Artificial Neural Network Test Support Development for the Space Shuttle PRCS Thrusters

Final Report
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ABSTRACT

A significant anomaly, Fuel Valve Pilot Seal Extrusion, is affecting the Shuttle Primary Reaction Control System (PRCS) Thrusters, and has caused 79 to fail. To help address this problem, a Shuttle PRCS Thruster Process Evaluation Team (TPET) was formed. The White Sands Test Facility (WSTF) and Boeing members of the TPET have identified many discrete valve current trace characteristics that are predictive of the problem. However, these are difficult and time consuming to identify and trend by manual analysis. Based on this exhaustive analysis over months, 22 thrusters previously delivered by the Depot were identified as high risk for flight failures. Although these had only recently been installed, they had to be removed from Shuttles OV103 and OV104 for reprocessing, by directive of the Shuttle Project Office. The resulting impact of the thruster removal, replacement, and valve replacement was significant (months of work and hundreds of thousands of dollars). Much of this could have been saved had the proposed Neural Network (NN) tool described in this paper been in place.

In addition to the significant benefits to the Shuttle indicated above, the development and implementation of this type of testing will be the genesis for potential Quality improvements across many areas of WSTF test data analysis and will be shared with other NASA centers. Future tests can be designed to incorporate engineering experience via Artificial Neural Nets (ANN) into depot level acceptance of hardware. Additionally, results were shared with a NASA Engineering and Safety Center (NESC) Super Problem Response Team (SPRT). There was extensive interest voiced among many different personnel from several centers. There are potential spin-offs of this effort that can be directly applied to other data acquisition systems as well as vehicle health management for current and future flight vehicles.

The preliminary ANN tool developed during this fellowship for the Component Test Facility (CTF) program was designed with the following concepts in mind:

1) Engineering expertise can be incorporated into software and utilized as a consistent diagnostic tool.
2) The tool will run in parallel with existing test equipment.
3) The tool will help technicians in the CTF evaluate and categorize hardware.
4) Data augmentation, storage, and ease of access will enhance the effectiveness of the tools diagnostic capability.

Further development of this tool is warranted based upon the results to date. Risks have been minimized with a proof of concept approach and the cost will be less than one refurbished valve. Plans have been developed with budgets and schedules to study, configure, test, document, and train operators for the final configuration in the CTF.

INTRODUCTION

Solenoids are used to control fluid flow electronically. A solenoid valve is a control unit which, when electrically energized or de-energized, either shuts off or allows fluid to flow. The actuator takes the form of an electromagnet. When energized, a magnetic field builds up which pulls a plunger or pivoted armature against the action of a spring. When de-energized, the plunger or pivoted armature is returned to its original position by the spring action.

With a direct-acting solenoid valve, the seat seal is attached to the solenoid core. In the de-energized condition, a seat orifice is closed, which opens when the valve is energized. With direct-acting valves, the static pressure forces increase with increasing orifice diameter which means that the magnetic forces required to overcome the pressure forces, become correspondingly larger. Internally piloted solenoid valves are therefore employed for switching higher pressures in conjunction with larger orifice sizes; in this case, the differential fluid pressure performs the main work in opening and closing the valve. Figure 1 illustrates the RCS pilot actuated valve which is the point of focus for this report.

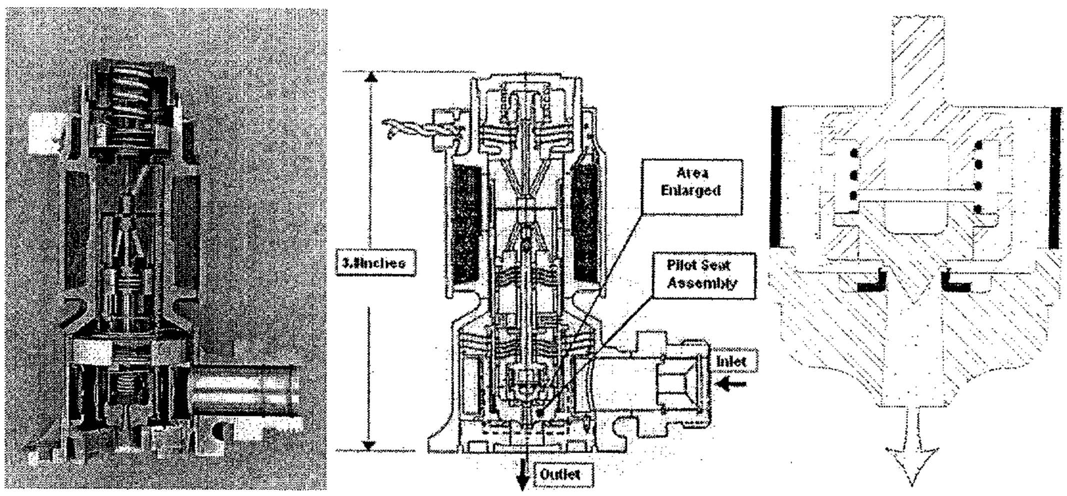

Figure 1: (Left) A cutaway internal view of the pilot-actuated value, (Middle) a diagram of the valve indicating the area of interest, (Right) an enlarged view of the pilot valve and extruded seal which hinders flow and reduces the pressure differential.

The deformation and extrusion of the pilot seal will cause an obstruction of fluid flow from the upper chamber during operation. Many papers have been written as to the cause of this extrusion and a definitive paper is being published. A full explanation as to the cause of pilot seal extrusion may be obtained by contacting the NASA colleague of this paper. However, if the seal obstructs the flow, then a sufficient pressure differential will not be created thereby causing main stage failure. This problem can be characterized by data acquisition of the current trace in the CTF which would then identify the valve for refurbishment.

ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Network is modeled upon the human brain's interconnected system of neurons. Neural networks imitate the brain's ability to sort out patterns and learn from trial and error, discerning and extracting the relationships that underlie the data with which it is presented. Most neural networks are software simulations run on conventional computers. Each neuron in the network has one or more inputs and produces an output; each input has a weighting factor, which modifies the value entering the neuron. The neuron mathematically manipulates the inputs, and outputs the result. The neural network is simply neurons joined together, with the output from one neuron becoming input to others until the final output is reached. The network learns when examples (with known results) are presented to it; the weighting factors are adjusted by training algorithms which bring the final output closer to the known result. Neural networks are good at providing very fast, very close approximations of the correct answer. Although they are not as well suited as conventional computers for performing mathematical calculations, neural networks excel at recognizing shapes or patterns, learning from experience, or sorting relevant data from irrelevant. Their applications[1] can be categorized into classification, recognition and identification, assessment, monitoring and control, forecasting and prediction.

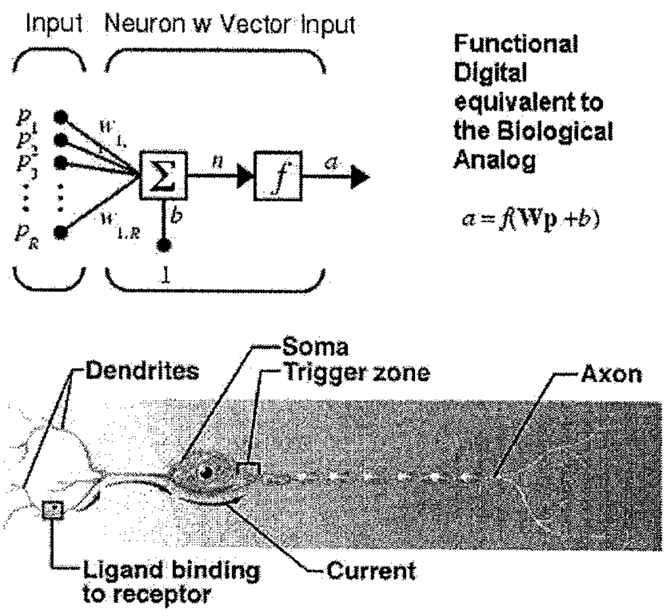

Figure 2: Depicting the Digital analogy of a single Neuron with that of its Biological equivalent.

DATA ANALYSIS

The first data set analyzed consisted of 20 current traces pulled from nominal and failed valves. These were typed utilizing a TPET presentation guideline followed in the CTF. A new category was developed for those square traces that were very close to nominal. Due to limited data, the NN was trained using a statistical approach. Boundaries were developed for the data using 2 standard deviations from the mean which limited the training set to 15 derived current traces given 5 categories. A back propagation neural network was built and trained with this initial data set. A cost function was developed to flatten the results outside of the normal NN training process.

The second data set consisted of 17 current traces. The NN found anomalies in several of the data traces. It identified 1 of the traces as unknown. On closer inspection this trace was taken using gas instead of water. Water traces are more consistent and they are the only data to be analyzed with this technique. Another anomaly occurred with a valve that went from unknown to round to nominal all within the same test day. This valve was thrown out since the data was extremely inconsistent. These 4 pieces of data were rejected and not included in this data set augmentation. Another new category was developed for valves that were rounded but very close to nominal. Figure 3 shows a sample analysis of the nominal data traces. The training data for the NN is located in the bottom panel. This represents the mean with 2 standard deviation limits.

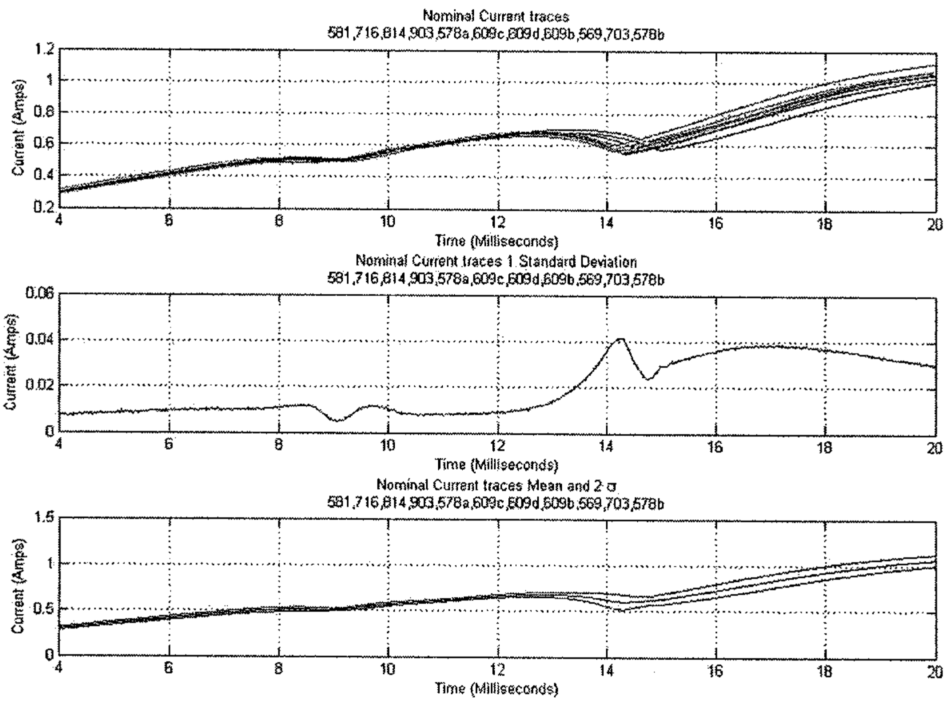

Figure 3: (Upper) Nominal current trace, (Middle) Standard deviation, (Bottom) Mean and 2 standard deviation boundaries.

Figure 4 depicts all categorical bounds and the finalized 18 training sets used in the NN analysis which became the network implemented in the Optics Lab and the CTF. There is substantial overlap in the boundaries which indicates that manual analysis would tend to be error prone for valves that fell between categories.

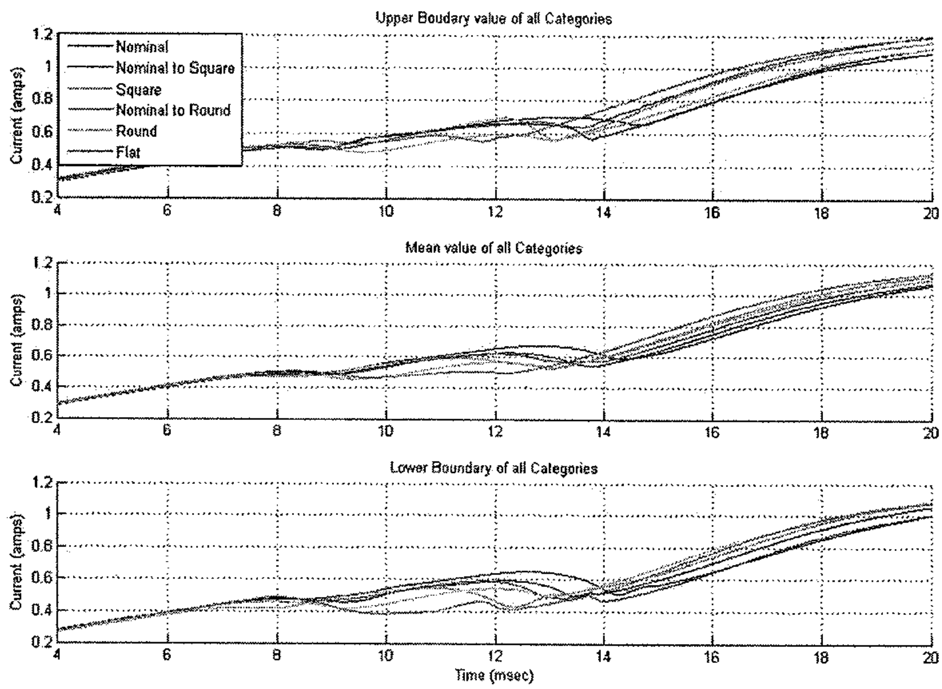

Figure 4: (Upper) Upper Boundary current trace, (Middle) Mean, (Bottom) Lower Boundary

STUDIES CONDUCTED

Once the NN was trained[2], then it was necessary to determine its predictive capabilities in the presence of noise, bias, and scale factor errors. A noise profile was developed to include all three of these characteristics. Though not depicted, the noise was normally distributed and increased with respect to time to its stated value in the figures to follow. Similarly, the biases where increased as a function of time to mimic bias conditions in the presence of scale factor errors.

Figure 5 shows that without any error, the training set and the extended data set obtained zero categorical errors when noise was absent. As the noise increased then so did the errors. The magnitude of the noise experienced in the CTF is 1/40 of that which would cause any significant degradation in performance. However, small negative biases or scale factor problems would tend to create unwanted errors. The NN could have been trained to account for these errors but the training time proved to be unnecessary. This result justified the preconditioning of the data by removal of biases and the careful determination of scale factors. All of which are easily accomplished when the interfacing hardware is built and the software are initialized.

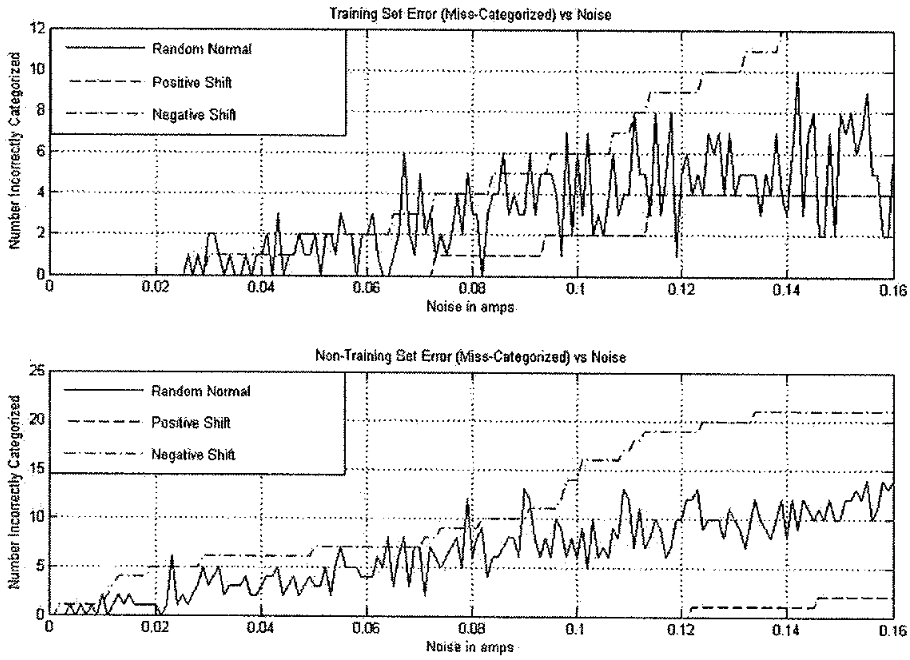

Figure 5: (Top) Categorization error for the training set as a function of Noise, Bias, and Scaling Errors, (Bottom) Categorization error for the data set as a function of noise.

The importance of passing good hardware vs. refurbishing bad hardware prior to an In-Flight Failure (IFF) or In-Flight Anomaly (IFA) should be explored in a little more detail than indicated above. Let us presume that instead of looking at numbers of errors we determine what types of errors occur given noise. Figure 6 shows in the top panel that as noise increases nominal hardware starts to fail. However, the bottom panel indicates by comparing the top that no failed hardware ever becomes nominal with an increase in noise. Also, the other categories only indicate the degree of failure so misdiagnosing a valve due to noise would still require action that would prevent an IFF/IFA. Therefore, the worst response that could happen with the present design configuration and an inordinate amount of noise would be refurbishment of good valves. The primary failure mode is not a safety concern but a cost and schedule consideration. This is an acceptable mode of failure which can be caught by monitoring failure rates and data traces which are already done in the facility as a matter of course. In addition, software can calculate the noise levels during any given run and indicate if this has impacted the ability of the NN to categorize the valve properly.

The studies above indicate that the present design concept would work very well in the CTF facility. All data traces were properly characterized given the statistical approach to train the network and correctly functioned under abnormal conditions. These promising results prompted the decision to attempt an actual test under simulated as well as actual CTF conditions.

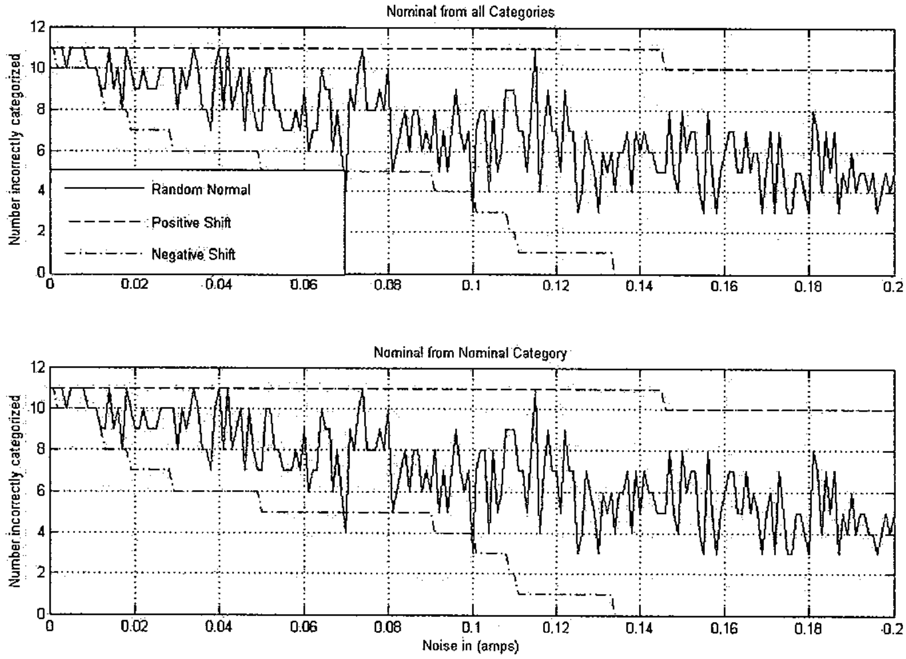

Figure 6: (Top) Nominal categorization error for the full data set as a function of noise, (Bottom) Nominal categorization error for the nominal data set as a function of noise.

PROGRAM IMPLEMENTATION AND DEVELOPMENT

The Artificial Neural Network (ANN) Algorithm was developed using MATLAB and the data recorded from the CTF which was reduced using the Znet tool. To develop software in the shortest time frame feasible it would be necessary to use as many existing components as possible. Therefore, the NN coefficients were transferred from MATLAB to a specially designed C++ program to duplicate the MATLAB results. The Znet program was written in C and its developer made minor modification to write the real time data to a file wherein the program would call the C++ NN program which would write the results to another file. Though dissimilar programs, the interface was reduced to reading and writing files.

Finally, the operator interface had to be designed and developed to convey all important information that the technician and engineers currently have to analyze by hand. The important information is plotted, compared as well as written. To categorize the valve as to type, the nominal limits are plotted in the top panel of Figure 7. The actual trace is simultaneously plotted for visual verification of the type which is printed in the title. (The bottom panel duplicates the trace as currently output in the strip charts.) The title contains the pilot opening time, bias, and noise characteristics to monitor data integrity.

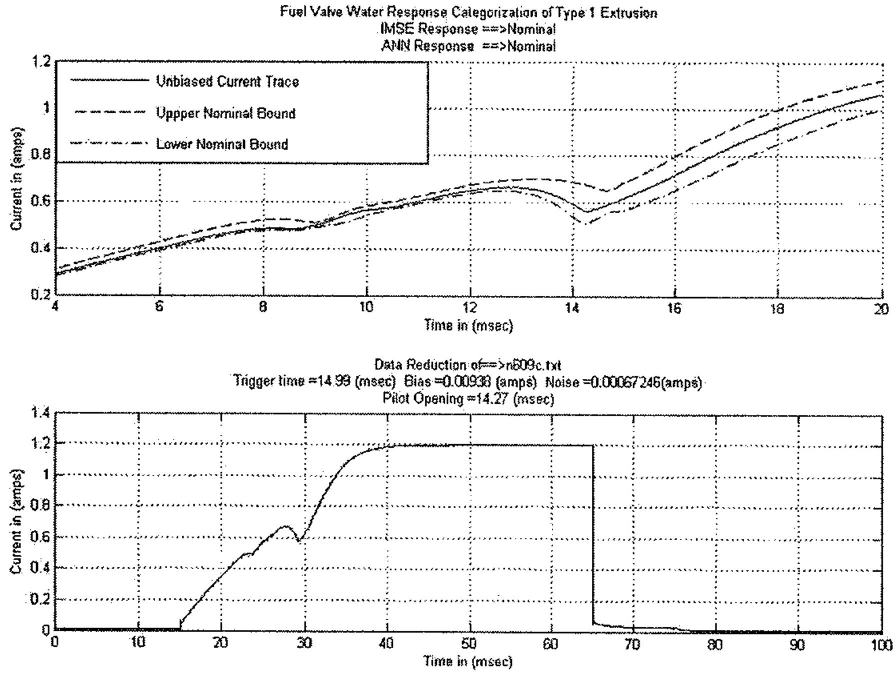

Figure 7: (Top) Operator interface showing the nominal boundary, a nominal data run and indicators for the category, (Bottom) Strip Chart analog of the current data trace with bias and pilot opening time.

OPTICS LAB TEST

The decision was made to proceed with actual hardware testing based upon encouraging research results and available time to structure a test of a mule valve in the Optics Lab. Hardware needed to be designed and built while software was simultaneously written and developed to accomplish a test which would put the design concept through its paces.

Figure 8 depicts the recorded results that would have been obtained using the ANN tool with valve SN 754. The data indicates a failed valve with a flat response. This represents the same operator interface which depicts the valve category, pilot opening time, bias, and noise characteristics. The purpose of presenting this valve characterization is simply to juxtapose with a like categorization of the mule valve that was available for our trial test.

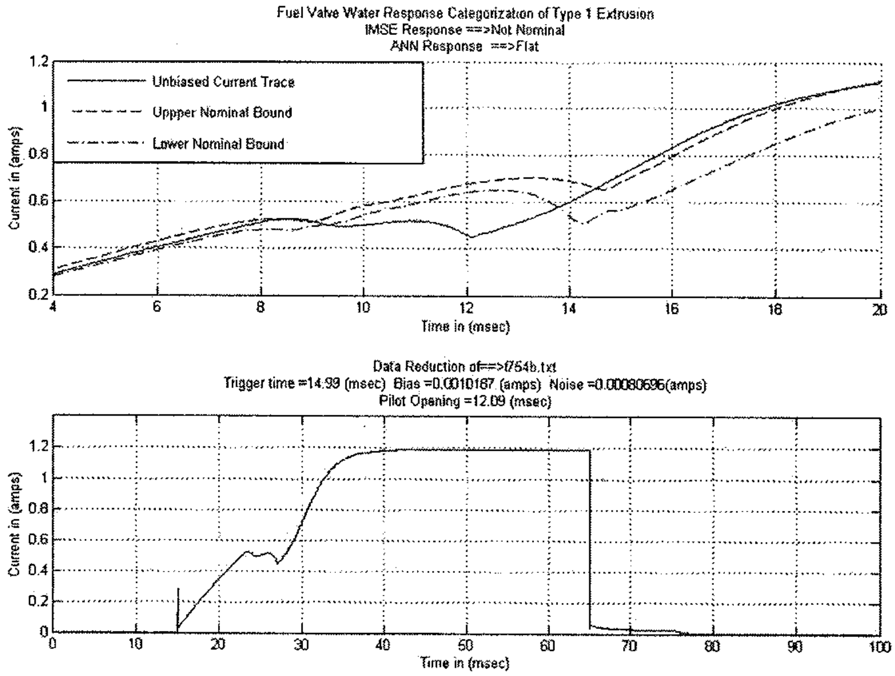

Figure 8: (Top) Operator interface showing the nominal boundary, a nominal data run and indicators for the category, (Bottom) Strip Chart analog of the current data trace with bias and pilot opening time.

The test setup in the Optics Lab consisted of a Laptop computer with the ANN software installed, a National Instruments DAQ pad, an oscilloscope, amplifier, FET switch and mule valve. The DAQ pad had been utilized in previous tests on a different project which resulted in several damaged I/O ports. This coupled with the power conditions in the lab probably were the cause of larger than expected noise levels. The mule valve was never an operational piece of equipment but did serve to simulate what could be expected in the CTF facility with actual hardware.

Therefore, when reviewing the mule valve SN 009 results (Figure 9) we see very similar tendencies as the previous failed flat response. The differences are due to the test setup and equipment utilized to obtain and analyze the data. The system experienced an increase of noise by a factor of 25 and still successfully categorized the valve. This is not surprising considering the levels that would be required to create categorical errors indicated in the Study section. The data in the CTF is much cleaner then our jury rigged testing done in the Optics Lab. The trigger pulse was initiated by hand and turned off by hand which is evident by the valve on time and the spike which initiates the current trace.

Characteristics that caused problems were not directly related to the NN software but had more to do with how to identify the trigger pulse in noise and where the pilot opening time was located in the noise. To compensate for noise effects, a variable bandwidth filter was developed and added to the software which feeds data to the ANN algorithm. With this small modification, any noise problem carried into the CTF facility with our test equipment would be neutralized.

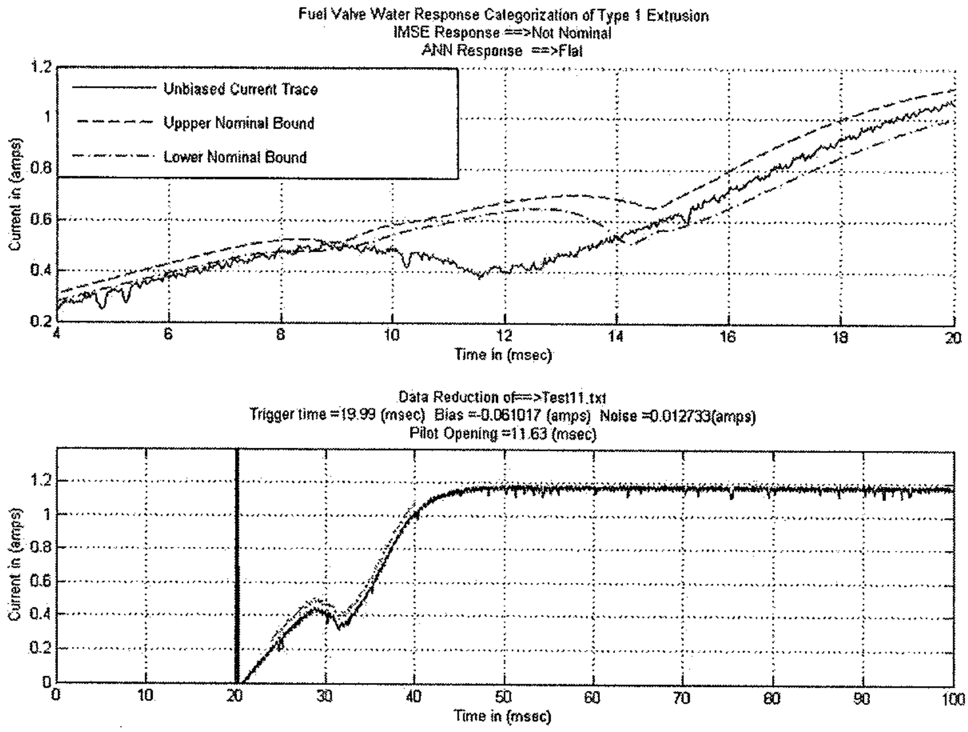

Figure 9: (Top) Operator interface showing a flat response from the Mule Valve in the Optics Lab, (Bottom) Strip Chart analog of the current data trace with bias and pilot opening time.

COMPONENT TEST FACILITY (CTF)

There was sufficient time during the development of the ANN tool to devise a demonstration of its utility with hardware and software in the CTF using actual RCS hardware. Cables were modified to run this Tool in parallel with the existing depot level test equipment. Valves that had been previously failed were identified for inclusion in this test process as well as the mule valve used in the Optics Lab Test.

The first process involved running the mule valve to verify that the cable modification did not make any difference to the results of the data. The first three runs were taken without any modification to the test equipment. The next 3 runs were taken with cable modifications to the test equipment as well as the ANN tool running in parallel. Figure 10 shows the results of all 6 runs. The variation from run to run was well within normal run to run variations associated with repeating the tests on the same valve. Valve opening times varied by less than .25 milliseconds

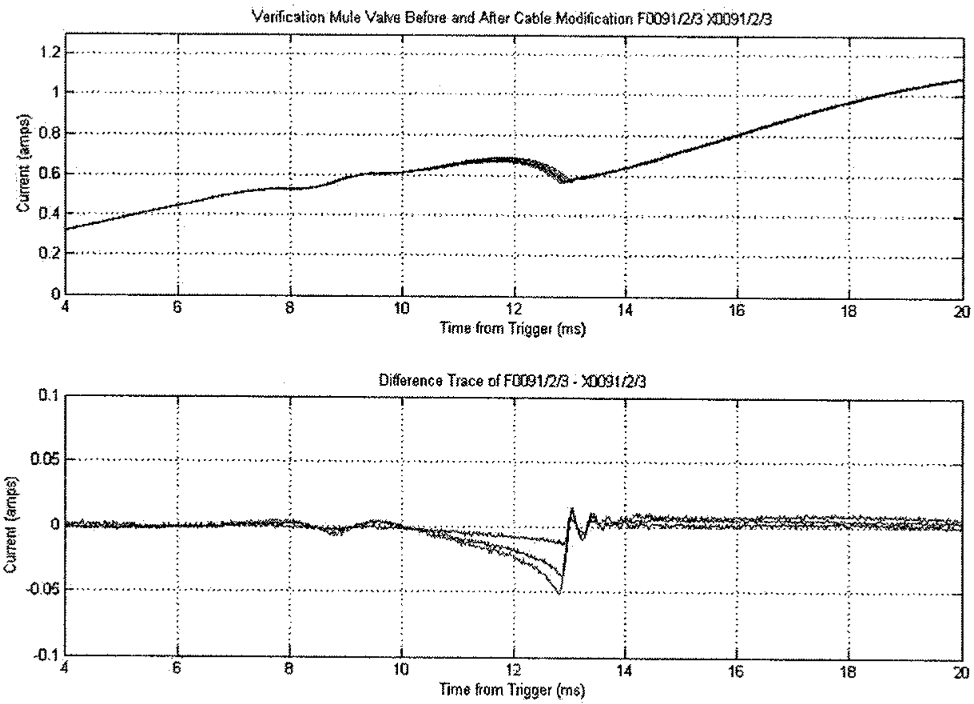

Figure 10: (Top) CTF verification run of mule valve, (Bottom) Difference trace of valve current comparing the modified cables.

The second process involved running the failed valves (SN 256 and 534) previously categorized as rounded by manual analysis. Figure 11 shows the results of this comparison. The test stand digital recording and the ANN tool recording are plotted and then differenced. The noise levels are about 10 times the magnitude as seen in the original data. This is due to the DAQ pad, as first seen in the Optics Lab test. The neural net was built to handle more noise than this. There is a .02 amp bias indicated as well from the DAQ pad but the ANN tool compensates by deleting the bias. Very little time was allocated for setting the scaling of the DAQ pad so initial results used a value with 2% error. This is shown by the difference slope increase. When corrected the scaling error was essentially zeroed, however the ANN tool was built to handle larger scaling errors so there was no need to compensate for this small error.

Figure 12 shows the final result for valve 256. Just as it had initially failed in the CTF facility prior to running the ANN Tool, it is evident that the valve is not nominal. It agrees with previous manual assessments that the valve has rounded characteristics which identifies the valve as unacceptable and should be scheduled for refurbishment.

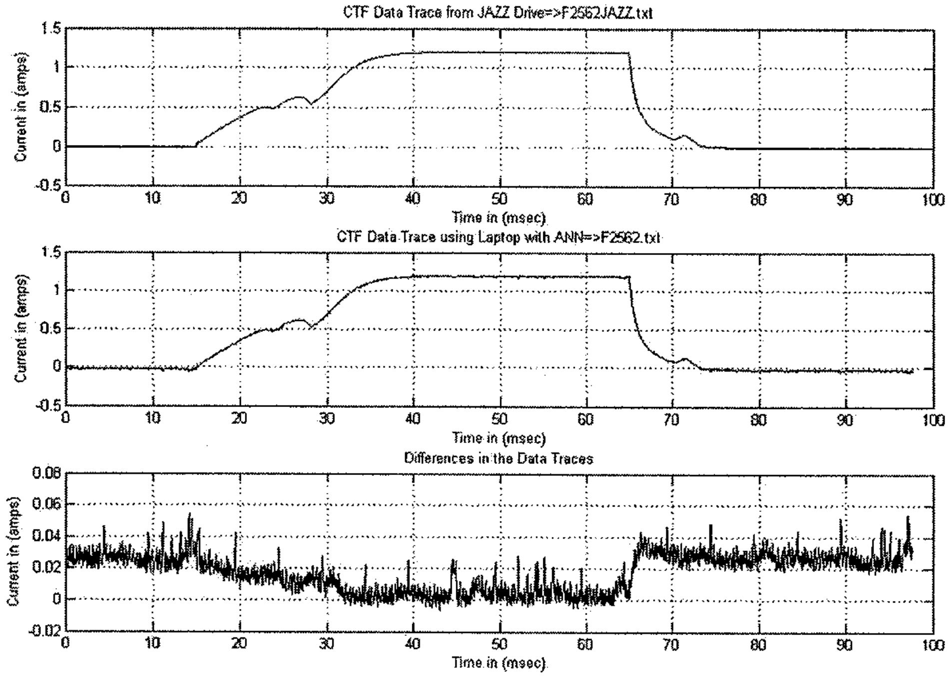

Figure 11: (Top) CTF 256 Valve trace using test stand hardware, (Middle) 256 Valve trace using parallel ANN Tool, (Bottom) Difference trace of current.

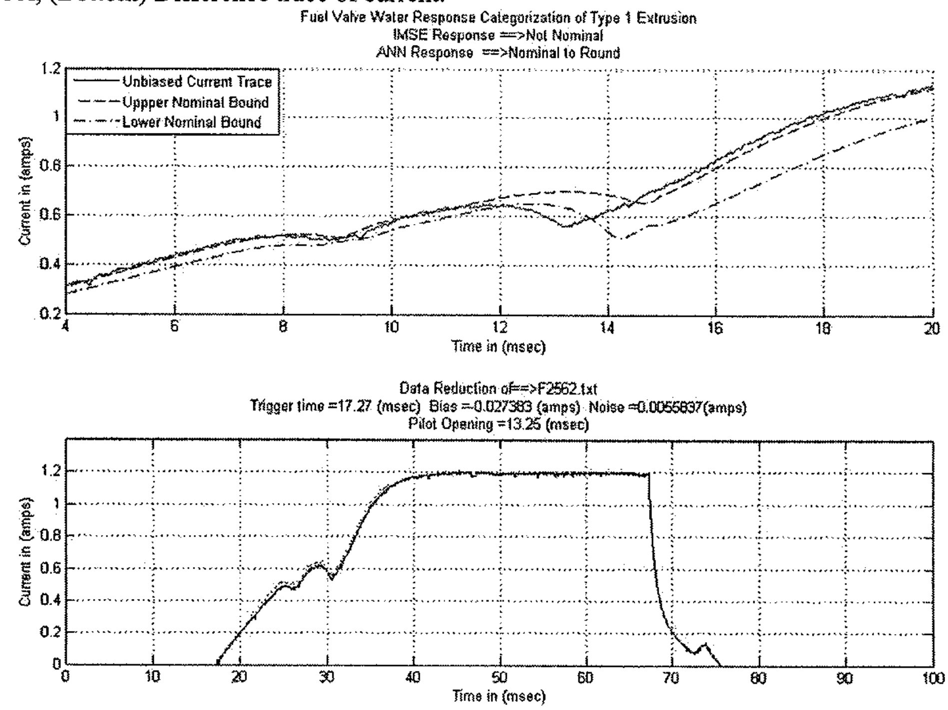

Figure 12: (Top) Operator interface showing a rounded response for the 256 Valve, (Bottom) Strip Chart analog of the current data trace with bias and pilot opening time.

CONCLUSIONS

It comes as no surprise that engineering expertise can be incorporated into software. Neural networks are suitable for pattern recognition which is the task currently required for categorization of the PRCS valves. The difference is that algorithmic implementations are consistent and non-subjective tools when compared to manual analysis.

The ANN tool is a software algorithm that will run in parallel with existing test equipment. It has been shown that there is no loss of data integrity and with minor modifications will represent a diagnostic tool that enhances the CTF's capability of typing and storing data. Further development of this tool is warranted based upon the results to date. Implementation risks have been minimized, success has been maximized, and the cost will be less than one refurbished valve.

PROPOSED PROJECT CONTINUATION

A single data trace was used to characterize and categorize the PRCS valves as a suitability test. Additional information in the form of pressure, accelerometer, and Hall-Effect traces should be incorporated to completely characterize the status of the thruster valve. Therefore, existing and historical data traces should be analyzed to enhance the accuracy of the results while augmenting the output of the current tool with the main valve opening times. Hardware and software should be configured and incorporated into the CTF as an assessment tool. Plans to this effect have been developed and presented during the final presentation of results to the WSTF management and staff.

Future studies would be important to optimize the performance of the neural network in the proposed ANN tool. These studies would determine the optimal neural network type, number of layers and neurons, training algorithm, and category refinement. In addition, the RCS valve simulation should be further development, understood and documented. This would help in fully understanding the properties of the valve and might be included in the ANN tool which could then predict seal extrusion and useful valve life before refurbishment.

REFERENCES

1) Corder, Mike. "Crippled but Not Crashed", Scientific American, August 2004, vol. 291, no. 2, pages 94-95

2) Hagen, Martin, et.al., Neural Network Design, University of Colorado, 1996.