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ENGINE HEALTH MONITORING SYSTEM FOR ADVANCED DIAGNOSTIC MONITORING FOR GAS TURBINE ENGINES

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A PROTOTYPE USAF ENGINE HEALTH MANAGEMENT (EHM) SYSTEM WAS DEVELOPED AND GROUND TESTED DURING THIS PHASE II SBIR PROGRAM. THE EHM SYSTEM IS CAPABLE OF REAL-TIME MECHANICAL MONITORING AND DIAGNOSTICS, AERO-THERMAL PERFORMANCE MONITORING AND DIAGNOSTICS, AND "ENGINE SIGNATURE" BASED LIFE ACCUMULATION. FOR THE FIRST TIME, STATE-OF-THE-ART ANOMALY DETECTION, MONITORING, DIAGNOSIS AND ADVANCED LIFE PREDICTION ANALYSIS WERE INTEGRATED TOGETHER IN A SINGLE REAL-TIME ENGINE HEALTH MONITORING SYSTEM. ADDITIONALLY, THE EHM SYSTEM WAS DEVELOPED TO ASSIST THE 2-LEVEL MAINTENANCE CONCEPT AND IHPTET INITIATIVES.

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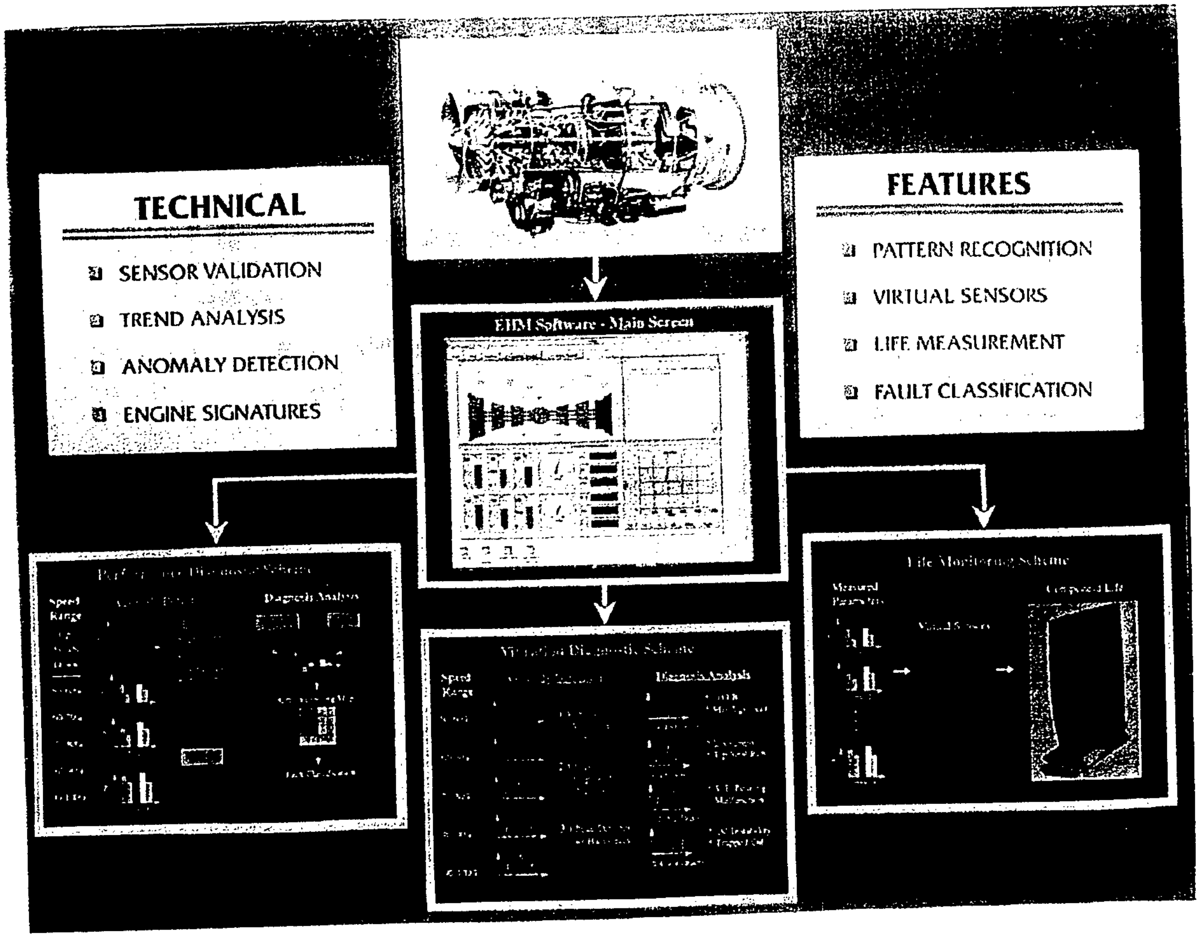


1.0 Executive Summary

A prototype USAF engine health management (EHM) system was developed and ground tested during this Phase II SBIR program. The EHM system is capable of real-time mechanical monitoring and diagnostics, aero-thermal performance monitoring and diagnostics, and "engine signature" based life accumulation. For the first time, state-of-the-art anomaly detection, monitoring, diagnosis and advanced life prediction analysis were integrated together in a single real-time engine health monitoring system. Additionally, the EHM system was developed to assist the 2-level maintenance concept and IHPTET initiatives.

The modular EHM system consists of four principal operating subsystems; they are the data management, health, diagnostic, and engine life engineering modules. Within these four modules, mechanical and performance related anomaly detection and diagnostics, mission-based life usage, sensor validation, virtual sensing, and long/short trending capabilities are performed in real-time. The real-time operation of the four modules is performed simultaneously within a PC-based computing structure under the Windows® NT operating system. Data transfer and real-time analysis was accomplished automatically within the flexible modular subsystems, allowing for the customized development of an EHM system for any chosen USAF engine. EHM system modules can now be developed for any class of engine, with engine specifics being incorporated into the engine specific diagnostic networks and algorithms after initial system installation.

The prototype EHM system was ground test verified on three (3) F405 (Adour) engines during production pass-off testing at Rolls-Royce plc in Bristol, England. Results from EHM system testing and follow-up analysis emphasized that an important balance must exist between the real-time diagnostic capabilities and the ability to deal with "real world" uncertainties from sensor signal transients, random measurement fluctuations and non steady-state performance and vibration parameter changes. Therefore, based on the results obtained from the ground testing, the developed EHM system demonstrated the ability to perform real-time diagnosis of sensor signals, mechanical/performance faults, and life usage estimates associated with the F405 (Adour) engine.

A Phase III program extending the principles demonstrated herein is currently underway that includes the development of a customized EHM system for the GE F101 USAF engine.

2.0 Program Overview and Objectives

2.1 Overview

The integration of life, vibration and performance monitoring/diagnostics that is capable of detecting and classifying developing engine faults is critical to reducing engine operating and maintenance costs while optimizing the life of "hot section" engine components. A modular, comprehensive engine health monitoring (EHM) system capable of integrated mechanical, performance, and life based monitoring has been developed in this Phase II SBIR program.

Engine data currently sensed and recorded for post flight processing is now analyzed in a continuous real-time mode as demonstrated in this program. The measured data from the EHM system is passed to redundant anomaly detection routines for analyzing both performance and mechanical related faults. These routines were developed based on extensive knowledge of how healthy engines operate under a range of operating conditions, and any deviation from this "normal" pattern of expected parameters will be detected and further analyzed. Faults resulting from sensor failure modes will be promptly isolated in the EHM "data management" module, while more complex faults will be identified by pattern classification schemes in the "health" and "diagnostic" modules.

Also developed during this program, advanced technologies for "virtual sensing" currently unmeasured engine parameters such as turbine entry temperature (TET) are used for input to critical component lifing algorithms. As a result, component life usage was determined more accurately based on real-time, model-based parameter estimates and actual engine conditions.

2.2 Objectives

The principal objective of this Phase II SBIR program was to develop a prototype Engine Health Monitoring (EHM) system capable of real-time mechanical diagnostics, aero-thermal performance monitoring, and critical component life usage. These aspects of the developed EHM system were directly coupled to an individual engine's mission profile and operating conditions. The architecture of the EHM system was influenced by the integration of existing technologies, namely neural networks, fuzzy logic, and probabilistic life prediction analysis, and has advanced the current state-of-the-art in USAF engine monitoring systems. The ultimate objective of the EHM system was to minimize scheduled/unscheduled engine downtime, maintenance manpower and component failures, while maximizing engine reliability through more accurate and timely diagnosis and life measurement capabilities.

A more detailed description of the Phase II program objectives is given below. This is the same list that was given in the original Phase II proposal, and as one can see, these objective have been satisfied under this program.

1.) Incorporate a more realistic measure of the engine operating life through better utilization of the currently measured and calculated parameters in component life accumulation algorithms.

2.) Develop artificial intelligence based modules for performing both real-time engine diagnostics and trend-based, long term mechanical diagnostics, and aero-thermal performance monitoring.

3.) Integrate engine component diagnostics, life usage, and trending capabilities within a modular data processing structure. Health, diagnostic, data management, and life modules will be developed for the F405 (Adour) engine on the T45 trainer.

4.) Enhance current low cycle fatigue (LCF) based life usage algorithms to include temperature and material creep effects. Produce more realistic component life estimates based on better mission representative information.

5.) Improve the timeliness by increasing automation and reducing the human intervention required with current monitoring systems. Calculating engine life usage at the end of each mission and offer a comprehensive diagnostic report.

6.) Develop real-time engine diagnostic networks in parallel with trended data expert systems to address the problem of fault severity and duration

7.) Develop fuzzy logic and deductive reasoning algorithms to determine the causes for the diagnosed failures or degraded performance.

2.3 Current USAF Trending/Diagnostic Systems

Current USAF engine health monitoring systems have many inefficiencies that can be overcome with the integration of advanced monitoring/diagnostic and life prediction technologies. Some of the current trending system shortcomings include; 1.) Data collection/trending is cumbersome and tedious, 2.) Diagnosis and recommended maintenance is only obtained from experienced individuals who can analyze the trended data, 3.) Human misinterpretation of data and labor intensive, 4.) Life accumulation is primarily based on TAC cycles, little account for thermal or vibratory effects, 5.) Exhaustive data transfer mechanisms, and 6.) Considerable time is needed to make a thorough diagnosis, resulting in delayed maintenance. Figure 1 is an illustration of the current labor and data intensive monitoring system, with its several interfaces.

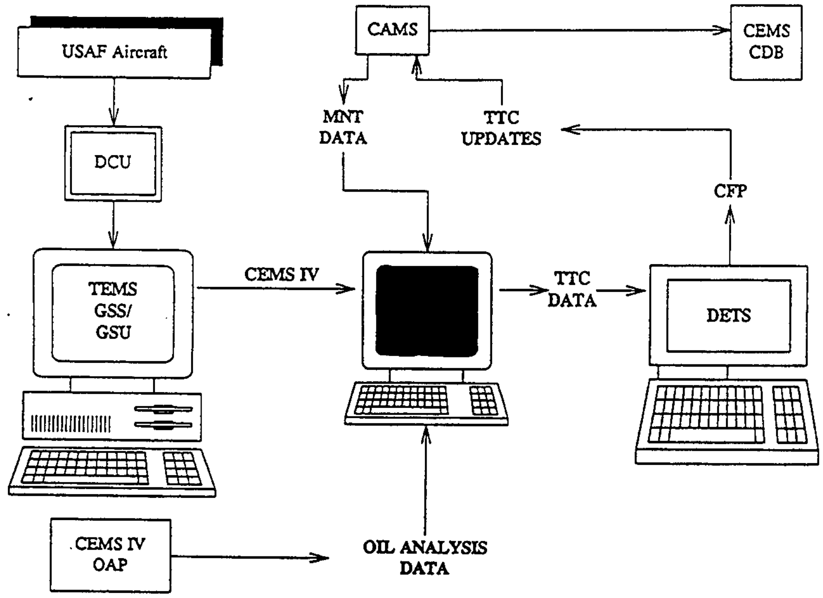


Figure 1 Current USAF Monitoring System Configuration

2.4 Benefits of EHM System

As a result of real-time engine diagnostics and more representative engine component life predictions, gas turbine engines will undoubtedly become more reliable and more efficiently and economically maintained. This will be accomplished through proper management of engine performance degradation, reduced scheduled and unscheduled downtime, lengthened inspection intervals, and improved logistics through advanced maintenance planning. Achieving these goals will undoubtedly help support 2-level maintenance and the IHPTET initiative

As an example of the cost savings that can be realized with the implementation of more "mission representative" engine life prediction schemes (therefore being able to safely increase inspection intervals), consider the following 5 year study associated with the inspection of engine disks. Over the five year period extending from October 1986 to September 1991, approximately 15,000 disks were inspected for safety critical size cracks. Of the 15,000 disks inspected, approximately 13,000 of those disks were returned to service without rework or modifications. The economic savings that could be gained from reducing this maintenance effort by a realistic 20-40 percent, while maintaining current safety requirements, would be great.

From a technical point of view, the application of advanced fault classifiers/algorithms to real-time engine diagnostics and more mission representative lifing algorithms, current engine health monitoring systems can be improved significantly. In particular, the incorporation of neural networks into the diagnostic process will yield great benefits in terms of processing speed, robustness, knowledge acquisition, and adaptability. Other important technical benefits of applying AI and advanced life prediction schemes to condition monitoring, diagnosis, and life usage are as follows:

1.) Enhanced ability to capture, organize, and utilize all relevant data, experience, and rules within a massively parallel, interconnected processing modules.

2.) Provides an automated procedure for incorporating data from several knowledge sources including; analytical FEM models, aerothermal performance models, empirical/trended test data, and heuristic (rules based) experience.

3.) Neural network system architectures are well suited for processing large quantities of non-linear, multidimensional, coupled parameters such as temperatures, pressures, etc. that occur within a gas turbine engine.

4.) Utilizing advanced diagnostic algorithms results in a process that is less dependent on human experts and more automated to facilitate quick decision making.

5.) Incorporating more information (i.e. currently unmeasured parameters) into the proposed life accumulation algorithms will provide a more accurate outlook on the remaining life of critical engine components.

3.0 Program Technical Approach

The technical approach and system development concept followed in this program is outlined below. Engineering module development, hardware issues (sensor signal processing), software development, and system testing are examined in general terms.

3.1 EHM Technical Approach

The real-time data acquisition scheme and structured database that exists at the core of the data management module was developed at the outset. The database architecture, incorporating multi-processing techniques and priority system interrupts was also developed at the start. A comprehensive database of engine parameter thresholds and ranges was initially compiled as a first condition with which to compare inflowing data. Engine data sensed out of these desired operating ranges, as determined from the "engine signature" models, triggers the health and diagnostic modules to examine current and trended data patterns for component faults and subsequent prognosis. An F405 (Adour) engine aero-thermal performance model was used to "virtually sense" the significant engine parameters that are not directly measured, i.e turbine inlet temperature, etc.

Engine signature based anomaly detection utilizing fuzzy-logic and associated rule bases were used in the health module to detect engine anomalies (both mechanical and performance related). The fuzzy-logic based anomaly detection was developed from non-normal deviation from the "engine signature" models. In addition, trended data algorithms were developed to sample data at precise and consistent instances during take-off conditions. This data was passed on to dedicated algorithms which interfaced with the real-time network diagnostics for determining fault severity and duration. The F405 (Adour) engine synthesis model and ground test data supplied by Rolls-Royce plc. were used to develop fault patterns associated with aero-thermal performance and vibration issues.

Pattern recognition utilizing neural networks, with pre and post processing capabilities, formed the heart of the EHM diagnostic module. Critically identified fault conditions with the most significant behavioral pattern relationships were initially identified so that network architectures could be developed. Recognized fault pattern diagnosis was accomplished in the diagnostic module using a combined fuzzy logic and neural network approach. The neural network input/output patterns were "clustered" using Kohonen Self Organizing Maps and further used to develop the fuzzy logic reasoning algorithms based on engine through flow models and experimental case histories. Diagnosed engine conditions that yield similar fault patterns were differentiated within this module and verified with the use of the F405 (Adour) engine model.

The engine life module analyzed the remaining life of the HP turbine blades and disk using BLADE GT (disk/blade) and Rolls-Royce provided empirical formulas to determine the amount of life consumption per sortie. Critical component life design algorithms used in the development of the F405 (Adour) engine were included in the EHM life accumulation algorithm.

3.2 EHM Capabilities and Architecture

Figure 2 illustrates a block diagram of the capabilities that are built into the developed EHM system. The four modules that perform the data management, health, diagnostic and engine life functions operate simultaneously, transferring real-time, trended, diagnostic, and component life data between the modules as needed.

The main responsibility of the Data Management Module is to acquire the real-time, sensed engine data. Next, the module utilizes a neural network predictor architecture to perform several quality control checks to ensure the integrity of the sensed data. Once the data is thoroughly checked, a larger set of engine parameters are derived from the directly sensed engine parameters using a standard back propagation network architecture. This larger set of engine parameters is used in the health and diagnostic modules. An engine duty monitor is also present in the data management module. Engine life is accumulated based on LCF and thermal cycles and is presented as a fraction of total available life for both the HP turbine blades and disk. The final function performed in this module was overall system data storage and retrieval. Raw sensed data, trended data, diagnosis results and engine life accumulation reports are all stored in this sub-module.

The Health Module is dedicated to examining the real-time engine parameter data set, trending it over time, and detecting any initial anomalies associated with the engine. Specific trend patterns and parameter ratios are taken at precise times during take-off to ensure consistent and accurate trending information. When an acquired engine parameter is detected as falling outside the "normal" engine operating signature, it is forwarded to the diagnostic module for detailed examination. Based on the trended data and fault pattern recognized, the severity and duration of the recognized fault is also determined. In this procedure, the difference between a sudden or abrupt fault can be distinguished from a slowly degrading engine performance related concern.

Once data is transferred to the Diagnostic Module, dedicated neural networks and fuzzy logic based algorithms determine the cause of the diagnosed failure or degraded performance. The neural networks developed and implemented in the health module are based on a Self Organizing Kohonen Map that clusters similar fault patterns and passes them to a standard back-propagation network that classifies the particular fault. The combination of these neural networks make it easy to examine and identify faults patterns from the clusters and not just rely on the "black box" approach of using a single back-propagation neural network. This "back-to-back" neural network approach is also very robust with respect to sensor noise and parameter uncertainty.

During a mission or test, data from the engine duty monitor within the Data Management Module is continuously being transferred to the Engine Life Module so that "mission representative" life may be accumulated. The life accumulation algorithm will include the engine specific parameters tracked throughout the entire mission. Hot section temperatures and corresponding material creep will be determined and used as input to the life accumulation algorithms. At the end of the mission, critical component life accumulated during that mission is reported and transferred back to the trending module for overall accumulation of each components life usage.

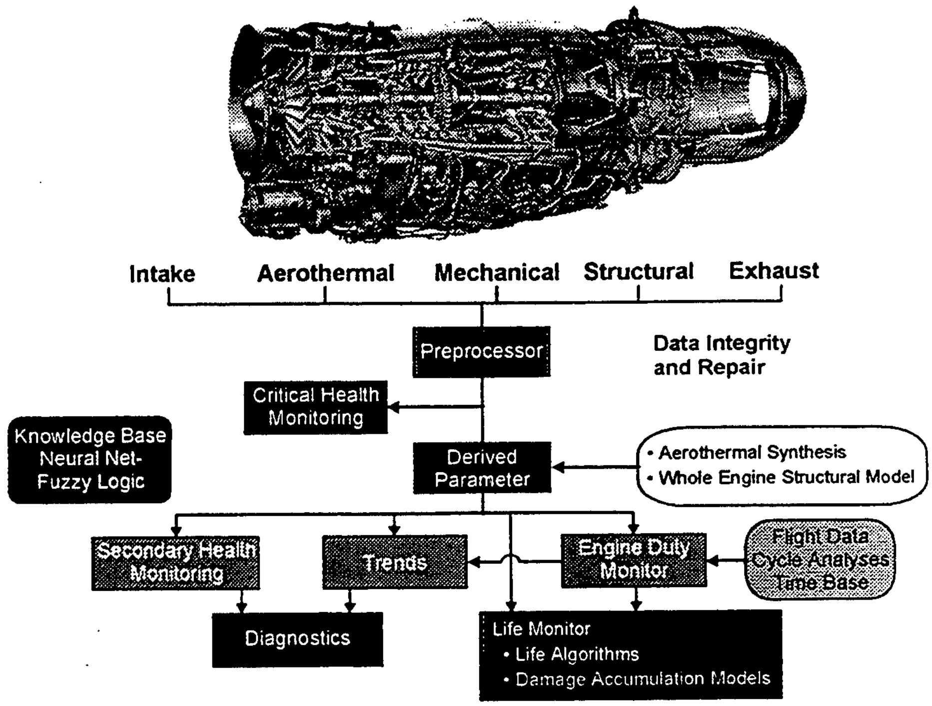


Figure 2 Engine Health Monitoring System Capabilities

3.3 Adour-Navy F405 Turbofan Engine Description

The Rolls-Royce Turbomeca Adour (F405) turbofan engine is now in general use as the powerplant for several subsonic combat aircraft and advanced trainer aircraft. The engine was originally designed to the requirements of the British and French Governments for the Jaguar aircraft, which is in operational service with the Air Forces of both governments. A similar power unit is fitted to the Japan T-2 trainer and Japan F-1 fighter support aircraft in service with the Japan Air Self-Defense Force.

An unaugmented version of the engine is fitted to the British Aerospace Hawk in service with the Royal Air Force, and, designated as F405-RR-401, is fitted in the McDonnell Douglas T45A Goshawk trainer for the US Navy. The F405-RR-401 shown in Figure 3 is a two-shaft turbofan engine with medium bypass and pressure ratios.

There are a total of seven stages of compression, two on the low pressure (LP) compressor and five on the high pressure (HP) compressor. Neither of the compressors are fitted with inlet guide vanes and there are no variables apart from a simple bleed valve which operates only during starting. Steel and titanium are extensively used in the compressor blading and all blades are of wide chord with large axial clearances between blade rows giving a high resistance to the effects of foreign object ingestion.

An annular combustion chamber makes possible a reduction in the engine length, volume and weight relative to tubular and annular systems. Temperature distribution can be improved minimizing surface cooling requirements, and the interconnection problems associated with individual flame tubes are eliminated.

The 18 air spray burners are designed such that air passes through a central passage in the burner head picking up fuel from an annular gallery. The fuel/air mixture is formed into a spray by passing over a cone and the spray profile is controlled by a further air flow passing externally over the burner head. Ignition is by two igniter plugs.

The engine main journal bearings are fitted inside "squeeze film" mountings in which the bearing outer track is supported on a thin annular cushion of oil fed from the normal oil system, as shown in Figure 4. Squeeze film mountings reduce the forces transmitted between the engine rotors and casings, lessening vibration and giving improved component life, particularly to sheet metal parts and accessory units.

The HP and LP turbines are each single stage. The high pressure nozzle guide vanes feature an advanced system of air cooling including impingement and film cooling at the leading edge, internal ribs and pedestals to maximize head dissipation in the airfoil, and cooling air ejection through slots in the trailing edge.

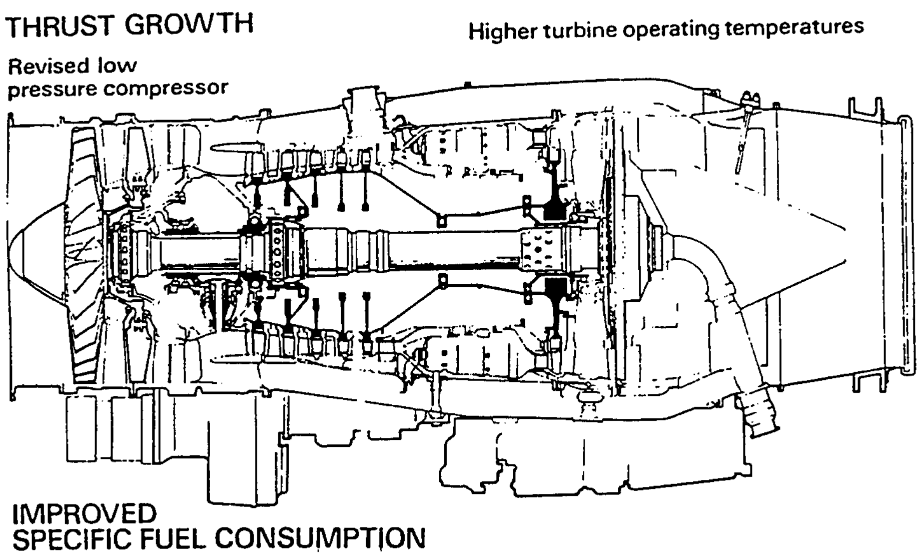
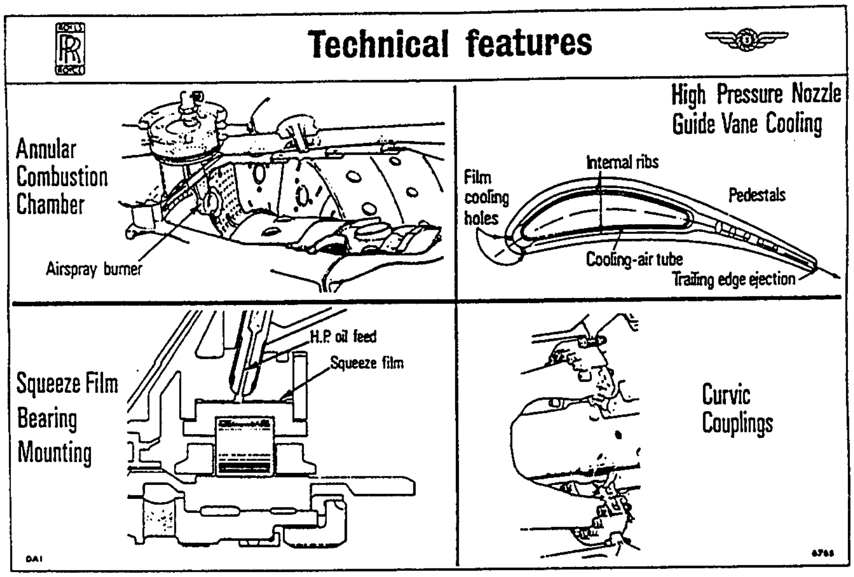


Figure 3 F405 (Adour) Turbo Fan Engine



The major components of the rotating assemblies are joined by curvic couplings which provide complete location by means of meshing teeth on the mating faces. These components can therefore be assembled without the need for individual fitting, such as taper reaming, at each joint. The increased ease of assembly makes modular exchange practicable for major rotating components in the same way as for static assemblies. A single external gearbox is fitted which is driven off the HP rotor.

The Adour engine in its various non-afterburning forms is available at thrust levels between 5200 and 5990 lbf. As an example the performance of the Mk 871 engine, of which the F405 is a modified version, is given below.

1.)	Take-off thrust	5990 lbf.
2.)	Bypass Ratio	0.76:1
3.)	Overall Pressure Ratio	11.3:1
4.)	Basic Power Unit weight	1299 lbs
5.)	Length	77 ins
6.)	Intake diameter	22ins.

The basic features of the engine, as a two-shaft turbofan engine, is typical of the engines in most gas turbine powered military aircraft today and, therefore, and ideal vehicle for evaluating and demonstrating the features of an intelligent engine health and life monitoring system.

<u>F405 (Adour) Engine Instrumentation</u>

The F405 service engine is fitted with various sensors which enabled the features of the EHM system to be comprehensively evaluated. The specific instrumentation is shown schematically in Figure 5 below and consists of:

1.)	LP spool shaft speed	NL
2.)	HP spool shaft speed	NH
3.)	HP compressor delivery pressure	P3
4.)	LP compressor delivery pressure	T2

5.)	Jet pipe temperature	T6
6.)	Fuel flow	Wf
7.)	Vibration transducer & charge amp.	Vb

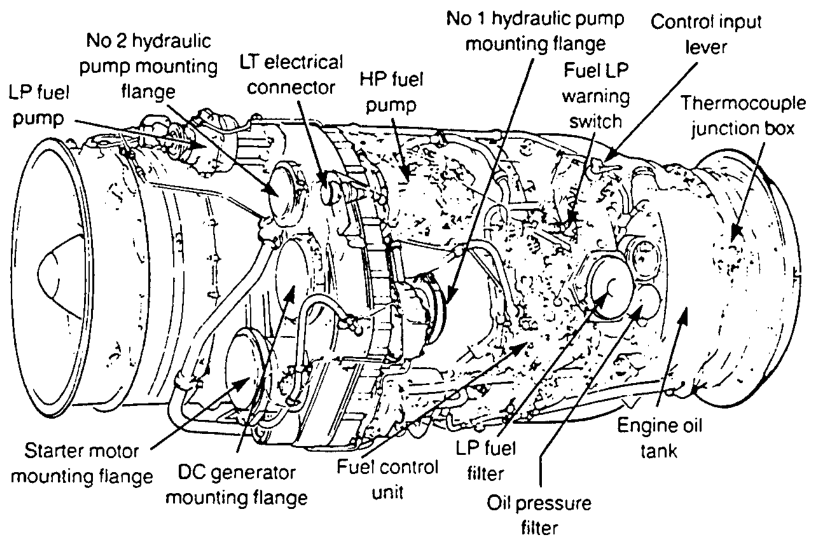


Figure 5 Adour Engine Instrumentation

In addition, on the T-45A Goshawk, the following data is available from the Aircraft Data Recorder system:

1.)	Power Lever Angle	PLA
2.)	Ambient Pressure	Po
3.)	Ambient Temperature	To
4.)	Altitude	Alt
5.)	Mach No	Mn

F405 (Adour) Engine Aero-thermal Performance Model

A complete aero-thermodynamic model of the engine is available within the RRAP (Rolls-Royce Aerothermal Performance) Computer Synthesis. This model provided the necessary algorithms for data reduction and additional parameter calculation within the EHM system. It was also used, together with an extensive empirical database, to generate a knowledge base for the neural net evaluation of engine status.

4.0 EHM System Development

The following section will describe the engineering developments and operations of the Engine Health Monitoring system. The specific algorithms and mathematical framework that was used in developing the EHM system will be presented in each of the functional modules described below.

4.1 EHM Engineering Modules

The Engine Health Monitoring system developed under this SBIR program consists primarily of four engineering modules that will perform sensor validation/recovery, trending, anomaly detection, diagnostics, and life usage functions. The four modules are named (1) data management, (2) health, (3) diagnostic and (4) engine life and operate simultaneously, transferring real-time, trended, diagnostic, and component life data between the modules as needed. The basic block diagram illustrating the functionality of each module is given below in Figure 6.

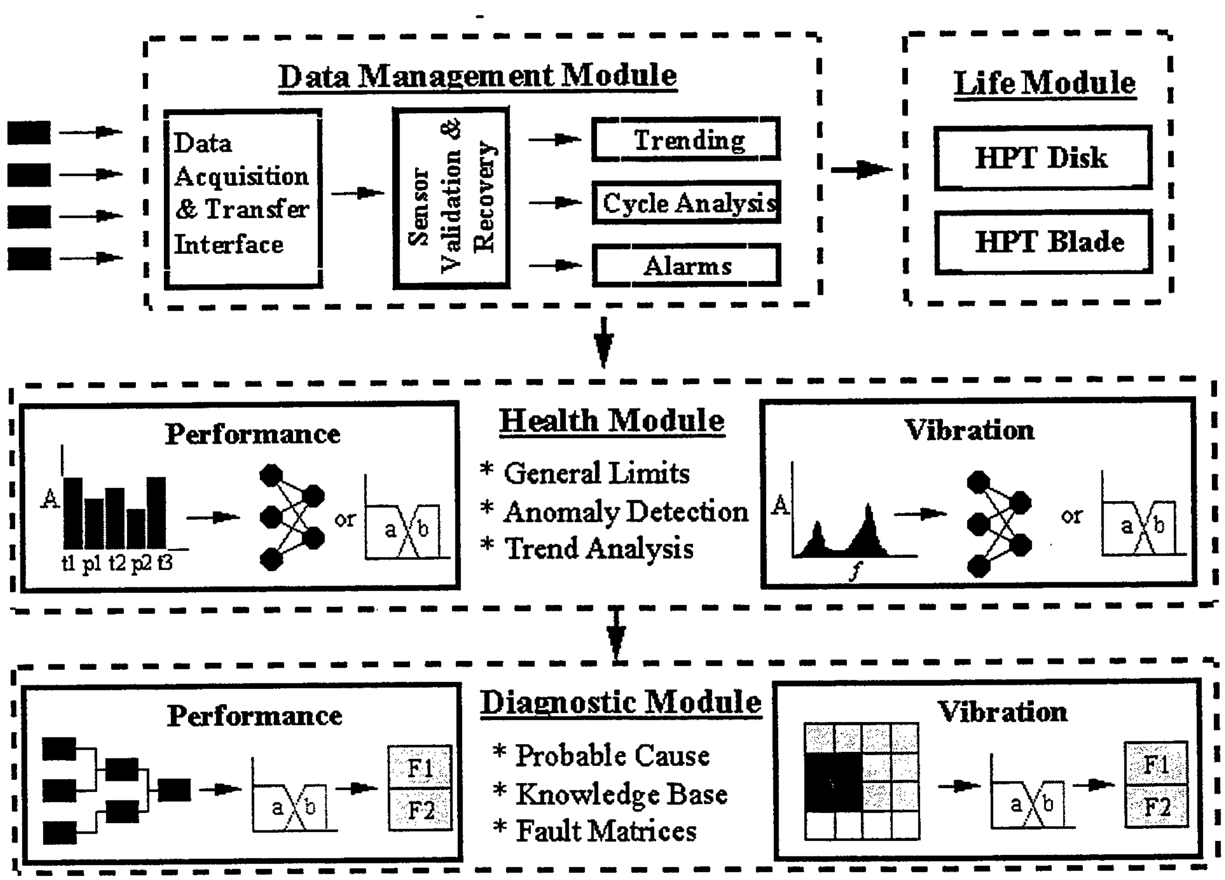


Figure 6 EHM Engineering Modules

4.2 Data Management Module

The primary function of the Data Management Module is to acquire the real-time, sensed engine data. In doing so, the module utilizes a feed-forward neural network predictor architecture to perform several quality control checks to ensure the integrity of the sensed data. Once the data is thoroughly checked, additional engine parameters are predicted in real-time from the directly sensed engine parameters using a standard back propagation network architecture trained by "engine synthesis" models. Hence, currently unmeasured engine parameters such as turbine entry temperature (TET) can be predicted and utilized in real-time just as the directly sensed parameters. These "virtually sensed" engine parameters are then used in the engine life module to obtain more accurate and realistic measures of hot component life parts. An engine duty monitor is also present in the data management module. Engine life is accumulated based on LCF, creep, and thermal cycles and is presented as a fraction of total available life. The final function to be performed in this module is overall system data storage and retrieval. Raw sensed data, trended data, diagnosis results and engine life accumulation reports are all stored in this sub-module.

One of the most critical functions of the data management module will be to evaluate the quality of the measured signals. This will include both tolerance bands as a function of a baseline parameter and the use of pattern matching with a database of known signal sets. Any anomalous signals will be identified and evaluated in comparison with the other prevailing signals to decide on acceptability or need for repair. As an example of data repair it may be necessary to recompute the average jet pipe temperature as a result of a loss of one of the 12 T6 thermocouples. If the signal is erroneous and cannot be repaired, a decision flow path manages subsequent analysis to account for the missing signal.

This submodule will also record any limit exceedances in addition to the normal engine control unit function. It will flag any overspeeds, pressure or temperature exceedances and record data until the exceedance event is over.

4.2.1 Sensor Validation and Recovery System

An advanced sensor validation scheme capable of detecting failed sensor hardware without sensor redundancy and during non-steady state monitoring conditions is a necessary "front end" to the EHM system. The developed approach utilizes neural networks and fuzzy logic to accomplish the desired goal (Harrison and Harrison, 1994) (Holbert et al., 1994). Neural networks are used to recognize the non-linear, inter-relationships between the different types of sensors used in either a transient or steady-state measurement environment (Lee, 1994). Fuzzy logic is used to pre- and post-process the measurement data in order to determine general characteristics about the state of operation of the engine.

A block diagram of the sensor validation system architecture is given in Figure 7. The speed/power sensor data is first accepted by two parallel fuzzy logic modules. The first module determines the state of the speed/power condition (i.e increasing, decreasing, or steady-state) and the second verifies the validity of speed/power sensor itself. The output of the speed/power condition module triggers a particular neural network module that was specifically trained to know the sensor relationships for either increasing, decreasing or steady power output. Only one neural network modules is triggered at a time, depending on the outcome of the prior fuzzy logic decisions. The sensor confidence values predicted by the neural networks are trended over time and passed through another fuzzy logic module to interpret the results. These extra steps are used to ensure that false alarms do not occur.

For the Adour (F405) engine application discussed herein, there are four primary performance related sensors (along with LP and HP rotor speeds) that are measured during turbine operation. These sensors include; fuel flow (Wf), HP compressor delivery pressure (P3), LP compressor delivery temperature (T2), and Jet Pipe temperature (T6). The developed neural network utilized a multi-layered, feed-forward architecture with six input nodes, five output nodes, and one hidden layer with 13 nodes. The outputs of the neural networks yield a confidence factor associated with the probability of a failed sensor. A confidence factor near one represents proper sensor operation, while a confidence factor near zero indicates a faulty sensor mode. A fuzzy logic module is used at the output of these neural networks to decide whether the sensor is good, bad, or somewhere in between. For instance, if a hard decision was utilized to alert the crew when a sensor confidence factor reached a level less than 0.80, false alarms would likely occur even though a sensor confidence factor of 0.78 might still indicate a properly working sensor.

SENSOR VALIDATION SYSTEM ARCHITECTURE
(NON-REDUNDANT; NON-STEADY STATE)

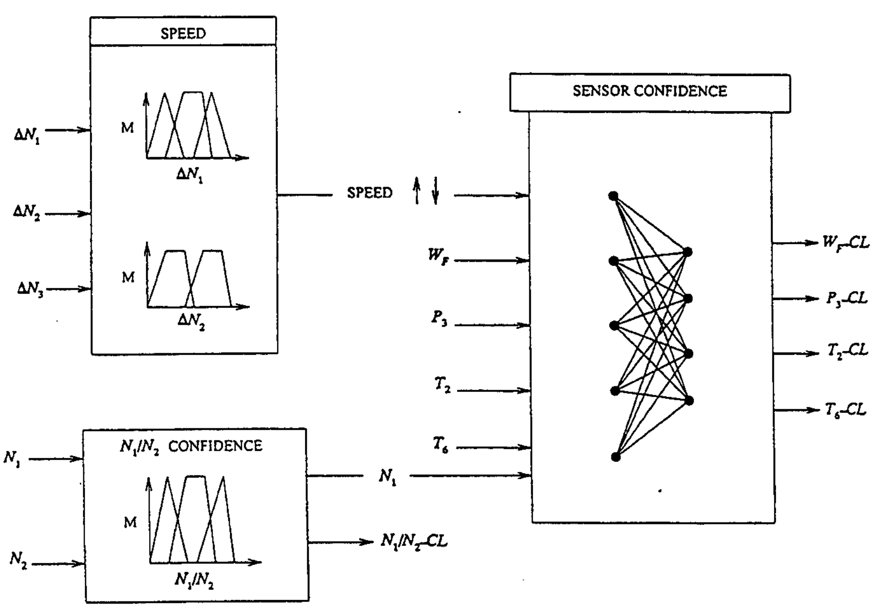


Figure 7 Sensor Validation Scheme

Neural Network Architecture and Training

Two different neural network architectures were examined for this application. Both networks utilized a multi-layered, feed-forward architecture with five input nodes and four output nodes. The first network contained one hidden layer with 13 nodes and the second used 2 hidden layers with 10 and 5 nodes respectively.

Determining the "optimal" number of hidden layers and nodes for each network is a non-trivial task and depends on many factors, some of which include; number of input/output nodes, quantity and accuracy of training data, complexity of problem, and resulting network generalization performance. The "standard" feed-forward architectures used for this problem were picked due to the large quantity of training data available and the resulting network generalization performance required.

The simulated gas turbine engine data used to train the neural network architectures was generated from the engine synthesis model. The data set represents sensed fuel flow, pressure, and temperature readings during a start-up condition. Simultaneously measured data staying within the illustrated confidence limits for each sensor would represent properly operating sensors. Data going outside these limits would indicate a failure mode associated with the particular sensor. For training purposes, any measurement within the confidence limits of each sensor for a particular engine speed would indicate a sensor confidence level of 1.0 (highest confidence). As a sensor measurement moves outside the confidence limits, the neural network output confidence level decreases from 1.0 towards 0.0 indicating the graduating sensor failure mode. Each network architecture was subjected to the same training data set consisting of 300 input/output pairs.

Training the sensor validation networks was accomplished with a supervised learning procedure. Each of the 300 training pairs or patterns used during the training process consisted of 5 sensor input signals and it's corresponding set of 4 outputs sensor confidence factors. The input and output training data was normalized to values between 0 and 1. An error-back-propagation algorithm was used to minimize the mean-squared error between the actual network output and the target values set by the training set. Training parameters such as the learning rate, gain of the activation function, and momentum coefficient were adapted during the training session to aid in minimizing the error. A final RMS error associated with all training pairs was reduced to 0.199.

Sensor Validation Neural Network Results

A computer generated data file simulating normal and faulty sensor measurements was developed to test the accuracy of the two neural network architectures. Figure 8 is an illustration of a small section of that file including a range of fuel flow measurement data. The data represented by the + signs are all within the confidence limits of normal operating sensor patterns. In this case, sensor confidence levels predicted by the neural network should all be close to one. The data indicated by X's and O's are outside the confidence limits and therefore indicate worsening sensor operation. The X's are just outside the confidence limits and should predict sensor confidences between zero and one. The O's are significantly outside the sensor confidence band and should predict sensor confidence levels close to zero. The results from this data file are given in Table 1 below. Note, the other sensor measurements including temperatures, pressure, and speed were all within the confidence limits.

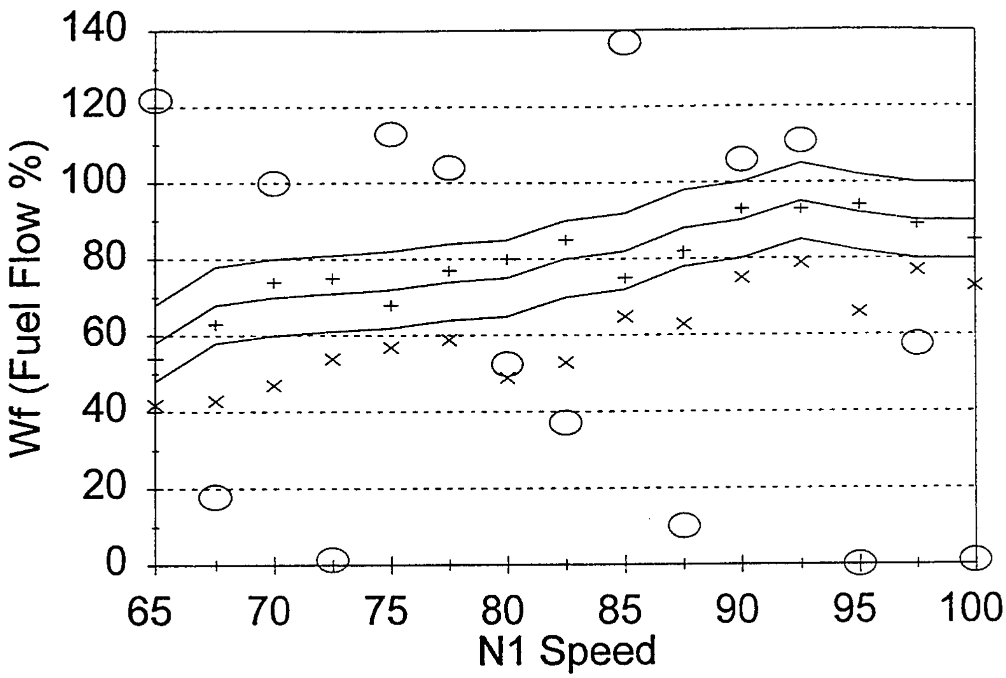


Figure 8 Simulated Fuel Flow Test Data

Table 1 Neural Network Results

Case #	"+"	"x"	"o"
1	0.9197	0.2711	0.0755
2	0.9990	0.1674	0.0543
3	0.9990	0.2625	0.0923
4	0.9861	0.7777	0.0500
5	0.9990	0.7700	0.0923
6	0.9990	0.7852	0.1061
7	0.9756	0.2378	0.4670
8	0.9112	0.1263	0.0380
9	0.9734	0.8133	0.1389
10	0.9723	0.3508	0.1736
11	0.8831	0.9244	0.4835
12	0.9259	0.9549	0.4616
13	0.8556	0.6185	0.2459
14	0.9345	0.9057	0.0980
15	0.9057	0.7111	0.1866

Note: The network output confidence levels for the other sensors were all above 0.975 for "+" test cases, above 0.927 for the "x" test cases, and above 0.946 for the "o" test cases.

Several test cases similar to the results described in Table 1 were conducted for the other sensor measurements, all yielding similar results. Although the trained network yielded good results in terms of accuracy and generalization capabilities, overtraining was a concern that was monitored carefully. Initially, 600 training patterns were used to train the network with output error similar to the 300 training pattern case. The resultant trained network had much worse generalizing capabilities than the network trained with only 300 patterns.

The network architecture with two hidden layers was trained and tested with the same data as used for the previous single hidden layer network. In this case, the output RMS error was only reduced to 0.289 and the network generalization capability degraded. The worsened generalization capability can be explained by the additional degrees of freedom that were introduced by the additional nodes (neurons) in the hidden layers. The higher network RMS error is most likely due to finding a "local" minimum associated with the gradient decent BPE algorithm. In theory, the error should have been reduced to at least the level of the previous single hidden layer network.

4.2.2 Virtual Sensors

Engine Health Monitoring (EHM) systems prefer as much directly sensed data from the engine as possible, without to much redundancy, so that accurate assessments associated with lifing critical components or diagnosing faults can be accomplished quickly and with a high degree of confidence. However, due to the limited amount of directly sensed parameters on many engines (resulting from either technology deficiencies or simply engine vintage) crude estimates are often made for important lifing parameters such as the turbine inlet temperature, etc. To solve this problem, "virtual sensors" were developed during this program that were capable of accurately estimating unmeasured parameters in real-time. In particular, the stator outlet temperature (SOT), mass flow (W1a), fan and compressor delivery temperature (T3), and turbine inlet temperature (T4) were all estimated in real-time utilizing a polynomial neural networks that were trained from the engine gas synthesis model. The results from the real-time neural network estimates as comparred to empirical based polynomial models are shown in Figures 9-12. In all cases, the neural network estimates were considered more accurate than the existing empirical polynomial fitted equations. In the case of estimating SOT, the empirical method was inaccurate by as much as 10%, while the neural network estimates were within 1%. An order of magnitude increase in accuracy.

Comparison of SOT Estimates

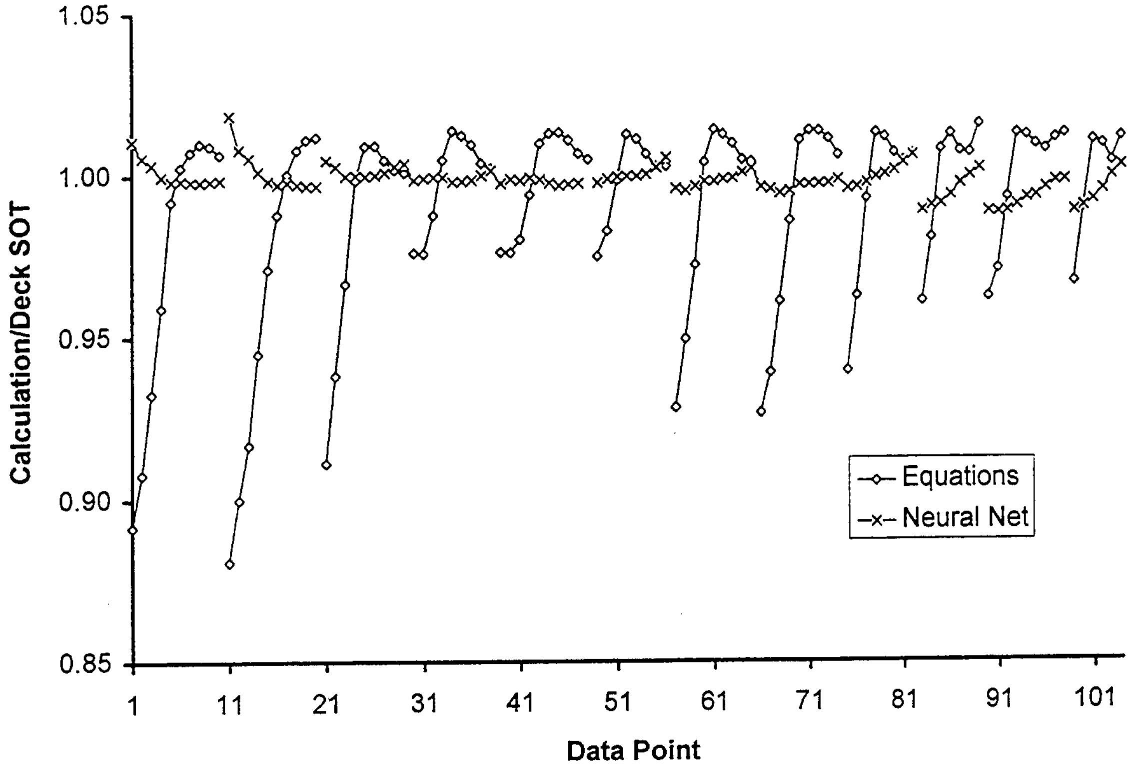


Figure 9

Comparison of T4 Estimates

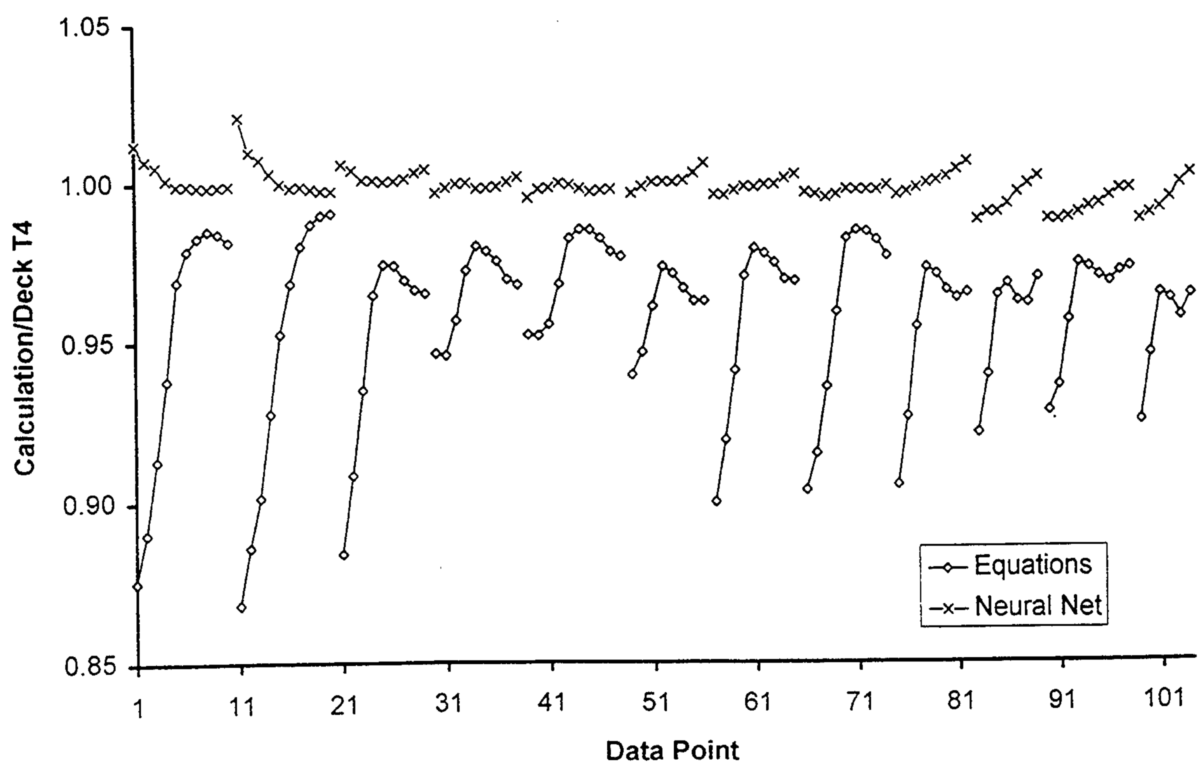


Figure 10

Comparison of W1A Estimates

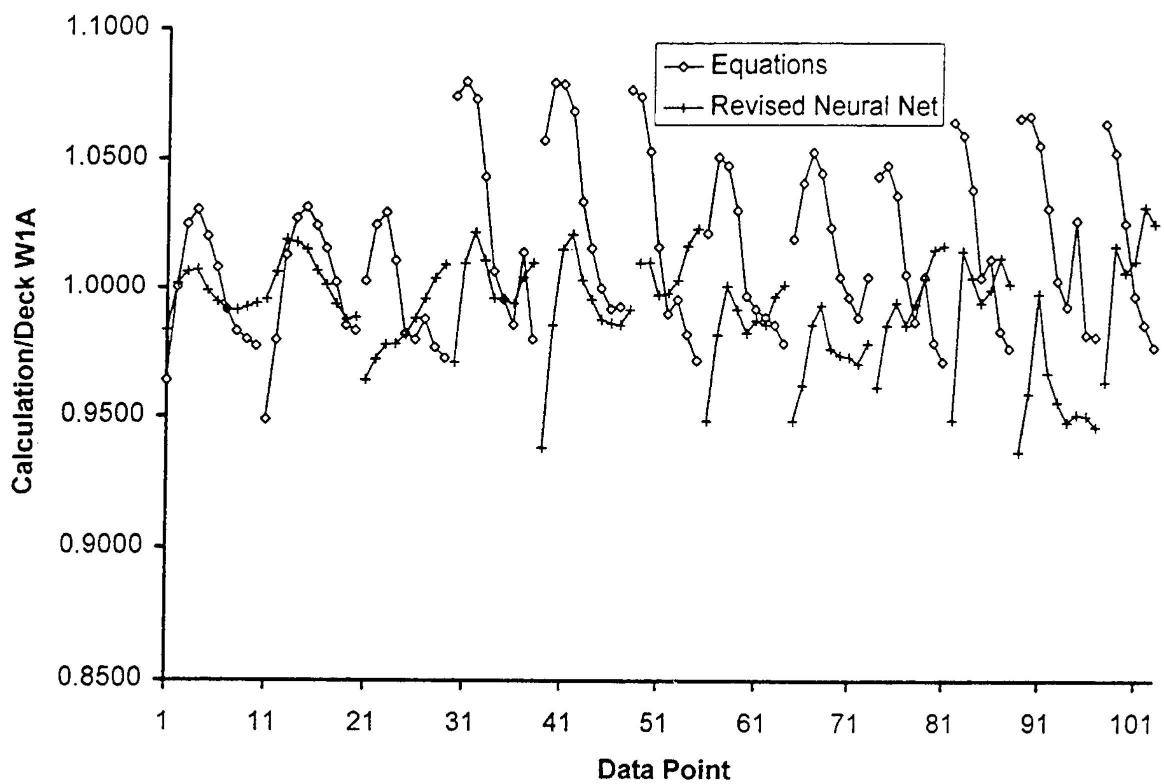


Figure 11

Comparison of T3 Estimates

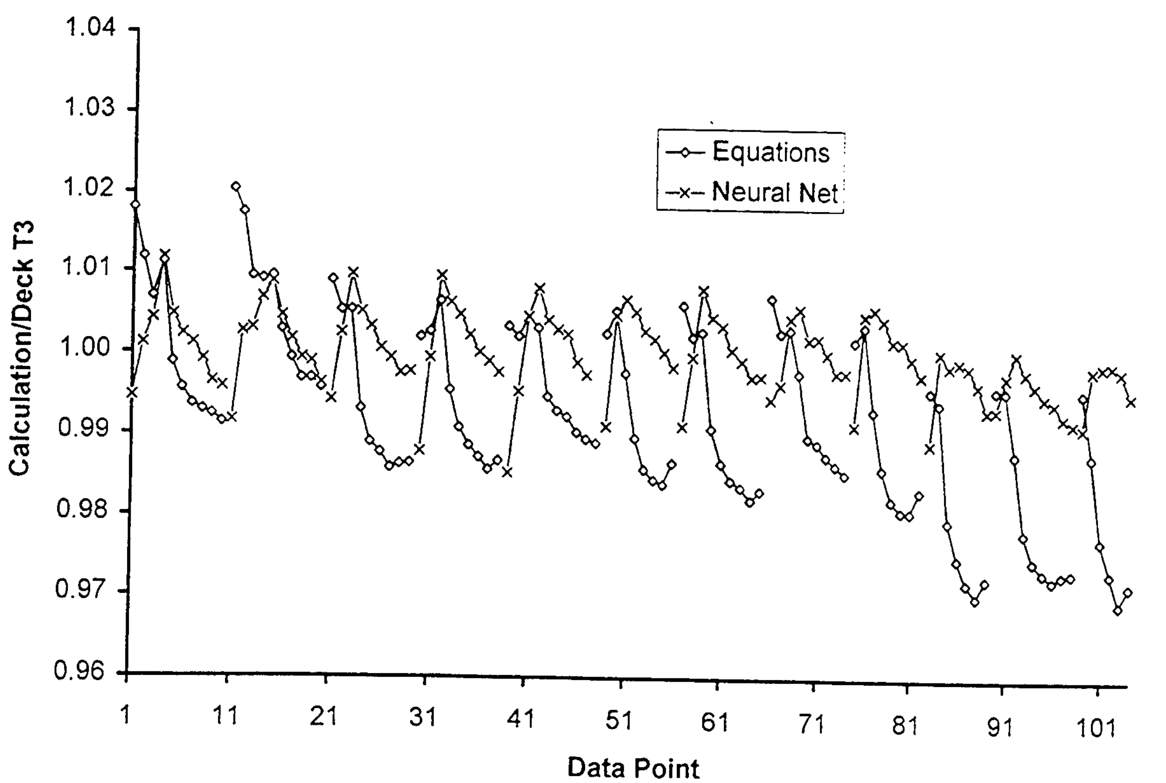


Figure 12

4.2.3 Long Term Trending Analysis

In an operational EHM system, data will be recorded at specific points during each flight, and the trending of these "consistent" data points observed over time. Ideally, an identical flight point or points and engine conditions would be used for each flight, but this is clearly impractical. Hence, for the purposes of this EHM system, weight off wheels (WOW) during take-off will be used to simulate a "common" engine condition.

The trend parameters chosen for this EHM system were based on "typical" non-dimensional parameter ratios that propulsion engineers look at if they suspect engine problems. The non-dimensional trending parameters are $NL/\sqrt{\Theta}$, T2/T1, P3/P1, T6/T1, and $Wf/\delta\sqrt{\Theta}$, all corrected to an $NH/\sqrt{\Theta}$ of 97.5%. If the fleet of engines were to behave truly non-dimensionally, there would be unique relationships between the non-dimensional groups. However, Reynold's number effects, variations in engine operating parameters, etc. introduce some variability in this process. Therefore, it is necessary to make trend comparisons at similar flight conditions and engine ratings to minimize the impact of these effects.

The non-dimensional trend parameters are calculated as follows:

1. Record the values of NH, NL, T2, P3, T1, P1, T6, Wf at the end of takeoff run.
2. Calculate: $\mathbf{NH/\sqrt{\Theta}} = NH/\sqrt{\Theta}(1 + (2.00\text{x}10^{-4}(T1\text{-}288)))$
3. $\Theta = T1/288.15$, $\delta = P1/14.696$, C=Fuel Calorific Value $\approx$ 10305 (CHU/lb)
4. $\mathbf{NL/\sqrt{\Theta}} = NL/\sqrt{\Theta}(1 + (2.346\text{x}10^{-4}(T1\text{-}288))) - 2.34635(NH/\sqrt{\Theta} - 97.5)$
5. $\mathbf{T2/T1} = T2/T1 - 0.018954(NH/\sqrt{\Theta} - 97.5)$
6. $\mathbf{P3/P1} = P3/P1 - 0.349522(NH/\sqrt{\Theta} - 97.5)$
7. $\mathbf{T6/T1} = T6/T1(1 = (2.378\text{x}10^{-4}(T1\text{-}288))) - 0.083489(NH/\sqrt{\Theta} - 97.5)$
8. $\mathbf{Wf/(\delta\sqrt{\Theta})} = Wf/(\delta\sqrt{\Theta}) \text{ x } (1 + (4.255\text{x}10^{-4}(T1\text{-}288))) - 0.931637(NH/\sqrt{\Theta} - 97.5)$

4.2.4 General Alarm Queue

All warnings and alarms detected by the EHM system will automatically be displayed and logged in the alarm queue provided in the "main screen" of the EHM program. This includes sensor validation, performance and vibration anomaly detection, performance and vibration diagnostic results, and unusually high consumption of component life. A pictorial version of the engine illustrating the principle modular sections is also displayed that changes color based on the warning or alarms that are detected. For example, if a P3 sensor is just beginning to malfunction, the HP compressor section of the engine pictorial is turned yellow, indicating a warning associated with that part of the engine. A complete description of the cause of the warning is given in the alarm queue text area. Once a fault goes beyond the warning stage, as determined by the EHM sysyetm, the engine pictorial section turns red, indicating an alarm status for that section of the engine. An example of the EHM "main screen" indicating an alarm associated with the P3 sensor is given below.

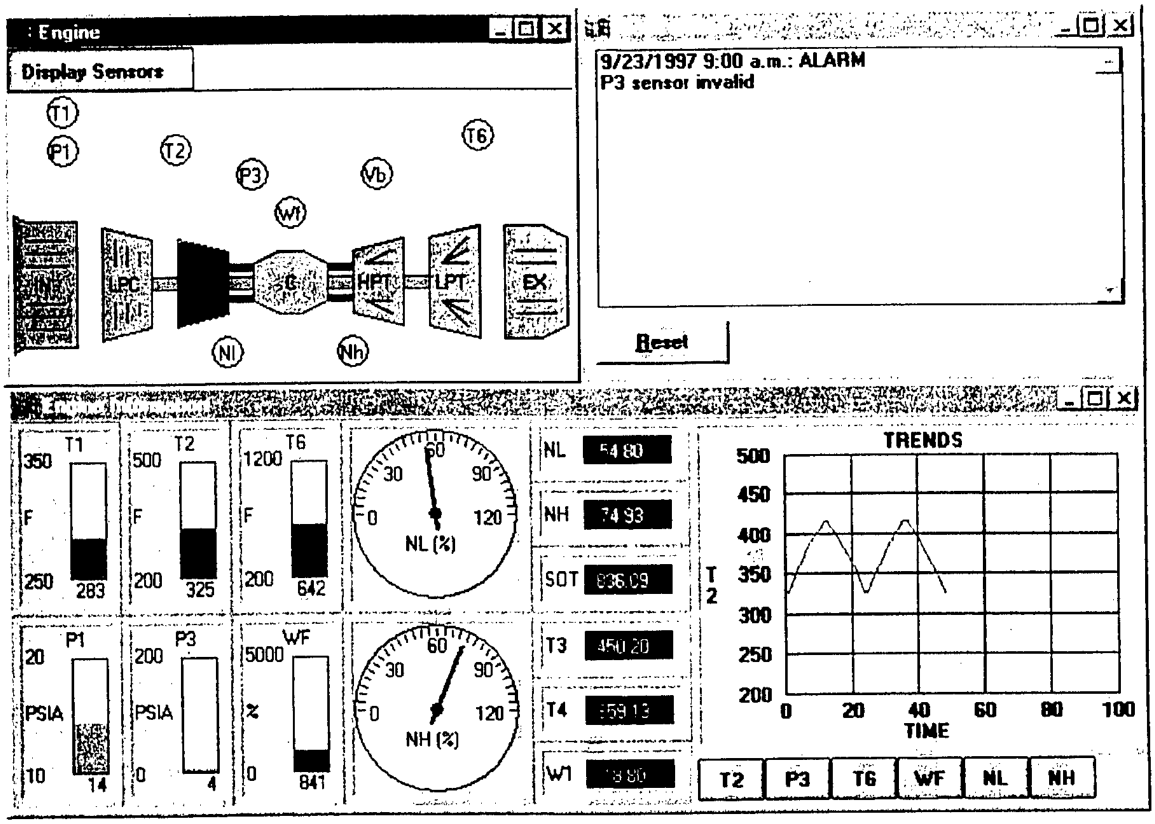


Figure 13 EHM "Main Screen" with P3 Sensor Problem

4.3 Health Module

The Health Module is dedicated to examining the real-time engine parameter data set and detecting any engine anomalies that exist with respect to the "normal" engine's operating signatures. This function is performed for both the performance parameters and vibration data. First, the measured performance parameters are examined within pre-determined speed bands during the entire mission to ensure consistent and accurate performance patterns scans. When a set of acquired engine performance parameters trigger an anomaly being detected, the current real-time performance data is forwarded to the diagnostic module for detailed examination. Based on the trended data and fault pattern recognized, the severity and duration of the recognized fault can be determined.

4.3.1 Performance Anomaly Detection

Engine performance anomalies are detected by comparing "normal" engine signatures with a set of current measured engine data. Normal engine signatures are obtained for each engine during the standard production pass-off tests. Each measured parameter (T1, P1, T2, P3, T6, Wf, NL, NH) on the engine is plotted against the HP rotor speed to yield a "normal" range of operation for that specific engine. Any deviations from the engine specific "fuzzy" bands encompassing these parameter signatures will trigger the anomaly detection routines. The "fuzzy" bands are implemented with a dedicated fuzzy logic routine that contains membership functions that are specifically related to the particular engine being monitored.

Engine signature models were necessary due to the large degree of "scatter" that exists between each similar type of engine in a fleet. Figure 14 is a plot illustrating the "scatter" between 20 similar engines with respect to the exhaust gas temperature. Figure 15 shows four plots of engine signatures for a particular set of engine pass-off data. The best polynomial fit upto a sixth order is used for each measured parameter on the engine.

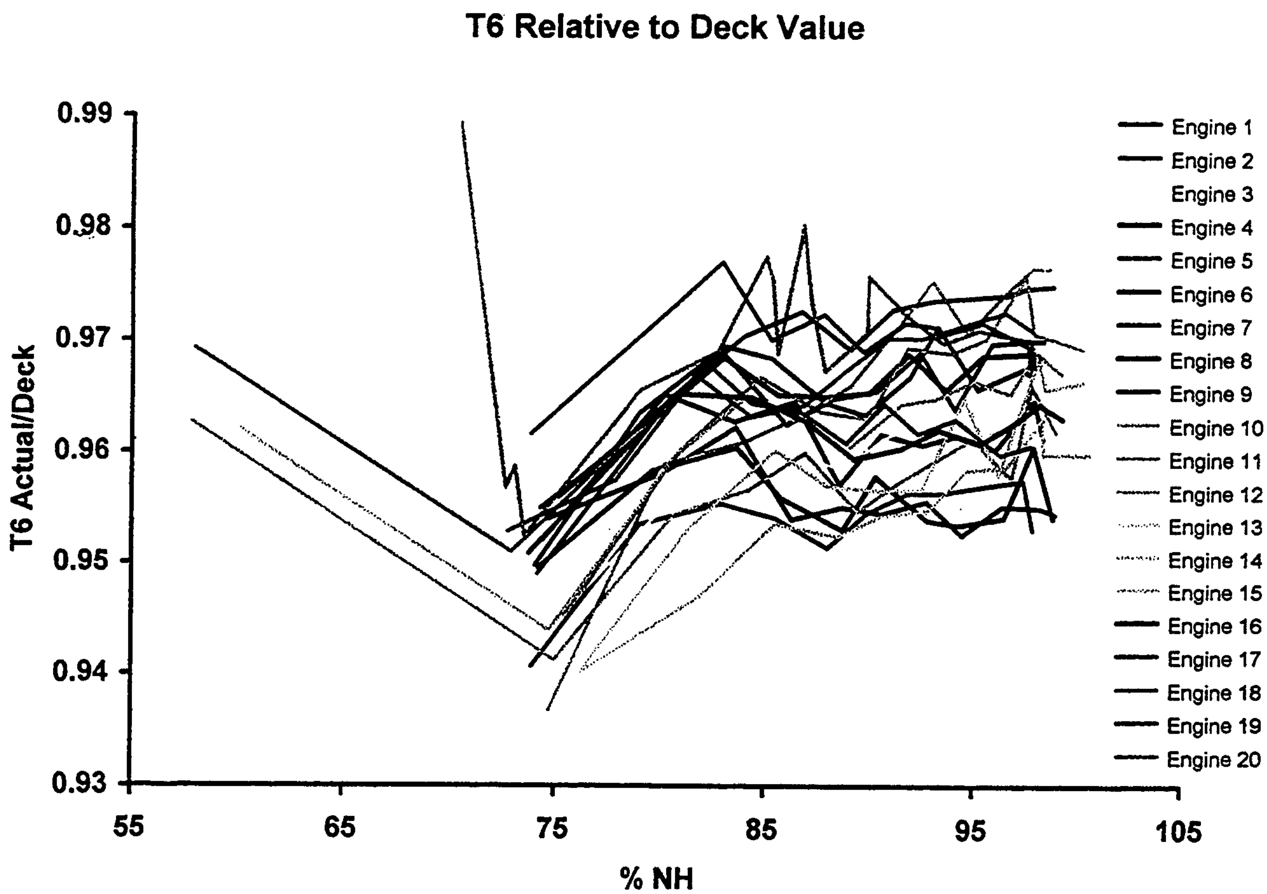


Figure 14 Engine "Scatter" for Exhaust Gas Temperature

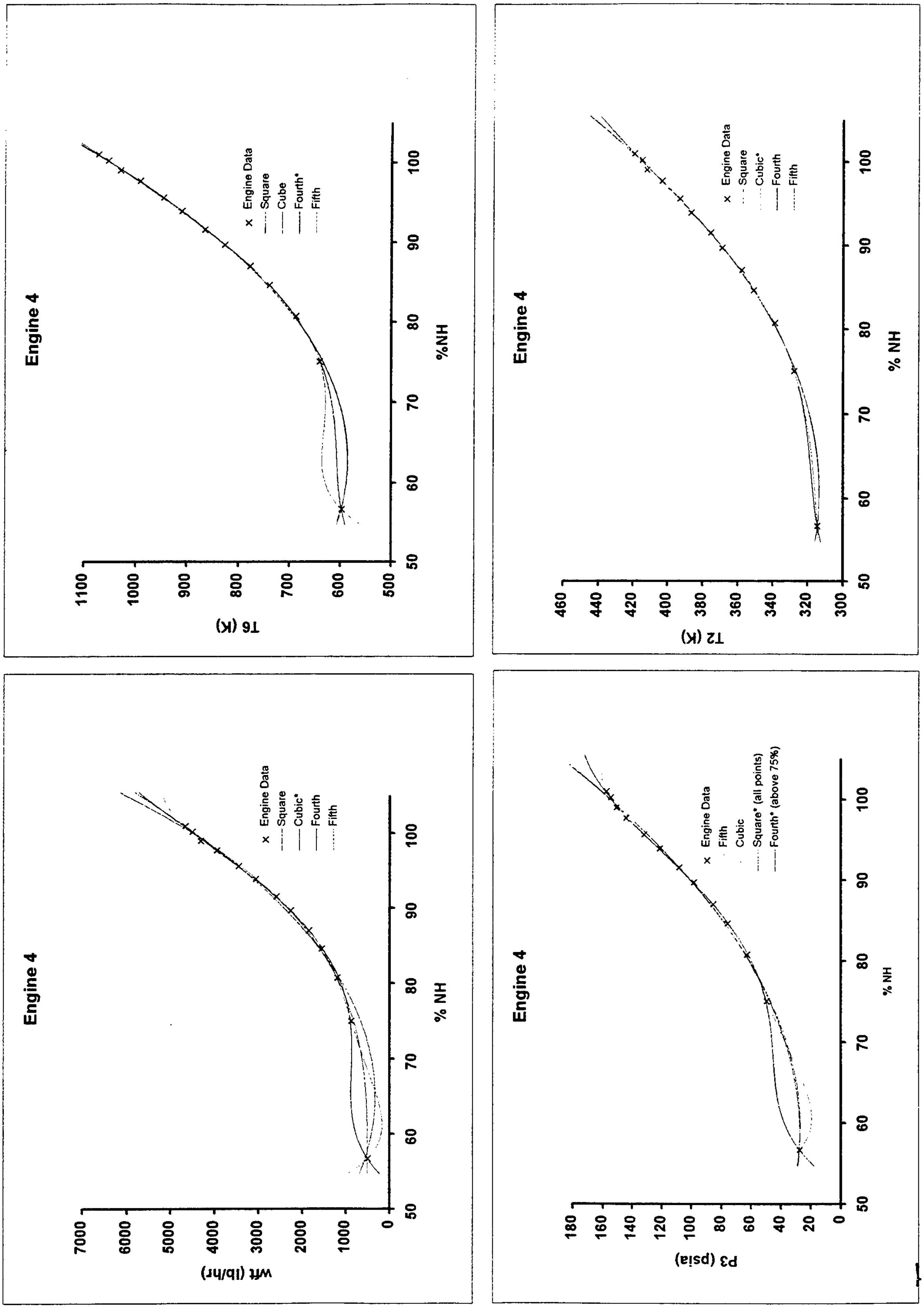

Engine 4
T6 (K)
%NH
× Engine Data
Square
Cube
Fourth*
Fifth
Engine 4
wf (lb/hr)
% NH
× Engine Data
Square
Cubic*
Fourth
Fifth
Engine 4
T2 (K)
% NH
× Engine Data
Square
Cubic*
Fourth
Fifth
Engine 4
P3 (psia)
% NH
× Engine Data
Fifth
Cubic
Square* (all points)
Fourth* (above 75%)

FIGURE 15

The following series of pages (8 pages total) titled "Fuzzy Logic Module - performance" gives the details associated with the fuzzy logic rulebase and membership functions that were used in the performance anomaly detection submodule of the "Health Module". The first page of this series shows a block diagram of the module including inputs and outputs. The inputs all designated as xx_delta (where xx is the sensor name) represent the difference between the engine signature model and the actual sensed data at a particular speed (approximate power level). The output is a measure indicating the level of any anomaly that might have occurred. The output membership functions will classify this module output as either OK, WARNING, or ALARM, depending on the observed differences between the model and measurements. The corresponding membeship functions and rulebase for each of the input/output parameters is also provided. Details describing the basics of fuzzy logic decision analysis are given in Appendix B.

4.3.2 Vibration Anomaly Detection

In addition to the performance anomaly detection described above, vibration anomaly detection and diagnostics is also performed within the real-time monitoring environment. Vibration spectrums from the available engine installed accelerometers are gathered at particular engine operating speeds to form a "current" database of the engine's vibration characteristics. The speed ranges at which the spectrums are stored for the F405 engine are 80%, 85%, 90%, 95%, and 100% maximum NH rotor speed. Figure 16 is an illustration of the vibration anomaly detection scheme for spectrums gathered from the starboard tangential and port radial accelerometers.

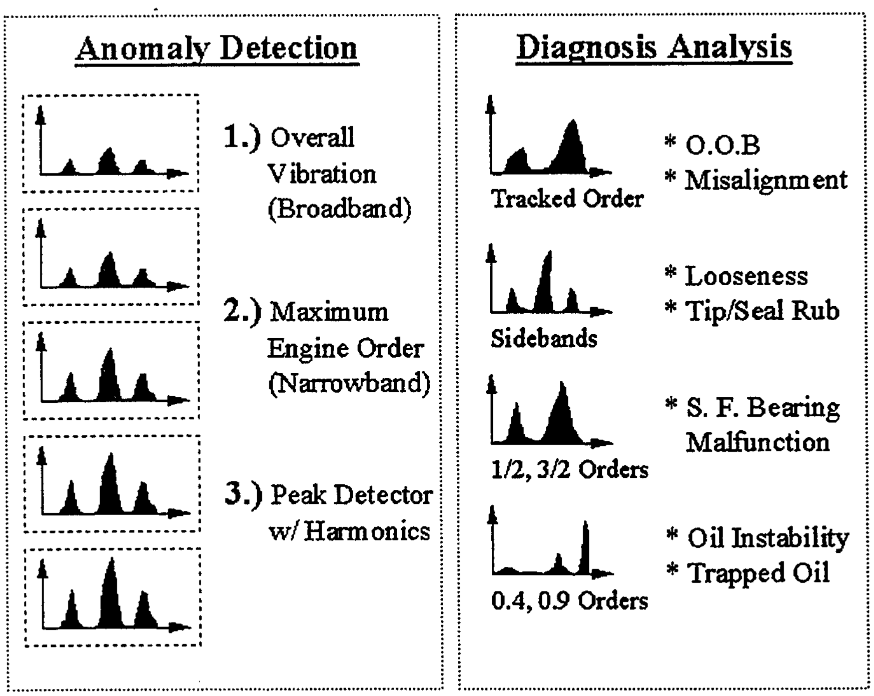


Figure 16 Vibration Diagnostic Scheme

The fuzzy logic based anomaly detection utilized the shaft speed tracked orders, other identified vibration peaks (synchronous and non-synchronous), and a broadband spectral density measure to detect anomaly levels as being OK, WARNING, or ALARM. The data analysis and preprocessing that was used to develop this subsystem were based on over 30 engines worth of data with various vibration faults. Due to the proprietary nature of this data, the vibration fault and normal spectrums can not be included in this report.

As in the case for the performance anomaly detection, the following series of 7 pages with "VIB_DET.PRJ" on the bottom of the pages, gives the details associated with the fuzzy logic rulebase and membership functions that were used in the vibration anomaly detection submodule of the "Health Module". The first page of this series shows a block diagram of the module including inputs and outputs. The inputs designated as nh_peak, nl_peak, peak_3, and b-band represent the spectral amplitudes at the particular frequencies as defined by NH (HP shaft speed), NL (LP shaft speed), peak_3 being the next highest peak, and b_band representing the broadband spectral density. The output is a measure indicating the level of any anomaly that might have occurred. The output membership functions will classify this module output as either OK, WARNING, or ALARM, depending on the observed spectral amplitudes. The corresponding membeship functions and rulebase for each of the input/output parameters is again provided.

4.4 Diagnostic Module

Once an anomaly is detected and the current data is transferred to the Diagnostic Module, dedicated neural network fault classifiers determine the probable cause of the fault or degraded performance.

4.4.1 Performance Diagnostics

A block diagram of the performance diagnostic procedure is given in Figure 17 shown below. The underlying design of this model-based, fault diagnostic module lies in the determination of changing conditions appearing in engine sensory data due to the existence of particular faults. These observed changes are compared with the "normal" operating engine process to recognize error residuals. These residuals and associated patterns are then analyzed for failure detection and diagnosis by comparing them with known failure signatures associated with a failed component on the operating engine.

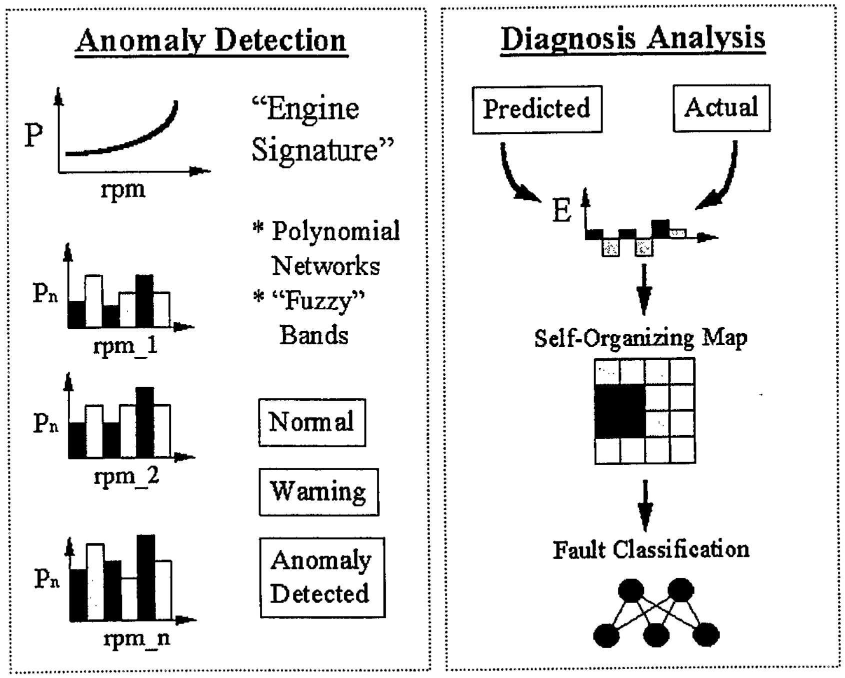


Figure 17 Performance Diagnostic Scheme

Engine fault signatures, which illustrate the effect of a failure on particular engine parameters, are generated from both historical engine data and engine synthesis models of the engine. In fact, a combination of these approaches is utilized in this EHM system. In the end, the failure diagnosis is accomplished with a neural network classifier to recognize the patterns of respective failure signatures. The performance diagnostic module in this program utilizes both self organizing neural network maps (to cluster and identify similar patterns) and trained network classifiers for specific problem diagnosis (Kohonen, 1987).

The real-time engine data for a particular speed-band is first compared with the corresponding "normal" operating patterns to determine measured parameter changes. These error patterns are then normalized with respect to the maximum measured parameter change and passed to a self organizing neural network map (Kohonen network) for initial pattern clustering. Figure 18 illustrates the results of Kohonen self-organizing map under noisy pattern conditions. Error pattern clustering was used as an initial diagnostic step because of its high robustness with respect to pattern noise. After the error pattern has been organized into a particular location on 10x10 interpretive Kohonen map, a trained back-propagation network classifies the coordinate location on the map into a specific diagnosis.

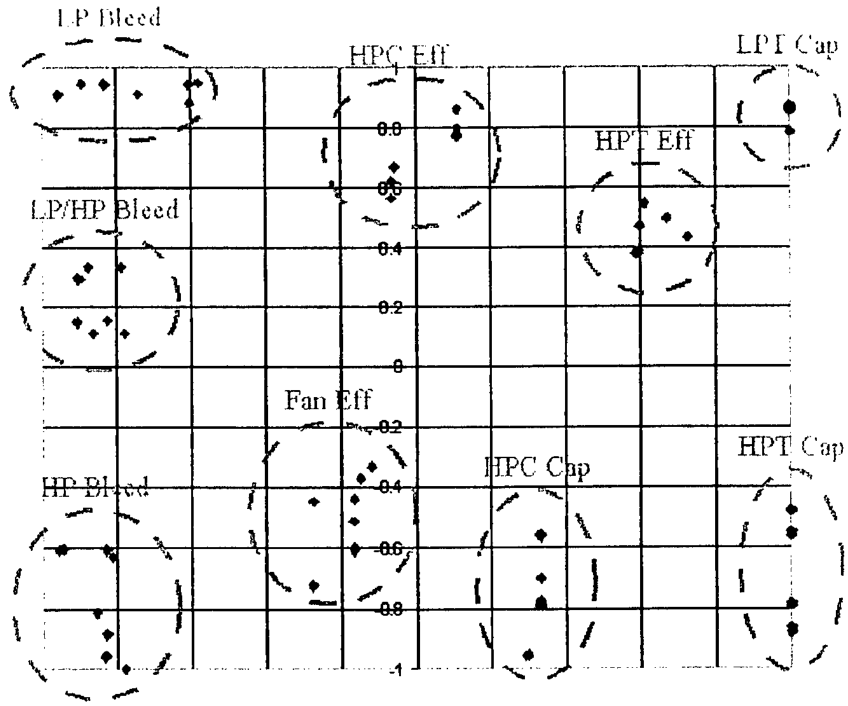


Figure 18 Kohonen Self-Organizing Map Diagnostics

The performanc diagnostic module dedicated to identifying particular performance degradation patterns in the engine has been trained to recognize the following abnormal engine conditions.

1. Inner fan efficiency drop
2. HP compressor efficiency drop
3. HP turbine efficiency drop
4. HP compressor capacity drop
5. HP compressor capacity rise
6. HP turbine capacity drop
7. LP turbine capacity drop
8. LP turbine capacity rise
9. HP system bleed off
10. LP system bleed off

Table 2 illustrates the results of the SOM neural network for recognizing performance degradation patterns with 30% noise added to them. The matrix-type table would be an identity matrix if the particular performance degradation patterns were recognized perfectly. One example of each performance degradation pattern is given in Table 2, but hundred of test cases provided similar results, shown the networks robustness to noise. The pattern numbers in the top row correspond to the pattern faults and numbers given above.

Table 2 SOM Neural Network Results for Performance Degradation

Fault #	1	2	3	4	5	6	7	8	9	10	11
case 1	0.98	-0.12	0.01	0.03	-0.12	-0.01	0.03	-0.11	-0.12	-0.09	-0.07
case 2	-0.11	1.03	-0.04	-0.12	-0.12	0.03	-0.13	-0.07	-0.12	-0.05	-0.10
case 3	0.04	0.03	1.00	-0.13	-0.11	0.06	0.02	-0.13	-0.11	-0.12	-0.12
case 4	-0.04	-0.12	-0.12	0.90	-0.05	-0.11	-0.03	-0.04	-0.01	0.00	0.01
case 5	-0.12	0.04	-0.12	0.01	1.00	-0.03	-0.12	0.04	-0.03	-0.01	-0.12
case 6	-0.12	-0.12	-0.13	-0.12	0.01	0.98	0.05	-0.11	-0.02	0.00	-0.11
case 7	-0.05	-0.12	0.01	-0.11	-0.12	-0.02	0.97	-0.10	-0.13	0.00	-0.12
case 8	-0.12	0.04	-0.12	-0.02	0.08	-0.09	-0.06	0.80	0.03	-0.04	-0.12
case 9	-0.13	-0.12	-0.12	-0.10	0.05	0.00	-0.05	0.03	0.98	0.00	-0.02
case 10	0.02	0.00	-0.11	-0.01	-0.12	-0.02	0.02	-0.04	-0.11	0.98	-0.01
case 11	0.00	0.01	0.02	-0.09	-0.12	-0.01	0.00	-0.08	0.02	0.04	1.01

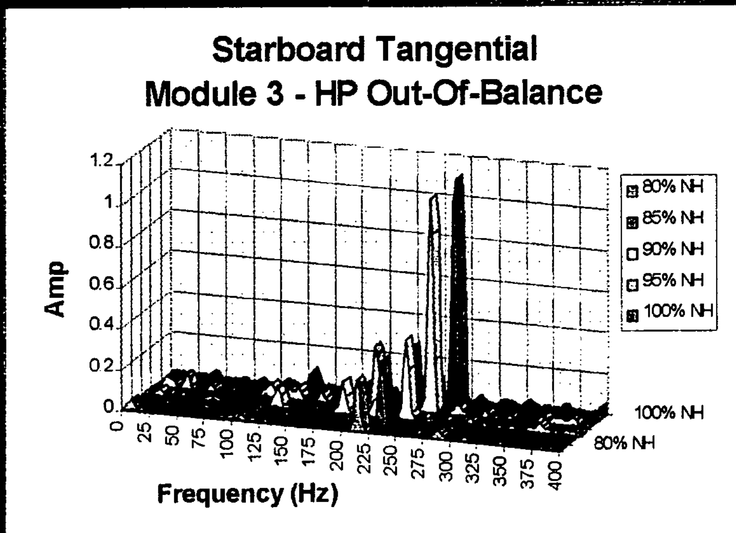
4.4.2 Vibration Diagnostics

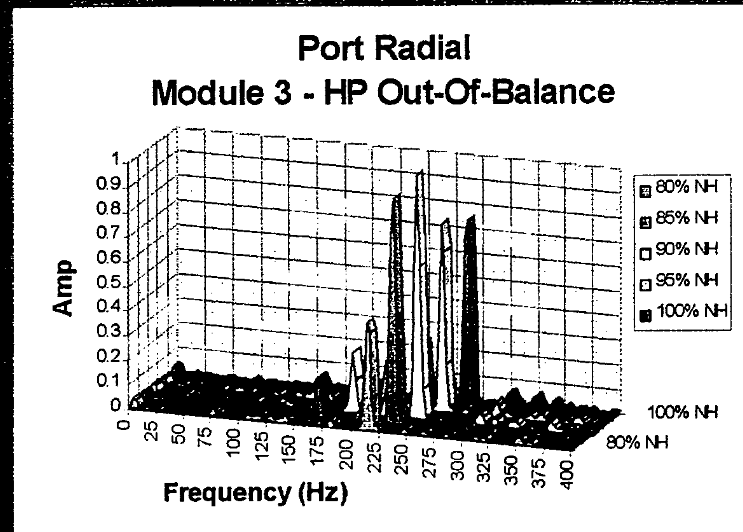
A block diagram of the vibration diagnostic procedure is given in Figure 19 shown below. Refering to Figure 19, once the acceleration power spectral densities are organized into their respective bins, the peaks of the NL and NH rotor speeds are examined for overall amplitude and location (in terms of the % max NH speed) of the peaks. This information is used by the fuzzy logic diagnostic algorithms to determine if the vibration is coming from either the compressor or turbine and if it is associated with the HP or LP shaft. Once the basic location of the vibration source is determined, a more detailed diagnosis of the vibration problem is predicted. Currently, the system has been trained to recognize vibration fault patterns including; 1.) Unbalance/Misalignment, 2.) Rotor Rub and Mechanical Looseness, and 3.) Deteriorated Bearing Conditions. Due to the Rolls-Royce proprietary nature of the algorithms used in diagnosing vibration faults, the specific rulebase for vibration diagnosis can not be included in this report.

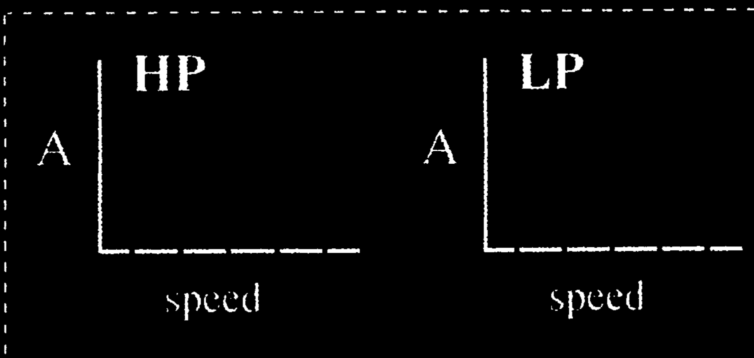
4.5 Engine Life Module

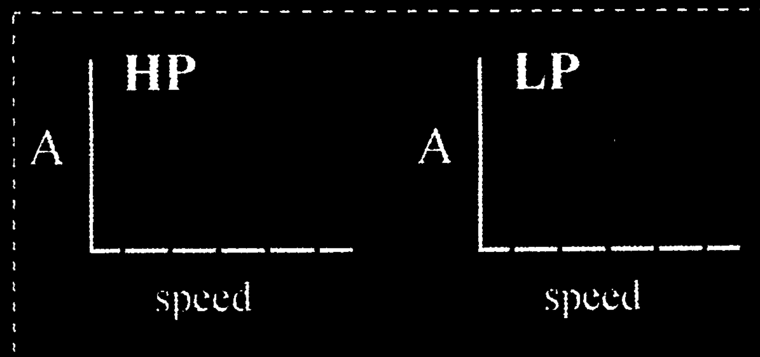
During the mission, data from the engine duty monitor within the Data Management Module is continuously being transferred to the Engine Life Module so that "mission representative" life may be accumulated. The life accumulation algorithm will include the engine specific parameters tracked throughout the entire mission. Hot section temperatures will be estimated in real-time based on a neural network architecture trained from engine synthesis models. Figure 20 is an illustration of the module functionality. Corresponding material creep and thermo-mechanical fatigue will therefore be more accurately determined based on actual mission severity. At the end of the mission, critical component life accumulated during that mission is reported and transferred back to the data management module for overall accumulation of each components life usage.

Vibration Diagnosis









Module Diagnosis

- [x] HP Compressor
- [ ] HP Turbine
- [ ] LP Compressor
- [ ] LP Turbine

Specific Diagnosis

- [x] Out-of-Balance
- [ ] Misalignment
- [ ] Bearing Condition
- [ ] Rubbing/Looseness

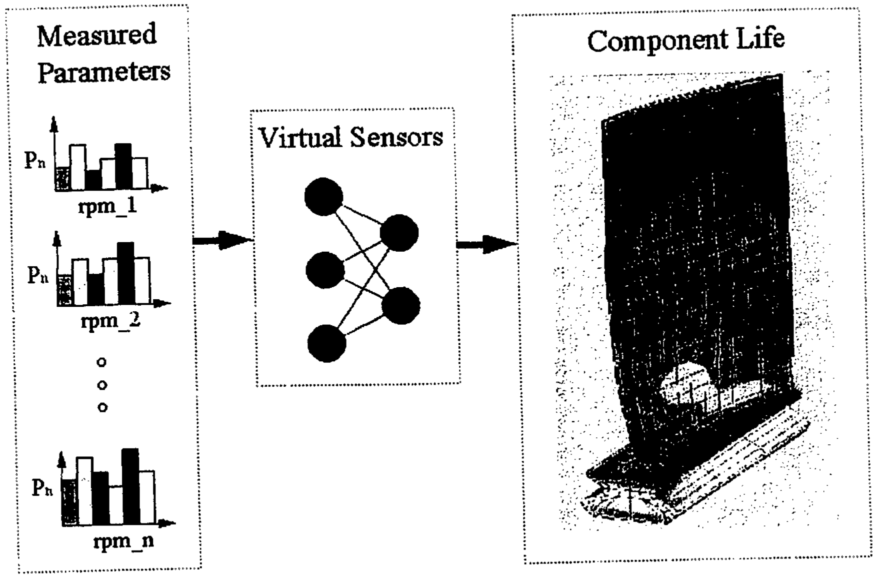


Figure 20 Engine Life Scheme

A principal advantage of integrating engine life usage with real-time engine diagnostics is that they both utilize the same engine data. Incorporating a more comprehensive set of engine parameters into component life accumulation algorithms will have a major impact on maximizing engine operational life without jeopardizing flight safety.

The described EHM system incorporates LCF, material temperature/creep, and thermo-mechanical fatigue aspects into a comprehensive damage accumulation algorithm. This represents a significant enhancement over the current life monitoring systems. Primarily, increased emphasis will be placed on "hot" components where these mechanisms play a large role in the failure process. The proposed approach of individually tracking the total life of each critical component will allow for a more representative and less conservative estimate of component life consumption.

The engine life module discussed in this paper concentrates on the HP turbine disk and blades. Other components can easily be added to the system if the necessary life algorithms are available. Engine life usage algorithms for creep and low cycle fatigue of critical parts are already included in the Aircraft Data Recording system on the T45A Goshawk aircraft. The algorithms for the HP disk will be refined to use the more specific data available from the Data Management module to record accumulated life usage.

5.0 EHM System Testing and Results

5.1 Objective of Ground Tests

The primary objective of the Engine Health Monitoring (EHM) system ground tests was to demonstrate the advanced, real-time monitoring, diagnostic and component lifing capabilities under actual engine operating conditions. Within this SBIR program, the EHM system has undergone successful ground tests on three (3) different Rolls-Royce Adour engines (Navy F405) in Bristol, England. The EHM system, developed as a Windows NT application program with user-friendly GUI's, performed the following functions during the three ground tests; 1.) real-time data acquisition of engine performance and vibration data, 2.) performance and vibration anomaly detection and diagnostics, 3.) critical component life accumulation, 4.) sensor validation, 5.) virtually sensed unmeasured parameters, 6.) advanced short and long term trending, and 6.) engine "signature" based performance degradation monitoring.

Advanced fault classification techniques including standard back-propagation neural networks, self-organizing map "clustering" networks, fuzzy logic decision analysis, and polynomial networks were trained from existing engine databases and gas path analysis (GPA) models to identify engine fault conditions. During the series of ground tests, a total of three different actual engine sensor anomalies were detected and diagnosed as well as some additional "seeded" faults that were also diagnosed. In particular, the T2 (LP compressor delivery temperature) and WF (fuel flow) test cell transducers both malfunctioned during the first engine test, both of which were detected and correctly diagnosed in real-time. In addition, an HP and LP shaft vibration anomaly was also diagnosed during the first two engine tests. Specific details associated with each engine test are described below. Overall, Rolls Royce engineers were extremely pleased with the operation of the automatic EHM system and are currently working with Stress Technology to advance the developments of the EHM system for use at Rolls Royce. The success of the EHM system ground testing can be summarized by the following quote that was made in a letter to STI from the Rolls Royce engineers:

"This is a new and probably first application of artificial intelligence techniques in a real-time, on-board engine monitoring system having the ability for diagnosing vibration, performance, and component life anomalies concurrently. Rolls Royce commends STI for the successful demonstration of this novel system."

H. R. Carr and R. G. Fox, Rolls Royce, plc.

Significant technical accomplishments of the EHM system that were demonstrated during the three engine tests are described below.

1. Integration of neural networks (unsupervised and supervised) and fuzzy-logic to identify engine anomalies, both performance and mechanical (vibration) related, and in turn provide specific diagnostics related to the identified fault in real-time.

2. Capability to provide real-time estimates of the life being consumed from critical engine components including HP turbine blades and disks. Virtually sensed turbine inlet temperatures, mass flow, etc. (currently not measured) are utilized to improve accuracy of the actual life being accumulated.

3. Advanced vibration diagnostics that is based on feature extraction from both spectral "waterfall" plots and tracked-order amplitudes. The results are passed through a fuzzy-logic decision analysis procedure for classifying mechanical engine faults.

4. Engine "signature" based performance degradation monitoring that accounts for steady-state and pseudo steady-state engine operation. Self organizing maps cluster performance faults with high degree of robustness with respect to pattern uncertainties.

5. Real-time sensor validation networks trained from "fleet-wide" engine test data taken during a wide range of engine operating conditions. Polynomial networks are implemented to recognize the non-linear relationships among the measured parameters.

5.2 Ground Test Results

The EHM system ground tests were performed at the Rolls-Royce MAEL test cells in Bristol, England. The EHM system's capabilities were tested thoroughly during each of the three engine tests with actual faults being diagnosed from test cell sensor faults and vibration signal calibration problems. In addition, sensor signal faults were purposely "seeded" to better assess the capability of the EHM sensor validation module. A sample of the actual ground test data acquired during the tests is used in the demonstration program included as part of this final report. The demonstrations are described in more detail in Section 6 of this report.

Test Cell Instrumentation and Calibration

Prior to the first engine test, several system implementation and integration checkouts needed to be performed on the EHM system. These checkouts included synchronization of the vibration and performance data acquisition systems, test cell transducer calibration, and frequency to voltage conversion of shaft speed tachometers and fuel flow signals. Transducer calibration was performed by both Rolls Royce test engineers and the STI team. This process included relating an arbitrary reference voltage from 0-10V to the maximum value a particular transducer can reach during a test. This ensured that the data acquisition card would never receive any voltages above the 10V operating range of the A/D card. The specific calibration factors used for all three engine tests are shown below:

Test Cell Calibration Voltages

NH	4.63V = 100% Max NH	**NL**	4.42V = 100% Max NL
T1	1.40V = 14 degrees C	**P1**	1.40V = 14 PSIA
T2	3.25V = 200 degrees C	**P3**	2.51V = 250 PSIA
T6	4.12V = 1000 degrees C	**Wf**	3.79V = 5420 lbm/hr

Two separate data acquisition systems were required by the EHM system to perform both performance and vibration related diagnosis and component lifing. This was primarily due to the fact that the Rolls Royce MAEL test cells had separate instrumentation hardware for each. The performance parameters including NH, NL, T1, P1, T2, P3, T6, and Wf were acquired using a standard 16-channel, parallel port data acquisition card manufactured by National Instruments, Inc. The vibration data acquisition was performed with a customized, test cell vibration diagnostic system developed by Rolls Royce referred to as DEVS (Diagnostic Engine Vibration System). The EHM system directly interfaced with this DEVS system during the ground testing through a standard serial port connection. Special software was developed to synchronize the two data acquisition systems for real-time operation.

A differential signal grounding configuration was utilized for the performance parameter data acquisition system. A differential signal is one in which each analog input signal has its own reference signal or signal return path. Differential input connections are typically used in situations were low level voltages are being acquired, connecting leads are greater than 10 ft., and signals travel through noisy environments. In general, differential signal connections reduce picked-up noise, increase common-mode noise rejection, and allow input signals to float within the common mode limits of the PGIA (programmable gain input amplifier). Figure 20 is an illustration of the differential signal connections that were used during the engine ground testing.

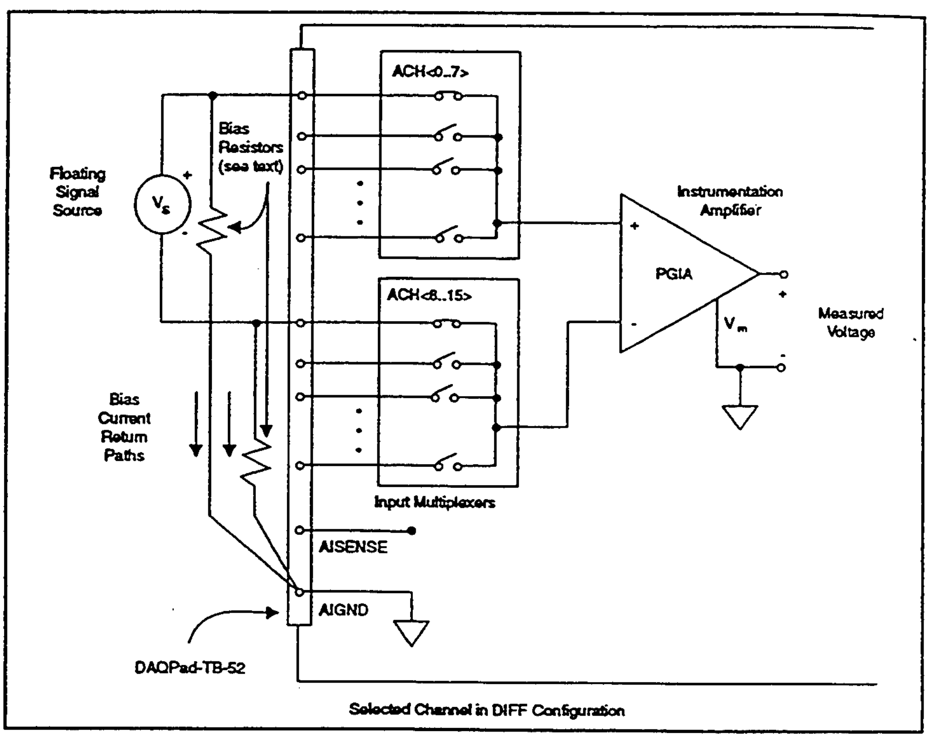


Figure 20 Differential Input Connections

Engine #1 Test **Engine Serial #: 9105** **Date: 10/21/97**

The EHM system was specifically developed to undergo an initial engine "training" period, where the EHM system monitors and records the "normal" engine operating "signatures" during steady-state and pseudo steady-state engine operating conditions for the full range of engine speeds/power. From this recorded engine data, a series of engine "signature" models are developed from which the engine performance anomaly detection algorithms are based. For the first engine test, the STI team was only able to perform initial engine "training" from a partial engine accel/decel. This was due to the fact that the engine in the test cell had already gone through most of the standard tests for production "pass-off" testing and repeating engine runs would put additional engine operating hours that would be considered undesirable. However, a working set of engine signature models was still able to be developed from this partial ramp-up/down engine run and utilized in the EHM system during the remaining few engine runs.

Ideally, a complete training database would need to be constructed during an initial monitoring phase of the engine over a period of a couple weeks. Having such a complete engine database, engine performance anomaly detection can be performed more accurately because the effects of engine non steady-state operating conditions can be "filtered out" properly. This of course means that engine performance degradation monitoring will not be assessed by the EHM system during engine transient conditions. This is a reasonable assumption because trying to detect minor engine efficiency or capacity changes during engine transients would be enormously difficult and too dependent on outside factors. However, all other aspects of the EHM system including sensor validation, vibration anomaly detection and diagnostics, and component lifing are still being performed continuously and during engine transient conditions.

Following the engine vibration sensor check-out run (partial ramp up/down), the engine underwent a "slow" accel/decel at a rate of approximately 2 minutes for the entire ramp up/down engine run. During this test, the EHM system performed very well considering the approximate nature of the engine "signature" models developed. In fact, three actual engine/sensor faults were identified in real-time by the EHM system. First, a malfunctioning Wf (fuel flow) sensor was diagnosed by the sensor validation module due to "phantom" fuel flow spikes occurring at 100% NH. Next, a fluctuating T2 (LP/HP compressor temperature) sensor was identified in the performance anomaly detection module due to test cell hardware "electronic noise". And finally, a vibration fault was identified by the vibration anomaly detection module and further diagnosed as an "HP stub-shaft out of balance" by the vibration diagnostic module. All three (3) of these faults were identified during the real-time operation of the engine.

Based on the real-time diagnostic results from this first test, both the fuel flow sensor (Wf) and HP/LP compressor thermocouple (T2) were examined by the Rolls Royce test engineers. The fuel flow sensor malfunction was identified as an intermittent electronic hardware problem and fixed prior to the next engine test by replacing the existing hardware with properly working set of electronics. However, the root cause of the T2 sensor fluctuations identified within the EHM system was not fixed until some "in-situ" testing was performed during the second engine test. The T2 sensor fluctuations turned out to be related to a grounding problem with the T2 sensor electronics and was temporarily fixed by placing a 47 μF capacitor in parallel with the T2 analog input signal to "smooth" it out. The engine vibration fault that was detected during the test resulted from improper calibration of the accelerometer's amplitude response. More specifically, the EHM system vibration diagnostic module was "trained" based on RMS acceleration amplitudes, (0.707 times the peak acceleration amplitude), but instead, the EHM system was measuring (receiving) the peak-to-peak acceleration values. This would mean that a measured value of 2 in/sec should have really have only been an RMS value of 0.707. Therefore, the EHM system detected and correctly diagnosed HP shaft order vibration faults, even though they really didn't exist but were perceived to have existed because of the sensor calibration problem.

The first set of five (5) figures (Figures 21-25) labeled "Engine Test #1", illustrate the measured engine test data that was acquired during the first test as compared with the "engine signature" models. Due to the limited (single engine ramp up/down) amount of engine training data that was recorded for this engine, the engine signature models predicted the engines response accurately from 75% NH up to about 95% NH for both the T2 and T6 thermocouples. However, even with limited training data, the engine signature models for the remaining sensors were very good, resulting in predicted engine responses less than 1% of the measured values. As illustrated in Figures 21-25, the engine models only utilized data recorded for NH speeds greater than 75% Max. Therefore the engine models and corresponding anomaly detection/diagnosis was only operational above this NH speed. Figure 23 clearly illustrates the electronic grounding problem that was encountered with the T2 sensor and Figure 25 shows the WF fuel flow spikes that occurred when the engine was near maximum speed and on the ramp down portion.

Engine #2 Test **Engine Serial #: 9106** **Date: 10/23/97**

The second engine test occurred three days following the first test and was scheduled as part of a standard production pass-off test. During such tests, steady-state performance scans are typically performed at 11 different speeds, ranging from approximately 55% NH Max (Idle) to 103% NH Max. A profile of the performance parameter scans taken during this test are given in Figures 26-30. The amount of time taken for each scan (at constant speed) is approximately 2 minutes, resulting in a total engine test time of less than 30 minutes.

The engine signature models for this engine were developed from the steady-state performance test scan data. Again, more data associated with pseudo steady-state operating conditions would have been beneficial, but this data set was again satisfactory for testing the EHM system capabilities. As shown in Figure 27, the intercompressor thermocouple (T2) sensor was fixed after a couple minutes into the test's performance scan data acquisition. This effected the engine signature model associated with the T2 prediction as shown in the ramp-down portion of Figure 27. However, the T2 model predicted values taken above the NH speed where the T2 sensor was fixed are excellent, with RMS errors between the actual and predicted values of less than 1%. The remaining performance parameter predictions were all calculated within the EHM system's ability to diagnose a 2% shift in either compressor or turbine efficiency. In other words, the errors between the predicted and measured performance parameters must be less than the corresponding parameter shift associated with a 2% efficiency shift. This allows the EHM system to detect performance degradation shifts once they have reached approximately 2% of the original engine signature baseline.

During the second test, the only engine fault identified was a repeat of the vibration anomaly that was detected in the prior test. Again, the EHM system was developed to assess the vibration spectral amplitudes as being RMS values, but instead the test cell was measuring and incorrectly passing to the EHM system the peak-to-peak values. This is equivalent to multiplying the real RMS value by $2\sqrt{2}$ (or 2.828), therefore yielding a perceived vibration anomaly that was detected by the system. Note, although the EHM system was developed to accept data from both the starboard tangential and port radial accelerometers, current F405 production engines only have the starboard tangential accelerometer installed. Hence, the redundancy (confidence level) factor and vibration diagnostic capability for locating the more precise source of the vibration is reduced for these engine configurations.

Engine #3 Test **Engine Serial #: 9107** **Date: 11/18/97**

The third engine tested as part of this SBIR program occurred approximately 3 weeks following the second engine test. This test was similar in profile to the second engine test because it was also a production pass-off test where performance scans were taken at 11 pre-determined NH speeds. The performance scan data was again used to develop the engine signature models used in the performance anomaly detection module. The vibration accelerometer calibration factor relating peak-to-peak amplitudes to RMS amplitudes was corrected during this test so that no false vibration anomalies were detected. In fact, no engine sensor or other faults were detected at all during this test. Because of this, the STI team decided to "seed" some sensor faults by opening and shorting the sensor signal leads during engine operation, of course with the consent of the Rolls Royce test engineers.

A set of test data associated with one of the performance scan tests performed on this engine is given in Figures 31-35. Towards the end of this test, the P3 (compressor delivery pressure) sensor was purposely shorted and the T2 (intercompressor temperature) sensor purposely open circuited. This resulted in an immediate response by the EHM system by diagnosing the corresponding sensor failure in both cases. In fact, the STI team "seeded" a sensor fault for each of the measured parameters with successful diagnosis results being identified by the EHM system in each case.

The next "seeded" fault type scenario investigated was related to simultaneous occurring sensor failures. In this case, two different sensor lead wires were open circuited to examine the EHM sensor validation module's ability to diagnose multiple sensor failures occurring at one time. Recall, that the sensor validation scheme with the EHM system is based primarily on a standard "feed forward" neural network architecture with back propagation of error using during the training. However, in addition to the neural network, a parallel sensor validation check is performed by examining the difference between predicted and measured engine parameters. By utilizing this redundant architecture, the multiple sensor faults were always identified by the

EHM system, but in some instances manifested themselves as only a single sensor fault. In either case, at least one sensor fault was always identified for all simultaneous sensor fault cases.

Based on the results from each of the three tests conducted, it was concluded that an important balance must exist between the real-time diagnostic capabilities and the ability to deal with "real world" uncertainties from sensor signal transients, random measurement fluctuations and non steady-state performance and vibration parameter changes. In is recommended that this balance be achieved through: 1.) Intelligent "engine specific" tolerances built into the EHM system and 2.) An engine signature approach to "normal" engine operation utilizing probabilistic engineering analysis. In order to address these concerns, the tested EHM system is currently being modified to perform vibration and performance anomaly detection with adaptable fuzzy-logic membership functions that are adjusted during an initial EHM system installation period. Also, EHM fault pattern recognition algorithms for vibration and performance related diagnosis were adjusted to perform selective averaging and trending over specific engine operating conditions. The modifications are expected produce more robust, consistent and accurate diagnostic assessments.

6.0 EHM System Demonstration Program

This EHM (engine health monitoring) demonstration program was developed by STI to illustrate the basic operation and functionality of the real-time engine health monitoring system. The EHM software provides dedicated sensor validation, long/short term trending, virtual sensors, vibration and performanece anomaly detection, vibration and performance diagnostic classifiers and decision analysis, and critical component life usage capabilities all in a real-time monitoring environment. The system has been successfully ground tested on three (3) different engines at the Rolls-Royce MAEL division in Bristol, England. Technical details describing the capabilities of the EHM system are given in the SBIR final report and an ASME paper attached to the end of the demonstration program description.

<u>Minimum Hardware Requirements</u>

This EHM demonstration program requires:

- Intel Pentium based or better IBM-compatible personal computer
- One of the following operating systems:
    1. Microsoft Windows NT 4.0 or above
    2. Microsoft Windows 95
- VGA graphics card or better
- 8 Mb of RAM minimum, 16 Mb of RAM recommended.
- Microsoft Mouse or other Windows compatible device
- 4 Mb of hard disk space

6.1 Installing EHM Demo Software

The EHM demonstration program is a 32-bit application designed for Windows NT or Windows 95 operating systems. To install the EHM demo:

1. **Start Windows NT or Windows 95.**
   No other application should be running while EHM is being installed.

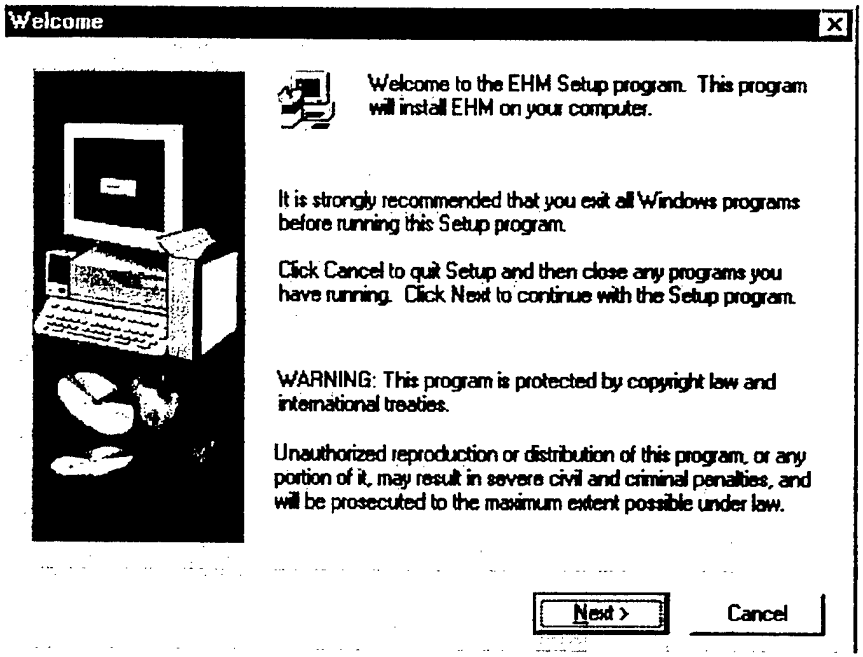
2. **Insert the disk labeled "EHM Disk 1" into your disk drive.**

3. **Select the "Start" button from the taskbar at the bottom of the screen and then "Run..." when running Windows NT or Windows 95.**
   The "Run" dialog appears.

4. **Type "A:\Setup" in the Command Line text box.**
   If you are installing from a drive other than A, substitute the letter for the source drive.

5. **Select "OK".**

The following welcome dialog appears:

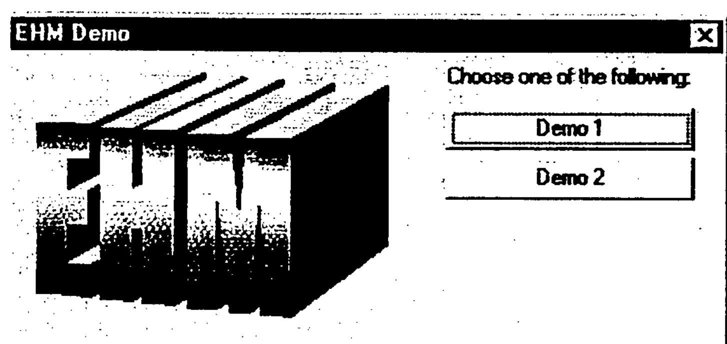


6. **Select "Next" to go to the next screen.**

7. **Change the default name and destination of the EHM directory if desired and Select "Next".**

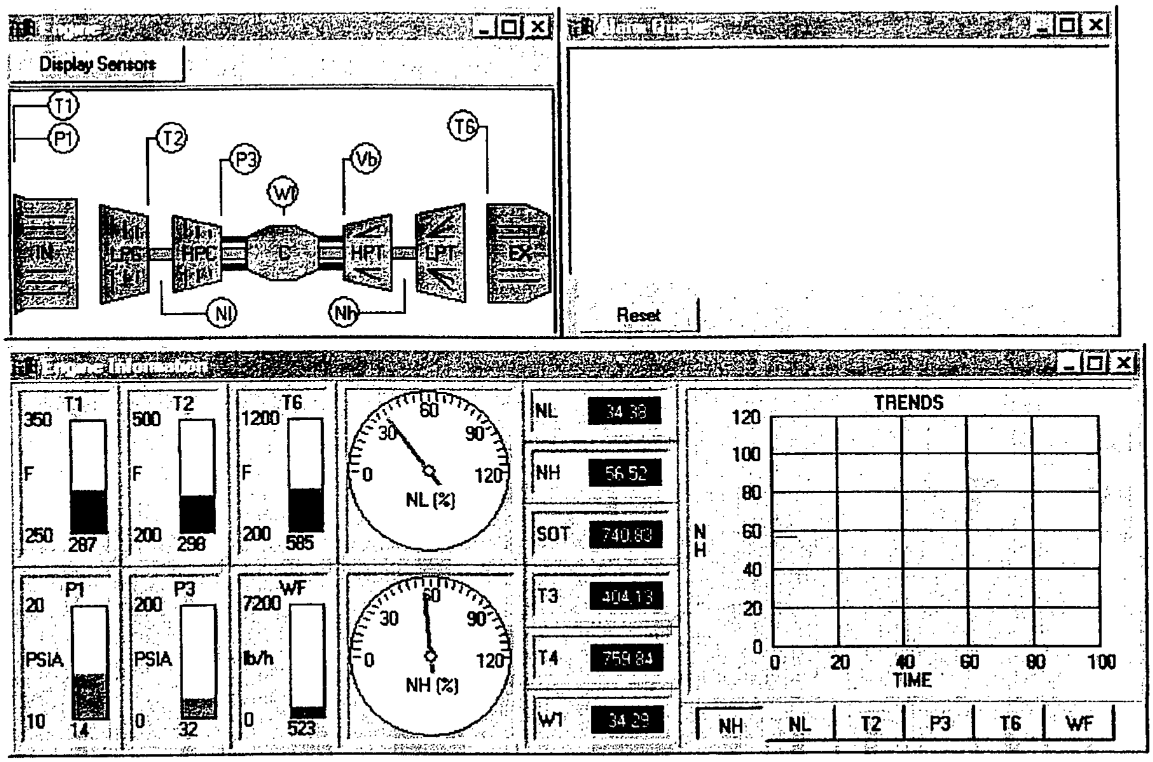
The installation program will then install the program in the specified directory. You will be told when to change diskettes. The installation program will also add EHM to the Program menu option under the taskbar at the bottom of the screen.

8. **To start the EHM program, select the "Start" button from the taskbar at the bottom of the screen, point to EHM, and then select EHM. Choose either Demo from the following Dialog box.**



6.2 Demonstration Files

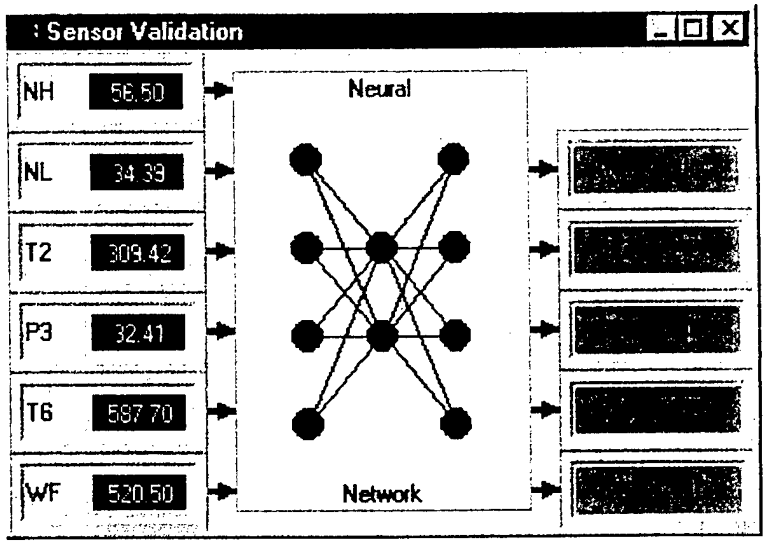
Once you have selected "Demo 1" from the dialog box show above, the EHM system will automatically begin operation as if the EHM system was processing real-time data from an engine. The EHM "main screen" shown below should now be active with the instrumentation panel changing with the data that is being received from the demonstration file. The various EHM system monitoring and diagnostic screens can be accessed from the top menu bar that is organized with respect to the different engineering modules that comprise the EHM system. These include the, 1.) Engine Instrument Display, 2.) Data Management, 3.) Health, 4.) Diagnostic, and 5.) Life modules.



EHM "Main Screen"

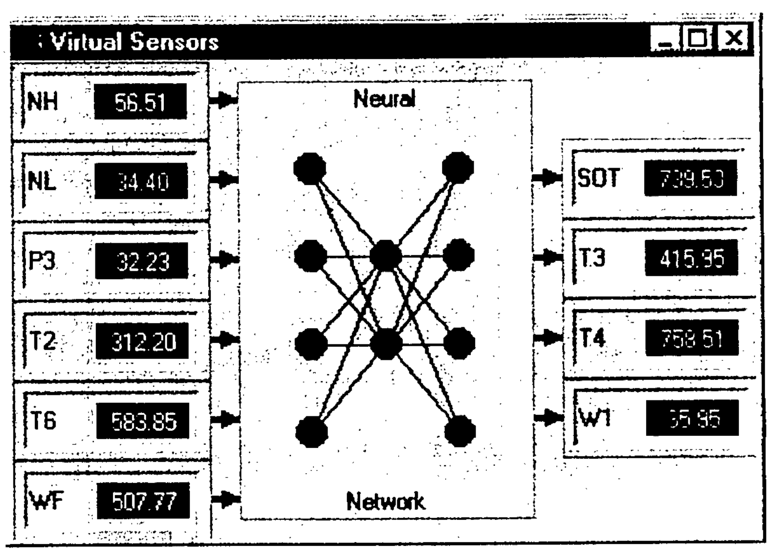
<u>"Data Management" Menu Bar</u>

First, from the top menu bar, select the "Data Management" menu option. Contained within this menu option exist the "Sensor Validation", "Virtual Sensor", and the "Long Term Trend Plot" screens. Select the "Sensor Validation" option and the screen shown below titled "Sensor Validation Screen" will appear. In this module, the measured data is being processed by a trained neural network in real-time to assess if a sensor fault has occurred. During this demonstration, a fuel flow (WF) sensor problem is diagnosed within this module when the NH speed approximately reaches 100% of its rated maximum value. When this fault is detected, the output from the neural network turns yellow illustrating the sensor is having a problem. The "Alarm Queue" is then updated showing that the fuel flow (WF) sensor has been diagnosed with a fault. The engine pictorial also shows a corresponding warning in the combustor area of the engine.



Sensor Validation Screen

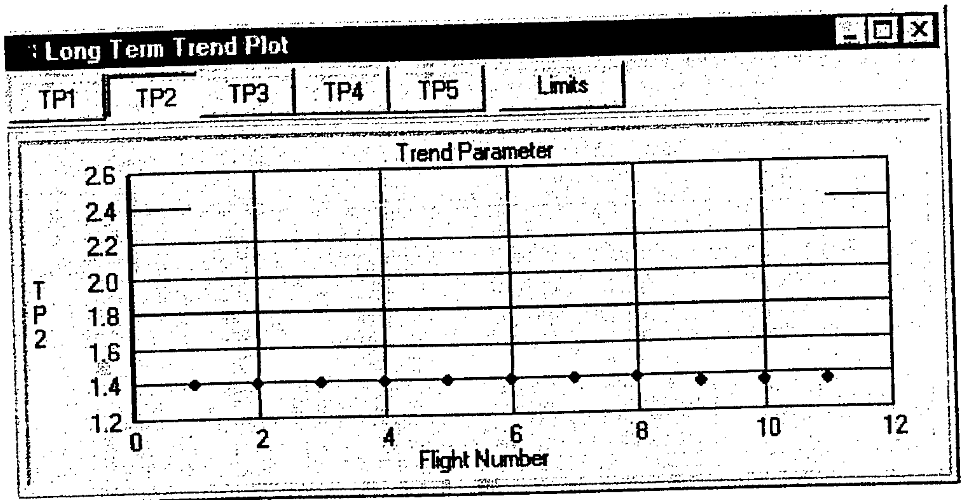
Next, open the "Virtual Sensor" screen shown below. This option displays the real-time, engine parameter estimates that are being predicted through the trained neural network. Specifically, the neural network (trained by an engine GPA model) is estimating in real-time important engine parameters that are currently not measured on the Navy F405 engine. The virtually sensed parameters include, 1.) Stator Outlet Temperature (SOT), 2.) Compressor delivery temperature (T3), 3.) Turbine Inlet Temperature (T4), and 4.) Gas Mass Flow. The significance of this technique is that the SOT and T4 virtual sensors provide accurate, real-time information that is critical to estimating remaining life associated with the HP turbine blades and disk.



Virtual Sensor Screen

The last option to be opened from the "Data Management" menu bar is called "Long Term Trend Plot". This option displays a plot of important, non-dimensional, long term engine parameter trends. The non-dimensional trending parameters, TP1 through TP5, are $NL/\sqrt{\Theta}$, T2/T1, P3/P1, T6/T1, and $Wf/\delta\sqrt{\Theta}$, respectively, all corrected to an $NH/\sqrt{\Theta}$ of

97.5%. The "Long Term Trend Plot" screen is shown below. Note, the only data point taken per flight is calculated form the measured parameters recorded at weight off wheels (WOW). For this demonstration, the WOW flight point is taken the first time a 95% NH value is reached.

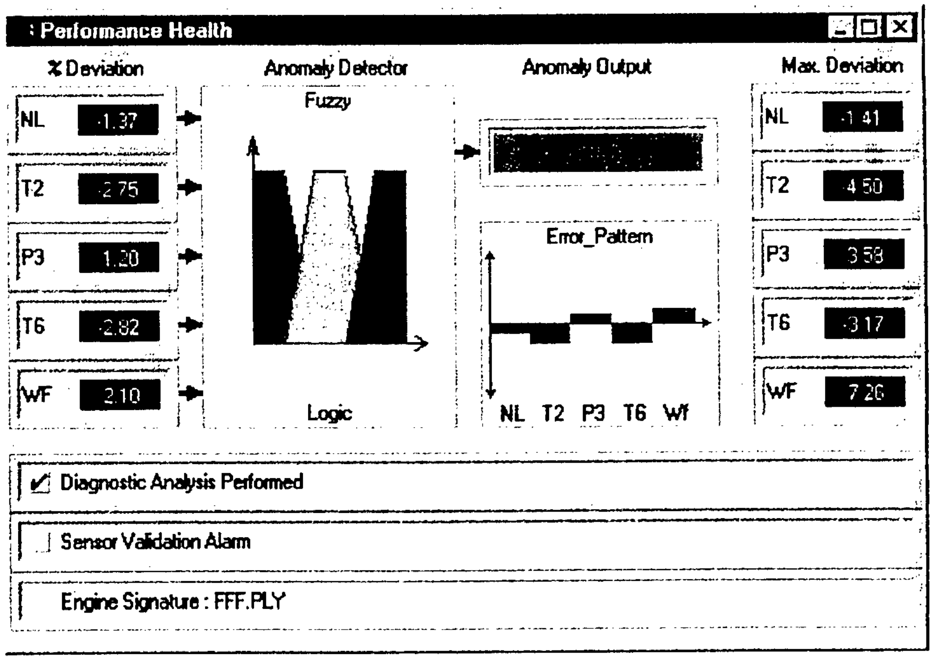


Long Term Trend Plot

"Health" Menu Bar

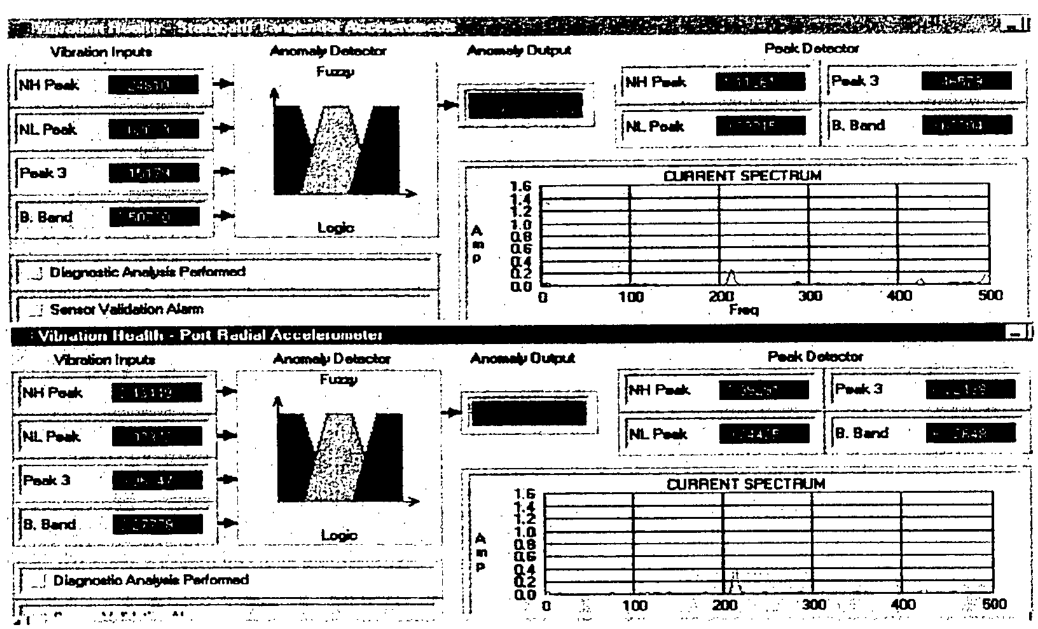
The next set of EHM diagnostic screens to be examined are part of the "Health" module menu options. There are two primary EHM health screens within this menu, they are the "Performance Health" and "Vibration Health" screens. The "Vibration Health" portion is broken up into the "Starboard Tangential" and "Port Radial" accelerometer response screens. Only the "Starboard Tangential" screen is currently active in this demonstration because it is the only accelerometer on the F405 production engine.

First, let's examine the "Performance Health" screen. This screen basically compares the difference between the measured engine parameters and those predicted by the engine signature models. When a parameter starts to "drift" outside the pre-determined fuzzy logic based membership function "bands", an anomaly is detected and sent to the alarm queue. The "Performance Health" screen is shown below. The Demo1 demonstration file produces a performance anomaly with repect to the T2 sensor. This was due to the fact that the sensor was producing small fluctuations not large enough to "flag it" as a sensor problem.



"Preformance Health" Screen

Next, open the "Starboard Tangential" submenu selection under the "Vibration Health" menu item. In this screen, the four most significant features associated with the vibration spectral densities are used as input to a fuzzy logic based anomaly detection algorithm. The four primary features include the NH and NL shaft speed tracked-order amplitudes, the maximum peak that is not related to NH or NL, and a broadband measure of the entire spectral density. Based on the value of these features and an extensive knowledge base consisting of "normal" and "abnormal" vibration spectrums, vibration anomalies are detected. The "Starboard Tangential" and "Port Radial" vibration health screens are shown below. HP and LP peaks cause anomaly alarms to trigger in this Demo1 file.

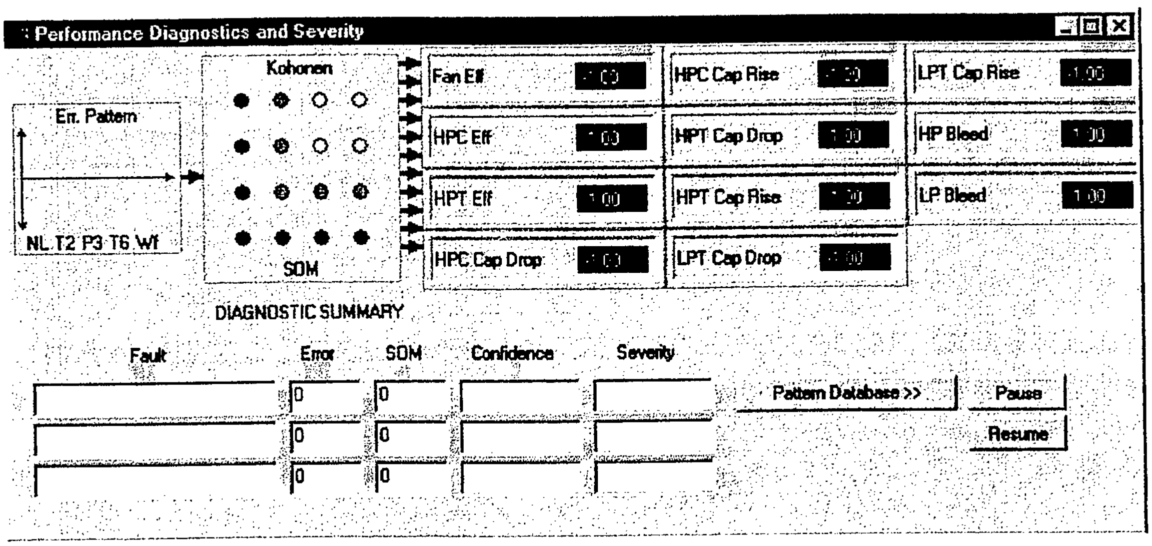


"Vibration Health" Screens

"Diagnostic" Menu Bar

When a vibration or performance anomaly is detected, the current set of measured data is passed to the corresponding Diagnostic module. The Performance Diagnostic module is shown below. Within this module, performance degradation fault patterns are assessed to determine the likely cause and general location within the engine of the detected performance anomaly. Averaging and long term trending of the performance degradation patterns is necessary to for accurate diagnostic results. Also within this screen, the diagnosed faults are rated in terms of confidence of a correct diagnosis and severity of the fault.

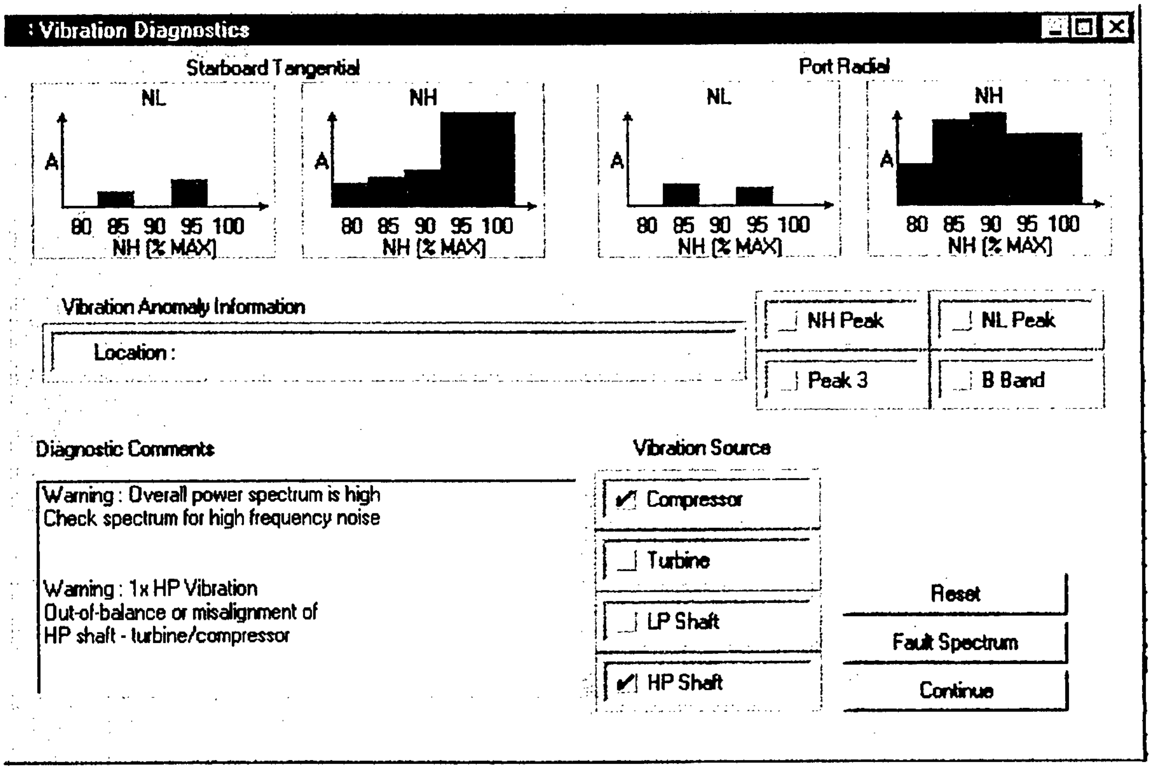
This demonstration file did not have any performance degradation fault patterns diagnosed as a particular fault. Afterall, the tests were performed on new production engines.



Performance Diagnostics Screen

The Vibration Diagnostic module utilizes the results from the anaomaly detector feature extration process, tracked-order amplitudes at different speeds, and an engine vibration database to diagnose specific vibration problems typical for the engine being monitored. The corresponding EHM screen is shown below. At the top of this screen the engine tracked-order vibration amplitudes are calculated, averaged, and placed in respective speed bins. This information is used by the vibration diagnostic rulebase to determine if the source of the vibration is on the compressor or turbine sections. Just below the tracked-order information, the anomaly detection features are listed with check boxes to display the particular anomaly. Based on the results from the engine knowledge-base, diagnostic comments are made to describe the fault in more detail. A button for accessing the vibration fault spectrum in question is also provided.

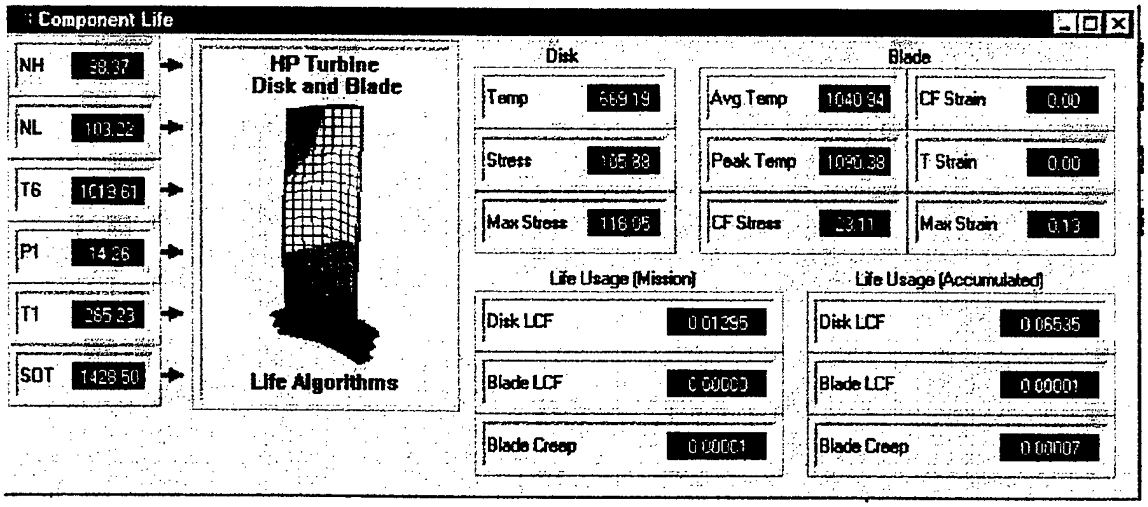
Within the Demo1 demonstration file, the HP and LP tracked-order vibration amplitudes were both measured over the "normal" alarm levels, and therefore the "HP and LP shaft unbalance or possible misalignment" was the proper diagnosis.



Vibration Diagnostics Screen

<u>"Life" Menu Bar</u>

The last EHM screen to be examined is related to the "Component Life" module. In this module the life usage associated with the HP turbine blades and disk are continuously monitored during each mission and summed for all missions. Note, the inputs to component lifing module are both directly measured parameters and "virtually" sensed parameters. This combination was concluded to give the most accurate lifing results based on the algorithms used. The outputs are separated into the disk and blade components. Outputs specifically showing the average and maximum thermal and cetrifugal stresses/strains are given above, while the accumulated life used during the mission and total for all missions is given below. Both LCF related to thermal and centrifugal stresses as well as creep life are considered in the lifing algorithms. When an accumulated life value reaches 1.0, then the total life of the component is calculated to be used up completely.

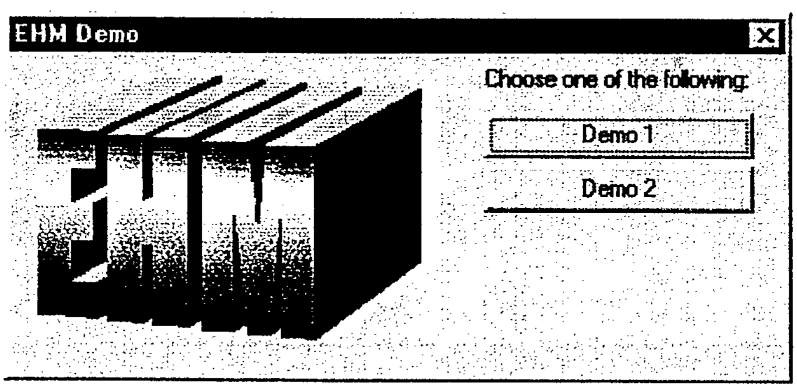


Component Life Screen

This is the end of the documentation associated with the first demonstration program. The documentation for the second demonstration will not include taking the user through each of the modules of the EHM program as just done with this demonstration. Instead, it is left up to the user to "click" through each of the EHM screens during the second demonstration file.

Demonstration #2

Once you have selected "Demo 2" from the dialog box show below, the EHM system will automatically begin operation as if the EHM system was processing real-time data from an engine. The EHM "main screen" will become active with the instrumentation panel changing with the data that is being received from the Demo 2 demonstration file. The various EHM system monitoring and diagnostic screens can be accessed from the top menu bar and include the Engine Instrument Display, Data Management, Health, Diagnostic, and Life modules.



Demo 2 Start-Up Screen

During this demonstration, the only fault that is detected and reported in the alarm queue is from the vibration health and diagnostic modules. From the top menu bar, select the "Vibration Health - Starboard Tangential" diagnostic screen and examine the vibration spectrums as the speed of the engine is increased. Once the HP tracked-order amplitude gets in the range of approximately 0.65 in/sec, a yellow warning is displayed. Quickly following this warning, an alarm is detected from the amplitude rising over approximately 1.0 in/sec. This alarm is then reported to the main alarm queue. The basic fault is caused by "higher than normal" tracked-order amplitudes with respect to the LP and HP shaft speeds. This fault is similar to the vibration fault detected in the Demo 1 demonstration file. Although no other faults are detected in this demonstration, the user is encouraged to examine the remaining diagnostic screens.

7.0 Conclusions

The SBIR program described herein has produced a **real-time** Engine Health Monitoring system that demonstrates advanced diagnostic classifiers for mechanical and performance fault detection, dedicated sensor validation, "virtual" sensors, long/short term trend monitoring and real-time component lifing algorithms for advancing the current state-of-the-art in real-time engine condition monitoring and diagnostics. In particular, the incorporation of advanced fault pattern recognition techniques (utilizing back-propagation neural networks, self organizing maps, and polynomial networks) and decision analysis (i.e. fuzzy logic and expert systems) into the diagnostic process has been shown to yield great benefits in terms of processing speed, robustness, knowledge acquisition, and adaptability. The real-time EHM technologies have been successfully demonstrated on three engines at the Rolls-Royce MAEL Test Cells in Bristol, England.

Further development and demonstration of the real-time EHM system capabilities are ongoing with a program to "re-train" the EHM system for the GE F101 engine. This program is of particular interest to the U.S. Air Force and in particular the Air Combat Command (ACC) in Oklahoma City where a large number of the GE F101's are maintained. Successful demonstration of the EHM system during this program could help build the necessary support required for implementing these cost saving life monitoring and diagnostic technologies for aging propulsion systems. In addition, a similar program is being planned with GE Aircraft Engines to consider transferring some of the technologies demonstrated under the F101 program to the JSF program.

A list of the program's significant technical benefits for applying AI and advanced life prediction schemes to real-time condition monitoring, diagnosis, and life usage are as follows:

- Integration of neural networks (unsupervised and supervised), fuzzy-logic, and expert systems to identify engine anomalies, both performance and mechanical (vibration) related, and in turn provide specific diagnostics related to the identified fault in real-time.

- Capability to provide real-time estimates of the life being consumed from critical engine components including HP turbine blades and disks. Virtually sensed turbine inlet temperatures, mass flow, etc. (currently not measured) are utilized to improve accuracy of the actual life being accumulated.

- Advanced vibration diagnostics that is based on feature extraction from both spectral "waterfall" plots and tracked-order amplitudes. The results are passed through a fuzzy-logic decision analysis procedure for classifying mechanical engine faults.

- Engine "signature" based performance degradation monitoring that accounts for steady-state and pseudo steady-state engine operation. Self organizing maps cluster performance faults with high degree of robustness with respect to pattern uncertainties.

- Real-time sensor validation networks trained from "fleet-wide" engine test data taken during a wide range of engine operating conditions. Polynomial networks are implemented to recognize the non-linear relationships among the measured parameters.

- Provides an automated procedure for incorporating data from several knowledge sources including; analytical FEM models, aerothermal performance models, empirical/trended test data, and heuristic (rules based) experience.

As previously mentioned, the EHM system has undergone successful ground tests on three (3) different Rolls-Royce Adour engines (Navy F405) in Bristol, England. The EHM system's capabilities were tested thoroughly during each of the three engine tests with actual faults being diagnosed from test cell sensor faults and vibration signal calibration problems. In particular, a total of three different actual engine sensor anomalies were detected and diagnosed as well as some additional "seeded" faults that were also diagnosed. First, the T2 (LP compressor delivery temperature) and WF (fuel flow) test cell transducers both malfunctioned during an initial engine test, both of which were detected and correctly diagnosed in real-time. In addition, an HP and LP shaft vibration anomaly was also diagnosed during the first two engine tests. Overall, Rolls Royce engineers were extremely pleased with the operation of the EHM system and summarized the testing results with the following quote:

"This is a new and probably first application of artificial intelligence techniques in a real-time, on-board engine monitoring system having the ability for diagnosing vibration, performance, and component life anomalies concurrently. Rolls Royce commends STI for the successful demonstration of this novel system."

H. R. Carr and R. G. Fox, Rolls Royce, plc.

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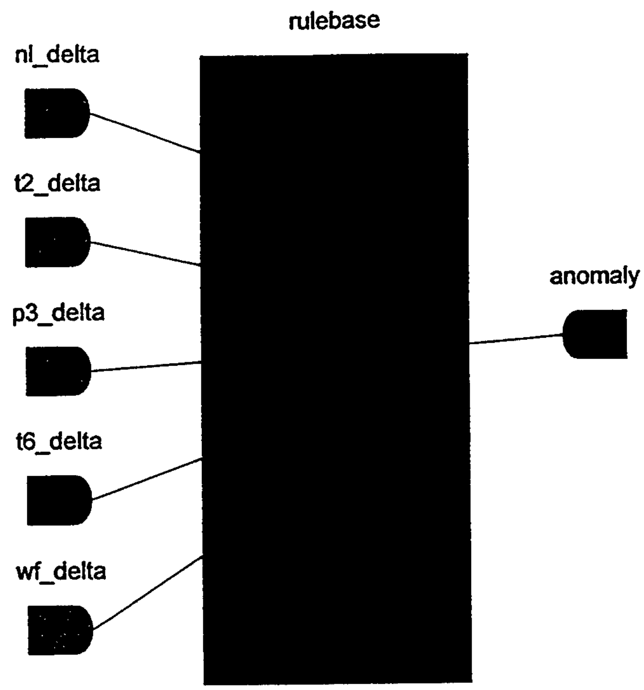
Section 4.3 Figures

PERFORMANCE ANOMALY DETECTION

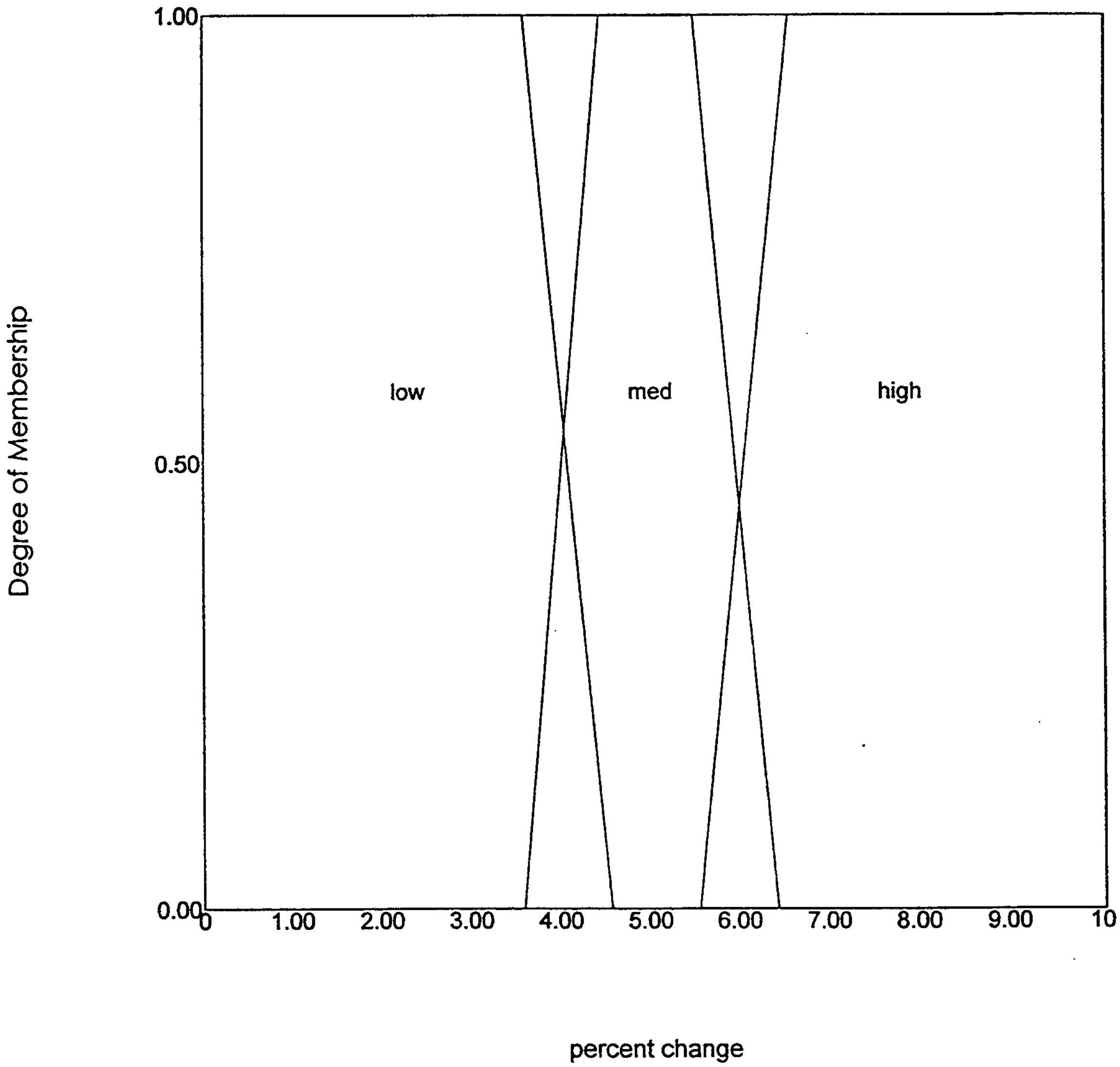
Fuzzy Logic Module **performance**



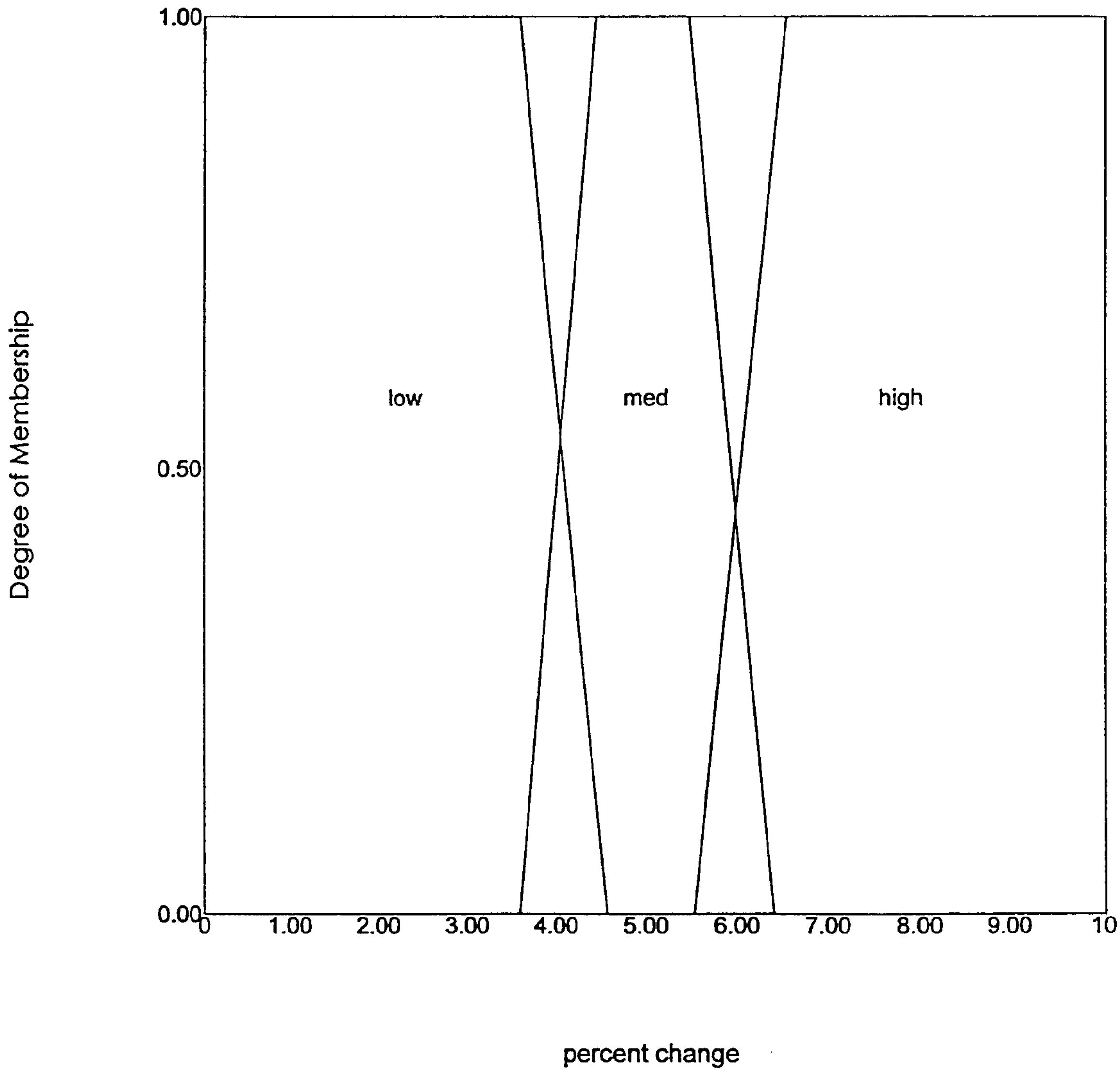
```
R1 :
  IF nl_delta IS low AND p3_delta IS low AND t2_delta IS low
    AND t6_delta IS low AND wf_delta IS low
  THEN anomaly is ok
R2 :
  IF nl_delta IS high AND (p3_delta IS high OR p3_delta IS med
    OR p3_delta IS low) AND (t2_delta IS high OR t2_delta IS med
    OR t2_delta IS low) AND (t6_delta IS high OR t6_delta IS med
    OR t6_delta IS low) AND (wf_delta IS high OR wf_delta IS med
    OR wf_delta IS low)
  THEN anomaly is alarm
R3 :
  IF p3_delta IS high AND (nl_delta IS high OR nl_delta IS med
    OR nl_delta IS low) AND (t2_delta IS high OR t2_delta IS med
    OR t2_delta IS low) AND (t6_delta IS high OR t6_delta IS med
    OR t6_delta IS low) AND (wf_delta IS high OR wf_delta IS med
    OR wf_delta IS low)
  THEN anomaly is alarm
R4 :
  IF t2_delta IS high AND (p3_delta IS high OR p3_delta IS med
    OR p3_delta IS low) AND (nl_delta IS high OR nl_delta IS med
    OR nl_delta IS low) AND (t6_delta IS high OR t6_delta IS med
    OR t6_delta IS low) AND (wf_delta IS high OR wf_delta IS med
    OR wf_delta IS low)
  THEN anomaly is alarm
R5 :
  IF t6_delta IS high AND (p3_delta IS high OR p3_delta IS med
    OR p3_delta IS low) AND (t2_delta IS high OR t2_delta IS med
    OR t2_delta IS low) AND (nl_delta IS high OR nl_delta IS med
    OR nl_delta IS low) AND (wf_delta IS high OR wf_delta IS med
    OR wf_delta IS low)
  THEN anomaly is alarm
R6 :
  IF wf_delta IS high AND (p3_delta IS high OR p3_delta IS med
    OR p3_delta IS low) AND (t2_delta IS high OR t2_delta IS med
    OR t2_delta IS low) AND (t6_delta IS high OR t6_delta IS med
    OR t6_delta IS low) AND (nl_delta IS high OR nl_delta IS med
    OR nl_delta IS low)
  THEN anomaly is alarm
R7 :
  IF nl_delta IS med AND (p3_delta IS med OR p3_delta IS low)
    AND (t2_delta IS med OR t2_delta IS low) AND (t6_delta IS med
    OR t6_delta IS low) AND (wf_delta IS med OR wf_delta IS low)
  THEN anomaly is warn
R8 :
  IF p3_delta IS med AND (nl_delta IS med OR nl_delta IS low)
    AND (t2_delta IS med OR t2_delta IS low) AND (t6_delta IS med
    OR t6_delta IS low) AND (wf_delta IS med OR wf_delta IS low)
  THEN anomaly is warn
R9 :
  IF t2_delta IS med AND (p3_delta IS med OR p3_delta IS low)
    AND (nl_delta IS med OR nl_delta IS low) AND (t6_delta IS med
    OR t6_delta IS low) AND (wf_delta IS med OR wf_delta IS low)
  THEN anomaly is warn
R10 :
  IF t6_delta IS med AND (p3_delta IS med OR p3_delta IS low)
    AND (t2_delta IS med OR t2_delta IS low) AND (nl_delta IS med
    OR nl_delta IS low) AND (wf_delta IS med OR wf_delta IS low)
  THEN anomaly is warn
R11 :
  IF wf_delta IS med AND (p3_delta IS med OR p3_delta IS low)
    AND (t2_delta IS med OR t2_delta IS low) AND (t6_delta IS med
    OR t6_delta IS low) AND (nl_delta IS med OR nl_delta IS low)
```

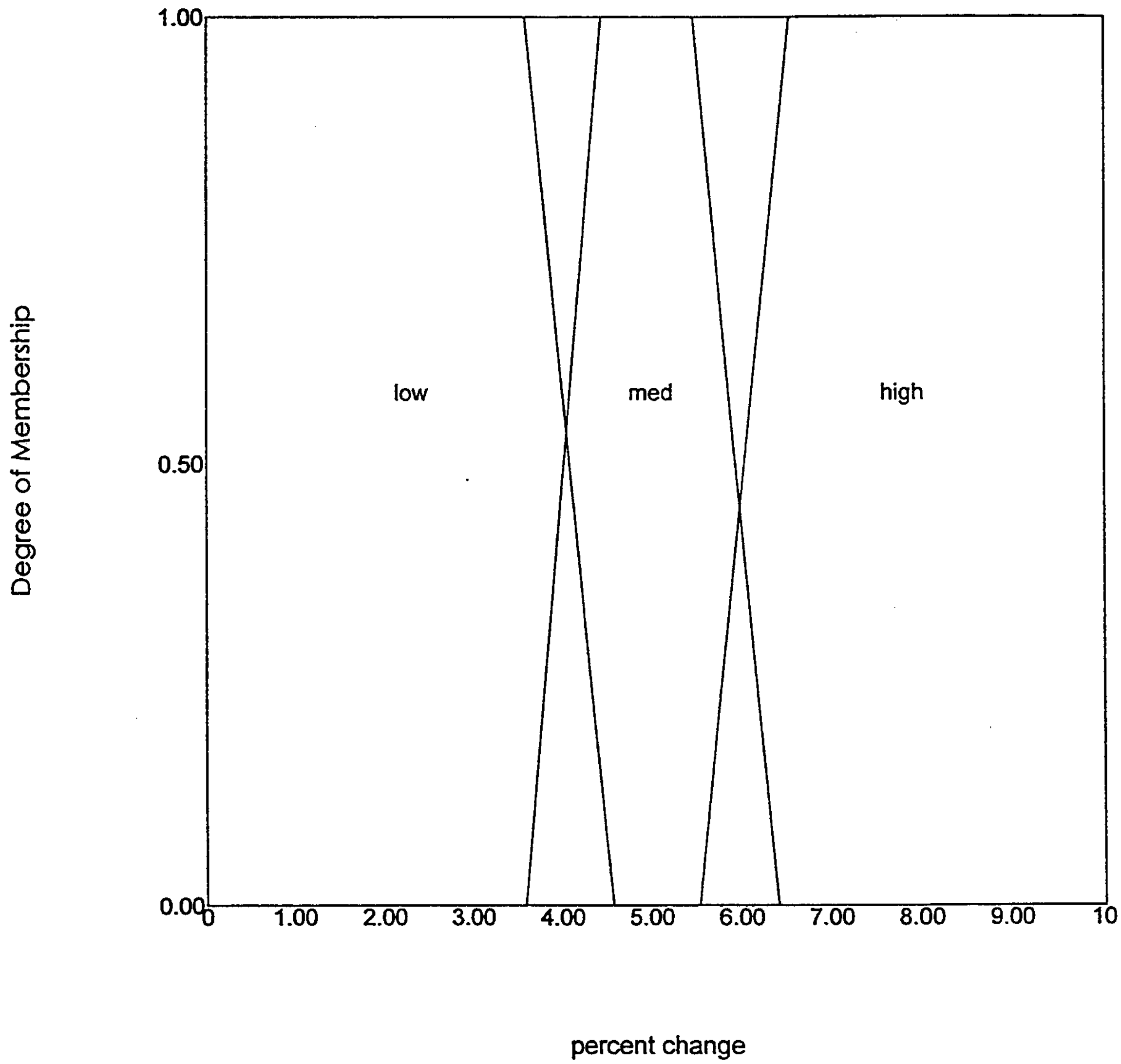
Membership Function Module

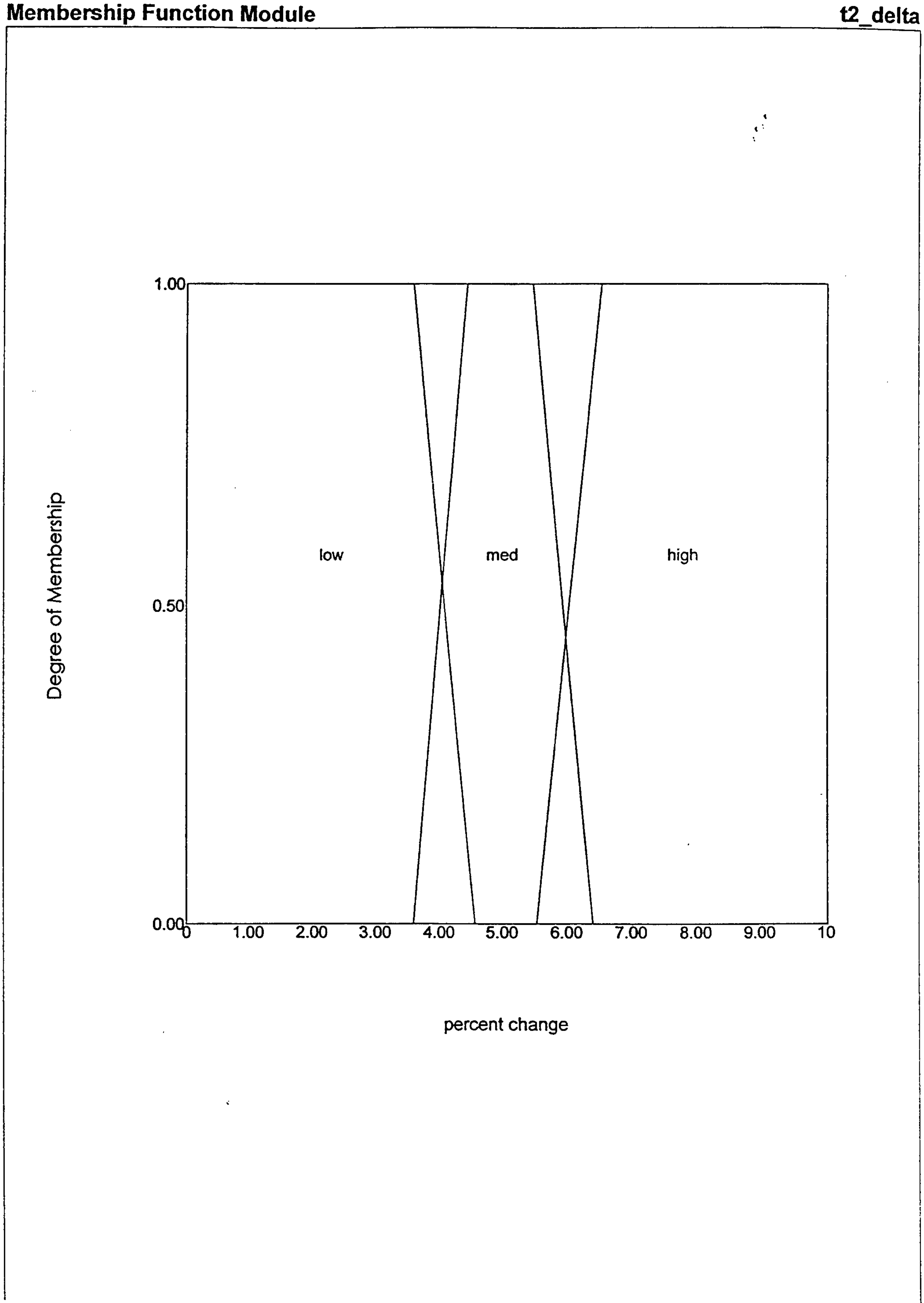
nl_delta



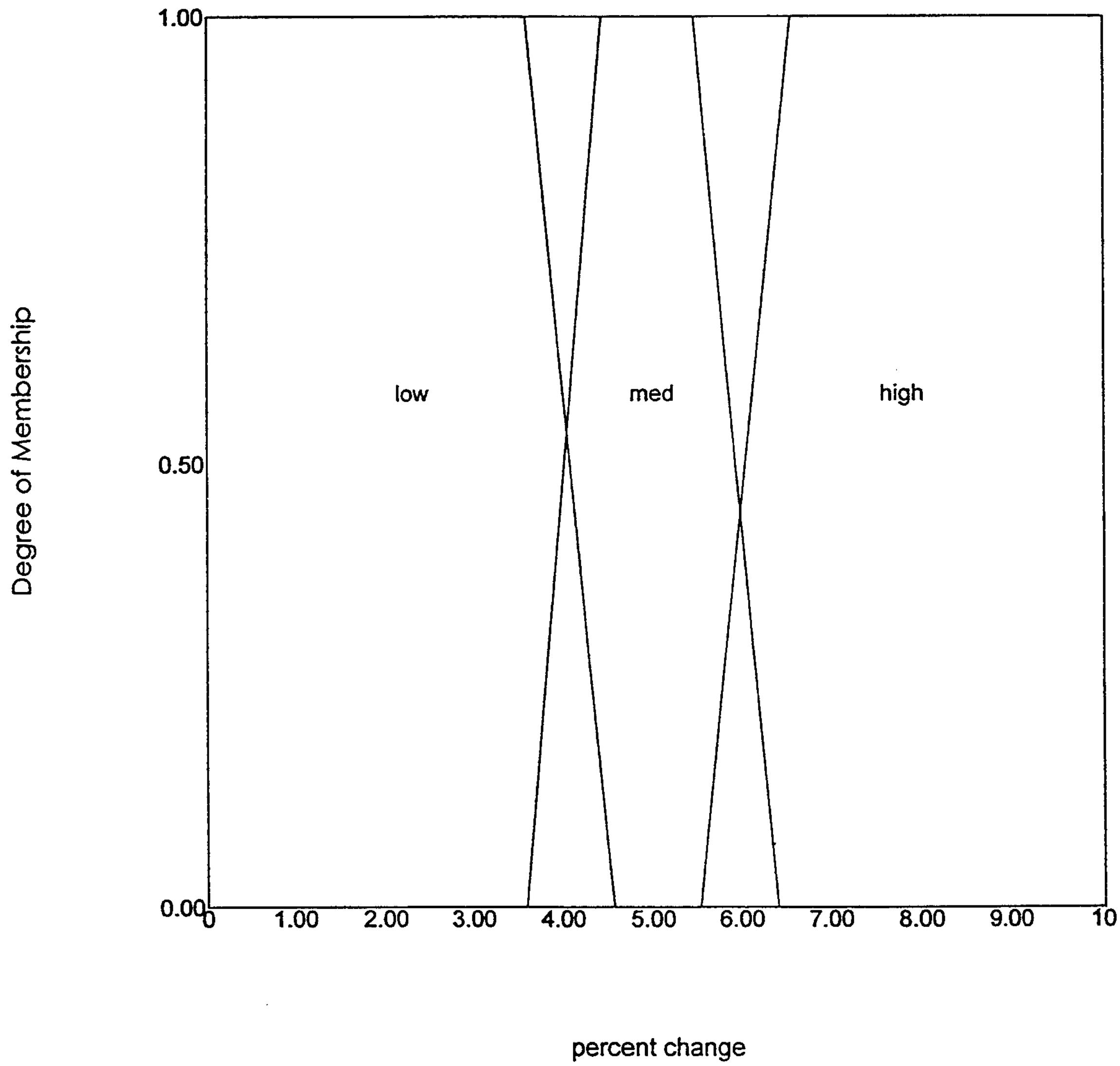
Membership Function Module **t6_delta**




1.00
0.50
0.00
Degree of Membership
low
med
high
0
1.00
2.00
3.00
4.00
5.00
6.00
7.00
8.00
9.00
10
percent change

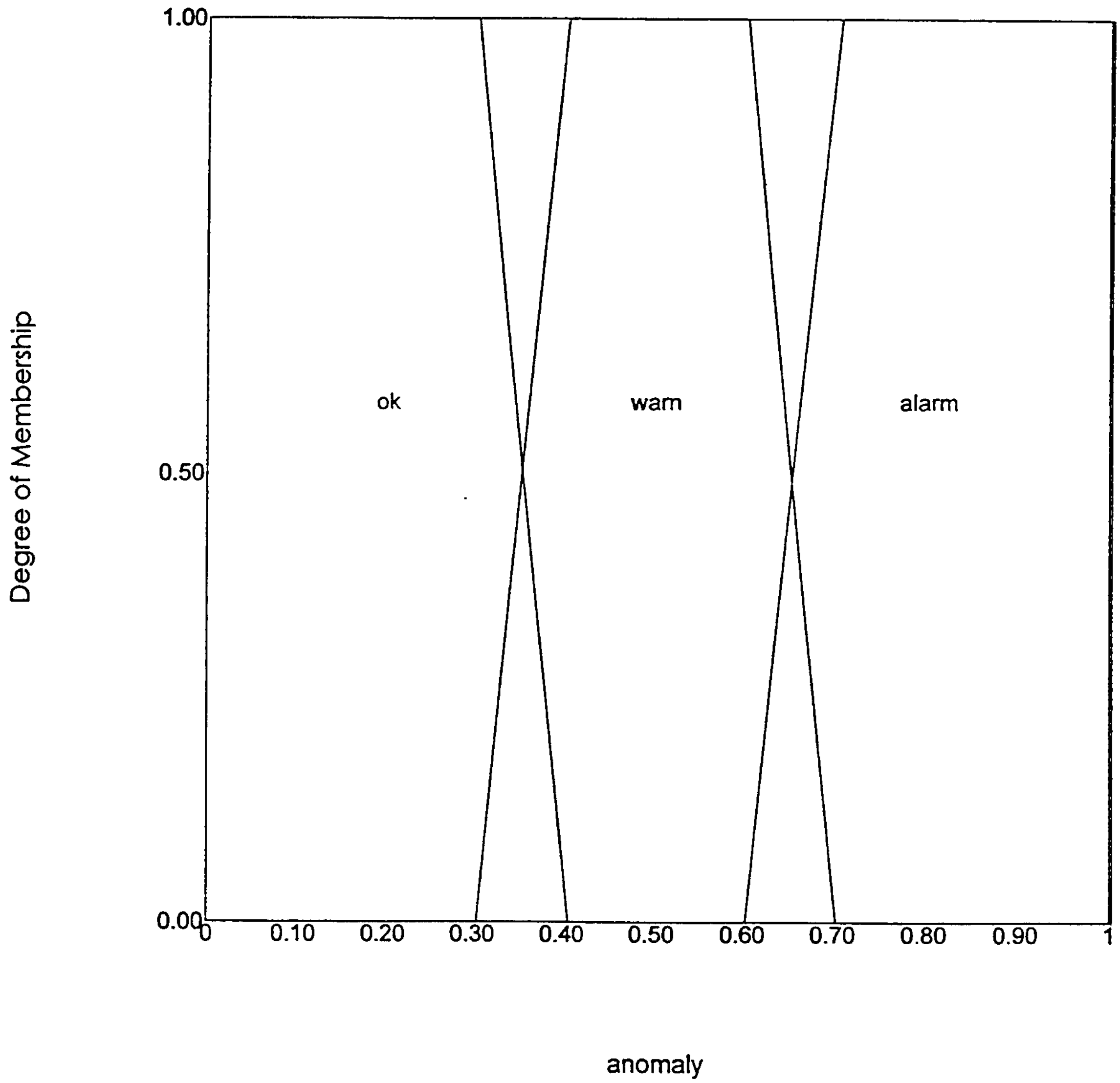


Membership Function Module
t2_delta
Degree of Membership
1.00
0.50
0.00
low
med
high
0
1.00
2.00
3.00
4.00
5.00
6.00
7.00
8.00
9.00
10
percent change


1.00
0.50
0.00
Degree of Membership
low
med
high
0
1.00
2.00
3.00
4.00
5.00
6.00
7.00
8.00
9.00
10
percent change

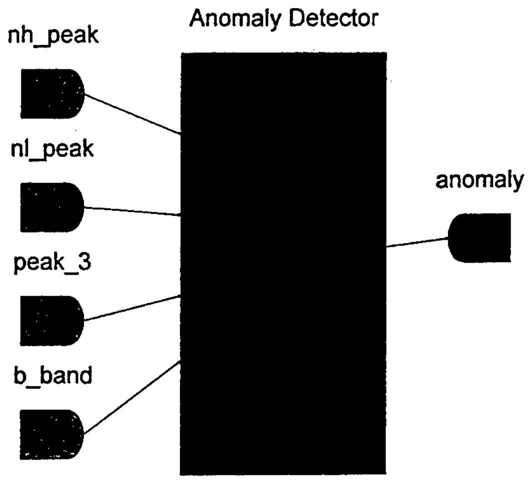
Membership Function Module

anomaly



Section 4.4 Figures

VIBRATION ANOMALY DETECTION


nh_peak
nl_peak
peak_3
b_band
Anomaly Detector
anomaly

R1 :
IF b_band IS low AND peak_3 IS low AND nl_peak IS low
AND nh_peak IS low
THEN anomaly is ok

R2 :
IF nh_peak IS high AND (nl_peak IS high OR nl_peak IS med
OR nl_peak IS low) AND (peak_3 IS high OR peak_3 IS med
OR peak_3 IS low) AND (b_band IS high OR b_band IS med
OR b_band IS low)
THEN anomaly is alarm

R3 :
IF nl_peak IS high AND (nh_peak IS high OR nh_peak IS med
OR nh_peak IS low) AND (peak_3 IS high OR peak_3 IS med
OR peak_3 IS low) AND (b_band IS high OR b_band IS med
OR b_band IS low)
THEN anomaly is alarm

R4 :
IF peak_3 IS high AND (nl_peak IS high OR nl_peak IS med
OR nl_peak IS low) AND (nh_peak IS high OR nh_peak IS med
OR nh_peak IS low) AND (b_band IS high OR b_band IS med
OR b_band IS low)
THEN anomaly is alarm

R5 :
IF b_band IS high AND (nl_peak IS high OR nl_peak IS med
OR nl_peak IS low) AND (peak_3 IS high OR peak_3 IS med
OR peak_3 IS low) AND (nh_peak IS high OR nh_peak IS med
OR nh_peak IS low)
THEN anomaly is alarm

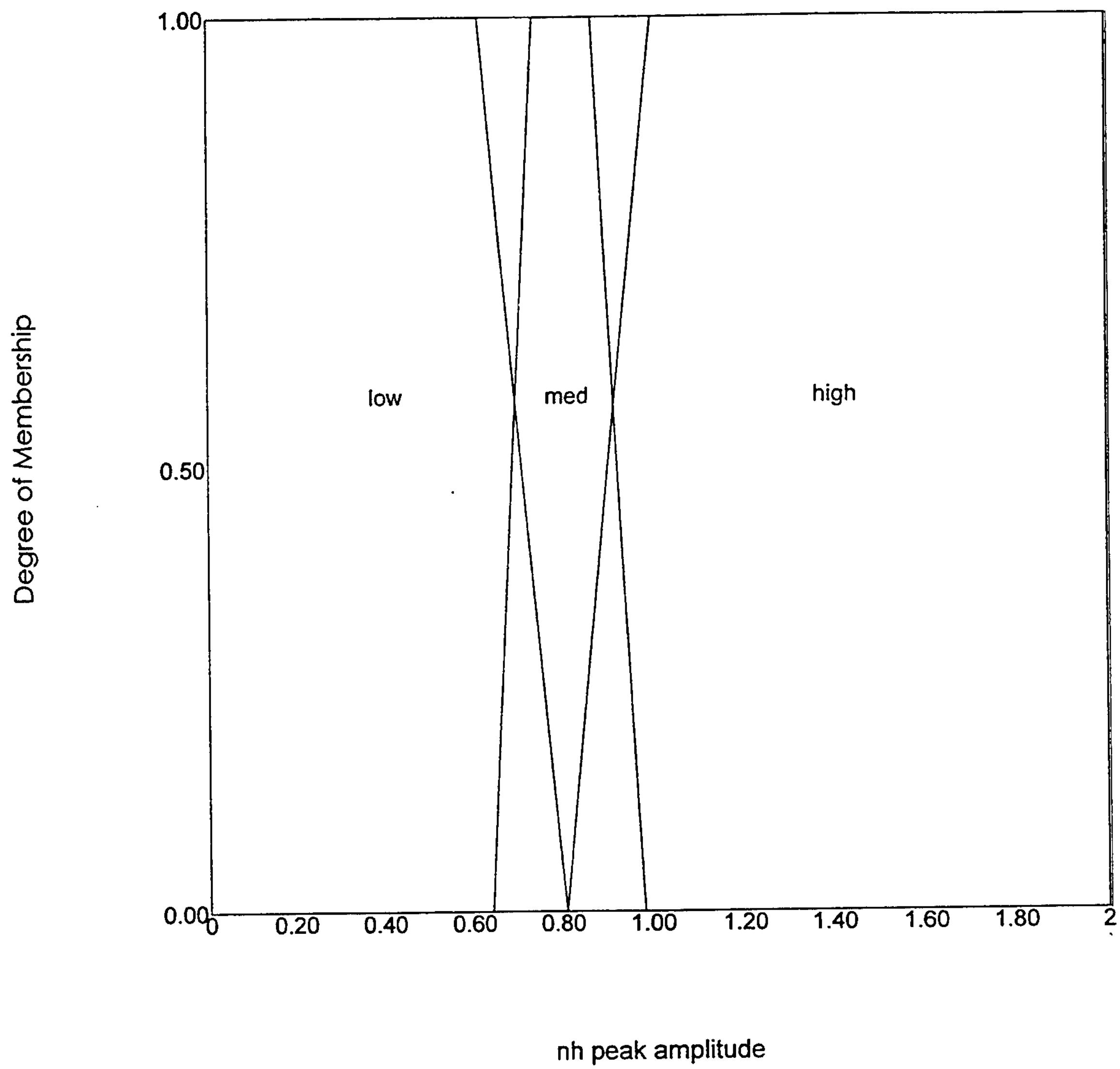
R6 :
IF b_band IS med AND (nl_peak IS med OR nl_peak IS low)
AND (peak_3 IS med OR peak_3 IS low) AND (nh_peak IS med
OR nh_peak IS low)
THEN anomaly is warn

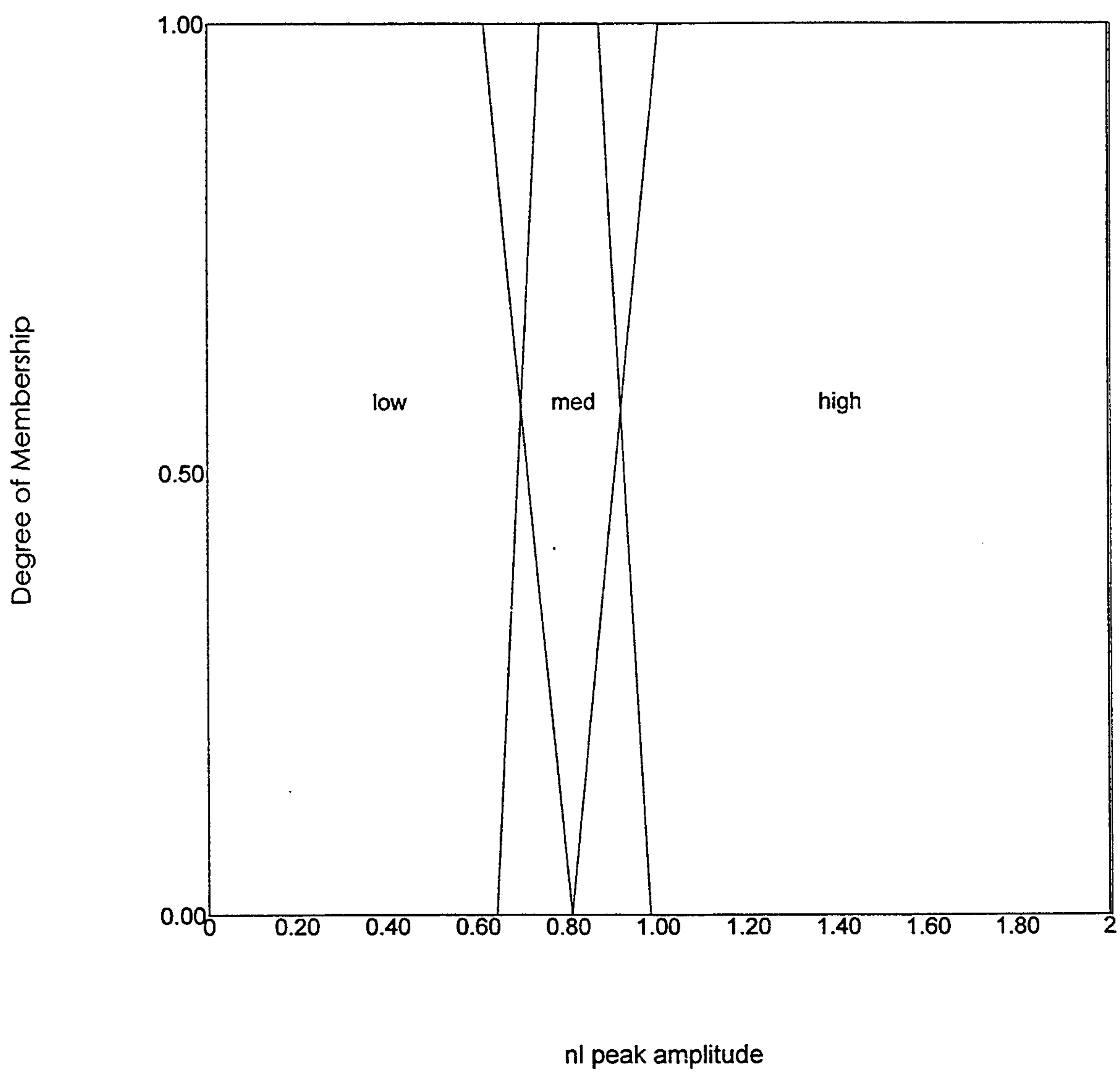
R7 :
IF peak_3 IS med AND (nl_peak IS med OR nl_peak IS low)
AND (b_band IS med OR b_band IS low) AND (nh_peak IS med
OR nh_peak IS low)
THEN anomaly is warn

R8 :
IF nl_peak IS med AND (peak_3 IS med OR peak_3 IS low)
AND (b_band IS med OR b_band IS low) AND (nh_peak IS med
OR nh_peak IS low)
THEN anomaly is warn

R9 :
IF nh_peak IS med AND (peak_3 IS med OR peak_3 IS low)
AND (b_band IS med OR b_band IS low) AND (nl_peak IS med
OR nl_peak IS low)
THEN anomaly is warn

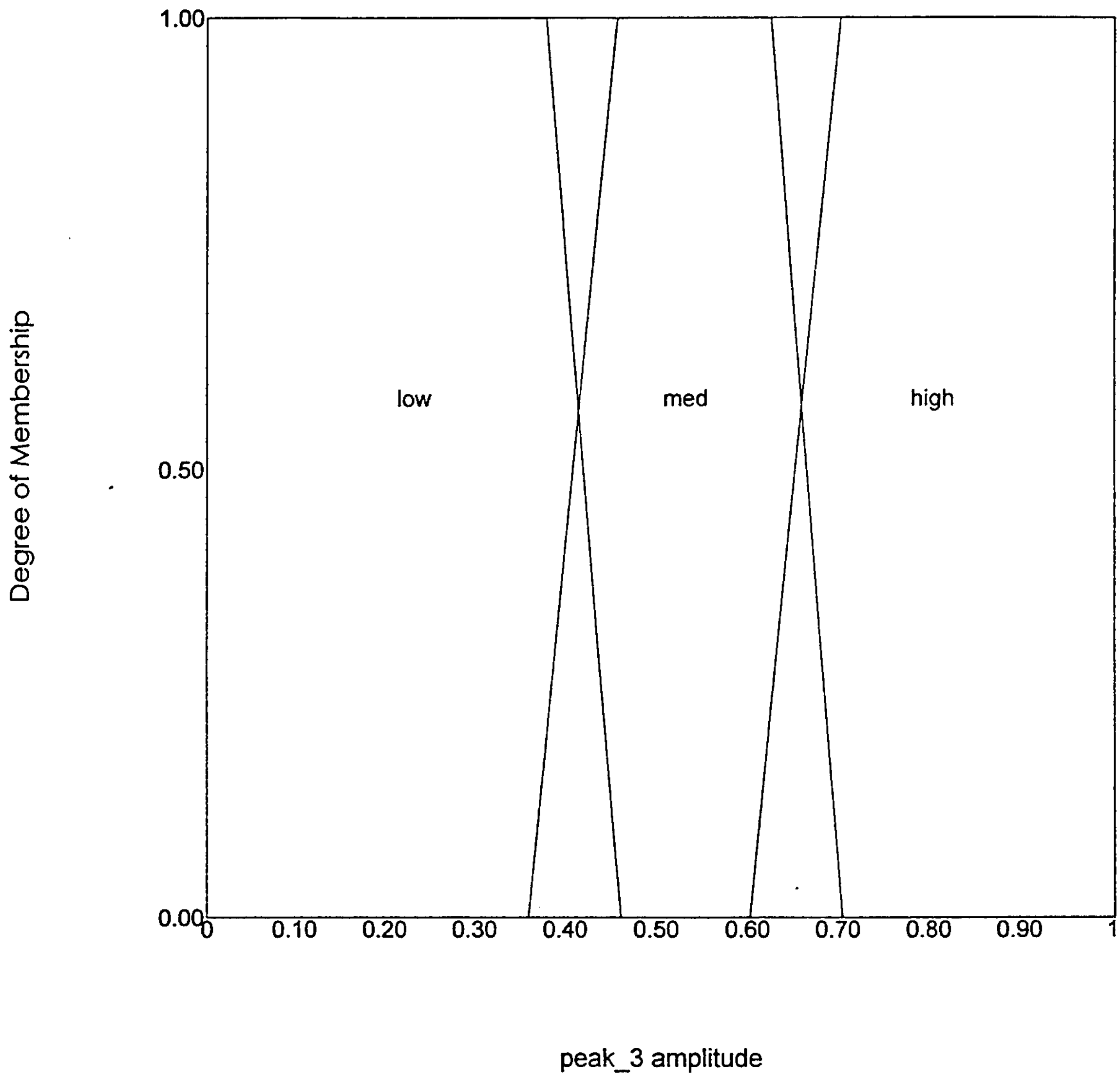
Membership Function Module

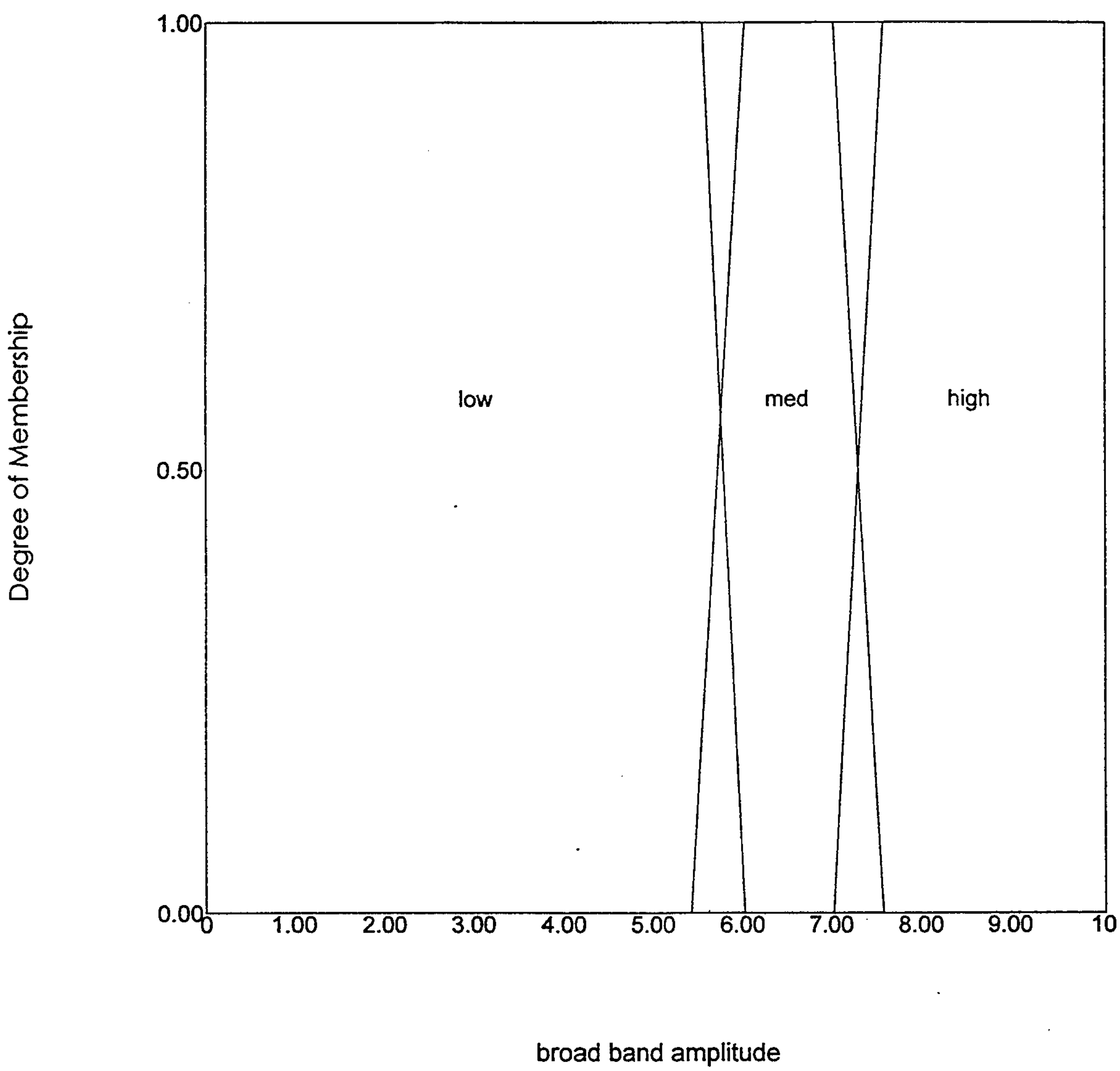



1.00
0.50
0.00
Degree of Membership
low
med
high
0
0.20
0.40
0.60
0.80
1.00
1.20
1.40
1.60
1.80
2
nl peak amplitude

Membership Function Module

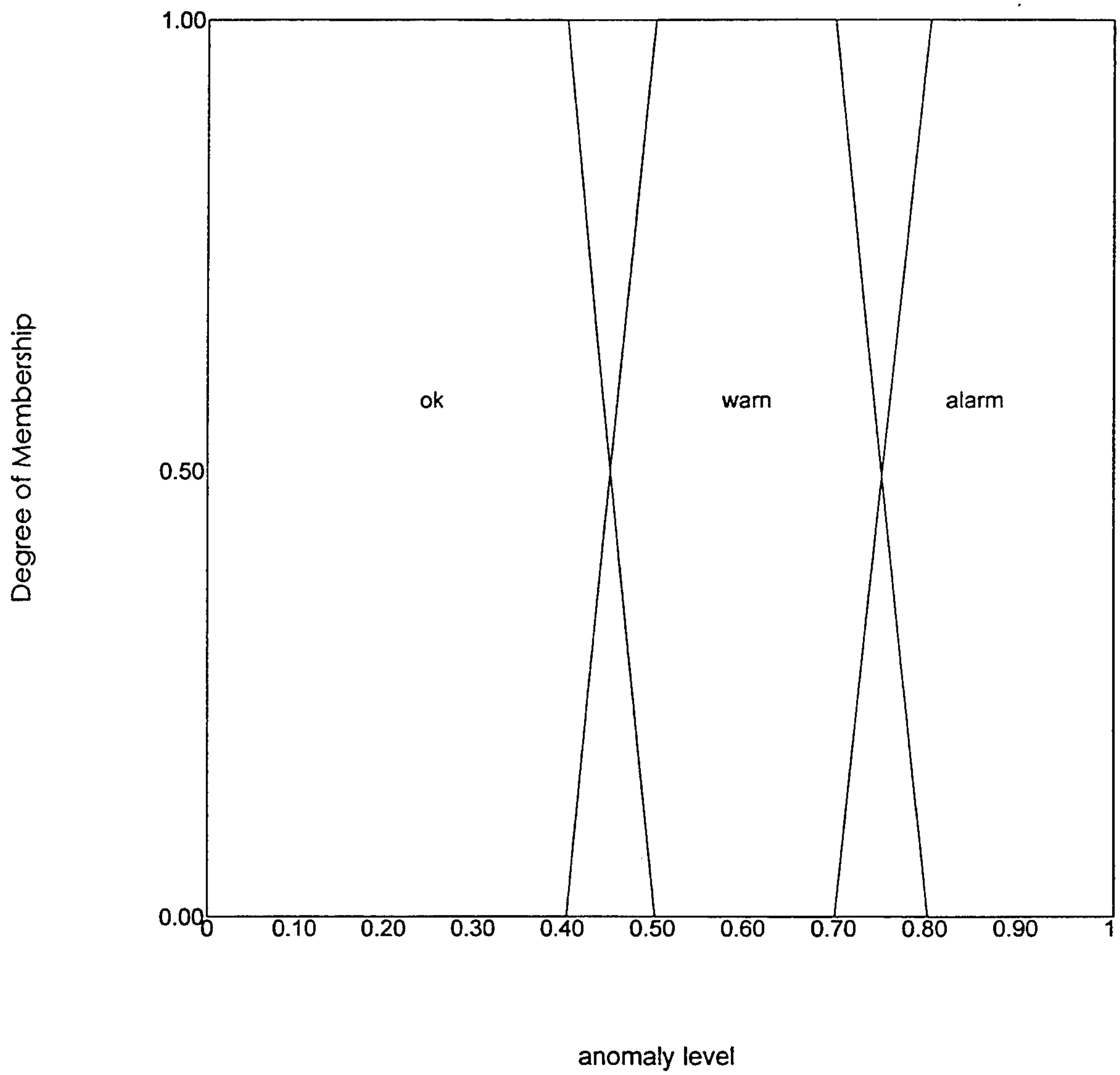
peak_3




1.00
0.50
0.00
Degree of Membership
low
med
high
0
1.00
2.00
3.00
4.00
5.00
6.00
7.00
8.00
9.00
10
broad band amplitude

Membership Function Module

output



Section 5.2 Figures

ENGINE TEST RESULTS

ENGINE TEST #1 (NL)

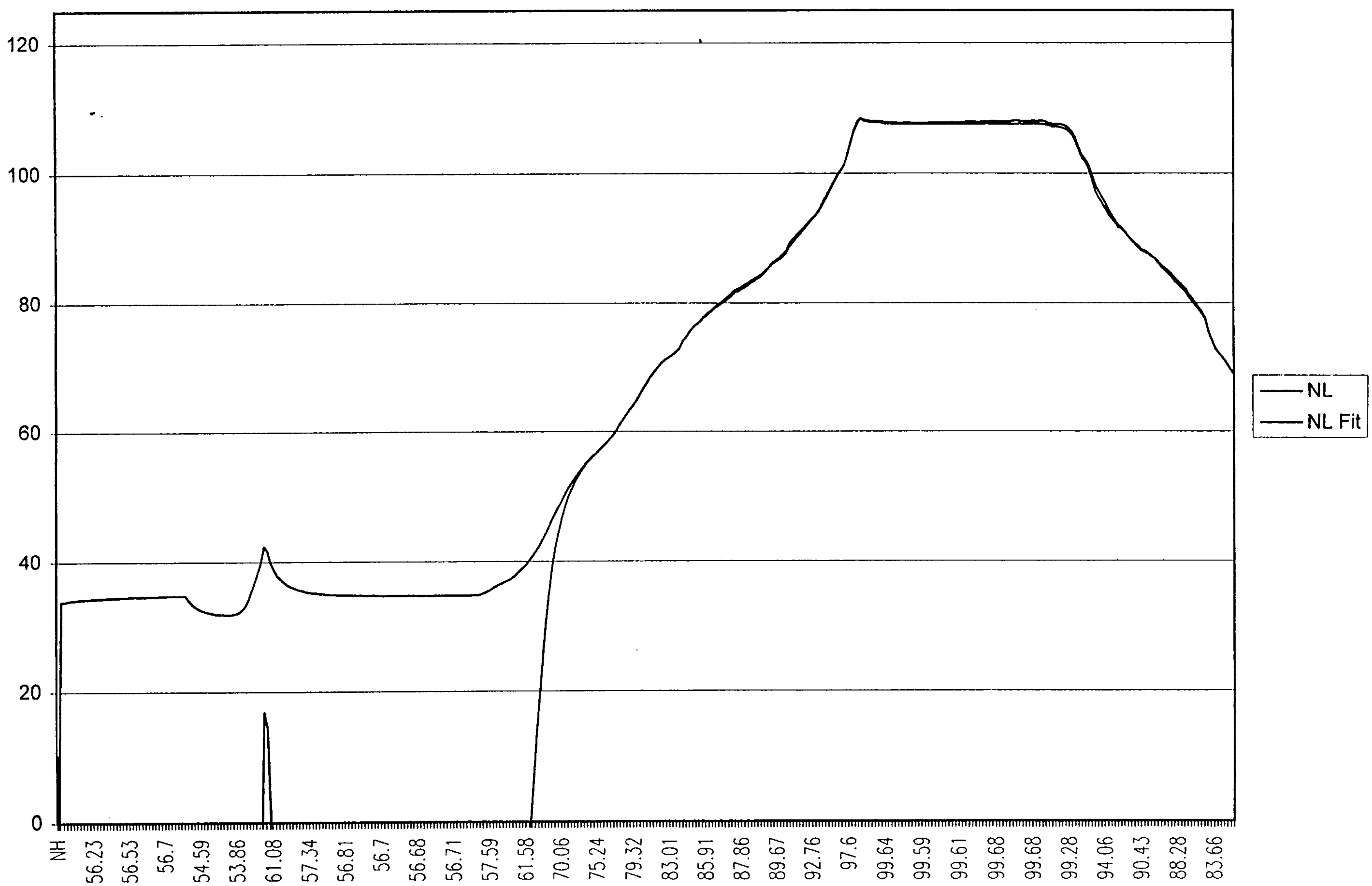


FIGURE 21

TEST #1 (P3)

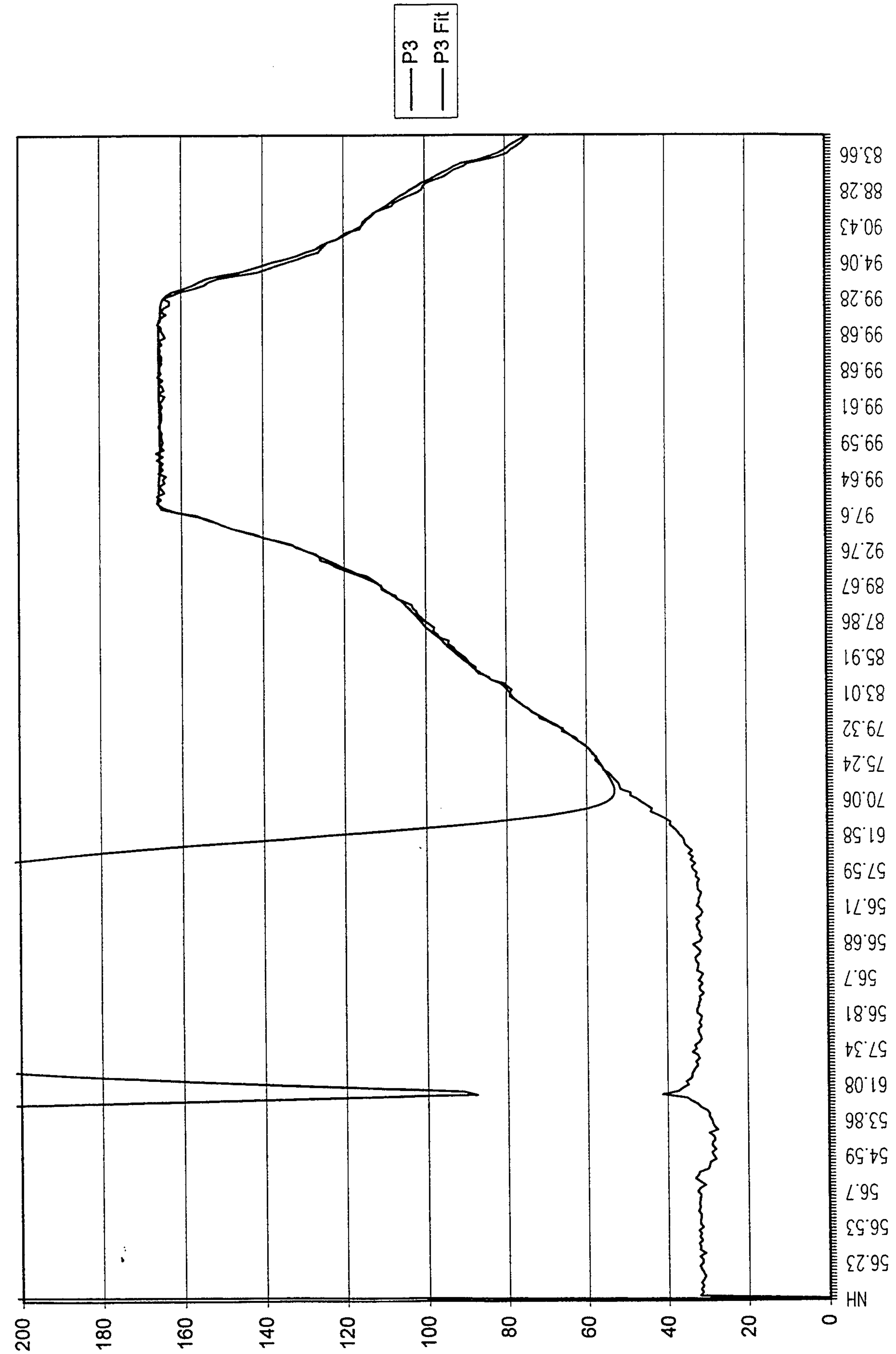
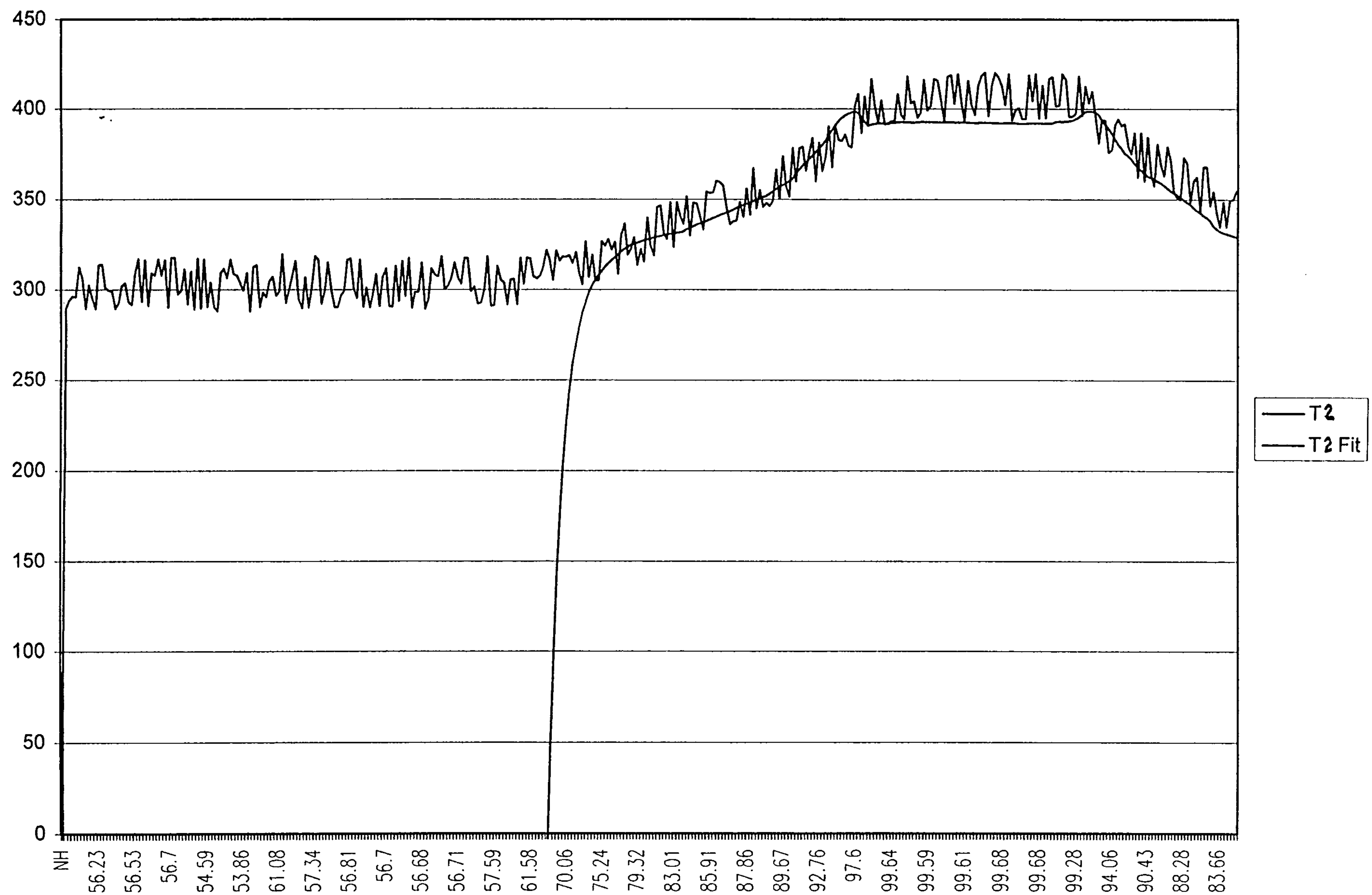


FIGURE #22

TEST #1 (T2)


450
400
350
300
250
200
150
100
50
0
NH
56.23
56.53
56.7
54.59
53.86
61.08
57.34
56.81
56.7
56.68
56.71
57.59
61.58
70.06
75.24
79.32
83.01
85.91
87.86
89.67
92.76
97.6
99.64
99.59
99.61
99.68
99.68
99.28
94.06
90.43
88.28
83.66
T2
T2 Fit

TEST #1 (T6)

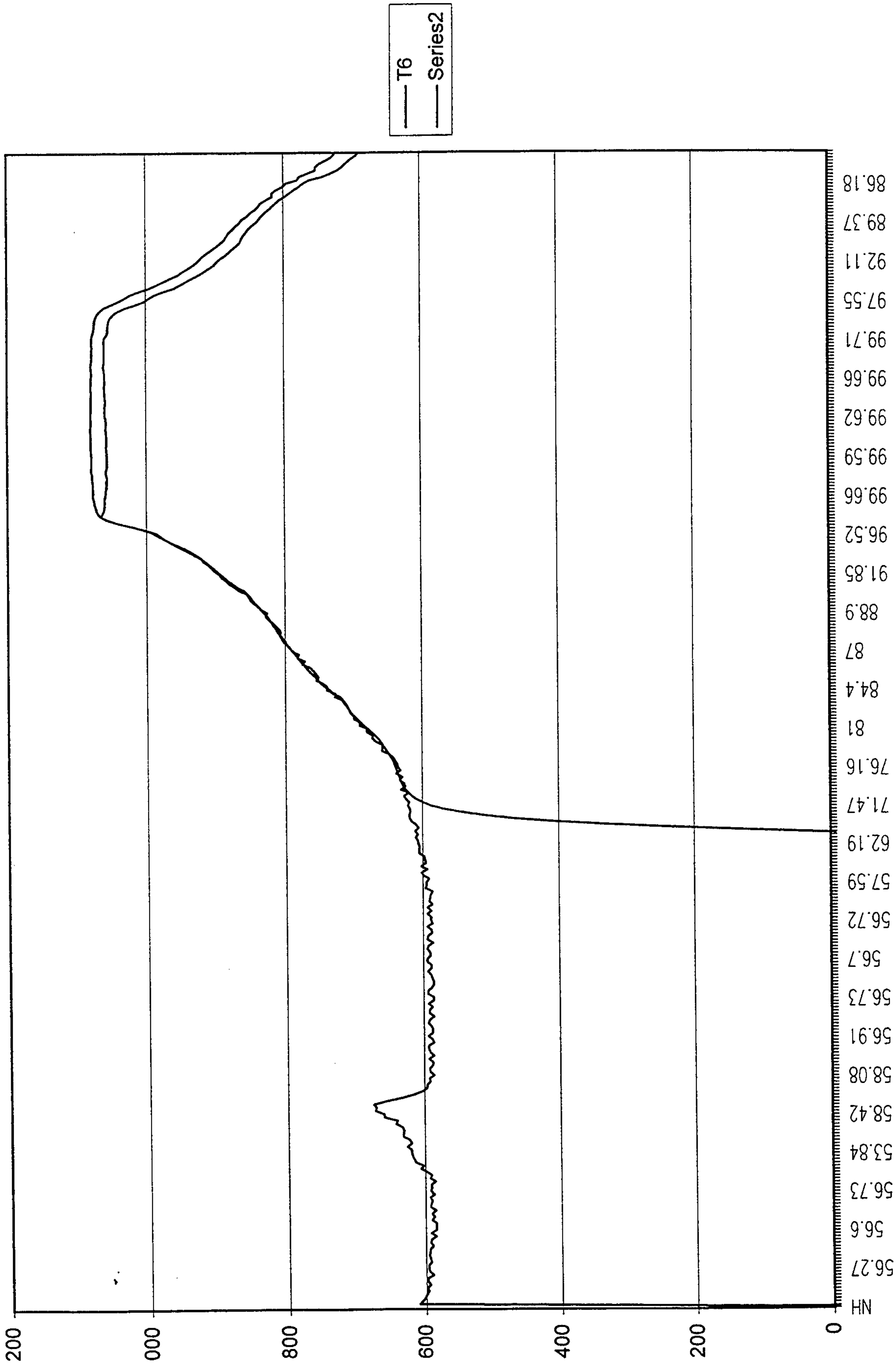


FIGURE # 24

TEST # 1 (wf)

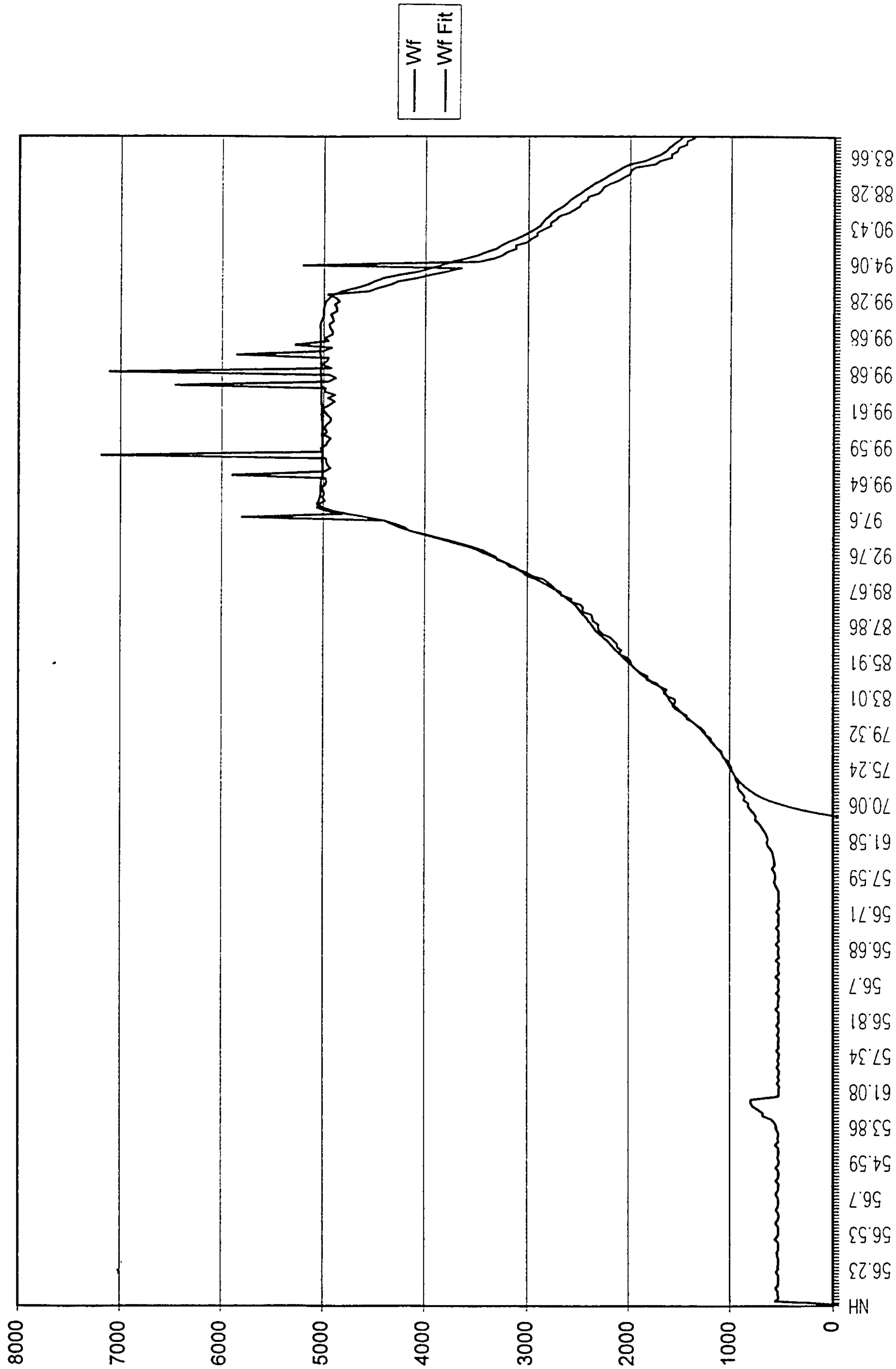
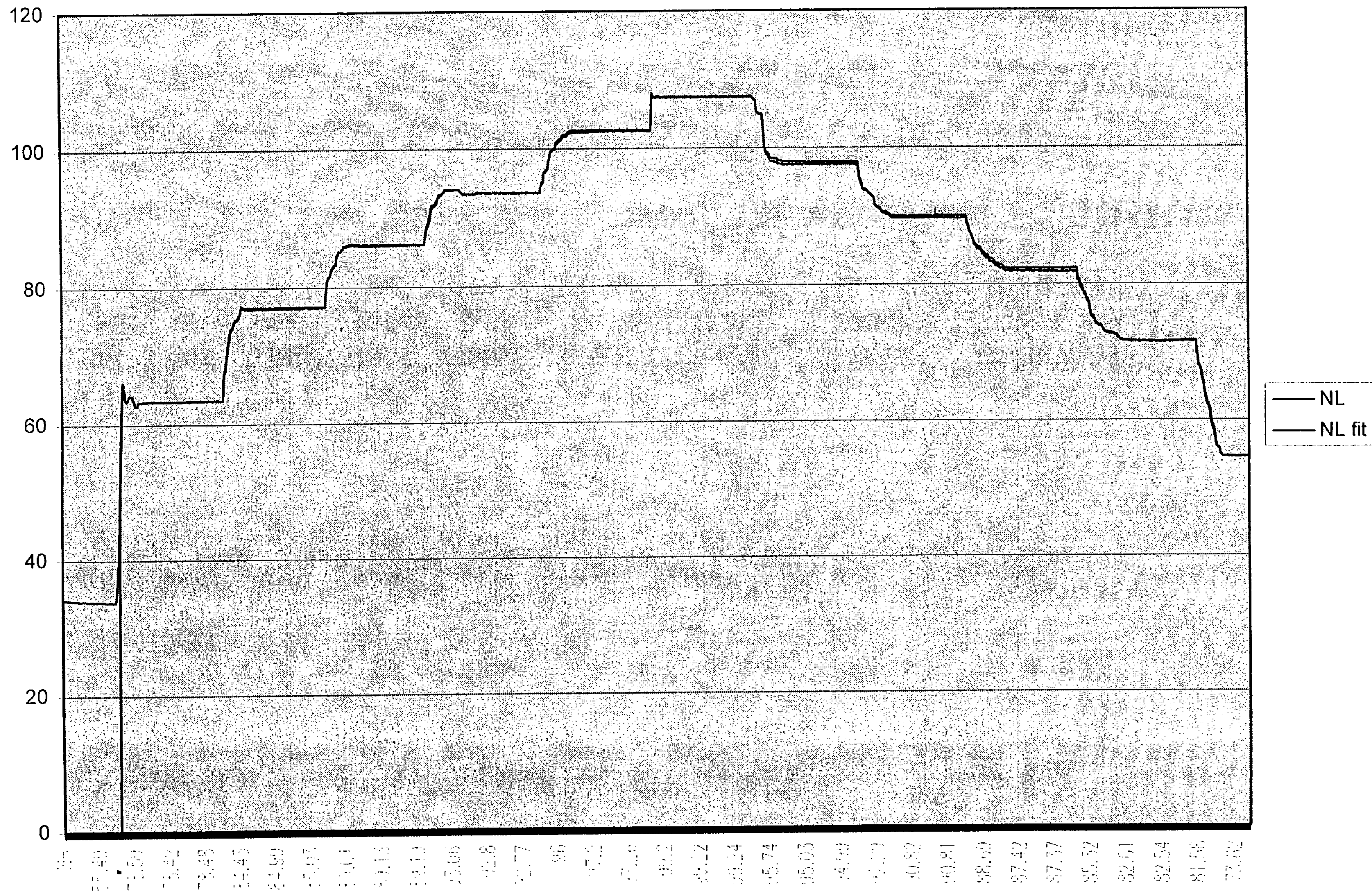
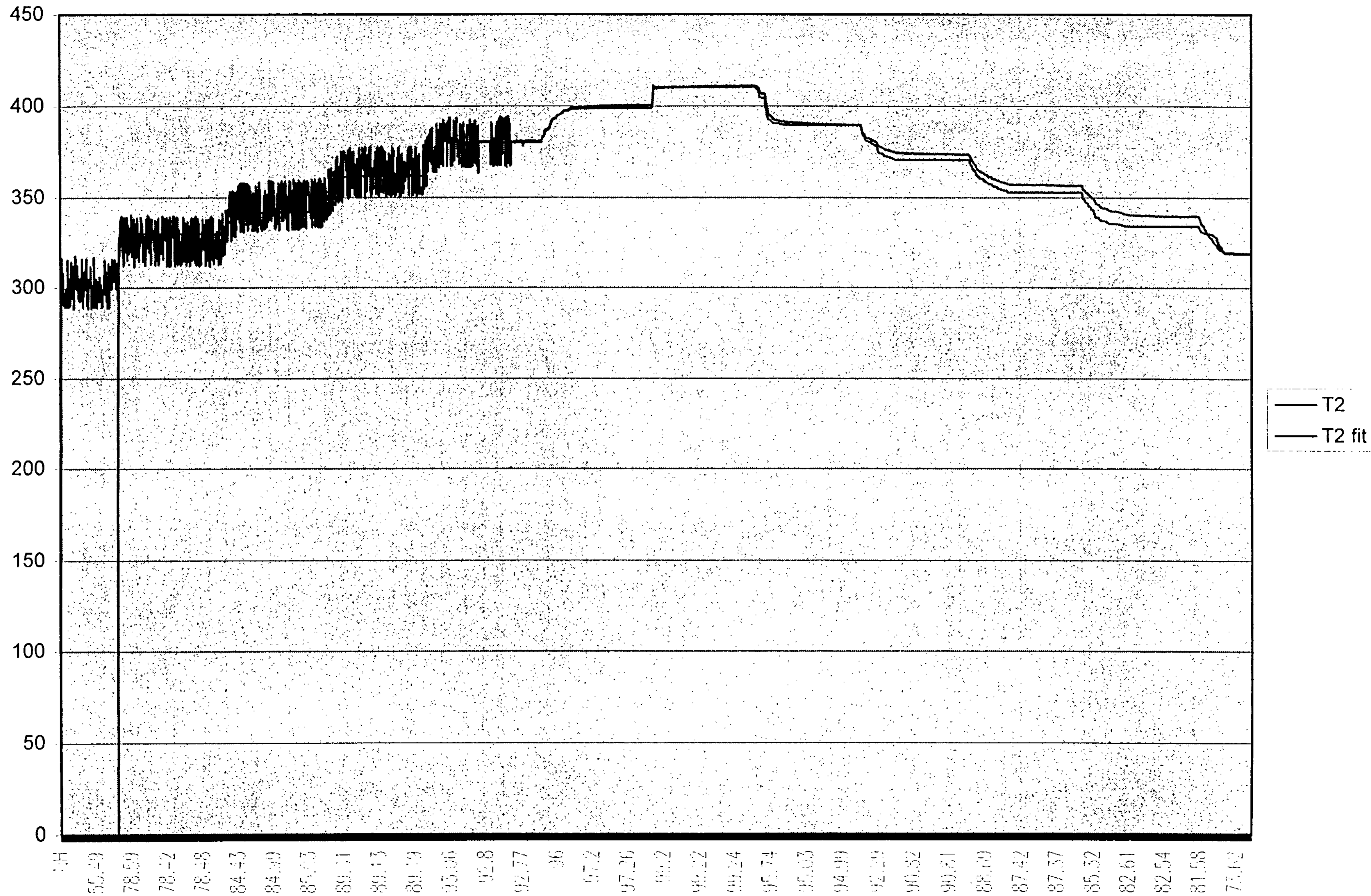


FIGURE # 25

ENGINE TEST #2



T2_1 Chart 1



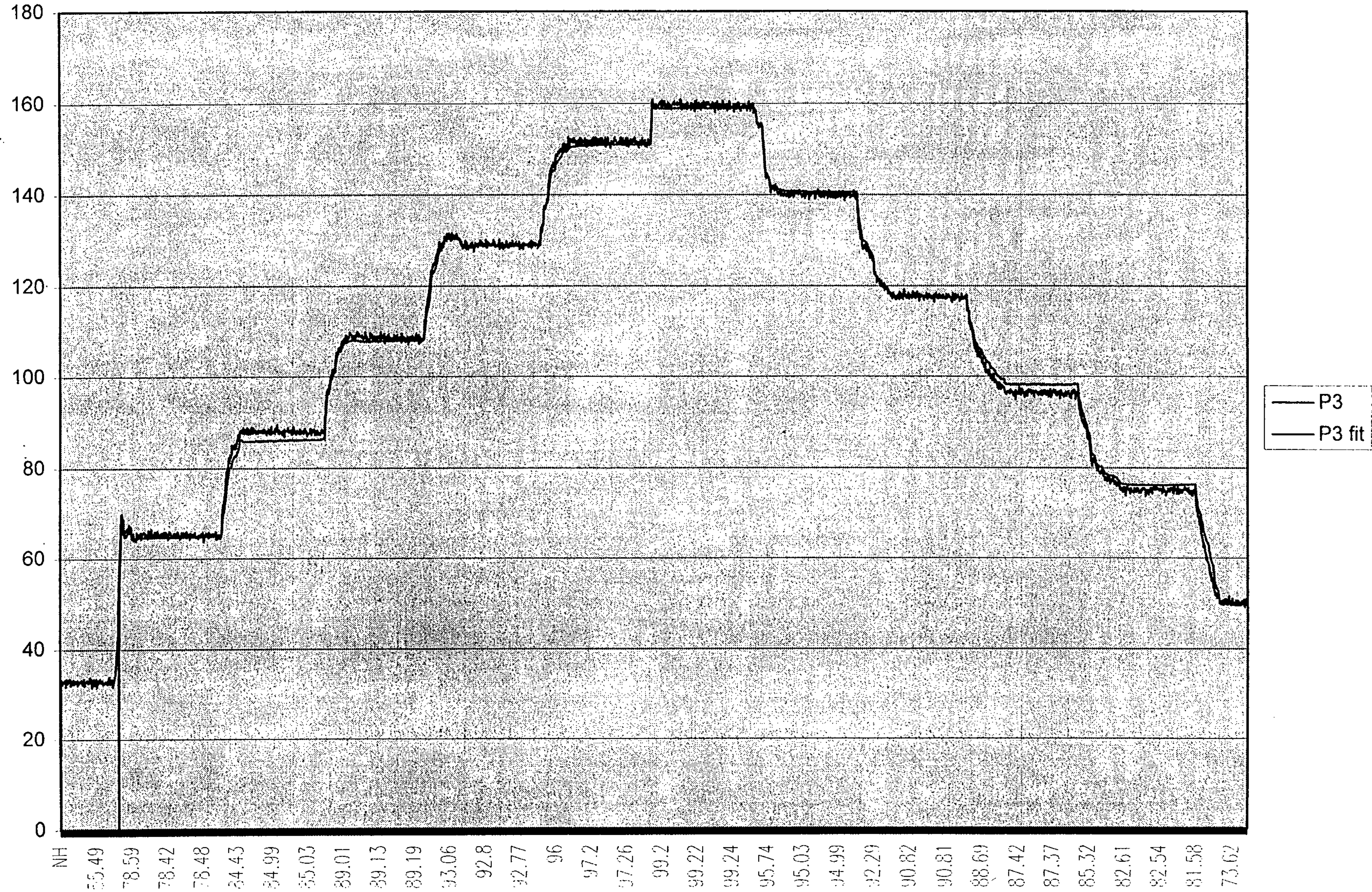

180
160
140
120
100
80
60
40
20
0
NH
55.49
78.59
78.42
78.48
84.43
84.99
85.03
89.01
89.13
89.19
93.06
92.8
92.77
96
97.2
97.26
99.2
99.22
99.24
95.74
95.03
94.99
92.29
90.82
90.81
88.69
87.42
87.37
85.32
82.61
82.54
81.58
73.62
P3
P3 fit

FIGURE 28

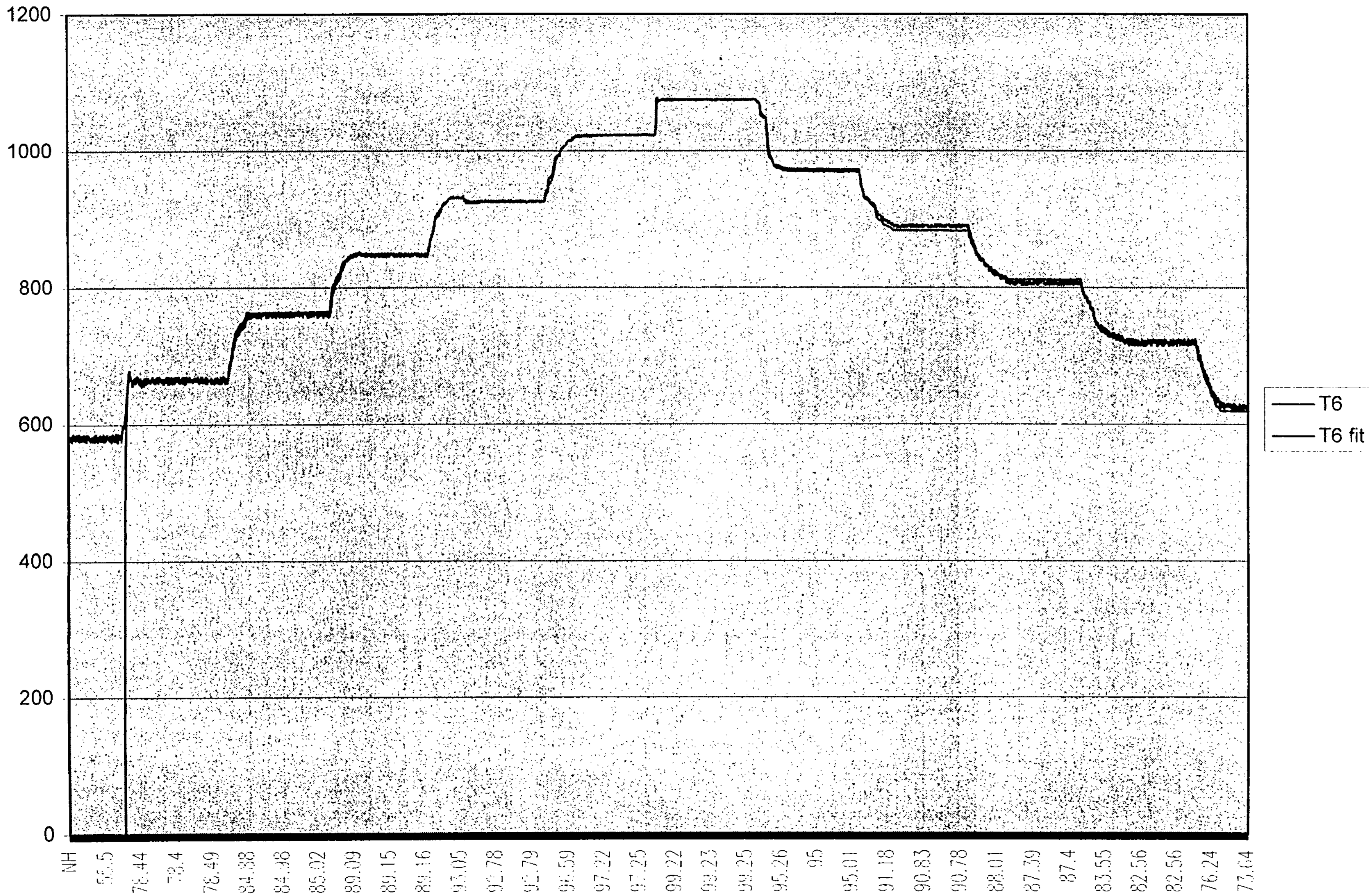

1200
1000
800
600
400
200
0
NH
55.5
78.44
78.4
78.49
84.38
84.48
85.02
89.09
89.15
89.16
93.05
92.78
92.79
96.59
97.22
97.25
99.22
99.23
99.25
95.26
95
95.01
91.18
90.83
90.78
88.01
87.39
87.4
83.55
82.56
82.56
76.24
73.64
T6
T6 fit

FIGURE 29

Wf_1 Chart 1

Page 1

FIGURE 20

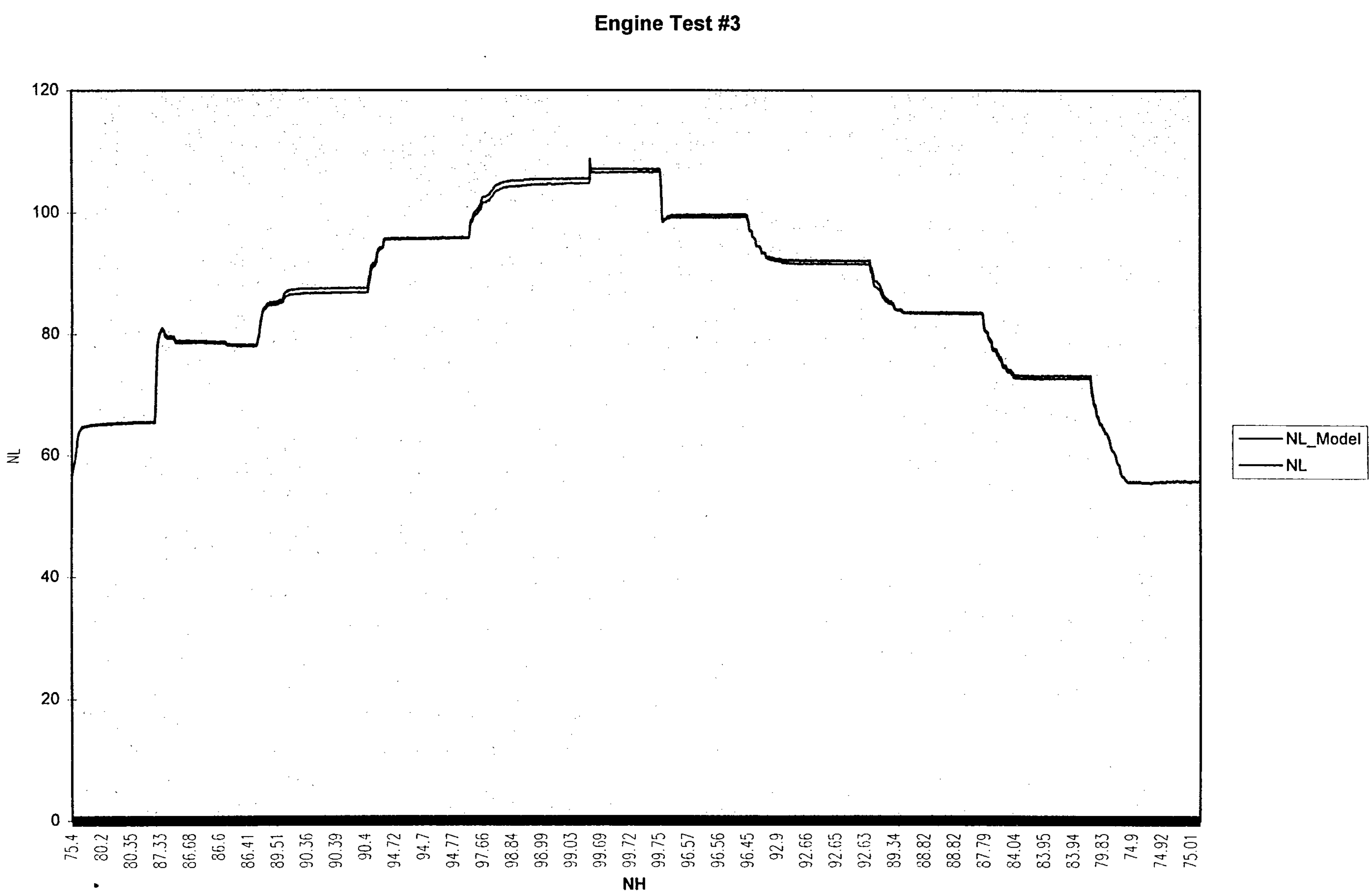

Engine Test #3
120
100
80
60
40
20
0
NL
75.4
80.2
80.35
87.33
86.68
86.6
86.41
89.51
90.36
90.39
90.4
94.72
94.7
94.77
97.66
98.84
98.99
99.03
99.69
99.72
99.75
96.57
96.56
96.45
92.9
92.66
92.65
92.63
89.34
88.82
88.82
87.79
84.04
83.95
83.94
79.83
74.9
74.92
75.01
NH
NL_Model
NL

FIGURE 31

Engine Test #3 (P3)

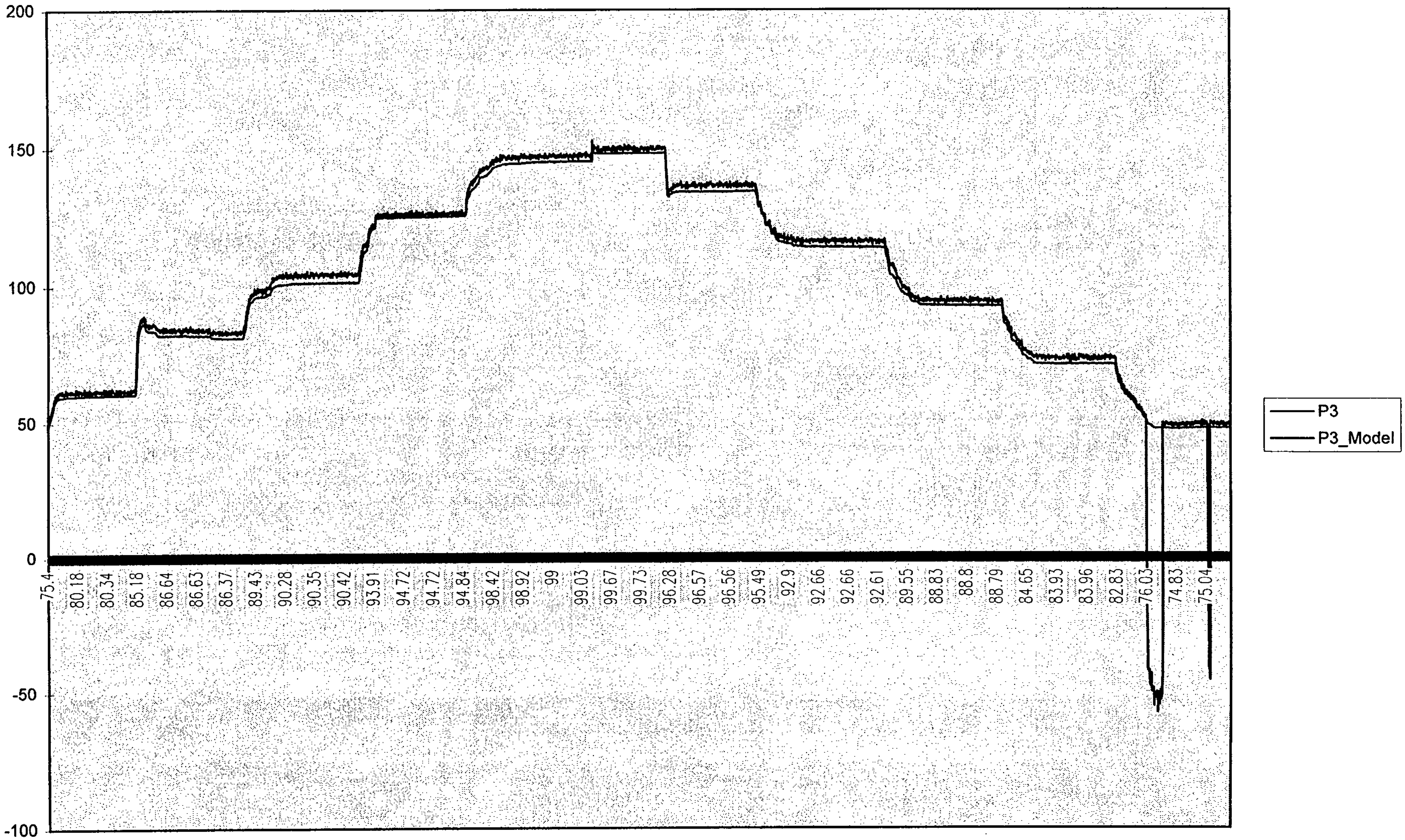


FIGURE 32

Engine Test #3 (T2)

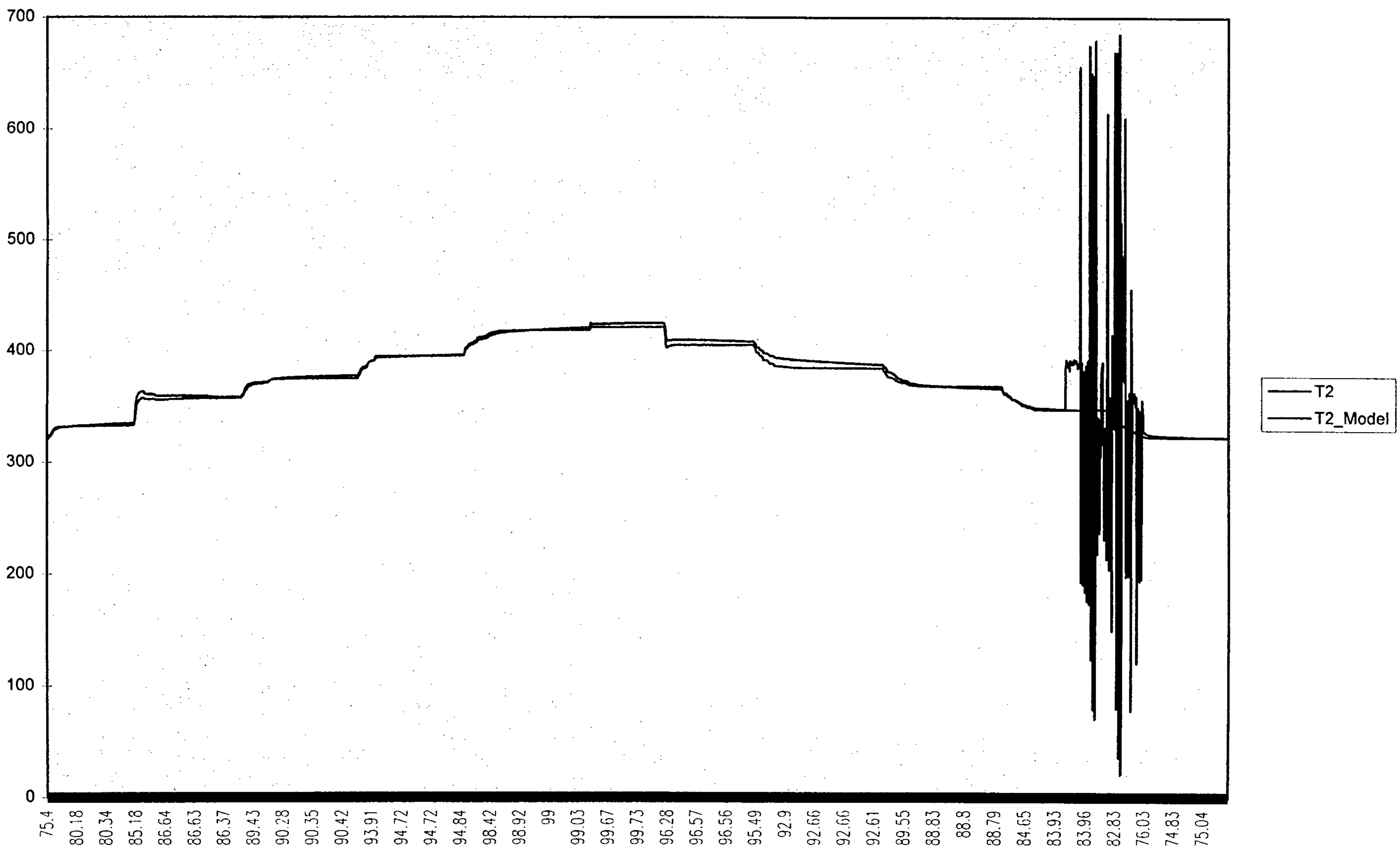


FIGURE 33

Engine Test #3 (T6)

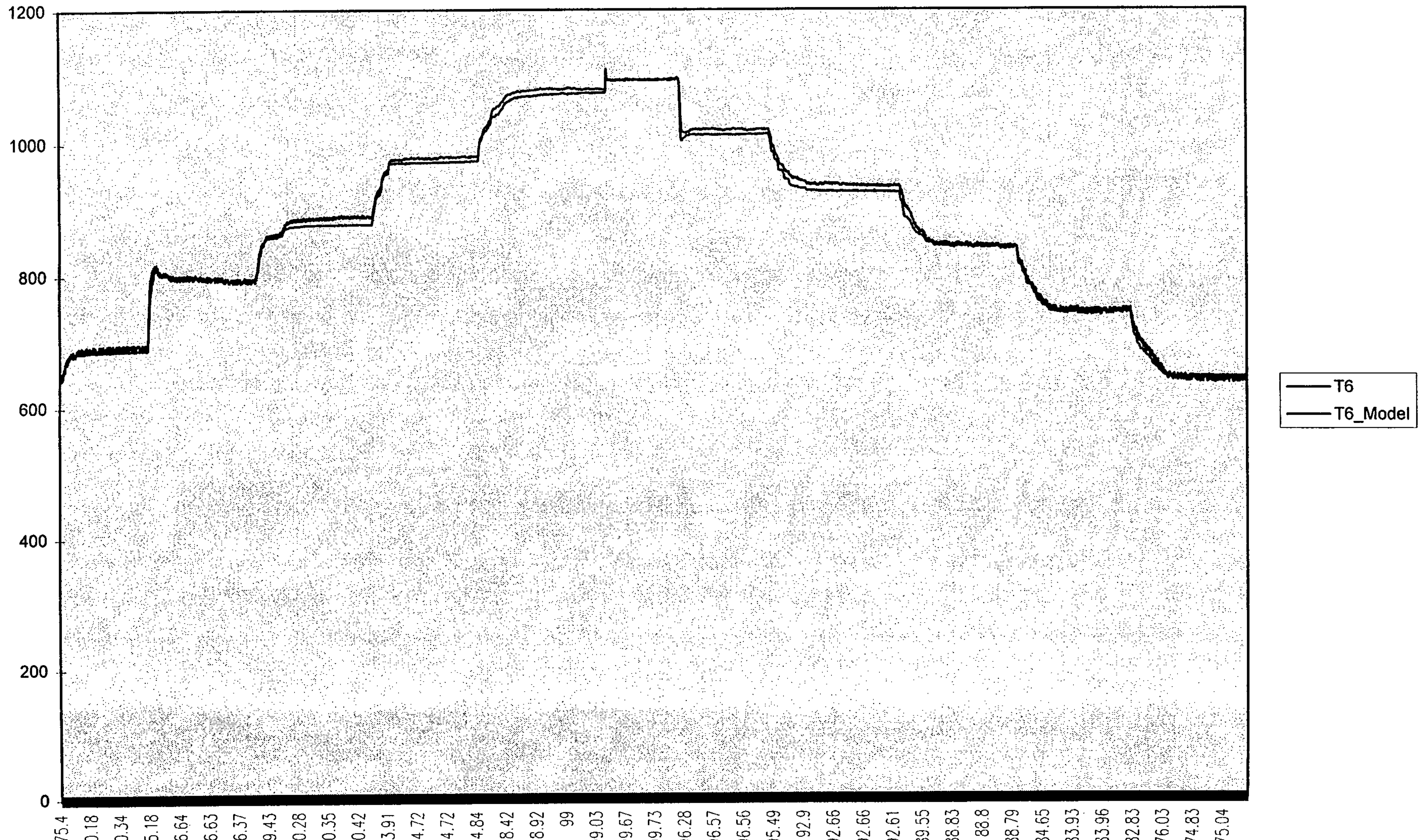


FIGURE 34

Engine Test #3 (WF)

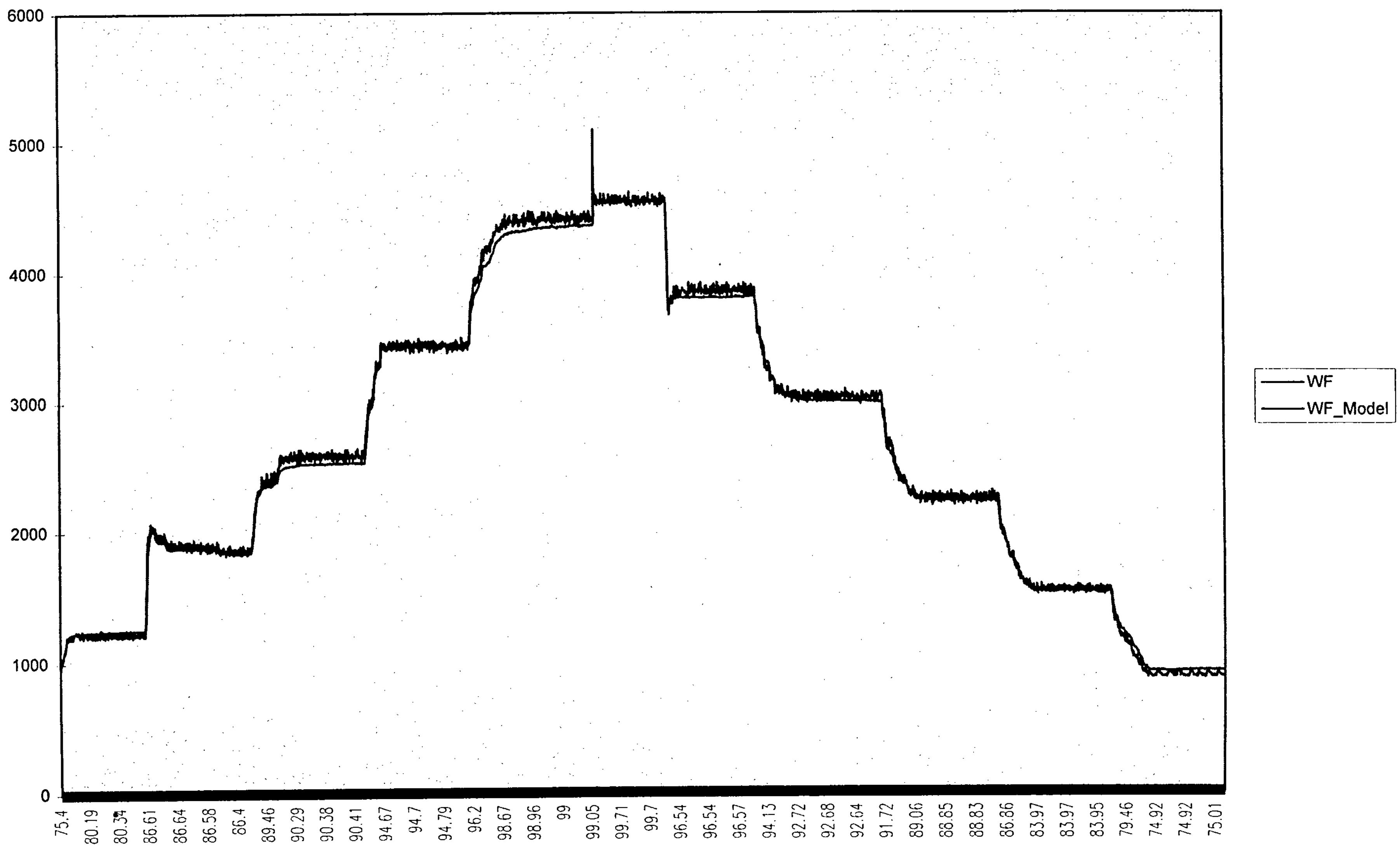


FIGURE 35

APPENDIX A

A.1 Neural Network Basics

Neural networks are systems of elemental processing units connected in a way analogous to how neurons are connected in the brain. Like the brain, neural networks exhibit learning and associative memory skills. A neural network is trained to perform a task by showing it examples of an input it will receive, paired with the output it is to deliver. The network learns the associations between these pairs of input examples and corresponding outcomes, and is able not only to reproduce these associations, but also to generalize these relationships for inputs that it has not encountered before. Neural nets are therefore capable of intelligent interpolation and therefore make them particularly well suited for this type of application.

The artificial neural network can be viewed as a collection of elemental processing units massively interconnected among themselves. Some of the processing units, sometimes called nodes, communicate with the outside environment. We distinguish between the different types of processing unit with the following nomenclature:

1.) Input Nodes: Receive signal from the environment

2.) Output Nodes: Send signals to the environment

3.) Hidden Nodes: No direct contact with the environment

The processing unit or node is the component within neural networks where the computations are carried out. The input signal come from either the environment or other processing units, and form an input vector containing all the inputs. Figure A1 is an illustration of one processing unit or node.

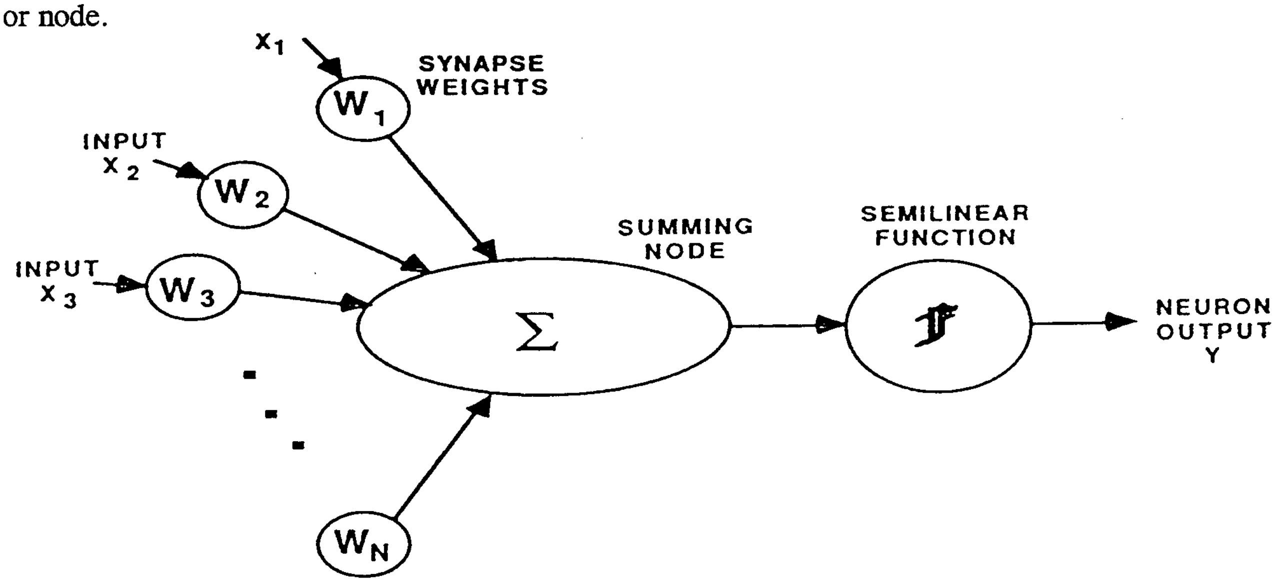


Figure A1 Neural Network Processing Unit or Node

Figure A1 also shows weights corresponding to each input. These weights are used to compute the output value of the processing unit. This computation is performed by taking the product of each input value x_i and its corresponding weight w_i. These products are then summed together and "passed" through a sigmoidal activation function to determine its final output activation level. Other types of activation function can be used, but the sigmoid is the most commonly used function.

When we talk about neural network's abilities to learn cause and effect relationships, we are really discussing the supervised learning procedure. Supervised learning involves the task of teaching the network associated input/output pairs. The network is presented with data that shows what response (output) should be generated by a given stimulus (input). The network then self adjusts its internal parameters in order to represent this underlying relationship between the inputs and outputs. This is the basis for a neural network's ability to generate appropriate outputs for all other inputs of a similar category, even if these inputs have never been previously encountered.

Neural Networks can also discover similarities between input patterns. In the training technique referred to as unsupervised learning, the network is shown various input patterns without any labels attached to them. The network looks at the patterns presented to it, and clusters them into groups of similar patterns based on a Euclidean distance computation. The number of clusters obtained can be changed by increasing or decreasing the cluster center radius. This changes the criterion of what constitutes similarity, and therefore changes the number of patterns within each cluster.

A.2 Fuzzy Logic Basics

Fuzzy logic is a programming tool that is capable of incorporating imprecise or ambiguous information into algorithmic expressions. However, contrary to its name "fuzzy", the mathematics involved are based on precise and rigorous calculations with respect to fuzzy sets or membership functions. The four basic processes required to develop fuzzy logic systems are fuzzification, rulebase development, inference, and defuzzification. The fuzzification process begins with the development of membership functions which relate linguistic variables like "cool", "hot", and "cold" to particular numerical ranges used in the "fuzzy" calculations. For instance, "cool" might have a membership value of 1.0 (the highest degree of membership) for 60 degrees F, a membership of 0.6 for 50 degrees F, a membership of 0.25 for 40 degrees F, and a membership of 0.0 (no degree of membership) for 30 degrees F.

The rulebase development is typical of any if/then rule set implemented in standard expert systems, except the rules now incorporate the "fuzzy" linguistic variables that have membership functions associated with them. An example of a rule would be; If *temperature* is <u>cool</u>, Then *velocity* is <u>medium</u>. In this rule, *temperature* is the *input variable* and *velocity* is the *output variable*, both or which have membership functions associated with them that include <u>cool</u> and <u>medium</u> respectively.

The strategies for "inferring" conclusions/decisions from cause-and-effect relationships provided by the rulebase and membership functions (knowledge base) are often called fuzzy inference techniques. Some inference techniques include; Product-Sum, Max-Min, and Min-Sum. The first expression of the inference technique name refers to the method for scaling the membership function variables. The second expression refers to the technique for combining the scaled membership function variables. A more complete description of the inference techniques is given in Reference [12]. The final process of calculating a single value from the scaling and combining of the variables described in the membership functions is called defuzzification. Techniques such as Centroid, Max-height, and Max-moment are used to determine the value that best represents the outcome of the fuzzy rule evaluations.