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AN ARTIFICIAL NEURAL NETWORK SYSTEM FOR DIAGNOSING GAS TURBINE ENGINE FUEL FAULTS

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Abstract: The US Army Ordnance Center & School and Pacific Northwest Laboratory are developing a turbine engine diagnostic system for the M1A1 Abrams tank. This system employs Artificial Neural Network (ANN) technology to perform diagnosis and prognosis of the tank's AGT-1500 gas turbine engine. This paper describes the design and prototype development of the ANN component of the diagnostic system, which we refer to as "TEDANN" for Turbine Engine Diagnostic Artificial Neural Networks.

Key Words: Artificial neural networks; expert systems; fault diagnosis; prognostics; turbine engine maintenance.

Introduction: The Army's maintenance practice employs diagnostic procedures that are generally performed manually. Rather than using automated diagnostic and prognostic paradigms, the current practice verifies only whether the operational states are within or out of tolerance. The paradigm does not reflect a real-time operational assessment, nor can it be readily modified to predict failures (perform prognostics).

Technology currently exists to markedly improve both the accuracy and timeliness of the current diagnostic paradigm. These improvements will not require an inordinate expenditure in either development or fielding costs. The purpose of this paper is to discuss improvements to the current maintenance practices and describe a prototype system that employs a real-time automated diagnostic paradigm. The prototype system will be referred to as the Turbine Engine Diagnostic Artificial Neural Networks (TEDANN). TEDANN is being developed to evaluate the feasibility of using Artificial Neural Networks (ANNs) to monitor turbine engine performance and diagnose failures in real-time. In addition, TEDANN will provide a testbed to evaluate the feasibility of developing a real time prognostics capability.

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Background: Because the current Army maintenance process is reactive (dependent upon a failure to occur before its initiation), it is incapable of predicting failures. The current diagnostic process depends upon humans to integrate, categorize and analyze currents and voltages. Diagnostics are based on individual experience, heuristics and rules of thumb. After the mechanic arrives at an initial diagnosis, he must analyze his initial hypothesis using a suite of analog and/or digital Test Measurement or Diagnostic Equipment (TMDE). The resultant analysis will either support or refute his hypothesis. The mechanic repeats this iterative process until it produces an accurate diagnosis.

For example, troubleshooting the AGT-1500 gas turbine engine requires the mechanic to take separate Digital Multimeter (DMM) readings at the Electronic Control Unit (ECU). This is accomplished by inserting test probes into an ancillary breakout box (BOB) attached to the ECU's diagnostic connector. Once the mechanic takes the required voltage readings he must manually analyze their significance through a manual computation and compare the results to diagnostic flow charts. This practice is time consuming and error prone due to the dependence upon proper application of mathematical conversion factors and correct placement of test probes into the BOB.

A suggested improvement to current maintenance practices is to automate diagnostics in a real-time system and to use prognostics to detect equipment faults before they occur. This would reduce the occurrences of No-Evidence-Of-Failure (NEOF) outcomes in diagnosing component failures. The NEOF occurs when a component is incorrectly diagnosed as faulty and is evacuated to a maintenance facility for repair. The receiving maintenance facility will, as a matter of course, verify the initial diagnosis. When the defective component is diagnosed as functional, a NEOF is initiated. At the present time certain electronic components exhibit a NEOF rate of approximately 60%. Hence, the requirement for an improved diagnostic and prognostic paradigm.

Objective: The technical objectives of this research are to

- explore improvement opportunities in turbine engine fault diagnosis through application of ANN technology;
- examine the application of ANN technology to an automated diagnostic and prognostic system for turbine engine maintenance.

The long-term operational objectives of this research are to achieve a reduction in NEOF, to reduce maintenance costs, and to increase operational readiness.

Approach: We chose Artificial Neural Network (ANN) technology for our prototype because it is well suited for diagnostics in real-world applications (see the box on Artificial Neural Networks). Each turbine engine is unique in its behavior as a result of its age, manufacturing tolerances, and the environment in which it is operated. All sensors are unique in their response and calibration. A diagnostic system using ANNs can automatically adapt to these individual variables for each turbine engine. Most conventional technologies such as expert systems would monitor each individual turbine engine as a generic engine. These generically-based diagnostic systems will not be as sensitive to individual turbine engines as an ANN-based system.

The TEDANN prototype demonstrates how current practices of manual diagnosis can be replaced by automated diagnostics and prognostics. The prototype analyzes values from on-board sensors in real-time.

Artificial Neural Networks

A brief description of Artificial Neural Networks (ANNs) is given here to help readers who are unfamiliar with this technology to appreciate the computational capabilities of ANNs.

ANNs are algorithmic systems implemented in either software or hardware. The concept of ANNs was inspired by the way the biological brain processes information. ANNs, like people, learn by example. Learning in the biological brain occurs in a network of neurons, which are interconnected by axons. A point of contact (actually most often a narrow gap) between an axon from one neuron to another is called a synapse. Learning is a matter of adjusting the electro-chemical connectivity across these synapses.

An ANN is a network of neurons or Processing Elements (PEs) and weighted connections. The connections correspond to axons and the weights to synapses in the biological brain. A PE performs two functions. It sums the inputs from several incoming connections and then applies a transfer function to the sum. The resulting value is propagated through outgoing connections to other PEs. Typically these PEs are arranged in layers; with the input layer receiving inputs from the real world and each succeeding layer receiving weighted outputs from the preceeding layer as its input. Hence the creation of a feed forward ANN, where each input is fed forward to its succeeding layer. The first and last layers in this ANN configuration are typically referred to as input and output layers. (Input layer PEs are not true PEs in that they do not perform a computation on the input.) Any layers between the input and output layers (usually 0-2 in number) are called hidden layers because they do not have contact with any real world input or output data.

Back propagation is one of several possible learning rules to adjust the connection weights during learning by example. Learning occurs when the network weights are adjusted as a function of the error found in the output of the network. The error is the difference between the expected output and the actual output. The weights are adjusted backwards (back-propagated) through the ANN network until the error is minimized for a set of training data.

A trained ANN, i.e., a network that has learned by example, can be applied to real world problems of considerable complexity. Their most important advantage is in the ability to process data that are too complex for conventional technologies—problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. In general, because of their abstraction from the biological brain, ANNs are well suited for problems that people are good at solving, but for which computers are not. This class of problems includes pattern recognition and forecasting or recognizing trends in data. ANNs have been applied successfully to hundreds of applications.

Figure 1 portrays the major components of the prototype diagnostic system. Initially, the TEDANN prototype will analyze AGT-1500 fuel flow dynamics, that is, fuel flow faults detectable in the signals from the ECU’s diagnostic connector. These voltage signals represent the status of the Electro-Mechanical Fuel System (EMFS) in response to ECU commands. The EMFS is a fuel metering device that delivers fuel to the turbine engine under the management of the ECU. The ECU is an analog computer whose fuel flow alorithm is dependent upon throttle position, ambient air and power turbine inlet temperatures, and compressor and power turbine speeds. Each of these variables has a representative voltage signal available at the ECU’s J1 diagnostic connector, which is accessed via the Automated Breakout Box (ABOB).

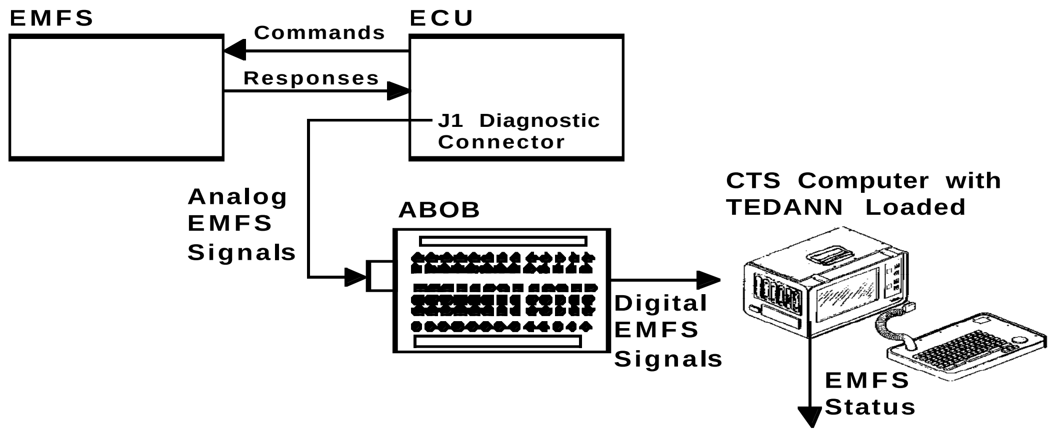

Figure 1. System Design of the TEDANN Maintenance System Concept

The ABOB is a firmware program capable of converting 128 separate analog data signals into digital format. The ECU's J1 diagnostic connector provides 32 analog signals to the ABOB. The ABOB contains a 128 to 1 multiplexer and an analog-to-digital converter, both operated by an 8-bit embedded controller. Army Research Lab (ARL) developed and published the hardware specifications as well as the micro-code for the ABOB Intel EPROM processor and the internal code for the multiplexer driver subroutine. Once the ECU analog readings are converted into a digital format, the data stream will be input directly into TEDANN via the serial RS-232 port of the Contact Test Set (CTS) computer.

The CTS computer is a ruggedized IBM compatible personal computer designed for tactical use on the battlefield. The CTS has a 50MHz 32-bit Intel 80486DX processor. It has a 200MB hard drive and 8MB RAM. The CTS also has serial, parallel and SCSI interface ports. The CTS will also host a frame-based expert system for diagnosing turbine engine faults (referred to as TED; not shown in Figure 1). Eventually TEDANN will be integrated with the TED expert system, which will receive inputs from TEDANN.

TEDANN was developed using the NeuroWindows ANN simulator software and Visual Basic as a user/computer interface development tool. Both of these software packages run in the MS-Windows environment.

Results: For the prototype development of the TEDANN system, we concentrated on three fuel flow faults: Bouncing main valve metering, stuck main valve metering and fuel flow errors. All three problems are difficult to diagnose and lend themselves to real-time analysis using ANNs. The analysis of fuel flow problems is based on an understanding of the operation of the EMFS, which is summarized in the box entitled "Fault Detection in the AGT-1500 Turbine Engine Electromechanical Fuel System."

TEDANN performs diagnostics using values from three fuel flow signals, ambient air and power turbine inlet temperatures, and compressor and power turbine speeds. For our prototype, these signal data were sampled during the first minute of the engine start sequence. Signal values are collected from the ECU's J1 diagnostic connector. The three fuel flow signals are referred to as: WF-request, WF-actual and WF-solenoid. These values determine the specific amount of fuel delivered to the engine according to the fuel schedule in the ECU. WF-request is the ECU's request for fuel flow, WF-solenoid is an ECU signal that positions the main metering valve in the EMFS in response to WF-request and WF-actual. WF-actual is the EMFS' feedback signal indicating the position of the main metering valve.

Fault Detection in the AGT-1500 Turbine Engine Electromechanical Fuel System

In the event a fuel flow fault occurs, the ECU initiates an engine protective mode. A fuel flow fault during the engine start sequence results in engine protective mode 1, which aborts the AGT-1500 start sequence. A fuel flow fault that occurs during normal operation results in protective mode 3, which causes the engine to run at a fixed, severely restricted power level.

AGT-1500 fuel delivery is accomplished by the main metering valve in the EMFS. A Linear Voltage Differential Transformer (LVDT) connected to the bottom of the main metering valve reports the valve's position (WF-actual) to the ECU. WF-request, the ECU’s request for fuel flow, controls the metering valve by generating a WF-solenoid current that modulates the solenoid’s stem; movement of the solenoid’s stem hydraulically positions the metering valve. When WF-request and WF-actual are equal, a nominal null (WF-solenoid) current of 275 milliamps is used to maintain the requested position of the metering valve. When WF-request increases (acceleration) or decreases (deceleration), WF-solenoid current increases or decreases respectively, causing the metering valve to move to the new position. The difference between WF-request and WF-actual during this transition generates an error signal that is used to correct the position of the main metering valve. When WF-actual again equals WF-request, WF-solenoid current returns to its null value of 275 milliamps.

Sensor data for the ANN training and testing were collected from turbine starts by Textron, the tubine engine manufacturer, and at Aberdeen Proving Ground by the U.S. Army Ordnance Center & School. The sensors were sampled at frequences ranging from 3 to 10 per second. Initial data sets were collected from mostly fault-free starts. These data were analyzed to understand how the sensor values behave during fault conditions. Our approach for training the ANNs required the use of data from starts with faults. Because of the difficulties in generating such data with a real turbine engine, we translated some data sets from fault-free starts to faulty starts. Additional data sets from fault-free and faulty starts are being incorporated into TEDANN.

Figure 2 shows the behavior of WF-request, WF-actual and WF-solenoid during a normal start and during the three monitored fuel faults. Normalized data are shown at a sampling rate of three per second. In general, the data tend to be quite messy; this underscores the advantage of the ANN approach. Figure 2a shows the normal condition in which actual fuel flow closely tracks the requested fuel. Figure 2b shows significant vertical motions in WF-actual. This condition of bouncing MMFV is caused by air penetration into the fuel system. Figure 2c (in the last 80 samples) shows a steady level on WF-actual caused by a stuck MMFV. Figure 2d shows irregular WF-actual motions that neither have significant vertical motions nor remain steady on one level. Also, the WF-solenoid varies substantially at several sampling times. We classify this fault type as a fuel flow error. Thus, the sensor behavior during a fuel flow error is characterized by data that cannot be attributed to the bouncing or the stuck MMFV.

TEDANN analyzes the sensor values in the form of "features" computed from the data. During development these features were recognized as discriminators among the three fault conditions. The use of sensor values alone as the input to a simple feedforward ANN do not capture information in the time domain. Thus, to capture changes in individual sensor values over time, we used first derivatives of sensor values and first derivatives of differences between pairs of sensor values as input to the ANN.

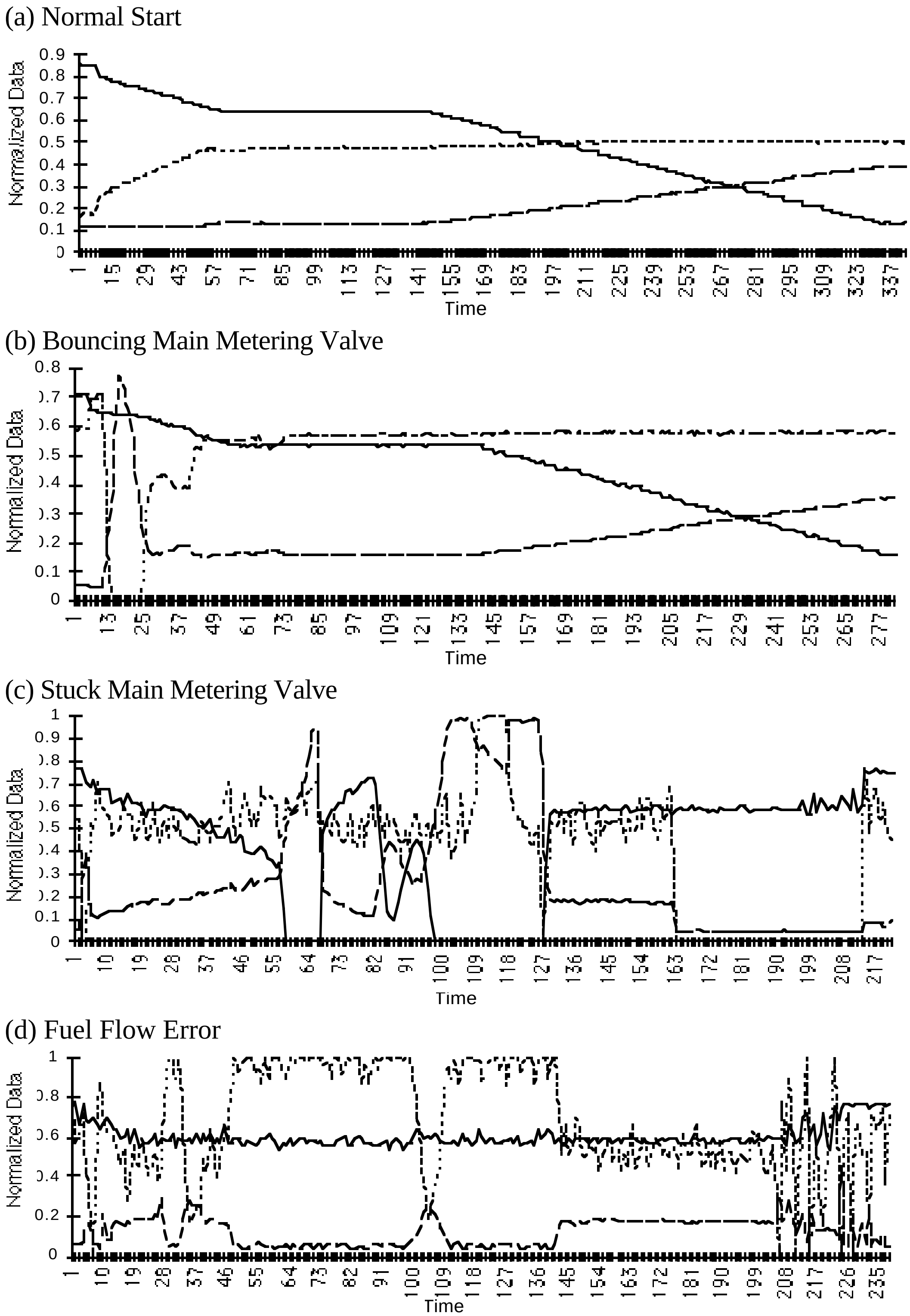

Figure 2. Sensor data plots for three sensor inputs to TEDANN (normalized data) under four engine status conditions: (a) normal start; (b) bouncing MMFV; (c) stuck MMFV; and (d) fuel flow error. Sensor data: WF-Request (solid line); WF-Actual (dashed line); WF-Solenoid (dotted line).

Preliminary studies on recurrent ANNs were performed to determine their applicability to this problem. Recurrent ANNs are specifically suited to capture time dependent data in time series, such as sensor values. These ANNs have not yet been incorporated in TEDANN because they require a large number of data sets for training, which was not available for the first prototype. In the future, when sufficient data are available (e.g., through automatic data collection), recurrent ANNs will be further evaluated for applicability to TEDANN.

Based on the analysis by the ANN system, TEDANN determines which fuel flow voltage readings are out of tolerance with EMFS nominal operational parameters. Having determined the operational condition of the EMFS, TEDANN will display either a fault status message identifying the EMFS faults or a message stating that the EMFS is fully operational. At a future date, when TEDANN and TED are integrated systems, the output of TEDANN will be submitted to TED for further processing.

TEDANN displays diagnostic information for each of the three monitored fuel faults, using a continuous severity scale from zero to one. Values close to zero indicate no fault, and values close to one signify a severe fault. We have arbitrarily assigned the following interpretation of the severity values:

0.00-0.25	no fault (normal)
0.26-0.75	warning (fault)
0.76-1.00	critical (fault)

In the future, we expect that the TED expert system will provide a more realistic interpretation using rule-based post-processing of TEDANN's output.

Preliminary results indicate that TEDANN performs the correct diagnosis. Table 1 shows a confusion matrix that compares TEDANN's output for the three fault diagnoses as a function of actual conditions. The tabulated results are TEDANN's outputs (severity of the faults for each type of fault, shown in the three columns), averaged over several start data sets. The rows represent the actual conditions under which the data were collected. The correctly diagnosed severity levels for the three faults are underlined. For example, in an actual condition of stuck MMFV, TEDANN diagnosed the fault to a severity of 1.0, and correctly failed to find evidence for the other faults. The bottom row shows the output for known no-fault conditions: in this case the diagnosed fault severity levels are appropriately low for the three faults.

Table 1. TEDANN's Diagnostic Performance

	Diagnosed condition:		
Actual conditions:	Bouncing MMFV	Stuck MMFV	Fuel flow error
Bouncing MMFV	<u>0.84</u>	0.22	0.06
Stuck MMFV	0.03	<u>1.00</u>	0.00
Fuel flow error	0.10	0.09	<u>0.47</u>
No fault	0.06	0.19	0.41

The main TEDANN displays are summarized in Figure 3. Two operational contexts are supported in the prototype to demonstrate the proposed concepts. First, a mechanic's context is supported in a simple display used to operate the system, summarize results, and access diagrams, schematics, or instructions to aid the maintenance process. Second, a development/expert context is supported by additional windows that display detailed diagnostic information (including the sensor data stream and continuous output of the ANN); an ANN training window for defining the ANN configuration and setting up or executing the ANN training phase; and a status summary window that provides status lights summarizing various engine components or subsystems. Available from most screens is an electronic maintenance guide, implemented using a hypertext design that can incorporate graphics, schematics, photographic images, and video. For illustrative purposes, the Main Screen is shown in Figure 4.

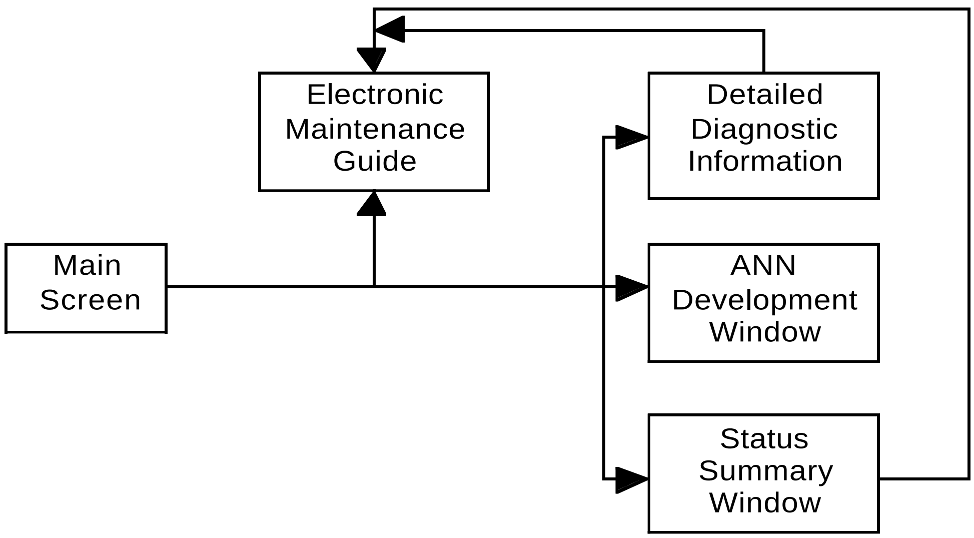

Figure 3. TEDANN prototype window/navigation summary.

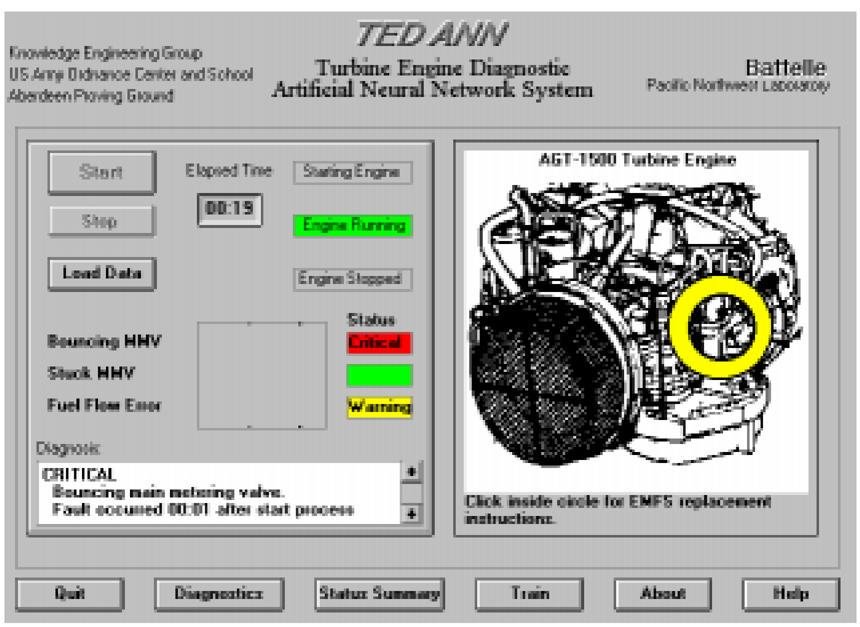

Figure 4. TEDANN Main Screen

Prognostic Capability: ANNs are capable of recognizing trends in data. This fact can be exploited for prognostics. In the short term, it would reduce the amount of man hours spent on diagnosing de facto failures. Further, it would decrease the requirement for ancillary TMDE as the predictive maintenance system is driven by internal sensor information. In addition, a robust predictive maintenance system would decrease the probability of erroneous replacement of operational components due to poor initial diagnosis. This would in turn reduce the number of NEOFs reported at maintenance facilities due to evacuation of operational components that were erroneously removed from systems.

In the long term, predictive maintenance technology would be a powerful and valuable tool to the design engineer as well as the system operator and maintainer. Once a robust and viable predictive maintenance system is developed, it would allow for a system design to be qualitatively analyzed across a range of operational parameters. This would enable design flaws to be corrected before the system is fabricated. In addition, it would enable the operator and maintainer to query the system about its relative operational state prior to the onset of any sustained operation. Any identified flaws could be detected and corrected. This capability would enable combat commanders to evaluate their systems before an engagement and obtain an accurate assessment of available combat power. Probable system failures could be transmitted through available communications media to support maintenance, and the required maintenance assets and repair parts could be dispatched to the unit before the battle. This capability would be a radical departure from the current maintenance support structure that is, by design, reactive in nature.

Conclusions: Preliminary results indicate that our approach to maintenance diagnostics will save time and improve performance. The ABOB's capability to automatically convert analog voltage readings to digital format will save time and markedly increase diagnostic accuracy. With the TEDANN/ABOB interface, a series of manual calculations and decisions may be eliminated to yield further improvements. The application of ANN technology appears to hold great promise for enhancing the effectiveness of Army maintenance practices.

The future of Army Maintenance technology is not dependent upon improvements within our current diagnostic's paradigm. Rather, it lies with the development of a predictive rather than reactive maintenance system. The amount of time and money required to develop this capability is arguably worth the investment, given the potential for reductions in both maintenance man-hours and erroneous replacement of operational system components. In addition, successful integration of predictive maintenance technology would result in the introduction of a new term in the Army lexicon—prognostics rather than diagnostics.

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