test Stand (SSATS) to evaluate the condition of armored vehicle shock absorbers. This system is an automated ITS that performs data acquisition and shock absorber evaluation in real-time. The system utilizes a hydraulic test stand to vertically oscillate the shock absorber at a preset frequency. The data acquisition system acquires data from sensors mounted on the test stand and attached to the shock absorber, including the force on the shock absorber, the resulting displacement of the shock absorber, the temperature of the shock absorber, and the oscillation frequency. This data is analyzed in order to classify the shock absorber as nominal or faulted. If the shock absorber is classified as faulted, the data is further analyzed by a neural network based classification scheme. A fully connected feed forward backpropagation network was successfully trained and tested to classify the faulted shock absorbers as Fault Type 1, 2, 3, or 4. These shock absorber fault characteristics are present due to physical anomalies such as a bent rod, leaky seal, damaged casing, etc. A significant advantage of SSATS, and of automated intelligent testing systems in general, is the capability to easily archive test results, enabling the user to track problems associated with shock absorbers and to monitor any significant trends with very little difficulty. For example, a high percentage of shock absorbers with leaky seals may represent a design problem which can be corrected by the manufacturer. The SSATS system provides a Statistical Process Control (SPC) routine for data archiving and product assurance.

Once developed and tested, the SSATS system was transitioned to Red River Army Depot, where it is being utilized to evaluate the condition of Bradley Armored Vehicle shock absorbers. The system was developed and first implemented to evaluate shock absorbers that had been previously tested at RRAD by visual inspection and an unscientific "touch test". It must be emphasized that the testing methodology utilized by RRAD resulted in incorrect classification of 40% of these shock absorbers. The SSATS system provides an accurate functional testing capability for Bradley Armored Vehicle shock absorbers. The utilization of this system significantly reduces vehicle downtime and shock absorber misclassification, resulting in an increase in combat readiness and a significant financial savings. World-wide the Bradley Armored Vehicle program spent $1,909,920 on replacement shock absorbers in 1993. The Bradley Armored Vehicle has continued to be a major part of the armored vehicle forces. Therefore, full utilization of SSATS will save an estimated $760,00 per year.

The methods used to develop the automated SSATS system can be implemented to develop other automated Intelligent Testing Systems, especially for other AFV shock absorbers. This is due to the fact that the backpropagation neural network algorithm can be utilized to create a classification scheme to correctly evaluate the condition of systems in which unique data patterns exist for different operational states. Future work will concentrate on "retraining" the neural network classification scheme to classify the condition of shock absorbers for different vehicles.

Acknowledgments

The authors would like to thank the U.S. Army Artificial Intelligence (AI) Center for continuing to support our development of AI-based systems and Eric Olsen, Judy Miller, Betty Gimlin, and Randy Soule from the Red River Army Depot for their assistance in providing logistical support and technical assistance pertaining to shock absorber testing. We would also like to thank Dick Suchter, formerly of Paul Munroe Corporation, for his assistance in providing technical data pertaining to the hydraulic test stand used for this project.

References

Baum, E., and Wilczek, F. 1988b. Supervised Learning of Probability Distributions by Neural Networks. In Proceedings of the 1987 IEEE Conference on Neural Information Processing Systems - Natural and Synthetic, 52-61. New York: American Institute of Physics.

Cater, J. 1987b. Successfully Using Peak Learning Rates of 10 (and Greater) in Backpropagation Networks with the Heuristic Learning Algorithm. In Proceedings of the IEEE First International Conference on Neural Networks: Vol. II, 645-651. San Diego: IEEE.

Dahl, E. 1987b. Accelerated Learning Using the Generalized Delta Rule. In Proceedings of the IEEE First International Conference on Neural Networks: Vol. II, 523-530. San Diego: IEEE.

Dietz, W.; Kiech, E.; and Ali, M. 1989b. Pattern-Based Fault-Diagnosis Using Neural Networks. In Proceedings of First International Conference on Industrial and Engineering Applications of AI and Expert Systems, 3-23. Chattanooga: University of Tennessee Space Institute.

Gorman, R. P., and Sejnowski, T. J. 1988a. Analysis of Hidden Units in a Layered Network Trained to Classify Sonar Targets. *Neural Networks* 1: 75-89.

Harris, C. M., and Crede, C. E. eds. 1988. *Shock and Vibration Control Handbook*, 3d ed.

Hush, D., and Salas, J., 1988b. Improving the Learning Rate of Backpropagation with the Gradient Re-Use Algorithm. In Proceedings of the IEEE International Conference on Neural Networks: Vol. I, 441-447. San Diego: IEEE.

Jacobs, R. 1988. Increased Rates of Convergence Through Learning Rate Adaptation. *Neural Networks* 1: 295-307.

Le Cunn, Y. 1987b. Models Connexiannistes de l'apprentissage. Ph.D. diss., Universitat P et M. Curie, Paris 6.

Minsky, M., and Papert, S. eds. 1969. *Perceptrons*. Cambridge, Mass.: MIT Press.

Moore, B., and Poggio, T. 1988a. Representation Properties of Multilayer Feedforward Networks. *Neural Networks Supplement: INNS Abstracts* 1: 203.

Parker, D. 1982. Learning Logic, Invention Report, S81-64, File 1, Office of Technology Licensing, Stanford University.

Rosenberg, C. R., and Sejnowski, T. J. 1987a. Parallel Networks that Learn to Pronounce English Text. *Complex Systems* 1: 145-168.

Rumelhart, D.; Hinton, G.; and Williams, R. 1986. Learning Representations by Backpropagating Errors. *Nature* 533-566.

Surkan, A. and Chen, M. L. 1988a. APL Implementation of a Neural Network with Dynamically Generated Middle Layers of Arbitrary Number and Length. *Neural Networks Supplement: INNS Abstracts* 1.

Werbos, P. 1974b. Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences, Ph.D. diss., Harvard University.