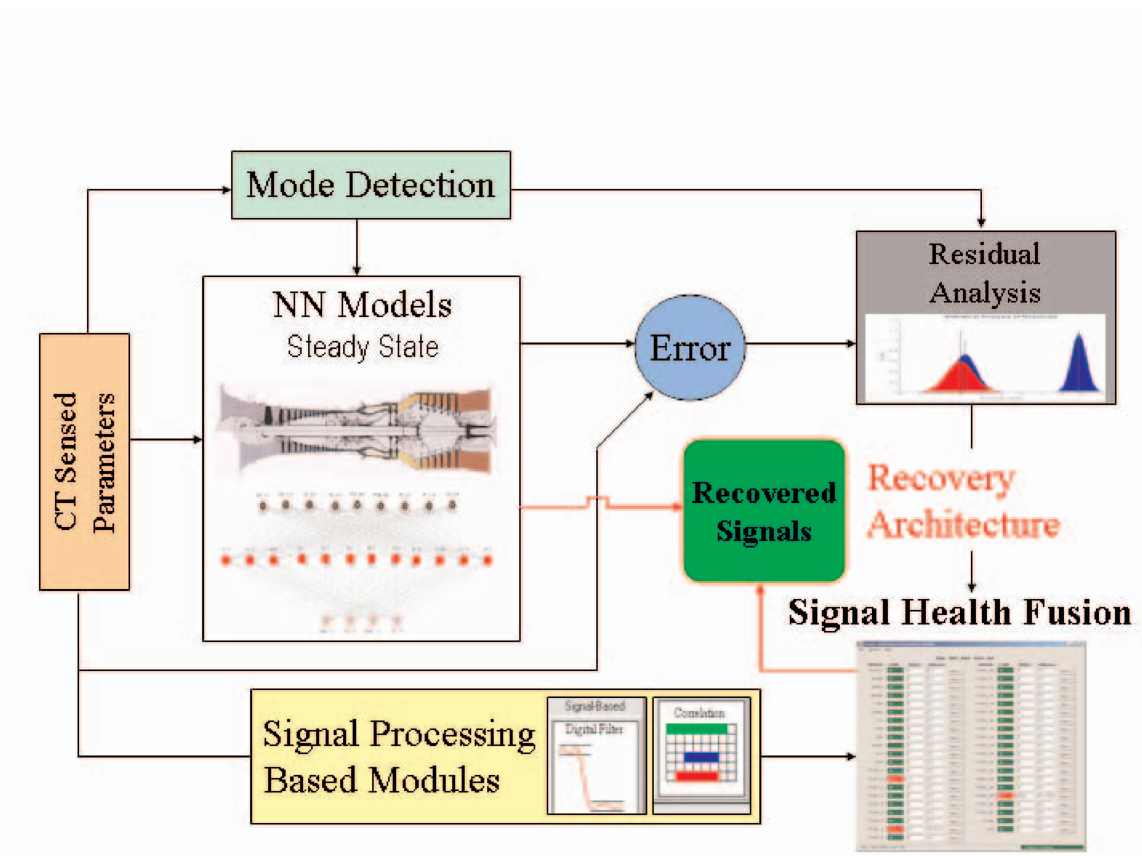
Combustion Turbine Diagnostic Health Monitoring

Sensor Validation and Recovery Module

Technical Report



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Sensor Validation and Recovery Module

1004969

Final Report, December 2003

Cosponsor
U.S. Department of Energy

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This report describes research sponsored by EPRI and U.S. Department of Energy.

The report is a corporate document that should be cited in the literature in the following manner:

Combustion Turbine Diagnostic Health Monitoring: Sensor Validation and Recovery Module, EPRI, Palo Alto, CA, and U.S. Department of Energy, Pittsburgh, PA: 2003. 1004969.

PRODUCT DESCRIPTION

The industrywide transition to condition-based maintenance strategies has prompted development of sophisticated, automated condition assessment tools. The sensor validation and recovery module (SVRM) presented in this report is the first of a suite of intelligent software tools being developed by EPRI and the U.S. Department of Energy (DOE) National Energy Technology Laboratory as part of the Combustion Turbine Health Management (CTHM) System. The CTHM System will be a significant improvement over currently available techniques for turbine monitoring and diagnostics.

Results & Findings

The CTHM System requires the integration of real-time anomaly detection with diagnostics of performance and mechanical faults as well as prediction of critical component remaining useful life and turbine degradation. Through proper application of these health management technologies, timely decisions can be made regarding unit operation and maintenance practices. A primary concern when implementing real-time or off-line health management technologies is to ensure the reliability of the measured parameters. When automated algorithms identify a performance or vibration fault, the diagnostic system must be confident that the faults are indeed occurring and are not the result of sensor errors. Therefore, a comprehensive sensor analysis module is recommended as a front end to validate the integrity of sensor signals, recover failed signals, and even predict important parameters not sensed on the combustion turbine.

The SVRM acts as a preprocessing step, utilized by automated condition assessment tools to validate the integrity of the sensor output. This validated output is later utilized by health assessment algorithms. The SVRM obtains information directly from the data archive and determines the presence of erroneous data, which does not reflect the current state of the underlying parameter. Upon completion of the validation assessment, should anomalous values be detected, the "recovery" portion of the module offers a reasonable proxy value for use in further health assessment algorithms. This report presents an in-depth discussion of issues encountered in the development of this land-based, combustion turbine SVRM technology. Topics covered include the 1) architecture employed, 2) selection of sensors to be validated, 3) data treatment considerations, including hysteretic effects and ambient conditions associated with the parameters, 4) validation techniques, and 5) sensor recovery.

Challenges & Objectives

The sensor validation process developed for use by the electrical power generation industry relies on collaborative techniques that are technically independent. Neural networks, fuzzy logic, and generic signal processing techniques are employed to thoroughly examine the integrity of the output received from the sensors being validated. The neural network operates by analyzing and exploiting the physical relationships existing between signals obtained from baseline empirical data from the turbine's performance parameters. The fuzzy-logic-based sensor validation continuously checks the "normal" bands (membership functions) associated with each sensor signal at the current operating condition. When a signal goes outside these membership functions, while others remain within, an anomaly is detected associated with those specific sensors. Concurrently, generic signal processing techniques determine the presence of any anomalies that may manifest themselves as jump discontinuities or excessive noise in the underlying signals. These parallel algorithms are combined in a probabilistic data fusion process, which determines the final confidence levels that a particular sensor has either failed or shows evidence of "suspect operation."

Applications, Values & Use

This report should be of great interest to engineering personnel concerned with maintaining optimal performance in simple and combined-cycle power generation systems. The SVRM described in this report serves as an enabling technology—critical as a preprocessing step in the development of robust health assessment technologies. Technology such as this empowers personnel with the ability to make informed decisions, unencumbered by erroneous sensor data that could otherwise result in inappropriate maintenance activities.

EPRI Perspective

Deregulation of the power generation industry has elevated the bar of marketplace competitiveness. Operators need to be more cautious and proactive in their maintenance programs in an effort to maximize output while minimizing unscheduled downtime. The SVRM is the first of the CTHM suite of intelligent software tools that offers customers an essential added level of confidence in the validity of results obtained from any performance diagnostic program.

Keywords

Sensor Validation
Generic Signal Processing Techniques
Model-Based Techniques
Neural Networks
Fuzzy Logic
Results Fusion
Sensor Recovery
Gas Turbines

ABSTRACT

Development of a comprehensive Combustion Turbine Health Management (CTHM) System will play a critical role in reducing the cost of electricity by improving reliability, availability, and maintainability. The real-time health management technologies under development use a combination of probabilistic and artificial-intelligence-based tools to assess both thermodynamic and mechanical health of combustion turbines. These technologies include sensor validation, performance diagnostics and prognostics, vibration diagnostics, and critical component remaining useful life assessments. Sensor validation is an important front end of the health management system that checks the integrity of sensed data before it is passed to the diagnostic and prognostic modules. The sensor validation software utilizes a combination or fusion of neural network model-based and generic signal-processing approaches to ensure the highest possible sensor fault detection confidence with minimal false alarms. In the event that a gas path sensor fault is detected, neural network models are used in calculating proxy or "recovered" signal values that allow diagnostic and component life assessments until the fault is corrected. The sensor validation and recovery module (SVRM) described in this report is demonstrated on a GE Frame 7FA application.

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1 INTRODUCTION

The industry wide interest in condition-based maintenance strategies has prompted development of sophisticated, automated condition assessment tools. Comprehensive Combustion Turbine (CT) Health Management includes the integration of real-time anomaly detection and diagnostics of performance and mechanical faults in addition to the prediction of critical component remaining useful life and turbine degradation. Through proper utilization of these health management technologies, timely decisions can be made regarding unit operation and maintenance practices. A primary concern when implementing real-time or off-line health management technologies is to insure the reliability of the measured parameters. When automated algorithms identify a performance or vibration fault, the diagnostic system must be confident that the faults are indeed occurring and are not the result of normal system transients or faulty sensors. Therefore, a comprehensive sensor analysis module is recommended as a front-end to validate the integrity of sensor signals, recover failed signals, and predict important parameters that are not sensed on the CT.

EPRI has sponsored the development of this module to act as a pre-processing step utilized by automated condition assessment tools, validating the integrity of the sensor output before being utilized by health assessment algorithms. This module will obtain data directly from the data archive and determine the presence of erroneous data. Here, erroneous data refers to data which do not reflect the current state of the underlying parameter. EPRI obtained the support of Progress Energy's Asheville plant for the data required for development. Upon completion of the validation determination, should anomalous values be detected, the 'recovery' portion of the module will offer a reasonable replacement value for utilization in further health assessment algorithms.

The sensor validation process employed in the CT Health Management Sensor Validation and Recovery Module (SVRM) utilizes technically independent, but collaborative techniques. Neural networks, fuzzy-logic, and generic signal processing techniques are employed to thoroughly examine the integrity of the output received from the sensors being validated. The neural network operates by comparing the physical relationships between signals as determined from a baseline empirical data from the turbine's performance parameters. The fuzzy logic based sensor validation continuously checks the "normal" bands (membership functions) associated with each sensor signal at the current operating condition. When a signal goes outside these membership functions, while others remain within, an anomaly is detected associated with those specific sensors. Finally, generic signal processing techniques are utilized to determine the presence of any anomalies that may manifest themselves as jump discontinuities or excessive noise in the underlying signals. These parallel algorithms are combined in a probabilistic data fusion process that determines the final confidence levels that a particular sensor has either failed or has suspect operation.

As previously stated, robust, automated CT condition assessment tools require verification of the integrity of the inputs. As such, the selection of parameters to be validated by the SVRM is based on the requirements of the performance algorithms to insure that the inputs are valid. The current CT health assessment utility requires a selection of inputs covering the gas path parameters in addition to ambient condition information (see Table 2-1).

The SVRM has been developed to operate in two modes in an effort to maximize its utility. The first is a batch analysis mode, which was established based on discussions with on-site personnel, to operate in an automated manner. A timer is utilized to initiate an analysis, in the early hours of the morning when network traffic is at its low point, on data from the previous day's operation. The second mode features a user defined, interactive mode. In this mode personnel can specify the time period over which the analysis will take place from a user interface.

An in depth discussion is presented in this report covering the components of the Sensor Validation and Recovery Module. This will include topics covering; the architecture of the SVRM, the selection of sensors to be validated, consideration of hysteretic effects on the parameters, validation techniques and finally sensor recovery.

2 DATA RETRIEVAL

Development of the Sensor Validation and Recovery Module (SVRM) requires large amounts of data. In order to build in the desired level of robustness the data must span all modes of operation encountered by the CT unit. Data for the development of the algorithms utilized by the SVRM was obtained from the two GE Frame 7F units operating at Progress Energy's Asheville, North Carolina facility. The CT units are single spool turbines capable of running on either liquid fuel or gas fuel. The base load for the generator units is approximately 165 MW in the summer and 192 MW in the winter.

The development of any automated condition assessment program is contingent upon the seamless flow of this data between the plant's data archive and the health appraisal tool. Open DataBase Connectivity, ODBC, has been developed to create an abstract means of passing data, using Structured Query Language (SQL), between the database and the application analyzing the data. Utilizing this architecture liberates the process from restrictions due to specific database Input/Output interaction. Secured queries are possible either internally, accessing the system through the plant's internal network, or externally by accessing the local network utilizing a Virtual Private Network to establish connectivity via the Internet.

Process Overview

Implementation of the various modules being developed for the CT Diagnostic Health Monitoring Program is dependent upon the supply of data being provided from the Asheville PI Historian system. For the development of this program, OSIsoft's PI system offers a Microsoft Excel Add-In called DataLink that is commonly used throughout the industry and can easily interface with the PI Historian via Excel in obtaining data. While the test facility utilizes the PI Historian, the same functionality can be replicated with any data archiving system utilizing the process outlined above.

The data exchange, which takes place between the CT Diagnostic Health Monitoring Program, Excel, PI DataLink, and the PI Historian, will take place behind the scene, invisible to the operator. The DataLink utility is comprised of several pre-defined functions, which can be called from within the cells of Excel. The data querying process begins with Excel starting as an ActiveX *server*. The application being developed becomes the ActiveX *client*. Information is passed back and forth seamlessly between the client and server as required by the necessary data queries. Queries are conducted based on the sensor *tags*, which are the sensor designations obtained from the *Mark V* control system utilized at the Asheville site. The basic process used in querying the tags is the same regardless of the current operating mode of SVRM, only the periods covered by the queries changes. Initially, a query of the *DWATT* (Generator Output) PI tag is conducted to determine if the unit in question reached a level of operation sufficient for further analysis, i.e. generator output in excess of 65 Megawatts. Upon confirmation of positive results, the remaining PI tags are queried. This process is followed by each query required to satisfy the investigation period defined by the user.

The ActiveX approach stems from the ability of ActiveX to handle formula arrays within Excel. Formula arrays are single formulas applied to a range of cells. The PI DataLink utility is based upon a set of function calls of this type. Upon completion of a data query initiated by PI DataLink from within Excel, examination of the cells reveals that each cell has the identical formula active within it. The formula consists of the DataLink function call with its' accompanying arguments, all contained in curly brackets, {}. This curly brackets designation is what signifies the contents of the cell as a formula array within Excel. Function calls of the type required the Ctrl+Shift+Enter keystroke to enter the function.

Data Querying

As stated above, the querying process is initiated by querying the *DWATT* tag to determine if the unit reached a sufficient level of operation. The search type (DataLink function) utilized here is *Compressed data (start time/end time)….* This function will conduct a search of the compressed data based on the desired tag and encompassing the date/time between the start time and the end time. Here, the start time and the stop time propagate in one hour increments until the entire period defined by the user for analysis has been covered. Arguments to be supplied to this function call include: "*Tagname*", "*Start Time*", "*End Time*", "*Output Cell*" and "*Filter Expression*." The data query process occurs in two steps. The first step is an initial inquiry, placed into only two adjacent cells, that yields the number of points which satisfy the search criteria. In this case the data archive is queried for data from the desired parameters, over a time period specified by the "*Start Time*" and "*End Time*" and filtered by an expression requesting only values corresponding to periods of generator output in excess of 65 MW. The result from this initial query will be the number of data points found that satisfy the search criteria. In the event that no points satisfy the query requirements, the next hour is queried. If a number of data points is returned, as shown in the left half of Figure 2-1, this integer value is then utilized in redefining a new region of cells to be activated in preparation for the second step in the querying process. This subsequent step of the query process then places the identical formula into each cell contained in the activated region, in the form of a formula array, and executes the function. This results in the designated region being populated by the sought after data values, as shown in the right half of Figure 2-1. The example shown illustrates the results obtained from querying the *CTD* tag for all values from July 11, 2003 for which the level of output from the generator exceeded 65 MW.

	A	B	C	D	E	F
1	G4:CTD					
2	data point	353				
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						

	A	B	C	D	E	F
1	G4:CTD					
2	data points:	353				
3	11-Jul-03 12:08:31	679.125				
4	11-Jul-03 12:08:38	684.75				
5	11-Jul-03 12:08:53	687.375				
6	11-Jul-03 12:09:16	688.625				
7	11-Jul-03 12:10:06	687.625				
8	11-Jul-03 12:10:22	689.625				
9	11-Jul-03 12:11:44	689.125				
10	11-Jul-03 12:12:33	690.1875				
11	11-Jul-03 12:13:36	690.4375				
12	11-Jul-03 12:13:46	692.5				
13	11-Jul-03 12:15:39	691.6875				

Figure 2-1
Screen Captures from Excel Illustrating the Results Obtained from the Two Data Querying Steps

The data values obtained from the queries are then returned to the SVRM for subsequent analysis. Table 2-1 is included to outline the sensors utilized by the performance assessment utility. The column *Comments* lists the availability of the respective sensors at the Asheville site. Sensors that are not available either have a default value, which is substituted into subsequent calculations or will restrict the performance calculations conducted.

Table 2-1
SCAMP Inputs Data Source (Adapted from the SCAMP Spreadsheet, Version 3, Computer Manual, Table 4-1)

Inputs Row #	Description	English Units	SI Units	Comments
3	Unit Name	N/A	N/A	Displays Name of Unit Being Evaluated
4	Date of Data Capture	N/A	N/A	MM-DD-YYYY
5	Time of Data Capture	N/A	N/A	HH:MM:SS
6	Firing Mode Option	N/A	N/A	0 = base, 1 = peak
7	Fuel Type Option	N/A	N/A	0 = natural gas fuel, 1 = liquid fuel
8	Ambient Temperature	°F	°C	Measurement Available
9	Barometric Pressure	" Hga	bara	Measurement Available
10	Relative Humidity	%	%	Calculated from Dew point
11	Compressor Inlet Temperature	°F	°C	Measurement Available
12	Inlet Filter Pressure Drop	" H_2O	mbar	Measurement Available
13	Total Inlet Pressure Drop	" H_2O	mbar	Default value available
14	Exhaust Pressure Drop	" H_2O	mbar	Default value available
15	Bellmouth Static Pressure Drop	" H_2O	mbar	Optional, used in air flow formula

Inputs Row #	Description	English Units	SI Units	Comments
16	Reserved for Future Use	N/A	N/A	
17	Compressor Discharge Press.	psig	barg	Measurement Available
18	Compressor Discharge Temp.	°F	°C	Measurement Available
19	Inlet Guide Vane Position	degrees	degrees	Measurement Available
20	Power	MW	MW	Measurement Available
21	Natural Gas Fuel Flow	lb/sec	kg/sec	Measurement Available
22	Liquid Fuel Flow	lb/sec	kg/sec	Measurement Available
23	Inlet Air Flow	lb/sec	kg/sec	Not Available on Asheville Units
24	Water Injection Flow	lb/sec	kg/sec	Measurement Available
25	Steam Injection Flow	lb/sec	kg/sec	Default value available
26	Dew Point Temperature	°F	°C	Measurement Available
27	Injected Water Temperature	°F	°C	Default value available
28	Injected Steam Temperature	°F	°C	Default value available
29	Gas Fuel Temperature	°F	°C	Measurement Available
30	Gas Fuel Pressure	psig	barg	Default value available
31	Liquid Fuel Temperature	°F	°C	Default value available
32	Exhaust Temperature	°F	°C	Measurement Available

3
DATA CORRECTIONS

Here we will discuss the considerations that went into laying out the architecture of the sensor validation and recovery module. Specifically, an analysis of the hysteretic effects experienced by the parameters as a result of normal operating transients is presented. Sensor output resulting from transient operating modes would require separate consideration if deviations from expected values resulting from hysteretic effects are severe. This study was completed to address this issue and determine the necessity of treating transient modes separately from steady-state operation.

Also presented is the procedure followed for correcting the effects of humidity on gas path parameters utilized in performance calculations. Humidity can have a great effect on performance calculations largely due to the effect it has on the properties of air. As such, if one wishes to eliminate as many variabilities due to atmospheric conditions as possible, it becomes necessary to address humidity as well as ambient temperature and pressure.

Transient Effects

Transient events manifest themselves in the gas path parameters as a deviation from the expected value for a given level of operation. The variance is due to the response lag of the parameters as the operating levels transition from one to the next. In the event that the response lags become too great, the difference between the parameter's value and the expected value becomes large enough to be interpreted by the sensor validation algorithms as an anomalous signal. To determine the necessity of accounting for hysteretic effects, a mode detection algorithm was applied to the GE Frame 7F data set. Corrected *Compressor_Discharge_Temperature* (CTD) values corresponding to steady-state operating mode data were compared to the complete data set for *Generator_Load* (DWATT) values of 98 Mega Watts and above. Figure 3-1 and Figure 3-2 illustrate the results obtained for corrected values of CTD.

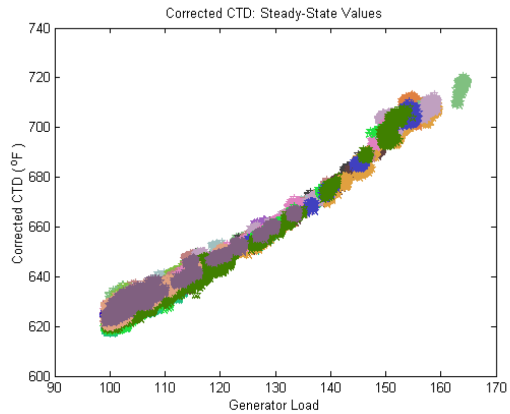

Figure 3-1
CTD Steady-State Values

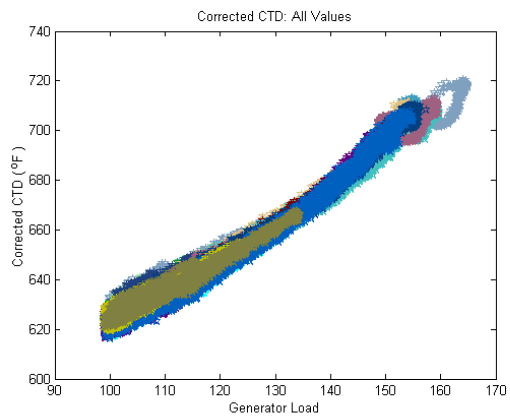

Figure 3-2
CTD Steady-State and Transient Value

Clearly the results shown in Figure 3-2 illustrate slightly broader data scatter across the range of operation characteristic of hysteresis as transient events occur. The scatter differential between the steady-state only data and the data set including transient data, however, is less than 1% of the expected value and therefore of little consequence with regard to the sensor validation module which focuses on much larger differentials. Figure 3-3 illustrates the analysis behind the determination. The curves represent the distribution of compressor discharge temperature values, corrected to "ISO standard day" conditions as covered in the following two sections, corresponding to a generator load of 110 Megawatts. This region of output was selected because it was one of the most densely populated. The distributions do appear to be different, however, within the framework of the sensor validation module these differences are not significant enough to warrant separation of the steady-state data from the transient data.

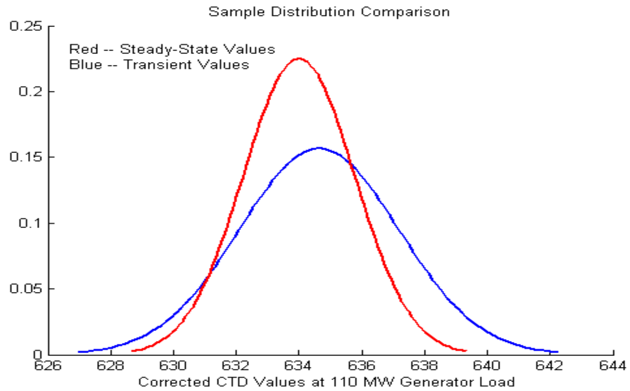

Figure 3-3
Distribution of Corrected CTD Data Corresponding to 110 MW Generator Load

Ambient Condition Correction

In an effort to increase the accuracy of the diagnostics modules, variations due to ambient conditions must be accounted for. These corrections include not only accounting for the effects of ambient temperature and pressure but also the effects due to humidity.

The ambient temperature and pressure are first order effects on the gas path parameters, and as such correcting for these influences is of critical importance. The temperature and pressure effects are accounted for by the standard delta and theta correction factors shown in equations (1) and (2).

$$\delta = \frac{P_{Ambient}}{P_{ISO}} \tag{1}$$

$$\theta = \frac{T_{Ambient}}{T_{ISO}} \tag{2}$$

These factors are then utilized to correct the gas path parameters as follows:

$$P_{Station\_Corr} = \frac{P_{Station}}{\delta} \tag{3}$$

$$T_{Station\_Corr} = \frac{T_{Station}}{\theta} \tag{4}$$

$$W_{f\_Corr} = \frac{W_f}{\delta\sqrt{\theta}} \tag{5}$$

The following figures (Figure 3-4 and Figure 3-5) are included to illustrate the effect of accounting for these first order influences on the gas path parameters. The data shown in blue are the original data obtained from the data archive. The points illustrated in red show the correction effect when accounting for the first order influences of ambient pressure and temperature. The points illustrated in green depict the correction for the second order effects of ambient humidity.

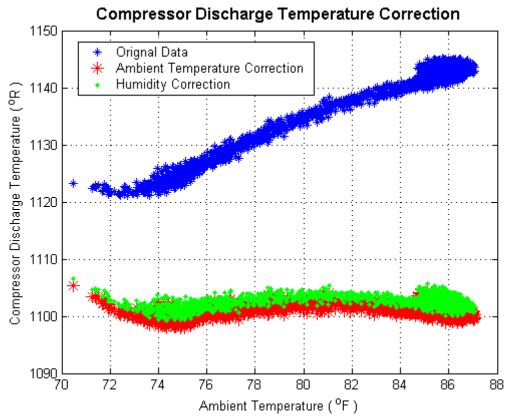

Figure 3-4
Results Obtained from Ambient Condition Corrections Made to CTD Values

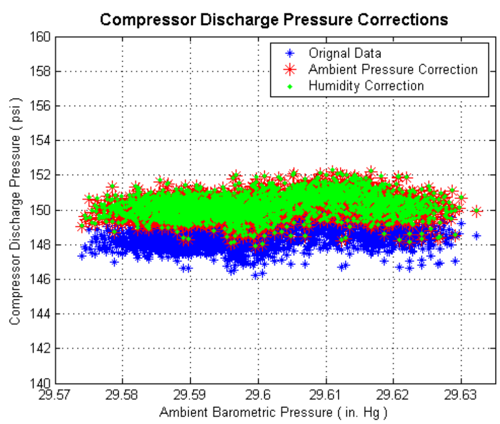

Figure 3-5
Results Obtained from Ambient Condition Corrections Made to CPD Values

The effects of humidity are a second order effect and as such have less of an impact on the data. However, in an effort to remove all possible variations due to the effects of atmospheric conditions, accounting for humidity is required. The presence of water vapor in dry air changes the values of the gas properties, namely, C_P (constant pressure specific heat), C_V (constant volume specific heat), R (gas constant), and γ (the ratio of C_P/C_V), primarily due to the molecular weight of water being far lower than that of dry air. Changing the gas properties can have a significant effect on thermodynamic processes throughout the CT. The correction algorithm utilizes generic exchange rates that are applied to the gas properties or specific gas path parameters, which may be utilized for first-order accuracy, to predict the effects of humidity on key performance parameters.[1]

The ambient humidity correction method used to adjust the gas properties and select gas path parameters to their corresponding values at 'standard day' relative humidity conditions employs the generic exchange rates given in Figure 3-6 and Figure 3-7, respectively. The humidity correction process utilized first converts the desired value to its corresponding zero-moisture, 'dry-air' value if necessary by dividing the value by the exchange rate given for the current specific humidity. A subsequent step is taken to further modify the property or parameter value to its 'standard day' value by multiplying the value by the exchange rate resultant of a specific humidity value of 0.0064, corresponding to a relative humidity of 60 %.

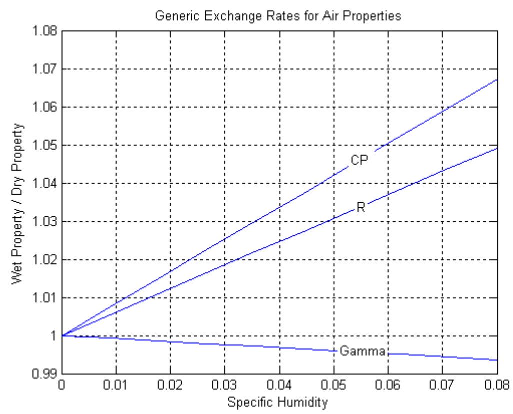

Figure 3-6
Exchange Rates for Ambient Humidity Correction of Gas Properties[1]

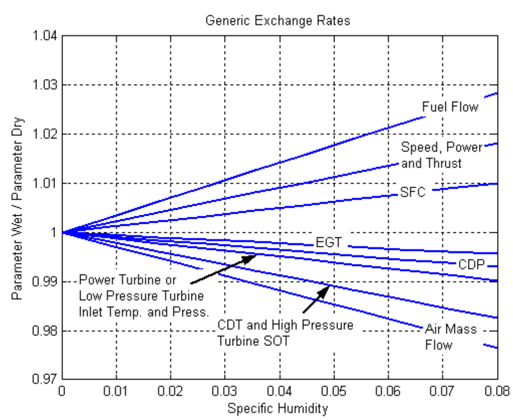

Figure 3-7
Exchange Rates for Ambient Humidity Correction of Select Gas Path Parameters[1]

4
SENSOR VALIDATION

The SVRM utilizes a suite of technically independent techniques to assess the overall health of the incoming signals. These independent methodologies have collaborative abilities in detecting various sensor failure modes. A final fusion process is used to combine results obtained from the different techniques to come up with a final overall health assessment. Table 4-1 outlines the validation techniques utilized by the respective sensors.

Table 4-1
Validation Technique by Sensor Type

Parameter Description	Generic Signal Processing	Model Based
AMBIENT_BAROMETRIC_PRESSURE	X	
AMBIENT_TEMPERATURE	X	
COMPRESSOR_DISCHARGE_PRESSURE	X	X
COMPRESSOR_DISCHARGE_TEMPERATURE	X	X
COMPRESSOR_INLET_DUCT_DIFFERENTIAL_PRESSURE	X	
COMPRESSOR_INLET_TEMPERATURE	X	
DEWPOINT_SENSOR	X	
GAS_FUEL_FLOW	X	X
LIQUID FUEL FLOW	X	X
GENERATOR_LOAD	X	
INLET_GUIDE_VANE_DEGREES	X	
RELATIVE_HUMIDITY	X	
EXHAUST_THERMOCOUPLE_1_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_10_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_11_COMPENSATED	X	X

Parameter Description	Generic Signal Processing	Model Based
EXHAUST_THERMOCOUPLE_12_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_13_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_14_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_15_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_16_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_17_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_18_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_19_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_2_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_20_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_21_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_22_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_23_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_24_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_25_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_26_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_27_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_3_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_4_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_5_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_6_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_7_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_8_COMPENSATED	X	X
EXHAUST_THERMOCOUPLE_9_COMPENSATED	X	X
WATER INJECTION FLOW	X	X

Sensor Validation Architecture

The architecture of the Sensor Validation and Recovery Module, illustrated in Figure 4-1, has been developed to employ parallel signal validation methods. As presented in Table 4-1, there is a high degree of overlap in the sensors validated and also the failure modes detected by the two methods. This repetition in sensor fault detection capabilities helps to insure that a minimal number of "false alarms" are declared. The architecture first employs a low level check, which detects if the sensor values fall within their expected range of operation. This check will detect sensor saturation, as well as possible cross-talk and erroneous sensor connections. Failing this check results in an immediate zero confidence level in the sensor's integrity. Subsequent to the initial low level check, parameter values are further evaluated by the generic signal processing and model-based validation techniques. The output from these methods is a zero to one confidence level where zero corresponds to no confidence and one corresponds to one hundred percent confidence in the integrity of the signal. The final step in the process is the combination of results to yield a final determination of the confidence in the sensor's output. This culminating step utilizes the Dempster-Schafer method of data fusion to ascertain the ultimate determination of overall sensor health. In the event that an anomalous signal is detected from a sensor which is validated utilizing the model-based techniques, the output from the corresponding neural network is obtained for submission as a replacement for the erroneous data.

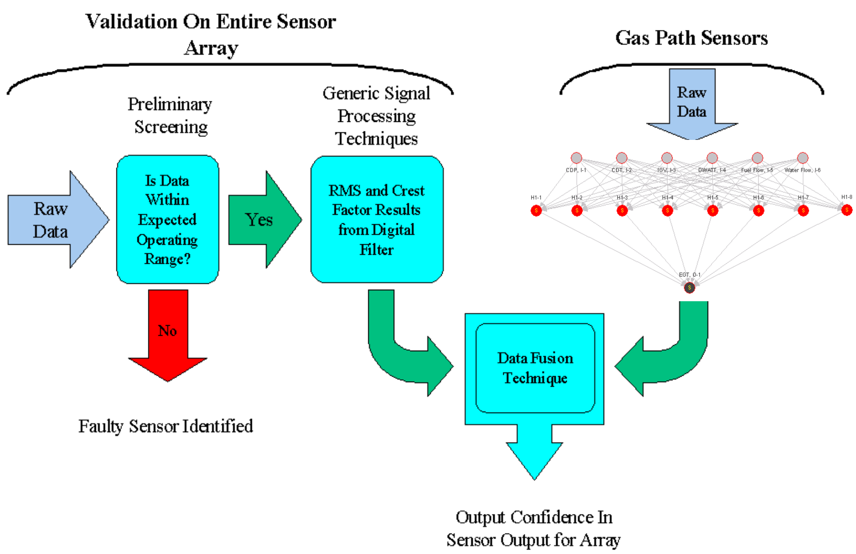

Figure 4-1
Architecture Utilized by the Sensor Validation Process

Generic Signal Processing Techniques

The motivation behind the development of generic signal processing techniques as a means of validating sensor output lies in the adaptability of the approach. The thought is to develop techniques that hold no regard for the type of parameter the sensor in question is monitoring. The signal processing based, sensor validation schema employs generic approaches that require minimal a priori information about the performance of the underlying system. Consequently, these techniques can be applied to virtually any sensor with minimal recurring design effort.

The initial check performed on the data is a basic saturation check. Exploiting the fact that each parameter has an expected range of operation determined by the physics involved, the incoming data is checked to determine if the values screened are physically possible. Though this is a very low level check, it is extremely useful in detecting sensor anomalies such as drop-outs and spikes.

A subsequent check of the data is made utilizing a digital high-pass filter. The engine signal digital filtering serves to screen the low frequency component of the sensor's signals (containing the relevant engine information), and allows any highly transient signal components that are greater than the highest transient expected from the CT to be passed through and isolated. The digital filtering algorithms are used to detect faults such as spikes, noise, intermittent signal loss, cross talk, clipping, and other anomalies, which manifest themselves by a rapid change in signal magnitude. These jump-discontinuities are passed by the filter and are the key metric utilized in detecting the failure modes mentioned.

The metric used to determine the presence of an anomaly in the signal is the standard deviation of the signal segment being examined. After filtering, the noisy signal will contain a standard deviation, which is an order of magnitude greater than that of the clean signal. This provides a clear distinction for detection of signal anomalies, which manifest themselves by a rapid change in magnitude.

Neural Network Model Based Technique

The model-based technique employs neural networks to capture inter-parameter relationships of the combustion turbine units throughout their range of operation. This methodology is highly data-driven and requires a sufficient supply of data to adequately capture all operating modes. Input data for training and subsequently during operation must be corrected to "ISO standard day" conditions before being supplied to the networks. This is done to remove variability in the resultant output due to fluctuations in ambient conditions. Results obtained from the neural networks are then utilized to calculate the residuals relative to the data from the sensors. The residuals are then analyzed by a fuzzy logic system to obtain the respective confidence level of the sensed data.

The artificial intelligence component of the sensor validation module utilizes a back-propagating artificial neural network (ANN's). Neural networks are adaptive systems, which can be trained to expect a particular outcome given certain conditions or inputs. To summarize, they “learn” from example. In this application, the neural network is taught to recognize the relationships that occur among the gas path parameters throughout the range of normal operation. As such, if one of the parameters deviates significantly from its expected value, without affecting any of the other sensors, the network is able to recognize this as a possible sensor fault.

Operation

Two distinct phases of neural nets are “training” and “operation.” The operation phase is simply "running" or "using" the trained network. The architecture utilized in back-propagation of the error is discarded and only the forward propagation of input data is needed. After the network converges on a training set, it is true that the particular architecture has learned the training set. But how well the network performs on new, unseen data depends on (i) whether the training data was a good representative sample of the universe of discourse for each variable, and (ii) whether the network structure is sufficiently compact for generalization. (If the neural net has excessive degrees of freedom (weights) it will "memorize" the training data set well, but generalize poorly on new data).

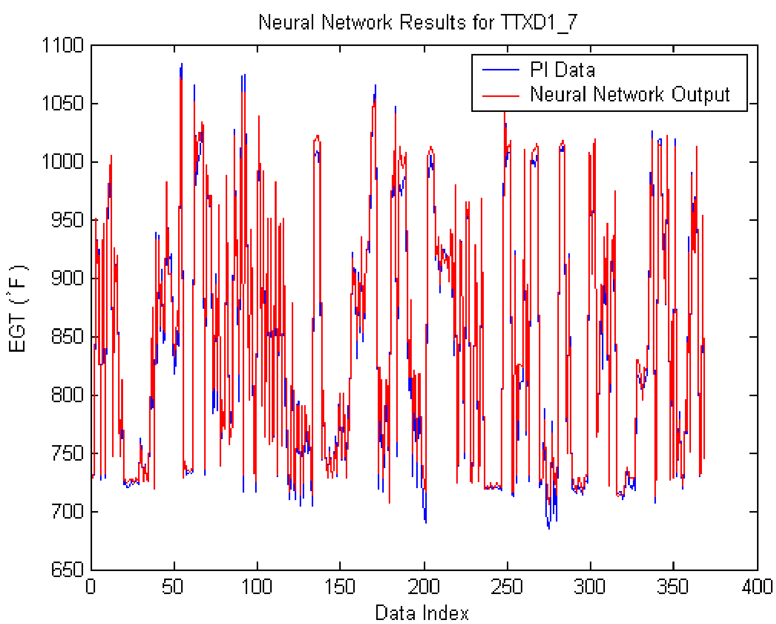

Figure 4-2
Neural Network Results for TTXD1_7 (Exhaust Gas Temperature)

Figure 4-2 illustrates the output results from the example network. The data illustrated is test data extracted from the PI Historian in the same manner as the training data and not a temporally sequential series.

As previously stated, implementation of the model-based techniques is also independent of the operating mode of the CT unit within the expected operating range, i.e. turbine running at full speed and the generator outputting a load between 65 MW and 170 MW. Again this goes back to the underlying assumption that the hysteretic effects encountered by the CT unit due to transients have little impact on the network's ability to determine the correct output. The neural networks have been developed to encompass the full range of reasonable operating values and conditions. Once the generalization is made that hysteretic effects can be ignored, the assumption can be made that each instant in time can be considered a pseudo steady-state condition. Now we are allowed to utilize the model-based techniques for all points whether the unit is at partial load or full load. Results obtained from analysis of the neural network's prediction compared to the actual data show consistent variation regardless of the operating mode. Figure 4-3 illustrates neural network results obtained for a sample set of data. The data sample reflects the actual operational modes experienced by the CT unit. Figure 4-4 and Figure 4-5 illustrate magnified views of two transient events encountered during operation. Figure 4-4 shows a long steady transient. The neural network does a very good job of tracking the actual compressor discharge temperature values through the transition. The results presented in Figure 4-5 illustrate a sharp transient. Again, the neural network does an excellent job of approximating the desired compressor discharge temperature values.

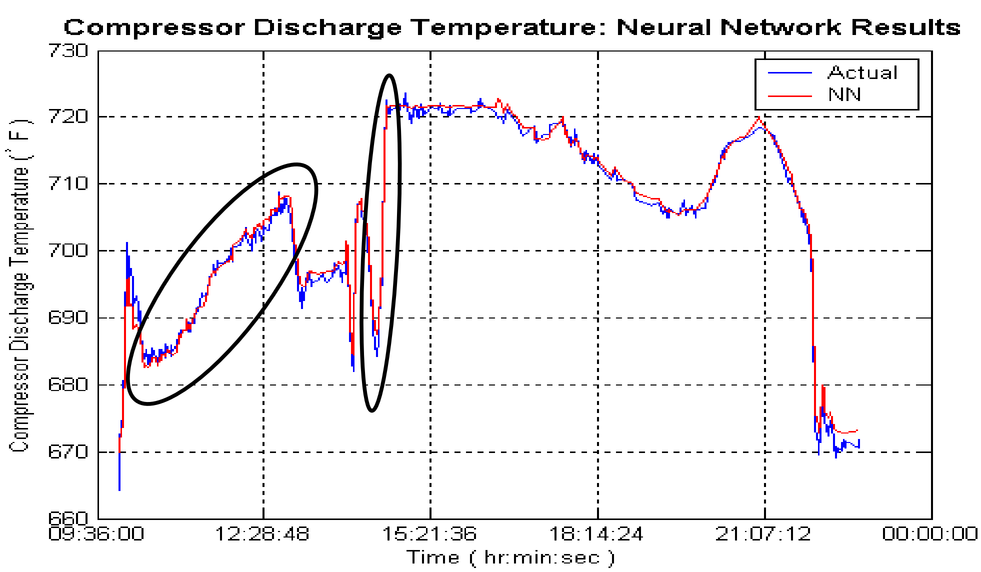

Figure 4-3
Sample Neural Network Results for Compressor Discharge Temperature

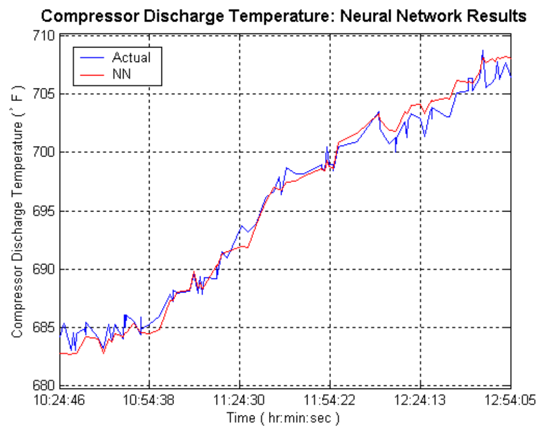

Figure 4-4
Neural Network Results Tracking a Gradual Transient

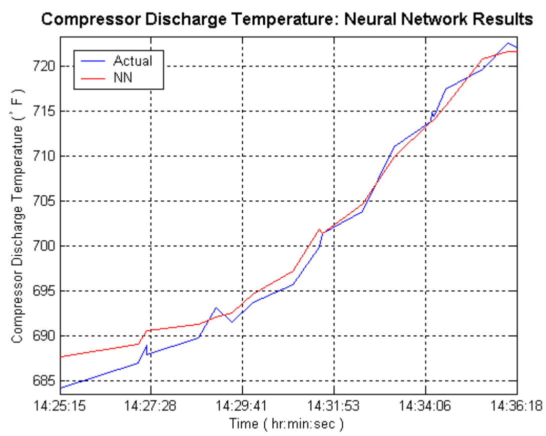

Figure 4-5
Neural Network Results Tracking a Steep Transient

One final consideration with respect to operating modes lies in the type of fuel being burned by the CT unit. We know that the Asheville units are required to burn liquid fuel during the winter months due to the drain they place on the gas pipeline when they are in operation. Analysis has shown that at low load conditions the characteristic response of the gas path parameters differs between the two fuel types. To compensate for this distinction two neural networks have been developed for each parameter, one for each fuel type. We should note that there is significantly less data available for periods of liquid fuel usage than for natural gas usage in the ten months of data available. This is due to the nature of the operation of the Asheville CT units. Recall the units there are ‘peakers’ and as such only come on line when the demand on the power grid is sufficient to warrant help in sustaining adequate supply. During the summer months the units will run from late morning through mid-evening with regularity. In contrast, during the winter months the CT units are generally only called upon for short durations, two to six hours.

The table below lists the networks employed within the Sensor Validation and Recovery Module. Recall that the input values presented to the networks have all been corrected to ‘ISO standard day' conditions in an effort to remove the effects of ambient conditions on the networks' results. Each parameter has two underlying networks ready to evaluate based on the type of fuel being utilized. Note: During transitional periods when both types of fuel are being used simultaneously, no model-based evaluation can be completed.

Table 4-2
List of Neural Networks Employed by the SVRM

Output	Inputs
COMPRESSOR DISCHARGE PRESSURE	COMPRESSOR DISCHARGE TEMPERATURE GENERATOR OUTPUT POWER GAS OR LIQUID FUEL FLOW EXHAUST GAS TEMPERATURE WATER FLOW
INLET GUIDE VANE ANGLE	INSUFFICIENT DATA IS CURRENTLY AVAILABLE TO PROPERLY DEVELOP THIS NEURAL NETWORK
COMPRESSOR DISCHARGE TEMPERATURE	COMPRESSOR DISCHARGE PRESSURE GENERATOR OUTPUT POWER GAS OR LIQUID FUEL FLOW EXHAUST GAS TEMPERATURE WATER FLOW
GENERATOR OUTPUT POWER	COMPRESSOR DISCHARGE PRESSURE COMPRESSOR DISCHARGE TEMPERATURE GAS OR LIQUID FUEL FLOW EXHAUST GAS TEMPERATURE WATER FLOW
GAS FUEL FLOW	COMPRESSOR DISCHARGE PRESSURE COMPRESSOR DISCHARGE TEMPERATURE GENERATOR OUTPUT POWER EXHAUST GAS TEMPERATURE WATER FLOW
LIQUID FUEL FLOW	COMPRESSOR DISCHARGE PRESSURE COMPRESSOR DISCHARGE TEMPERATURE GENERATOR OUTPUT POWER EXHAUST GAS TEMPERATURE WATER FLOW
GAS FUEL TEMPERATURE	INSUFFICIENT DATA IS CURRENTLY AVAILABLE TO PROPERLY DEVELOP THIS NEURAL NETWORK

Output	Inputs
EXHAUST GAS TEMPERATURE	COMPRESSOR DISCHARGE PRESSURE COMPRESSOR DISCHARGE TEMPERATURE GENERATOR OUTPUT POWER GAS OR LIQUID FUEL FLOW INLET GUIDE VANE ANGLE WATER FLOW
WATER FLOW	COMPRESSOR DISCHARGE PRESSURE GENERATOR OUTPUT POWER GAS OR LIQUID FUEL FLOW EXHAUST GAS TEMPERATURE

Each parameter requires two networks be developed since the characteristic behavior of the parameters varies depending on the fuel used, natural gas or liquid. The ‘Output’ from the neural networks can be used to validate and recover either the voted value or the values output from the individual sensors used to monitor the parameters if they are available.

Fuzzy Logic System

As previously stated, the residuals obtained from the comparison of the neural network outputs to the original, corrected parameter values are evaluated by a fuzzy logic system in determining the associated confidence level in the sensor’s integrity.

A fundamental concept of fuzzy sets is that its elements can belong to a set to varying degrees -- i.e. every element is characterized by a degree of membership within the set. A mapping of the domain interval to its degree of membership defines a membership function. The number of membership functions assigned to input/output variables and their shapes comprise an essential part of the "knowledge" embodied in a fuzzy logic system. This information is supplied by the domain expert, and when combined with the rulebase, forms a complete knowledge base for a particular application.

This system utilizes a pre-processing step, which determines the “hard input.” Here, the hard input is the difference between the measured value and the expected value in a normalized format. The fuzzy logic system then “fuzzifies” the hard input by utilizing the *max-min inference method* (see Appendix B) for assessing the appropriate rules from the rulebase utilizing the values obtained from the “membership functions.” The “membership functions” determine the degree of membership of the associated input into the three fuzzy classifications, “Low”, “Medium” and “High.” Developing the membership function requires determining the “Universe of Discourse” which defines the range of hard input values expected by the fuzzy system. Figure 4-6 and Figure 4-7 illustrate levels of displacement used to develop the membership function shown in Figure 4-8. Clearly the one percent and two percent levels fall within the three-sigma boundary of expected values; therefore, these levels will be used to define the “Low” region. The five percent to ten percent displacement range, while a substantial amount in the realm of performance evaluation, is a “Medium” offset within sensor validation. Twenty percent offset will bound the upper limit of the “High” region.

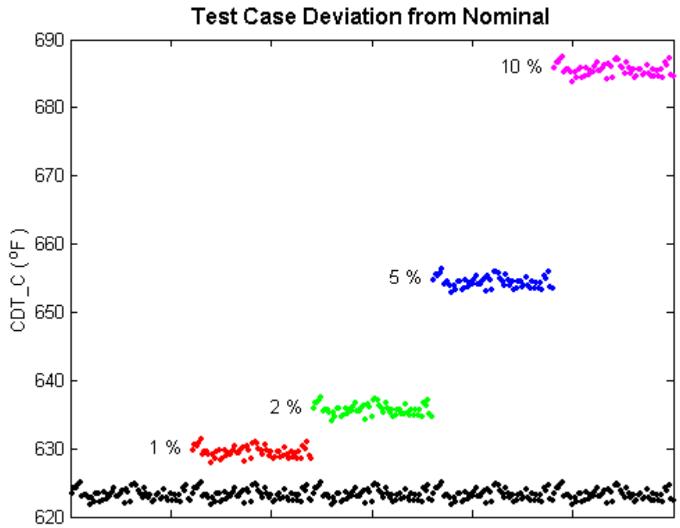

Figure 4-6
Levels of Displacement from Expected Values

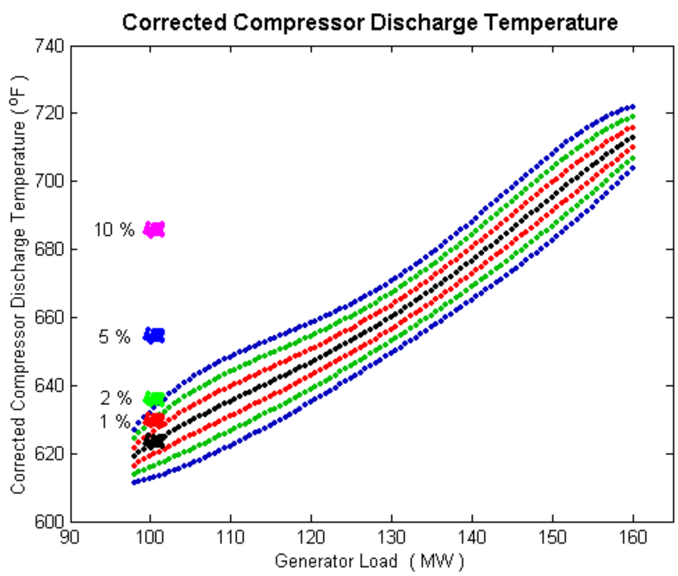

Figure 4-7
Levels of Displacement Shown on Operating Signature Curve

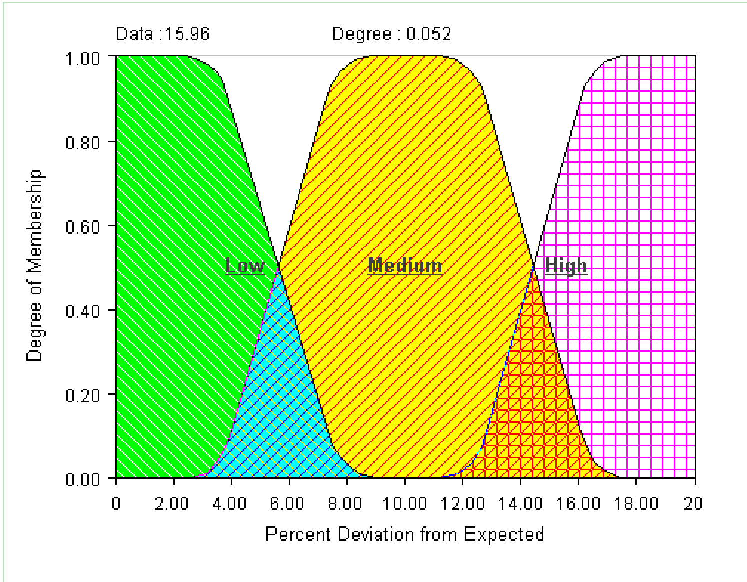

Figure 4-8
Fuzzy System Input "Fuzzification" Membership Function

The end result of the fuzzification step is the determination of the "fuzzy set." The "fuzzy set" is a geometric subset of the original membership functions. The shape of the "fuzzy set" is determined by the degree of membership of the hard inputs in the membership functions based on the applicable rules encountered in the expert rulebase. This fuzzy set is subsequently converted back into a hard output by a "de-fuzzification" process. The de-fuzzification process employed here utilizes the *centroid method*. Intuitively, the centroid method can be viewed as a "compromise" among the output actions recommended by different rules. The output value obtained as a result of the de-fuzzification process can now be interpreted as the signal confidence level obtained from the model-based validation technique.

Results Fusion

The results fusion process consists of the synergistic combination of collaborative information from the sensor validation techniques in order to provide an accurate and effective assessment of the observed sensor's past and present integrity. The result obtained from the Dempster-Shafer fusion process possesses greater certainty than the individual confidence with uncertainty levels when evaluating collaborative evidence.

An example of the Dempster-Shafer fusion process is shown in Figure 4-9. Here, Method #1 can represent the generic signal processing technique results and Method #2, the data driven model based results. The net result of the fusion process is a diagnostic confidence that is more accurate and robust than could be obtained by any single information source.

Example of Dempster-Shafer Belief Method

Sensor Confidence from Method #1 = 80% +/- 15%

Sensor Confidence from Method #2 = 30% +/- 10%

Therefor: m1(A) = 0.65 m1(A') = 0.05 m1(A,A') = 0.30
m2(A) = 0.20 m2(A') = 0.60 m2(A,A') = 0.20

	m2(A)	m2(A')	m2(A,A')
m1(A)	0.13 {A}	0.39 {0}	0.13 {A}
m1(A')	0.01 {0}	0.03 {A'}	0.01 {A'}
m1(A,A')	0.06 {A}	0.18 {A'}	0.06 {A,A'}

$$Belief\,(Hn) = \frac{\sum_{A\cap B=Hn} m_i(A)\cdot m_j(B)}{1-\sum_{A\cap B=0} m_i(A)\cdot m_j(B)}$$

m1(A) + m2(A) {True} = (0.13 + 0.13 +0.06)/(1-(0.01 + 0.39)) = 0.53

The uncertainty in this result is:

m(A,A') + m(B,B') = 0.06 / (1-(0.01 + 0.39)) = 0.10

Hence, the probability of Fault A having actually occurred given the diagnostic classification is **0.58 +/- 0.05**

Figure 4-9
Dempster-Shafer Fusion Process

5 SENSOR RECOVERY

“Recovery” of signals from failed sensors has been identified as a highly valuable feature for enabling robust diagnostics on combustion turbines. “Sensor recovery” refers to the capability of the Sensor Validation and Recovery Module (SVRM) to substitute reasonable parameter values for data obtained from malfunctioning sensors. In the event that an anomalous value is detected a replacement value can be provided to the performance worksheet and the assessment can continue.

The addition of the sensor recovery feature will enable the health diagnostics modules being developed to utilize suggested substitute parameter values upon identification of an anomalous sensed value. To this end, the artificial intelligence networks necessary to predict parameter values given the current operating state are called upon to serve dual duty. Initially, the neural networks are vehicles for supplying the model-based expected parameter values. As a subsequent duty, upon identification of anomalous sensor values, the output from the neural network is supplied to the performance algorithms as replacement values for the erroneous data. Each individual parameter requiring recoverability must have two corresponding neural networks developed, one for each type of fuel used. The neural networks developed utilize four to six inputs as specified in Table 4-2 that are used to define the current level of operation and predict the appropriate output. These inputs are primarily sensed gas path parameters, which are already being used in the sensor validation and performance analysis modules. Output from the network is a reasonable approximation of the expected output value, based on the inputs, which can be used to replace anomalous sensor output if necessary.

The architecture of the SVRM needed to be augmented to accommodate the functionality of parameter recovery as shown in Figure 5-1. The output from the neural networks needs to be retained until final results are obtained from the data fusion process. Should an anomalous sensed value be identified, the corresponding replacement value must be obtained from the appropriate neural network output. The modifications are highlighted in red in Figure 5-1. Feedback from the final sensor health assessment step is utilized to obtain any required replacement values from the original neural network output. This output is then post-processed to reintroduce the effects of the ambient conditions at the corresponding instance in time, i.e. revert back from ISO standard day conditions, to obtain an approximation of the original data for replacement in subsequent performance calculations.

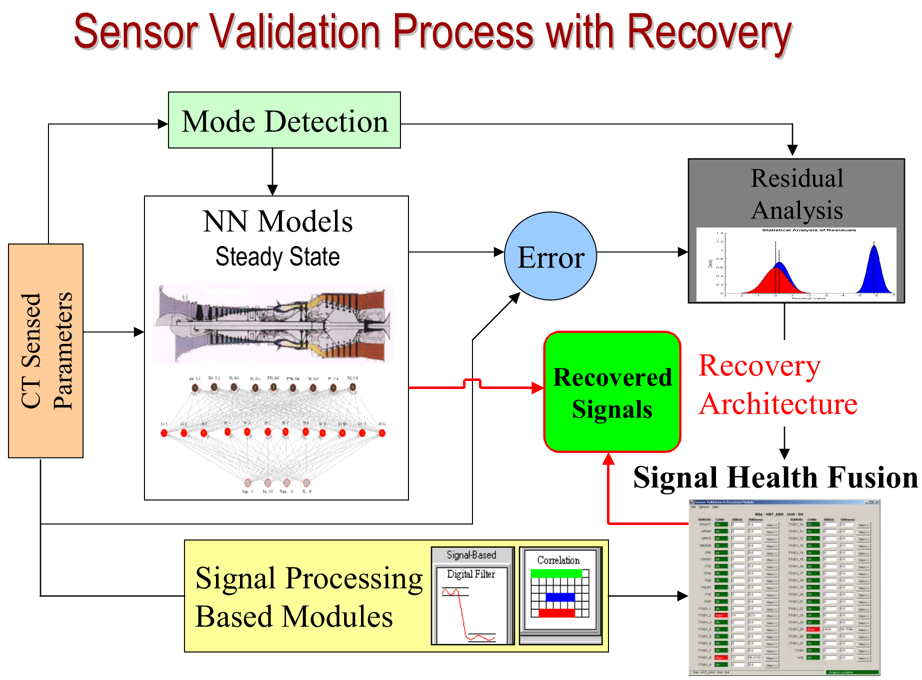

Figure 5-1
Sensor Validation Architecture with Recovery Capabilities

Neural Network Based Approach

The absence of rigorously matured empirical models necessitates the development of low cost, easy to develop alternatives, which can be developed reasonably quickly for varying CT unit types. These alternative methods are usually data driven requiring extensive amounts of data, sufficient to capture all modes of operation experienced by the combustion turbine unit. The Sensor Validation and Recovery Module utilizes this data driven approach in developing the neural networks utilized in the model-based validation technique and subsequently in the value recovery process. Neural networks lend themselves very well to this type of application due to their ability to "learn" inter-parameter relationships which exist and generalize these learned relationships to adapt to "unseen," during training, inputs.

6
SVRM FEATURES

Features of the SVRM Interface

The main graphical user interface (GUI) has been developed to present plant personnel with key information required for validation and subsequent performance assessment. The GUI, written in Tcl/Tk, provides an organized and aesthetically appealing way of presenting the information concerning sensor anomalies found in the data set being scrutinized, as shown in Figure 6-1. The SVRM GUI contains four fields for each sensor listed. The four fields are: '*SENSOR:*', '*COND:*', '*ERR(#):*', and '*ERR(sev):*'. Also included for each sensor is a '*View >>*' pushbutton, which calls a new window for viewing the underlying time series. An in-depth discussion of this functionality is forthcoming. Other features of the main SVRM graphical user interface include display of the site and unit currently being accessed by the data querying utility. Finally, a color-coded status field is presented in the lower right corner to allow easy recognition of the status of the current analysis.

Field Descriptions

The '*SENSOR:*' field is a static field that contains the name of the sensor. The sensor name coincides with the tag name utilized within the PI Historian. The '*COND:*' field is a dynamic Boolean field. This field is updated by the SVRM, is color-coded, and contains text. The response to a sensor with no anomalies detected will be a green field with 'OK' text. A red field with 'Alarm' text will signify an anomalous sensor. The '*ERR(#):*' field is also a dynamic field updated by the SVRM. This field acts as a counter for the number of anomalous points found. The final field is '*ERR(sev):*'. This field is utilized to rate the severity of the faults identified. Within the sensor validation module, the algorithms assign a confidence level to each sensor's output. This determination reflects the level of confidence that the output of each sensor reflects the actual parameter value. Calculating one hundred minus this confidence level gives the *error severity level*, which can be interpreted as the certainty, expressed as a percentage, that the sensor's output is erroneous. A sensor fault is identified when the error severity level crosses a pre-determined threshold. When numerous sensor faults have been identified, the error severity values are totaled and averaged by the number of faults found. This figure may be interpreted as an indication of the overall health of the sensor and the ability to use the data given to assess performance measures. Finally, a pushbutton is available for each sensor marked '*View >>*'. Selection of the pushbutton opens a new window, which contains a 'notebook' to view the time series data which has just been evaluated by the SVRM. Each 'notebook' contains at least one 'tab' or 'sheet' that contains the time series plot on it. In the event that multiple time series have been evaluated a separate ‘tab’ is created for each individual time series and the user may view the individual time series by selecting the different tabs.

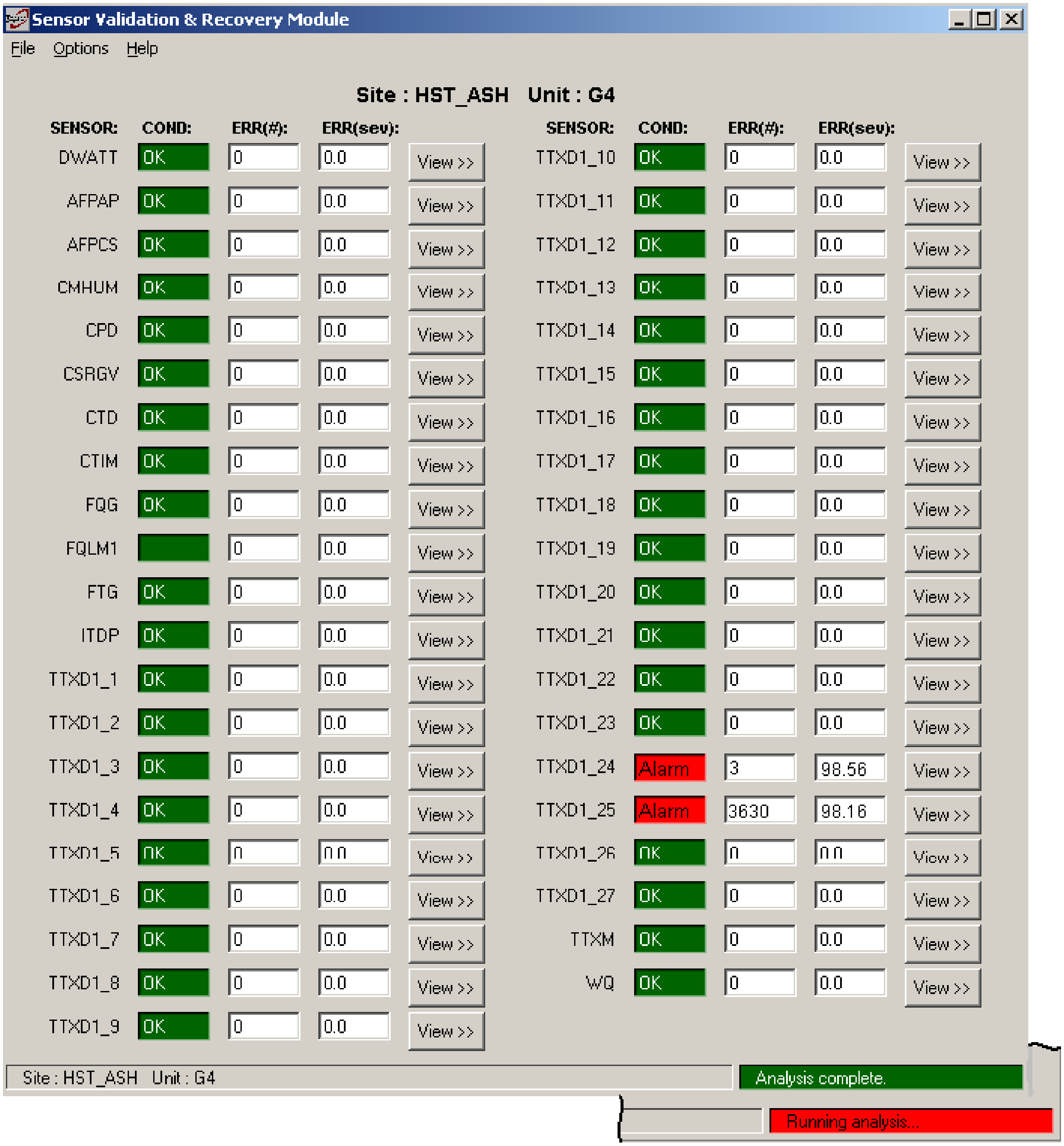

Figure 6-1
Sensor Validation and Recovery Module’s Graphical User Interface

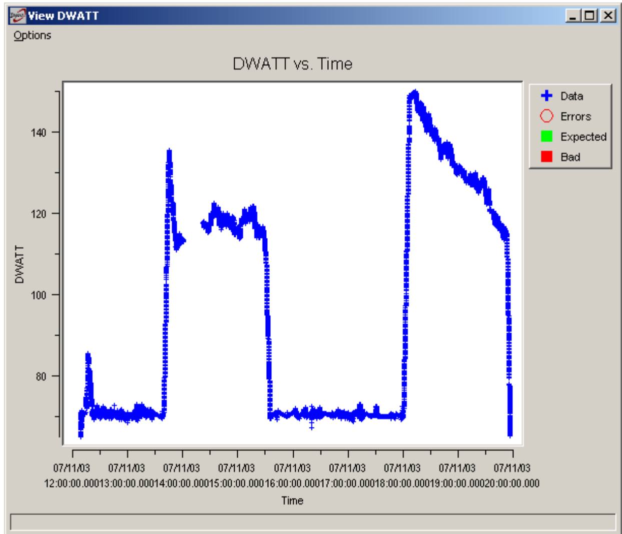

Figure 6-2
Generator Output Power for July 24, 2003

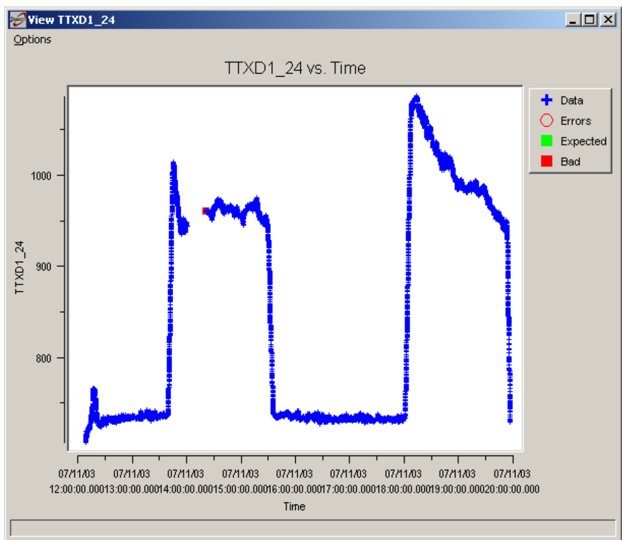

Figure 6-3
Exhaust Gas Temperature Output, Thermocouple Array -- #24

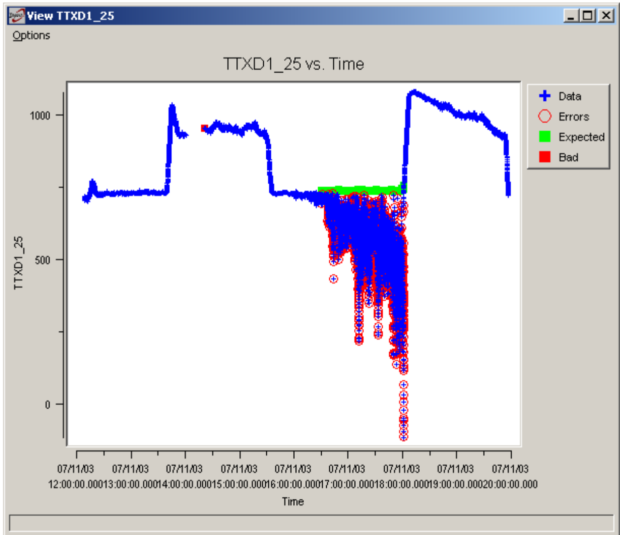

Figure 6-4
Exhaust Gas Temperature Output, Thermocouple Array -- #25

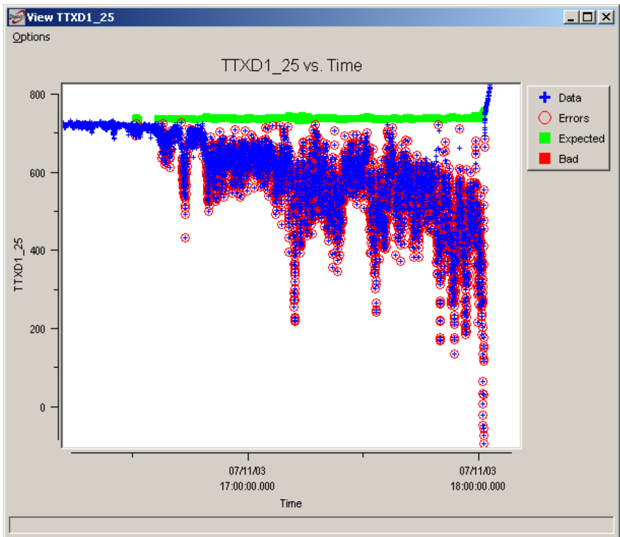

Figure 6-5
Magnified View of Region Around Thermocouple Drop-Out

Figure 6-2 through Figure 6-5 are screen shots illustrating the viewing capabilities of the GUI. Figure 6-2 and Figure 6-3 are presented for comparison purposes to illustrate “normal” sensor output for the period of the analysis. Figure 6-4 and Figure 6-5 illustrate anomalous output from a thermocouple monitoring exhaust gas temperature. A *ZOOM* feature is available utilizing a user specified *click and drag* box to define the region to be magnified, shown in Figure 6-5. Looking at the results for the *TTXD1_25* sensor it is clear that anomalous points were detected. The results shown in Figure 6-1 depict the results of the validation analysis, ‘ERR(#):’ equal to 3630 erroneous points were detected, resulting in an error severity level, ‘ERR(sev):’, of 98.16 %,.

E-Mailing Capabilities

File → Email Analysis Results…

The SVRM batch analysis operating mode was set up to enable the SVRM to operate as a behind the scenes application which would run unnoticed by CT operators unless a problem was detected. In the event that an anomalous signal is detected, specified e-mail recipients will receive a report detailing the exceptions found. The desired e-mail addresses are entered in the configuration file. Beta testing revealed that this functionality would also be a desirable feature when utilizing the SVRM module in its interactive operating mode. To this end a dialogue box, shown below, has been made available during all modes of operation that allows the user to enter an e-mail address and send the recipient results from the current analysis.

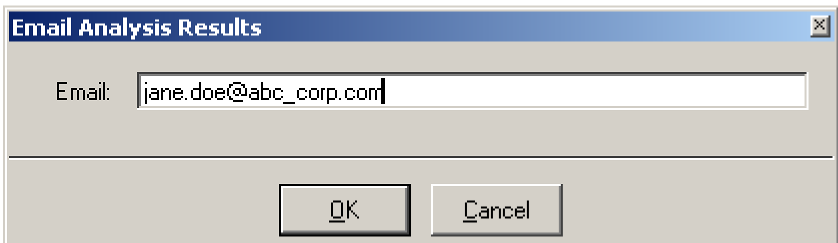

Figure 6-6
Dialogue Box Enabling Entry of E-mail Recipient's Address

Configuration Capabilities

The configuration capabilities are driven by the desire to make the Sensor Validation and Recovery Module as easy to use and as adaptable as possible. To this end the options made available to the user through the three tabs, which make up the *Configuration* window allow the user to tailor the capabilities of the SVRM to suit their requirements.

Options → Configuration…

The *Configuration* dialogue box has been modified to contain three tabs. The first tab, *Program*, is primarily used to select and enter information required by the DataLink Add-In utility pertaining to the desired CT unit to be analyzed. Here, the user can also now specify whether or not the SCAMP module is run.

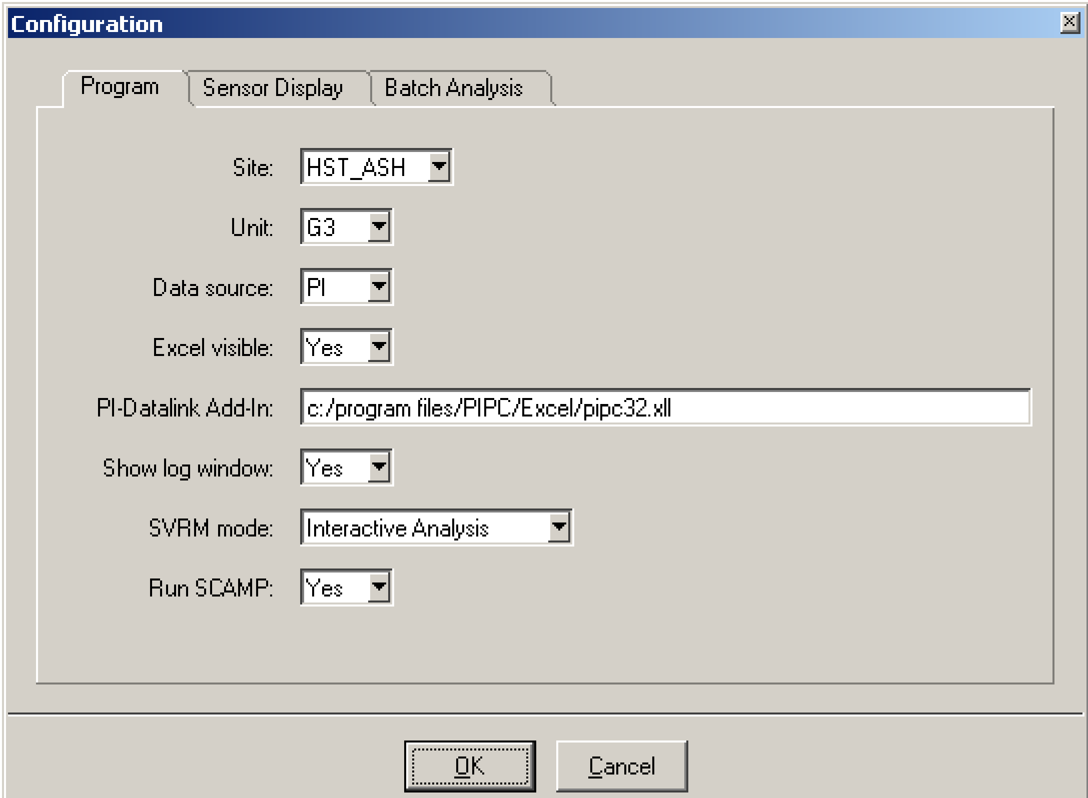

Figure 6-7
***Program* Tab of the *Configuration* Dialogue Box**

Feedback from beta testing revealed that an added benefit would be attained if the user could specify which parameters were displayed on the main SVRM window. Certain sensors may be thought of as extraneous to the current scope of interest when the user sits down to use the SVRM and as such can now be "turned off." The second tab of the *Configuration* dialogue box, *Sensor Display*, configures which parameters are displayed on the main Sensor Validation and Recovery Module screen. The user simply checks which parameters to be viewed.

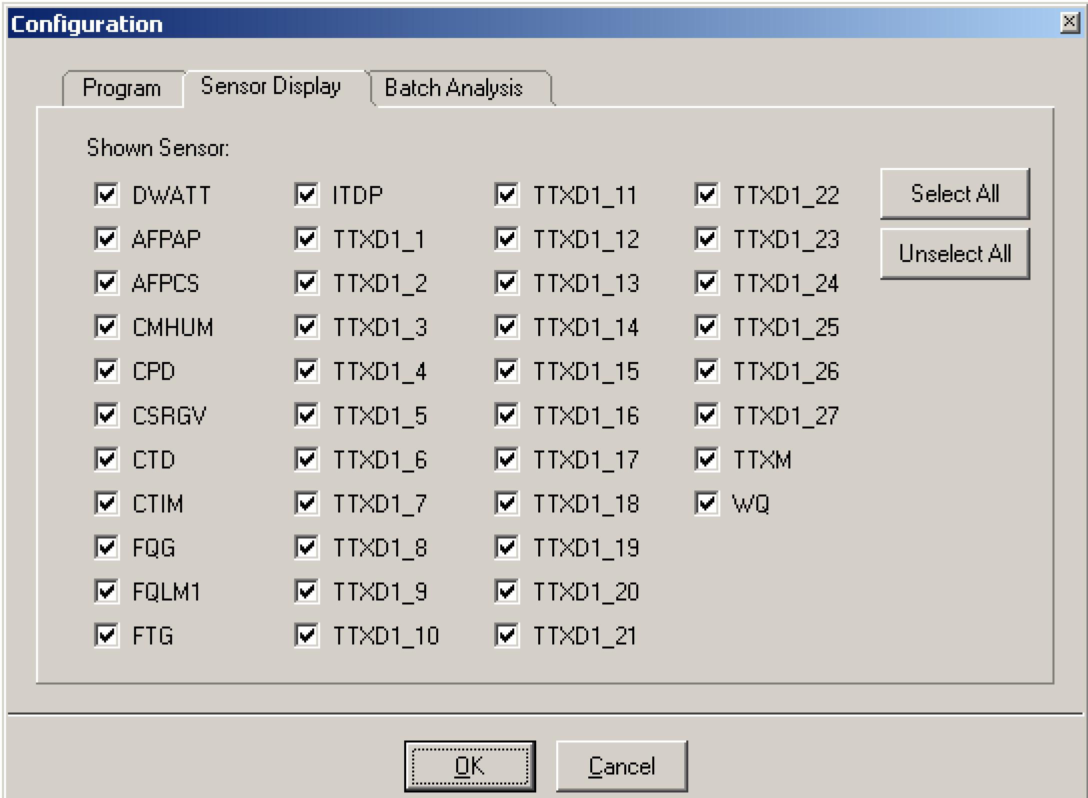

Figure 6-8
Sensor Display **of the** ***Configuration*** **Dialogue Box**

The final tab, *Batch Analysis*, facilitates configuration of the SVRM when in batch analysis mode. Respondents to beta testing thought the original set-up of querying the previous twenty-four hours of data for analysis at or near mid-night, when network traffic is low, too constrictive. Utilizing this dialogue box the user can now dictate the duration of the window of time being analyzed and specify when the analysis takes place. For example, with the settings as they appear in Figure 6-9 an analysis would be initiated at mid-night and query the previous hour's data. Subsequent analyses would then start each hour after that on the respective previous hour's data.

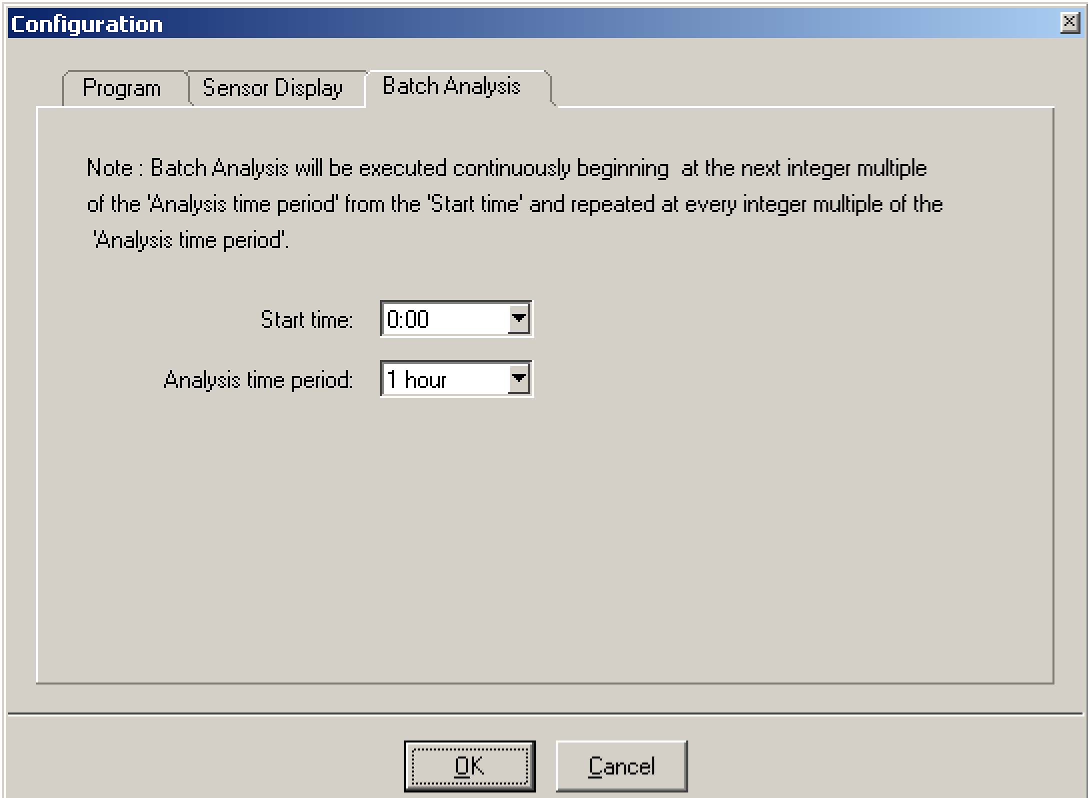

Figure 6-9
***Batch Analysis* Tab of the *Configuration* Dialogue Box**

Options → Run Sensor Validation (User Defined Time Period)…

Further key feature improvements included as a result of testing is an improved dialogue box for defining the time period of the analysis when using the SVRM in its interactive analysis mode. The addition of the new dialogue box allows the user to quickly and easily specify the date and time of interest. Figure 6-10 illustrates the dialogue box. Clicking the arrows at the top of the calendar will scroll through the months. A date is selected and subsequently highlighted by the click of the mouse. Finally, the hours of interest can be highlighted in the pane at the right to specify the hours of data being analyzed.

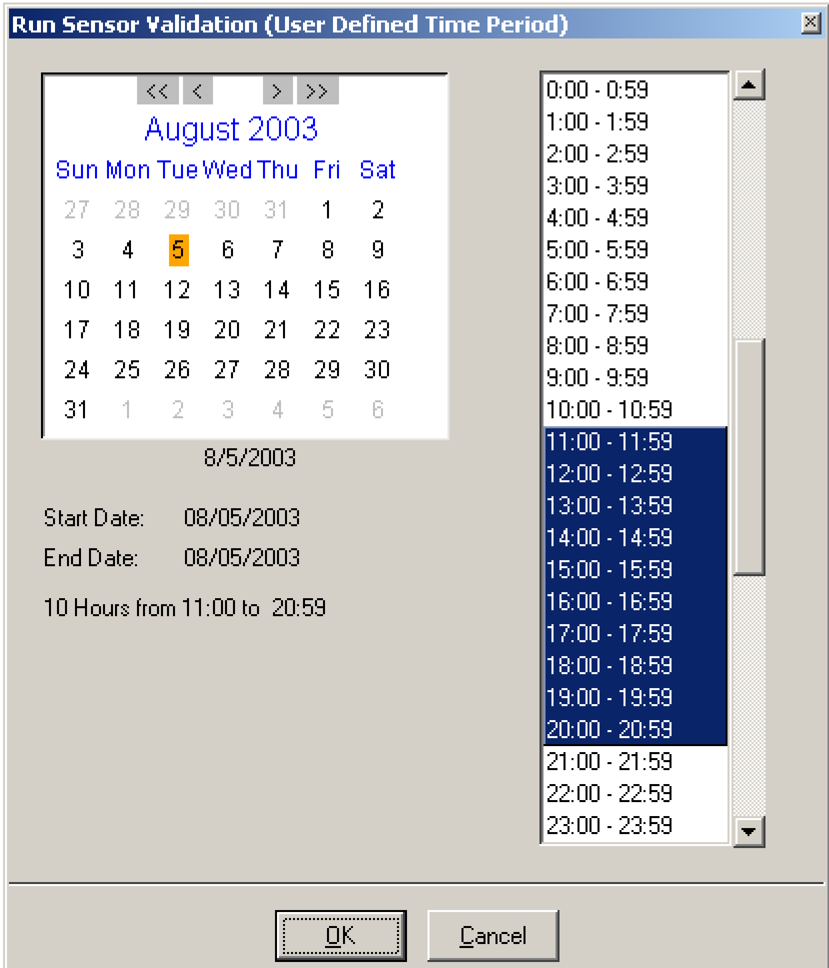

Figure 6-10
Dynamic Dialogue Box for Specifying *Interactive Analysis* Time Periods

Monitoring Multiple Units

Development concerning the issue of monitoring multiple CT units at the same time is in progress. At this time it is possible to monitor multiple units concurrently by launching multiple instances of the SVRM in batch mode and initiating their respective queries in non-coincident hours, e.g. the module monitoring G3 initiates on even hours for an analysis duration of two hours while the module monitoring G4 initiates on the odd hours for an analysis duration of two hours. This scenario has been difficult to test since the two units have not run at the same time very often.

7
RECOMMENDATIONS FOR FUTURE DEVELOPMENT

Virtual sensing of currently unmonitored parameters has been discussed as a possible avenue of future development. Certain gas path parameters, such as station total pressures and combustor discharge temperature, are very beneficial in calculating hot section performance. They are, however, impractical to monitor on all units. Virtual sensing of the parameters entails the development of predictive tools that assess the current state of operation of the unit and then map that state to a probable value of the virtually sensed parameter. Neural networks, like those currently utilized in the SVRM, are well suited to this type of application.

Another possible area of development would be to mature the ability to write recovered values back to the PI Historian. In the event that erroneous data values are detected as the result of analysis by the Sensor Validation and Recovery Module, the recovered values could be written back to an appropriate place in the PI Historian. Having these values available could be advantageous for use in any subsequent analysis, which may take place or if verification/duplication of already completed analysis is ever required.

8
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1. Walsch, Fletcher, Gas Turbine Performance, (pp. 113, 115, 565 & 585) Blackwell Science Ltd., ASME Press, 1998

2. SCAMP Spreadsheet. Vers. 3, Fern Engineering, Inc. 2003 Spreadsheet and Computer Manual, Figure 1-1

3. O'INCA Design Framework for MS-Windows. Vers. 1.1. Computer Software. Intelligent Machines, Inc., 1995

A
NEURAL NETWORKS

Artificial neural networks (ANN's or NN's) utilize a network of simple processing units ("*neurons*"), each having a small amount of local memory. These units are connected by "communication" channels ("*connections*"), which usually carry numeric data. The units operate only on their local data, which is received as input to the units via the connections. Most ANN's have some sort of *training* rule by which the weights of connections are adjusted based on some optimization criterion. Hence, ANN's learn from examples and exhibit certain capability for generalization beyond the training data (examples). ANN's represent a branch of the artificial intelligence techniques that have been increasingly accepted for data fusion and automated diagnostics in a wide range of applications. Their abilities to recognize patterns, and to learn from samples have made ANN's attractive for use with large data sets from complex systems.

The ANN *structure* is sometimes called *architecture*, or *topology*, which is an expression of the number of processing units and of the connections among these units; this is illustrated in Figure A-1. Most processing units are arranged in *layers* (a layer is a collection of the units aligned for the same computational sequence), and the ANN is often referenced by the number of layers and the number of units in each layer.

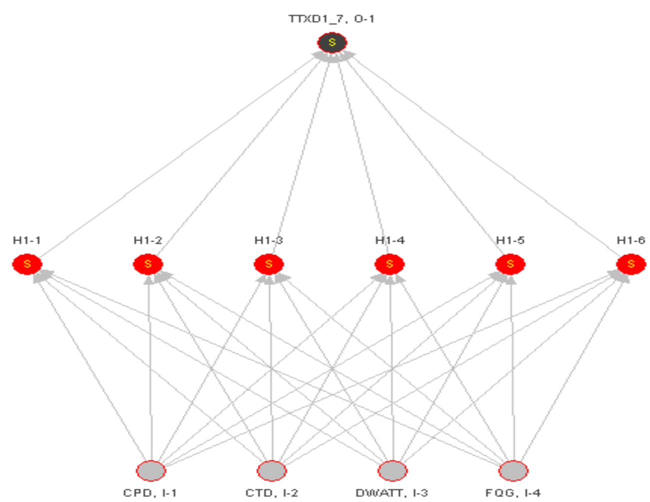


Figure A-1
Neural Network Architecture Utilized in the Sensor Validation/Recovery Module

Each solid connection line in Figure A-1 represents a numerical value called the *weight,* representing the connecting strength between the two inter-connected units. Each circle is a unit and it performs three sequential computations: the first is to multiply the weight by the output of the unit on the other end of the connection; the second is to sum the *weighted outputs* from all connections; and the third is to apply the *weighted sum* to a function (usually nonlinear and bounded) called an *activation* function. One of the most common activation functions is called the sigmoid function and the binary *f(x)* and bipolar *g(x)* versions are given below.

$$f(x) = \frac{1}{1+e^{-\alpha x}}; g(x) = \frac{1-e^{-\alpha x}}{1+e^{-\alpha x}}$$

The functional value of the weighted sum is called the *output* (or *threshold*) of the unit. This sequence of computation is carried out for each unit and for each layer until the outputs layer of the ANN is reached.

Training

The ANN's utilized within the SVRM for the sensor recovery are multi-layered, feed forward neural networks, often referred to as "back-prop" neural networks. The back-prop designation comes from the training algorithm used in the learning phase. Networks of this type require a supervised learning process. Supervised training means that every "set" of data presented to the neural network for training is accompanied by a corresponding desired result that is also presented. Here, "set" implies an instantaneous snapshot of the input and output parameters, which form a "training pattern." Complete and proper training requires that a sufficient number of patterns be presented to the network to represent the entire range of operation of the parameters. However, presenting too many patterns causes "overtraining," which limits the networks' ability to generalize and interpret the inputs. In the supervised training mode, error for the output units can be determined from the difference between the actual output value and the target (desired) value. Back-prop minimizes the mean squared error for the training set by modifying the weights according the negative of the partial derivative of the error term with respect to the weight space.

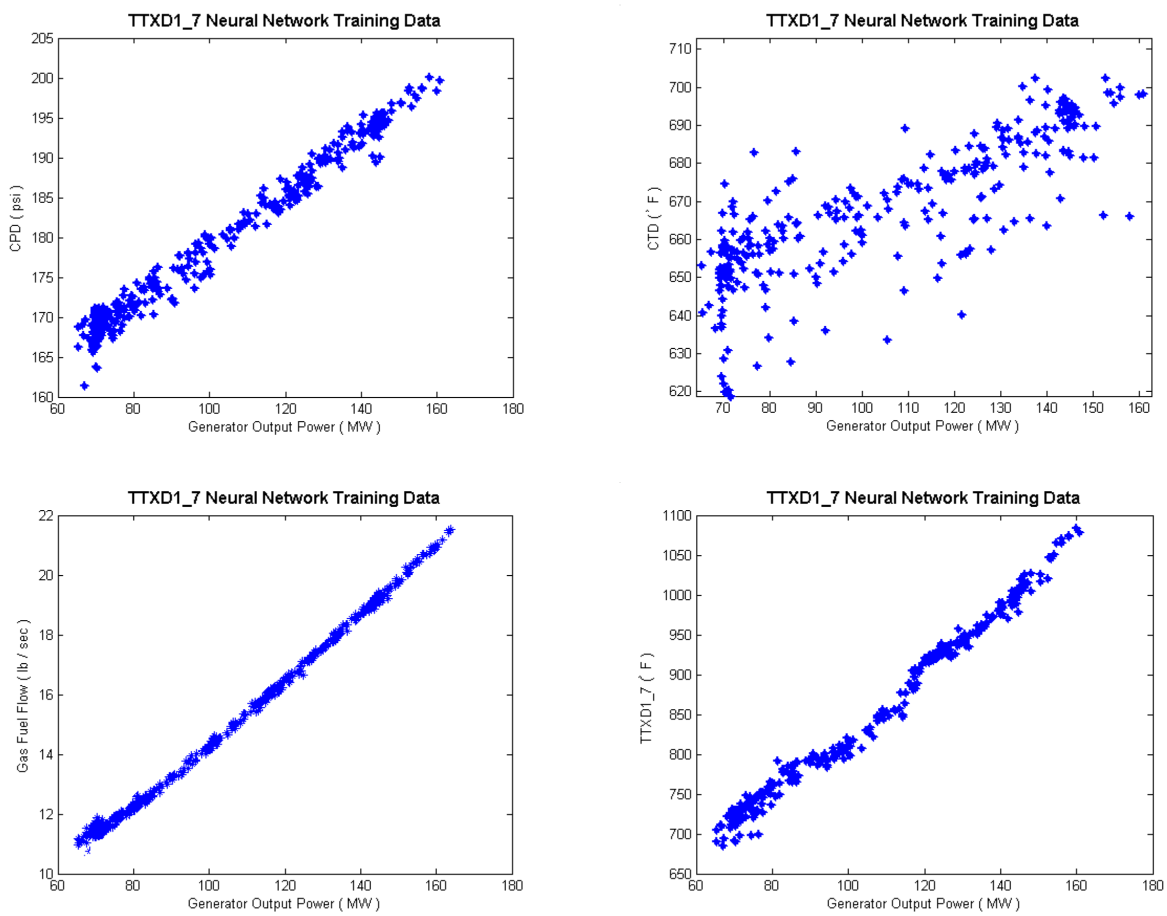


Figure A-2
Training Data Sample for the TTXD1_7 Neural Network

Training data has been obtained from the PI Historian. Query results, similar to those utilized in the development of the operating signature curves, are first referred (corrected) to International Standard Atmosphere (ISA) sea level ('ISO standard day') static inlet conditions to account for the changing environmental conditions that occur over the course of operation. Sub-sets, as shown in Figure A-2, are then extracted from the referred data to be presented to the neural networks as training patterns. The neural network used for illustration is for the TTXD1_7 sensor, a thermocouple in the array measuring exhaust gas temperature. Compressor discharge pressure and temperature (CPD and CTD respectively), gas fuel flow (FQG) and generator output power (DWATT) are utilized as inputs for this network. Sixteen points have been selected from each period the CT unit, G3 in this case, was in service. The operating range of generator output power (DWATT) encompassing 65 MW to 165 MW was divided into four sub-ranges and four points extracted from each sub-range. Corresponding points were taken from CPD, CTD, FQG and TTXD1_7 based on the time stamp accompanying the DWATT data selected.

B
FUZZY LOGIC SYSTEMS[3]

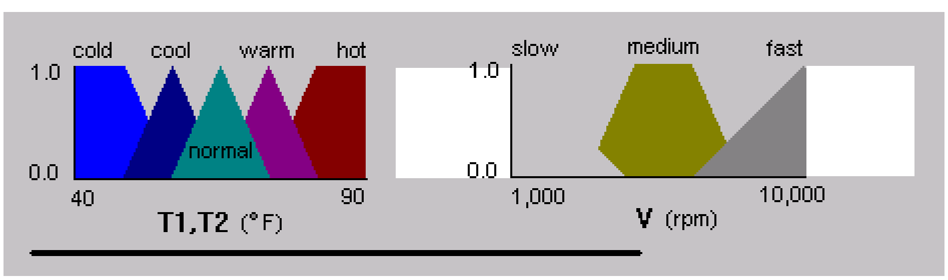
Overview of Fuzzy Logic Systems

Fuzzy logic refers to a mode of reasoning based on imprecise/ambiguous information. Fuzzy logic technology enables machines to perform "approximate reasoning" and improves their performance through (i) efficient numerical representation of vague terms and concepts [such as 'dirty', 'slow', 'tall', 'heavy'], (ii) increasing their range of operation in ill-defined environments and (iii) decreasing their sensitivity to noisy data. Fuzzy logic also offers useful solutions to complex problems where mathematical models are unavailable nor cost-effective to develop. Contrary to its nomenclature, fuzzy logic (or "fuzzy") systems operate based on precise, rigorous arithmetic of fuzzy sets. A fuzzy set that relates a domain interval to their "degree of membership" to a specific label (category) describes a membership function of the corresponding variable. After membership functions are defined over a variable's universe of discourse, relations between input and output fuzzy sets can be defined through a list of rules in the form: IF <condition> THEN <conclusion>. Sequence of operations in a fuzzy system can be described by three phases named fuzzification, inference, and defuzzification.

Many implementations of fuzzy systems are in the form of knowledge-based expert systems. Applications suitable for fuzzy logic range from systems modeling in science and economics, natural language man-machine interfaces, emulation of human decision making processes, to controlling nonlinear dynamic systems.

Max-Min Inference

Suppose the membership function sets for T1, T2 and V are as shown below. If T1 and T2 use the same membership function set, and the following three rules are applied:



Rule 1: IF T1 IS warm OR T2 IS warm, THEN V is fast
Rule 2: IF T1 IS normal AND T2 IS warm, THEN V is fast
Rule 3: IF T1 IS normal AND T2 IS hot, THEN V is medium

Assume that fuzzification results are:

T1: cold=0.0, cool=0.0, normal=0.3, warm=0.7, hot=0.0
T2: cold=0.0, cool=0.0, normal=0.0, warm=0.4, hot=0.6

In the max-min inference method,

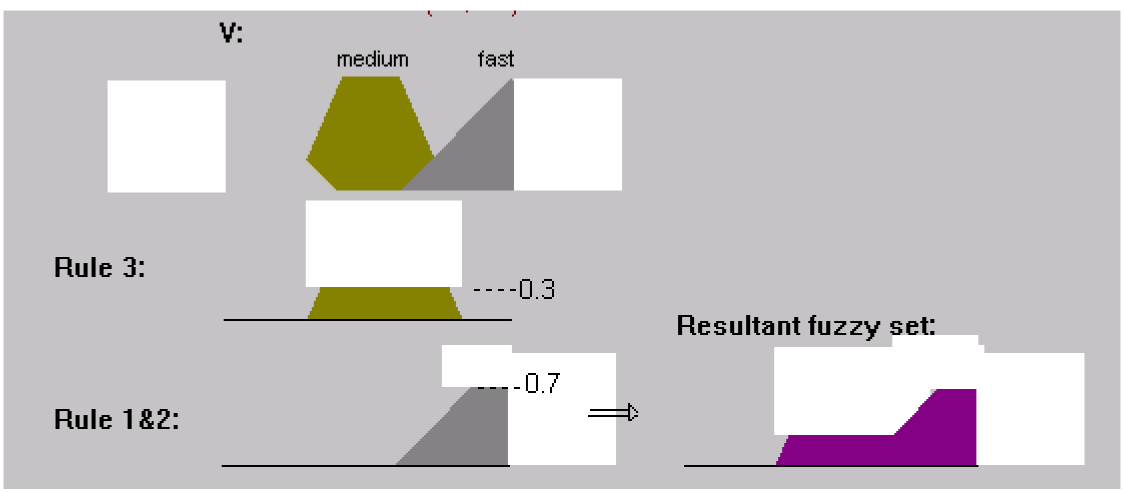
min operation $[\mu_A \cap \mu_B]$ is used for the AND conjunction (set intersection) and
max operation $[\mu_A \cup \mu_B]$ is used for the OR disjunction (set union)

to evaluate the grade ("strength") of the antecedent clause in each rule:

Rule 1: max(0.7, 0.4) = 0.7 fast
Rule 2: min(0.3, 0.4) = 0.3 fast
Rule 3: min(0.3, 0.6) = 0.3 medium

These values are used to clip the corresponding output membership function shapes. If multiple rules have the same consequent label, max operation is used to resolve conflicts. Since Rule 1 and Rule 2 have the same consequence label (fast), max operation is used:

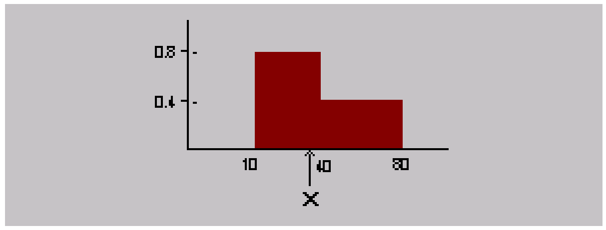
Rule 1 & Rule 2: max(0.7, 0.3) = 0.7 fast



The clipped membership functions are then merged to produce one final fuzzy set. The max operation is used to merge overlapping regions.

Centroid Defuzzification

Referred to as the "center-of gravity" method, this process produces crisp data by computing the horizontal-axis (abscissa) component of the geometric centroid of the fuzzy set. Intuitively, the centroid method can be viewed as a "compromise" among the output actions recommended by different rules. For each output using this defuzzification method, the resultant fuzzy sets from all contributed rules are merged into a final aggregate shape. For example, the defuzzified result of the following shape is x=39:



The operation to use when merging overlapping shapes depends on the inference algorithm: (maximum for max-min and sum for max-dot and product-sum).

Program:

Combustion Turbine and Combined-Cycle O&M

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