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TEDANN: TURBINE ENGINE DIAGNOSTIC ARTIFICIAL NEURAL NETWORK

Lars J. Kangas, Frank L. Greitzer
Pacific Northwest Laboratory, Richland, WA 99352

and

Major Orlando J. Illi, Jr.
U.S. Army Ordnance Center and School
Aberdeen Proving Ground, MD 21005

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Background

The U.S. Army Ordnance Center and School and Pacific Northwest Laboratory have developed a system that employs Artificial Neural Network (ANN) technology to perform diagnosis and prognosis of fuel flow problems in the AGT-1500 gas turbine engine of the M1A1 Abrams tank. This paper describes the design and prototype development of the diagnostic system, referred to as "TEDANN" for Turbine Engine Diagnostic Artificial Neural Network.

Artificial Neural Network (ANN) technology is applicable to problems like turbine engine fault diagnosis because of the ability of ANN systems to recognize anomalies in data and to generalize across a variety of data. ANN technology is also appropriate for this real-time diagnostic application because ANN systems often perform real-time diagnosis faster than conventional systems, such as model based reasoning systems.

The initial scope of the system focuses on the turbine engine startup sequence to diagnose three faults in the main metering fuel valve: bouncing valve, sticking valve, or stuck valve. To perform the diagnosis, TEDANN monitors a set of seven sensor values. Fuel flow and turbine speed are examples of the type of data that are provided by the seven sensors. The ANN analyzes features, e.g., rate of change or slope of fule flow over time, computed from the sensor values for the purpose of extracting information for detecting occurrences of the faults. This process is called “sensor fusion.” An example of a feature is the rate of change or slope of fuel flow over time.

Introduction

The initial focus of TEDANN is on AGT-1500 fuel flow dynamics: that is, fuel flow faults detectable in the signals from the Electronic Control Unit’s (ECU) 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 algorithm is dependent upon throttle position, ambient air and turbine inlet temperatures, and compressor and turbine speeds. Each of these variables has a representative voltage signal available at the ECU’s J1 diagnostic connector, which is accessed via the Automatic Breakout Box (ABOB). 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,

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both operated by an 8-bit embedded controller. The Army Research Laboratory (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 an IBM compatible personal computer designed and constructed 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 (ADPA Conference, 1994), 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.

Turbine Engine Data

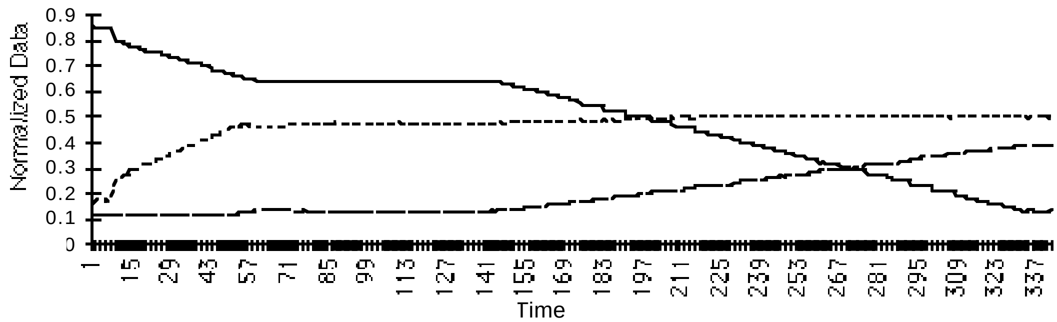
Sensor data for the ANN training and testing were collected from turbine starts by Textron (the turbine engine manufacturer) and by the U.S. Army Ordnance Center and School at Aberdeen Proving Ground. The sensors were sampled at rates of 3 to 10 per second. Initial data sets were collected from mostly fault-free starts. The 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, some data sets were translated from fault-free starts to faulty starts. Additional data sets from fault-free and faulty starts are being incorporated into TEDANN.

Figure 1 shows the behavior of three sensor data values (WF-request, WF-actual, and WF-solenoid) during a normal start and during the three monitored fuel faults. The 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 1a shows the normal condition in which actual fuel flow closely tracks the requested fuel. Figure 1b shows significant vertical motions in WF-actual. This condition of bouncing MMFV is caused by air penetration into the fuel system. Figure 1c (in the last 80 samples) shows a steady level on WF-actual caused by a stuck MMFV. Figure 1d 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. This fault type is classified 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.

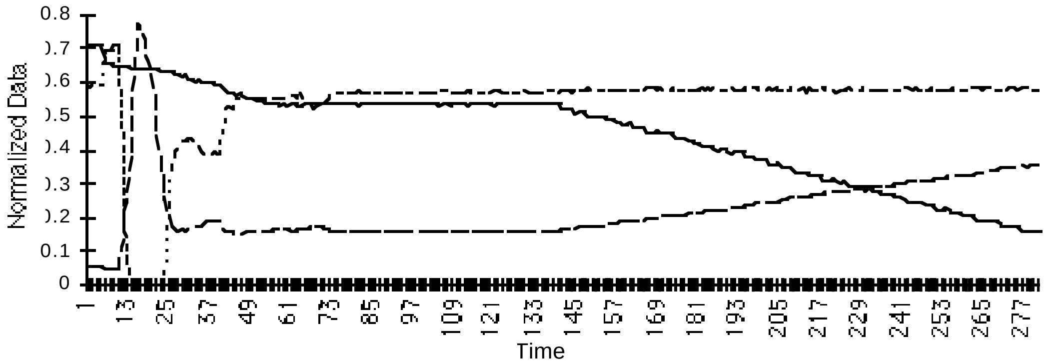
TEDANN analyzes the sensor data in the form of "features" computed from the data. During development these features were recognized as discriminators among the three fault conditions. However, use of sensor values as the one input to a simple feedforward ANN do not capture information in the time domain.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

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 the TED expert system for further processing.

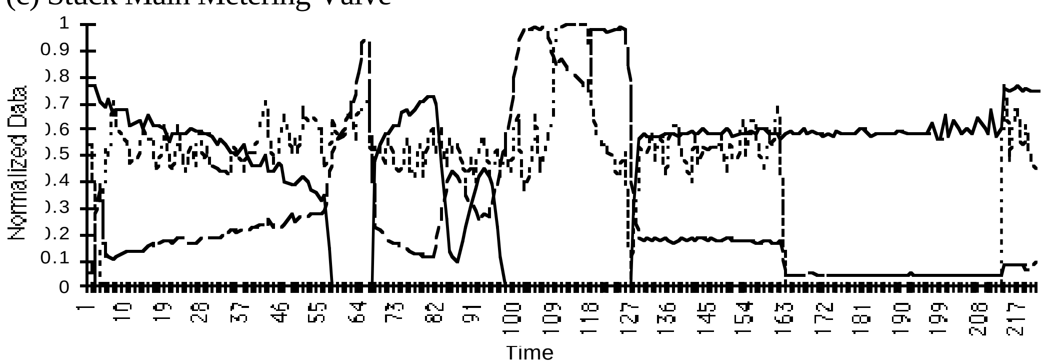
(a) Normal Start



(b) Bouncing Main Metering Valve



(c) Stuck Main Metering Valve



(d) Fuel Flow Error

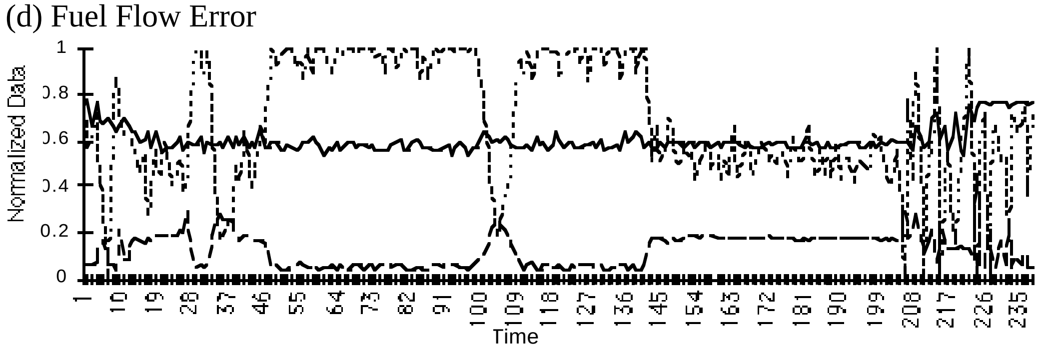


Figure 1. Sensor data plots for three sensor inputs to TEDANN (normalized data) under four engine status conditions: (a) normal start, (b) bouncing MMFV, (c) stuck MMFV, and (d) fuel flow error. Sensor data: WF-Request (solid line), WF-Actual (dashed line), and WF-Solenoid (dotted line).

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. Severity values are defined as follows:

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

Future integration of TEDANN and the TED expert system will provide a more realistic interpretation of the fault values 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>1.00</u>	0.00	0.00
Stuck MMFV	0.00	<u>0.98</u>	0.00
Fuel flow error	0.00	0.00	<u>1.00</u>
No fault	0.03	0.02	0.08

The main TEDANN displays are summarized in Figure 2. 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 3.

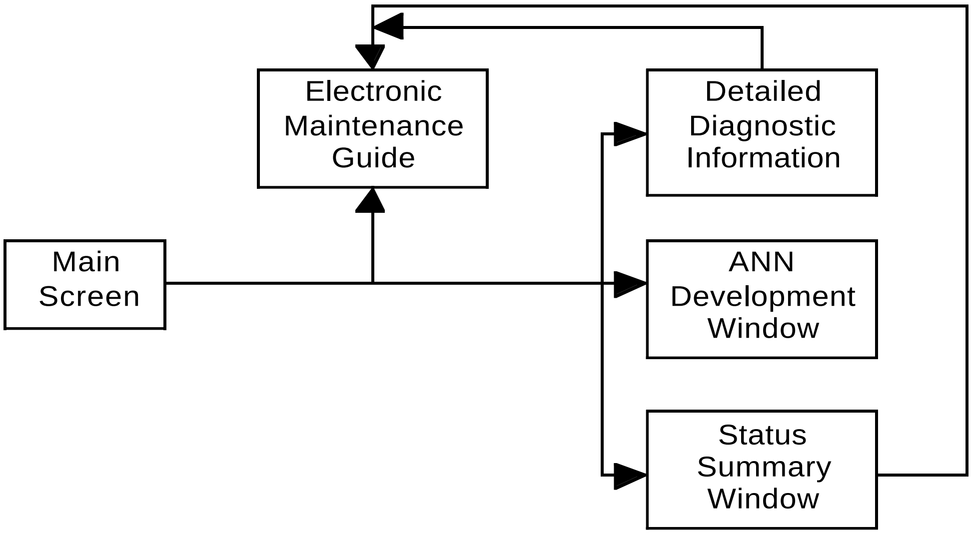


Figure 2. TEDANN prototype window/navigation summary.

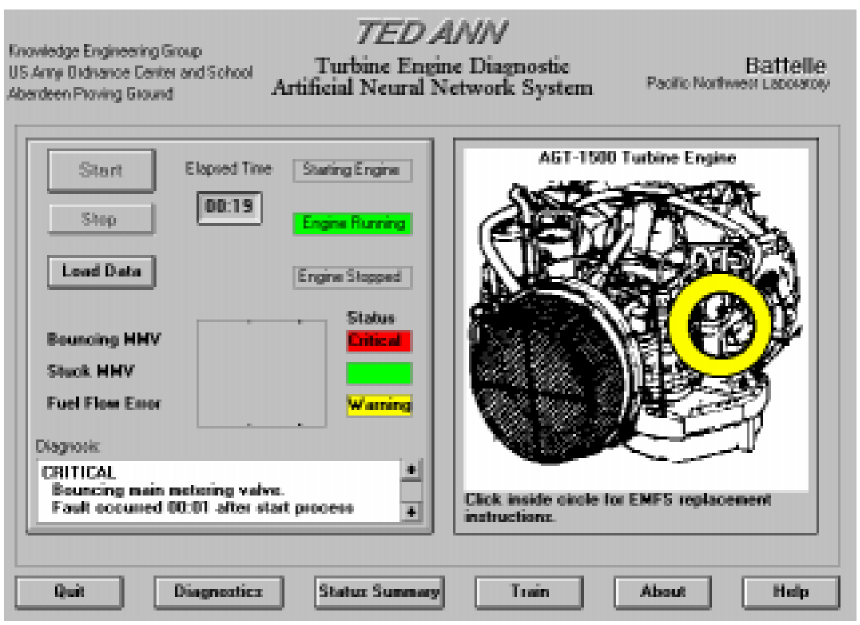


Figure 3. TEDANN Main Screen

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.

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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 was 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.

The technology used to develop TEDANN is being applied to a civilian medical application to enhance radiologic diagnostics. The Radiology Artificial Neural Network (RADANN) is a diagnostic system aimed at determining anomalies in medical images. It is a joint DOE National Laboratory/Civilian research program, led by Pacific Northwest Laboratory and with participants from Sacred Heart Medical Center (Spokane, Washington) and Eastern Washington University. RADANN's functionality will complement current radiological procedures. An initial prototype has yielded 83% accuracy and its potential has been recognized by participating radiologists.

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