Advanced Monitoring to Improve Combustion Turbine/Combined Cycle CT/(CC) Reliability, Availability and Maintainability (RAM)

Semi-Annual Report

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Abstract

Power generators are concerned with the maintenance costs associated with the advanced turbines that they are purchasing. Since these machines do not have fully established operation and maintenance (O&M) track records, power generators face financial risk due to uncertain future maintenance costs. This risk is of particular concern, as the electricity industry transitions to a competitive business environment in which unexpected O&M costs cannot be passed through to consumers.

These concerns have accelerated the need for intelligent software-based diagnostic systems that can monitor the health of a combustion turbine in real time and provide valuable information on the machine's performance to its owner/operators. Such systems would interpret sensor and instrument outputs, correlate them to the machine's condition, provide interpretative analyses, forward projections of servicing intervals, estimate remaining component life, and identify faults.

EPRI, Impact Technologies, Boyce Engineering, and Progress Energy have teamed to develop a suite of intelligent software tools integrated with a diagnostic monitoring platform that will, in real time, interpret data to assess the "total health" of combustion turbines. The Combustion Turbine Health Management System (CTHM) will consist of a series of dynamic link library (DLL) programs residing on a diagnostic monitoring platform that accepts turbine health data from existing monitoring instrumentation.

The CTHM system will be a significant improvement over currently available techniques for turbine monitoring and diagnostics. CTHM will interpret sensor and instrument outputs, correlate them to a machine's condition, provide interpretative analyses, project servicing intervals, and estimate remaining component life. In addition, it will enable real-time anomaly detection and diagnostics of performance and mechanical faults, enabling power producers to more accurately predict critical component remaining useful life and turbine degradation.

Executive Summary

Introduction

Power producers are justifiably concerned with the maintenance costs associated with the advanced combustion turbines (CTs) they are purchasing today. While more efficient and environmentally clean than previous models, some advanced CT models do not have fully established operation and maintenance (O&M) track records. And without accurate information upon which to base maintenance decisions, optimizing system life while minimizing costs can be extremely difficult for operators. As a result, power producers face financial risk due to uncertain future maintenance costs and turbine life. This risk is of particular concern in today's increasingly competitive business environment in which reserve margins are shrinking and unexpected O&M costs usually cannot be passed through to consumers.

These concerns have accelerated the need for intelligent software-based diagnostic systems that can monitor the health of a CT in real time and provide owners and operators with valuable information on machine performance. While commercial systems—ranging from time-history database/display systems to model-specific operation/performance monitoring systems—are available, they have limited diagnostic capability and their results typically require expert interpretation. To date, neither CT manufacturers nor owners have developed a comprehensive diagnostic monitoring system, primarily because of the cost and the need for historical data from many units operating over the entire commercial operating spectrum.

To meet this need, the Department of Energy selected EPRI to lead the development of a comprehensive suite of intelligent diagnostic tools for assessing the total health of CTs. The resulting Combustion Turbine Health Management (CTHM) system will improve the RAM of CTs in simple-cycle and combined-cycle configurations.

The CTHM system will be a significant improvement over currently available techniques for turbine monitoring and diagnostics. CTHM will interpret sensor and instrument outputs, correlate them to a machine's condition, provide interpretative analyses, project servicing intervals, and estimate remaining component life. In addition, it will enable real-time anomaly detection and diagnostics of performance and mechanical faults, enabling power producers to more accurately predict critical component remaining useful life and turbine degradation.

Project Objective

The objective of the proposed project is to develop new monitoring techniques for CT power generation in simple or combined-cycle configurations aimed at improving reliability, availability and maintainability (RAM) and overall performance/capacity factor. The project team will develop advanced, probabilistic and artificially intelligent performance and mechanical fault diagnostics algorithms, sensor validation and recovery modules, as well as prognostics for maintenance-intensive CT areas. The objective stated above will be achieved via the following tasks:

Task 1: Sensor validation, recovery virtual sensor module
Task 2: CT/CC performance diagnosis and prognostics

Task 3: CT/CC combustion process diagnostics.
Task 4: CT/CC stall detection and surge margin risk assessment
Task 5: CT/CC mechanical anomaly detection and fault pattern diagnostics
Task 6: CT/CC life limiting component prognostics
Task 7: CT/CC database management and health management integration
Task 8: Field validation
Task 9: Project management and reporting

Conferences and Publications

- A Kick-off Meeting with DOE was held in Pittsburgh, PA on December 17, 2001. EPRI, Impact Technologies, Boyce Engineering, and Progress Energy were represented at the meeting.
- EPRI attended the "Next Generation Turbine and Condition Monitoring Conference" held at Galveston Texas on February 25- 27, 2002. EPRI presented a program summary at this conference.
- EPRI attended the "Power-Gen International Conference" held at Orlando, Florida on December 11- 14, 2002. EPRI presented a program summary at this conference.
- The Sensor Validation Module (SVM) demonstrated and reviewed at Progress Energy's Raleigh headquarters February 2003.
- EPRI attended the "International Gas Turbine Institute Conference" held at Atlanta, Georgia on June 11- 14, 2003. EPRI presented a program summary at this conference.
- EPRI attended the "CAM-GT Conference" held at Brussels, Belgium on July 11- 14, 2003. EPRI presented a program summary at this conference
- A Progress Review Meeting with DOE was held in Pittsburgh, PA on August 8, 2003. EPRI, Impact Technologies, Boyce Engineering, and Fern Engineering were represented at the meeting. The progress to date was accessed and found satisfactory by the DOE personnel. Suggestions by DOE personnel with regard to the relevancy to IGCC applications were well received and have been incorporated in the program.

Status

Activities during the current period of performance initially focused on "recovery" of signals from failed sensors. "Sensor recovery" refers to the capability being built into the SVM that infers (through trained parameter correlations) parameter values for signals identified as malfunctioning. Primary focus was placed on the development of a set of Neural Networks that can predict all key gas path parameters utilizing correlated parameter data.

The addition of the sensor recovery feature enables the health diagnostics modules being developed to utilize suggested substitute parameter values upon identification of an anomalous sensed value. To this end, the development during this period of performance has been creation of the artificial intelligence networks necessary to predict parameter values given the current operating state. Each individual parameter requiring recoverability must have a corresponding neural network developed. The neural networks developed utilize three or four inputs that are used by the network to define the current level of operation. 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 current output value that can be used to replace the detected anomalous sensor output.

Development was concluded on the integrated Sensor Validation and Recovery Module (SVRM) in preparation for delivery on June 30 and on-site beta testing at Progress Energy's Asheville CT location. Development subsequently concentrated on integration of SVRM with the performance degradation module.

The Performance Degradation Module (PDM) consists of two Microsoft Excel spreadsheet-based performance-monitoring programs, one for analyzing simple cycle combustion turbine performance (CTPDM) and the other for overall combined cycle (CCPDM) plant performance analysis. Both programs are capable of being linked real-time to plant operating data via third-party data historian software and can be set up to run automatically at user-specified intervals to create a continuous record of key performance indicators. These indicators include both actual and expected performance parameters such as compressor efficiency and overall plant or gas turbine power output. These parameters are trended using pre-configured graphs in Excel to allow the user to quickly identify areas of degradation. The programs are capable of monitoring performance over the full range of plant operation including part-load and can also monitor gas turbines running on syngas for IGCC operation.

Development was concluded on the combustion turbine performance degradation module (CTPDM) in preparation for delivery on September 30 and on-site beta testing at Progress Energy's Asheville CT location. The combined cycle performance degradation module (CCPDM) with two 7FA gas turbines has been installed and is undergoing field testing at the Arthur von Rosenberg power plant owned by City Public Service of San Antonio, Texas.

The final focus of effort during this period of development has centered on refining the SVRM. Issues which had previously been identified and which arose during beta testing were addressed. Some of the improvements made include adding the capability: to e-mail results of analyses conducted in the "Interactive Analysis" mode as well as "Batch Analysis" mode, to add and delete sensors from the SVRM main window, to define the duration and frequency of the data examined when using the "Batch Analysis" mode and to define the time period when using the "Interactive Analysis" mode using a much mode intuitive and user-friendly dialogue box.

Approach

Introduction

Power generators are concerned with the maintenance costs associated with the advanced turbines that they are purchasing. Since these machines do not have fully established operation and maintenance (O&M) track records, power generators face financial risk due to uncertain future maintenance costs. This risk is of particular concern, as the electricity industry transitions to a competitive business environment in which unexpected O&M costs cannot be passed through to consumers.

These concerns have accelerated the need for intelligent software-based diagnostic systems that can monitor the health of a combustion turbine in real time and provide valuable information on the machine's performance to its owner/operators. Such systems would interpret sensor and instrument outputs, correlate them to the machine's condition, provide interpretative analyses, forward projections of servicing intervals, estimate remaining component life, and identify faults.

EPRI, Impact Technologies, Boyce Engineering, and Progress Energy have teamed to develop a suite of intelligent software tools integrated with a diagnostic monitoring platform that will, in real time, interpret data to assess the "total health" of combustion turbines. The Combustion Turbine Health Management System (CTHM) will consist of a series of dynamic link library (DLL) programs residing on a diagnostic monitoring platform that accepts turbine health data from existing monitoring instrumentation.

The CTHM system will be a significant improvement over currently available techniques for turbine monitoring and diagnostics. CTHM will interpret sensor and instrument outputs, correlate them to a machine's condition, provide interpretative analyses, project servicing intervals, and estimate remaining component life. In addition, it will enable real-time anomaly detection and diagnostics of performance and mechanical faults, enabling power producers to more accurately predict critical component remaining useful life and turbine degradation.

Program Goals, Research Objectives and Project Objectives

The goal of this proposed project is to improve the reliability, availability and maintainability (RAM) and overall performance/capacity factor of combustion turbines by developing advanced health monitoring and management techniques. The objective is to develop a suite of intelligent software tools integrated with a diagnostic monitoring platform that will, in real time, interpret data to assess the "total health" of combustion turbines.

Methodology

The project team will apply and adapt know-how developed under prior DOD/Navy/NASA programs aimed at advanced health monitoring of aviation gas turbines. The project team will develop advanced probabilistic and artificially intelligent performance and mechanical fault diagnostics algorithms, sensory validation and recovery modules, and prognostics for maintenance-intensive CT areas.

Description of the Technology

The Combustion Turbine Health Management System (CTHM) will consist of a series of dynamic link library (DLL) programs residing on a diagnostic monitoring platform that accepts turbine health data from existing monitoring instrumentation. The real-time CTHM application algorithms proposed are intended to produce a comprehensive array of intelligent tools for assessing the "total health" of a combustion turbine, both mechanically and thermodynamically. CTHM 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.

Advanced signal processing algorithms utilizing correlation and coherence detection are combined with artificial intelligence and model-based algorithms to provide comprehensive coverage of the critical CT failure modes of interest. Prognostic algorithms have also been developed that accept diagnostic system results, model-based remaining useful life predictions, operating/maintenance histories and historical RAM data to provide real-time predictions on reliability and degraded performance of key CT components. Through proper utilization of these health management technologies, timely decisions can be made regarding unit operation and maintenance practices.

The neural network algorithm operates by comparing the physical relationships between signals as determined from either a baseline empirical model or computer model of 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, signal correlation and special digital filters are used to determine if even small levels of noise are present on a particular signal. These approaches are implemented in parallel and then combined in a probabilistic data fusion process that determines the final confidence levels that a particular sensor has either failed or has suspect operation.

The integration of prognostic technologies within existing diagnostic systems begins with validated sensor information on the engine being fed directly into the diagnostic algorithms for fault detection/isolation and classification. The ability of an enhanced diagnostic system to fuse information from multiple diagnostic sources together to provide a more confident diagnosis is emphasized along with a system's ability to estimate confidence and severity levels associated with a particular diagnosis. In a parallel mode, the validated sensor data and real-time current/past diagnostic information is utilized by the prognostic modules to predict future time-to-failure, failure rates and/or degraded engine condition (i.e., vibration alarm limits, performance margins, etc.). The prognostic modules will utilize physics-based, stochastic models taking into account randomness in operation profiles, extreme operating events and component forcing. In addition, the diagnostic results will be combined with past history information to train real-time algorithms (such as neural networks or real-time probabilistic models) to continuously update the projections on remaining life. The specific approaches and algorithms for determining these component prognostic results are described in this proposal.

Once predictions of time-to-failure or degraded condition are determined with associated confidence bounds, the prognostic failure distribution projections can be used in a risk-based analysis to optimize the time for performing specific maintenance tasks. A process that examines the expected value between performing maintenance on an engine or component at the next opportunity (therefore reducing risk but at a cost of doing the maintenance) versus delaying maintenance action (potential continued increased risk but delaying maintenance cost) can be used for this purpose.

The difference in risk between the two maintenance or operating scenarios and associated consequential and fixed costs can then be used to optimize the maintenance intervals or alter operational plans. As key aspect of the proposed technical approach, this project will tap a unique resource of engine fault data developed under the Navy and Air Force with its resulting diagnostic knowledge base. This test cell engine fault data is unavailable for heavy frame machines and will require many machine-operating years to duplicate. The project substantially reduces its development costs and subsequent field validation by using experts and limited land-based CT data to modify the existing flight engine diagnostic database.

Anticipated Benefits

There is a great opportunity for power generation combustion turbines to become more reliable, operationally available and economically maintained through the use of enhanced diagnostic and prognostic strategies such as those presented in this proposal. The development and integration of enhanced diagnostic and prognostic algorithms that can predict, within a specified confidence bound, time-to-failure of critical engine components can provide many benefits including:

- Reduced overall life cycle costs of engines from installation to retirement
- Ability to optimize maintenance intervals for specific engines or fleets of engines and prioritization of tasks to be performed during the planned maintenance events
- Increased up-time/availability of all engines within a fleet
- Provides engineering justification for scheduling maintenance actions with corresponding economic benefits clearly identifiable
- Improved safety associated with operating and maintaining combustion turbine engines

The maintenance outage factors for the F/FA frame and the mature frame technology are significantly divergent, with CT core systems being the primary drivers with outage factors of 10.074% and 5.080%, respectively. The core combustion turbine system problems can be attributed to new-design introduction centered on inherent design flaws, manufacturing/assembly problems, and the combustion system. These design break-in issues will eventually be supplanted by service-imposed mechanical/electrical degradation and outage assembly problems. Diagnostic monitoring as an integral component of a proactive maintenance program should certainly meet mature fleet RAM performance. By avoidance of serious damage and improved maintenance scheduling, 2% availability points are achievable.

For each 500 MW combined cycle, this improvement represents 72,000 MWhr valued at $3M per year. For a 100 unit combined cycle fleet, or approximately half of the 30 GW new generation projected, a $300M per year cost-avoidance savings appears achievable.

DOE has long played an essential role in bringing high performance CTs with its enabling metallurgy into the U.S. generation mix. The higher performance and fuel savings certainly offset the higher maintenance costs when compared to conventional CTs. Yet concerns exist about the overall RAM capability of the fleet in light of shrinking reserve margins and higher gas prices. With DOE and EPRI, important maintenance engineering and management tools can be delivered on a timely basis that would otherwise take an additional 5 years to deliver.

These tools would be made available to all CT operators regardless of their EPRI membership status and direct contributions. Since all operators routinely calculate life consumption and perform hot section NDE, the introduction of new and improved validated methods will readily find acceptance with plant engineers and maintenance planners. Training courses and software maintenance fees would further support the expanded application and periodic necessary updating.

Discussion

The prior semi-annual report reviewed the completion of the beta version of the Sensor Validation Module (SVM). The SVM was demonstrated and discussed at Progress Energy's Raleigh headquarters in early-February 2003. This report focuses on "recovery" of signals from failed sensors, the development of an integrated sensor validation and recovery module (SVRM), and the subsequent development and integration of the SVRM with the performance degradation module.

During this report period the integrated Sensor Validation and Recovery Module (SVRM) was delivered on June 30,2003 for on-site beta testing at Progress Energy's Asheville CT location. Also, development was concluded on the Combustion Turbine Performance Degradation Module (CTPDM) in preparation for delivery on September 30, 2003 and on-site beta testing at Progress Energy's Asheville CT location. The Combined Cycle Performance Degradation Module (CCPDM) with two 7FA gas turbines has been installed and is undergoing field testing at the Arthur von Rosenberg power plant owned by City Public Service of San Antonio, Texas.

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Neural Network Developments

Two types of networks have been evaluated for use in the Sensor Validation/Recovery Module. Feed-forward, back propagating networks, discussed in the previous status report, have been found to give very good results and are widely accepted for use in function approximation applications. A second type of neural network, generalized regression neural network (GRNN), is also often used for function approximation. The GRNN has particularly good qualities with respect to generalization based on scatter I the training data.

Generalized Regression Neural Networks[1]

General Regression Neural Networks (GRNN) are a specialized form of a *Radial Basis Function* neural network. Radial basis function (RBF) networks may require more neurons than standard feed-forward back propagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available.

Neuron Model

Figure 1 illustrates a radial basis network with *R* inputs.

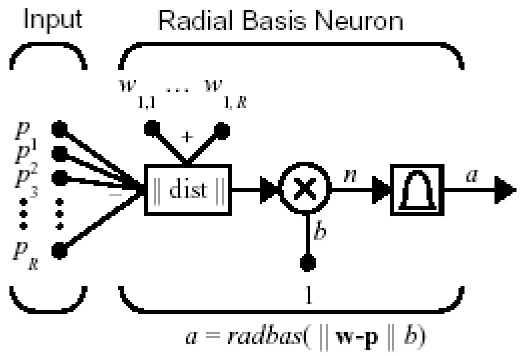

Figure 1 – Model of a Radial Basis Neuron

The inputs to the radial basis transfer function is the vector distance between its weight vector **w** and the input vector **p**, multiplied by the bias *b*. (The box in Figure 1 accepts the input vector **p** and the single row input weight matrix, and produces the dot product of the two.) The transfer function for a radial basis neuron is:

$$radbas(n) = e^{-n^2}$$

Figure 2 is a plot of the radial basis transfer function.

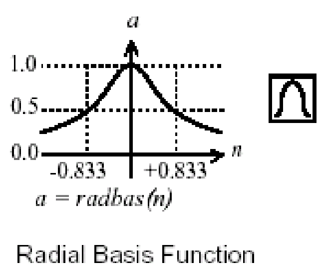

Figure 2 – Radial Basis Transfer Function

The radial basis function has a maximum of 1 when its input is 0. As the distance between **w** and **p** decreases, the output increases. Thus, a radial basis neuron acts as a detector that produces 1 whenever the input **p** is identical to its weight vector **p**. The bias *b* allows the sensitivity of the radial basis neuron to be adjusted. For example, if a neuron had a bias of 0.1 it would output 0.5 for any input vector **p** at vector distance of 8.326 (0.8326/*b*) from its weight vector **w**.

Network Architecture

Radial basis networks consist of two layers: a hidden radial basis layer of Q neurons (the number of input sets presented to the network), and an output linear layer, as shown in Figure 3. The box in this figure accepts the input vector **p** and the input weight matrix $\mathbf{IW}_{1,1}$, and produces a vector having Q elements. The elements are the distances between the input vector and vectors $_i\mathbf{IW}_{1,1}$ formed from the rows of the input weight matrix. The bias vector $\mathbf{b}_1$ and the output of are combined via element-by-element multiplication.

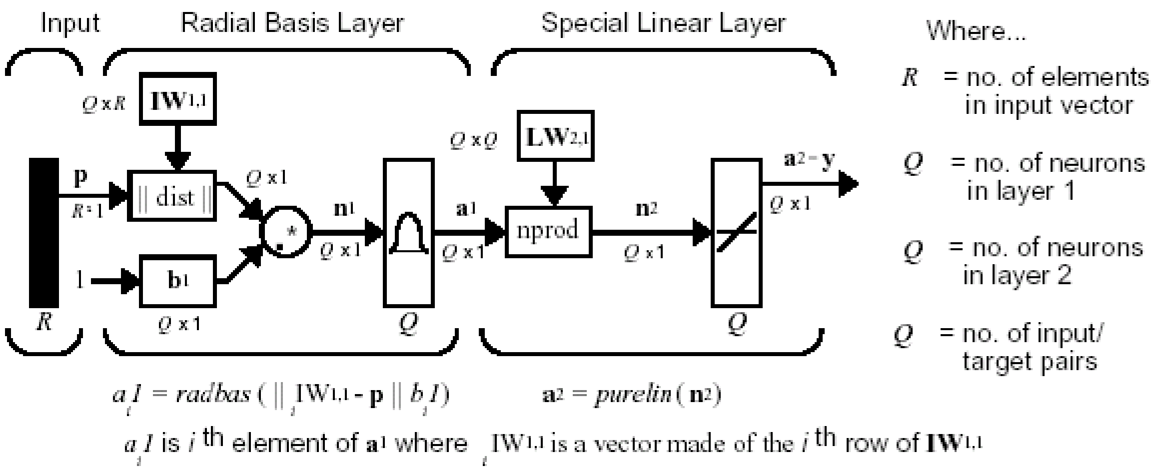

Figure 3 – Architecture of a Generalized Regression Network

Here the **nprod** box shown above produces Q elements in vector $\mathbf{n}_2$. Each element is the dot product of a row of $LW_{2,1}$ and the input vector $\mathbf{a}_1$, all normalized by the sum of the elements of $\mathbf{a}_1$.

We can understand how this network behaves by following an input vector **p** through the network to the output $\mathbf{a}_2$. If we present an input vector to such a network, each neuron in the radial basis layer will output a value according to how close the input vector is to each neuron's weight vector. Thus, radial basis neurons with weight vectors is quite different from the input vector **p**, which will have outputs near zero. These small outputs have only a negligible effect on the linear output neurons.

In contrast, a radial basis neuron with a weight vector close to the input vector **p** produces a value near 1. If a neuron has an output of 1 its output weights in the second layer pass their values to the linear neurons in the second layer. In fact, if only one radial basis neuron had an output of 1, and all others had outputs of 0's (or very close to 0), the output of the linear layer would be the active neuron's output weights. This would, however, be an extreme case. Typically several neurons are always firing, to varying degrees.

Examining the first layer, each neuron's weighted input is the distance between the input vector and its weight vector. Each neuron's net input is the element-by-element product of its weighted input with its bias. Each neuron's output is its net input passed through the radial basis transfer function. If a neuron's weight vector is equal to the input vector (transposed), its weighted input is 0, its net input is 0, and its output is 1. If a neuron's weight vector is a distance of spread from the input vector, its weighted input is spread, its net input is sqrt(-log(.5)) (or 0.8326), therefore its output is 0.5. The second layer also has as many neurons as input/target vectors, but here LW{2,1} is set to the target array from the training set.

A larger spread (associated with the radial basis functions) leads to a large area around the input vector where layer 1 neurons will respond with significant outputs. Therefore, if the spread is small, the radial basis function is very steep so that the neuron with the weight vector closest to the input will have a much larger output than other neurons. The network will tend to respond with the target vector associated with the nearest design input vector. As the spread gets larger, the radial basis function's slope gets smoother and several neurons may respond to the input vector. The network then acts like it is taking a weighted average between target vectors whose design input vectors are closest to the new input vector. As spread gets larger more and more neurons contribute to the average with the result that the network function becomes smoother.

Neural Network Results

The decision concerning which type of network to use was based on accuracy of the resultant prediction, speed of execution and size of the networks. Based on these metrics, the generalized regression neural networks were selected as the best neural network type for implementation in the sensor validation/recovery module. Though the GRNN has many more nodes in the developed networks than the feed-forward networks, their speed of execution was much faster, with the results being comparable for each as shown in Figure 5.

Table 1 contains a list of the networks, which have been developed for implementation in the sensor validation/recovery module. Each network utilizes four, highly correlated input parameters with the exception of the inlet guide vane (CSRGV) sensor, which only utilizes three.

Table 1 -- List of Neural Networks Employed by the SVRM

Output	Inputs
CPD	CTD DWATT FQG or FQLM1 TTXD1_18
CSRGV	DWATT TNH WQ

Output	Inputs
CTD	CPD TTXD1_7 TTXD1_13 TTXD1_22
DWATT	FQG or FQLM1 TTXD1_12 TTXD1_18 TTXD1_27
FQG	TTXD1_5 TTXD1_11 TTXD1_17 TTXD1_26
FQLM1	TTXD1_4 TTXD1_10 TTXD1_16 TTXD1_25
FTG	TTXD1_3 TTXD1_9 TTXD1_15 TTXD1_24
TNH	TTXD1_2 TTXD1_8 TTXD1_14 TTXD1_23
TTXD1_*	TTXD1_1 TTXD1_7 TTXD1_13 TTXD1_22
WQ	DWATT TTXD1_5 TTXD1_14 TTXD1_19

Each parameter requires two separate networks, since the characteristic behavior of the parameters varies depending on the fuel used, natural gas or liquid. Figure 4 illustrates this difference for the corrected compressor discharge temperature. There are clearly two paths followed by the data as it progresses through the lower regions of the generator output power range. Compressor discharge temperature increases along a first order track throughout the entire range of operation when burning natural gas fuel. In contrast, a different track is shown for compressor discharge temperature corresponding to generator output loads of 65 MW to 90 MW when the fuel selection is liquid.

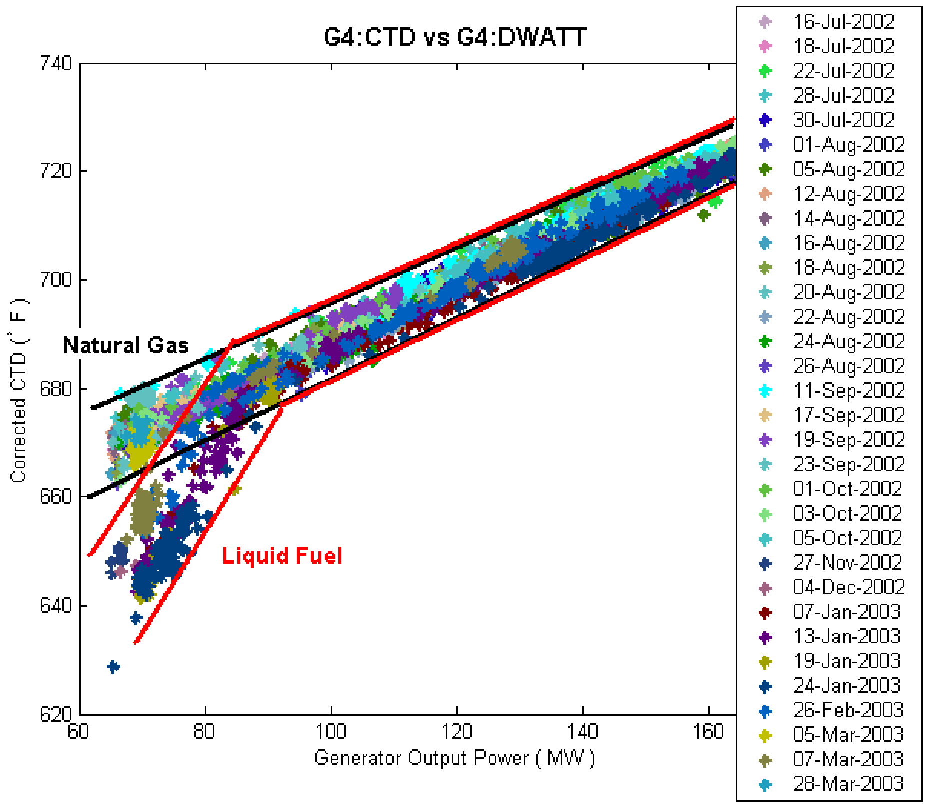

Figure 4 – Illustration of Variation in Corrected Compressor Discharge Pressure Due to Fuel Selection

Figure 5 shows a comparison of the results obtained from the two types of neural networks examined. In this study, each network was trained on the identical set of training data. The training data was obtained from five sequential passes through the data available for days the CT units ran on the respective fuel type. On each pass, random data was extracted in an effort to fully cover the expected range of values experienced by each parameter during operation. The results shown are from a test set of data, approximately 2100 points long, extracted from typical operation. The data was first corrected to standard day atmospheric conditions and then input into the two networks. Both networks show very good prediction of parameter values. For the results shown, the feed-forward, back-prop network required 3.06 seconds while the GRNN required only 1.62 seconds. The size of the feed-forward, back-prop network was only 36 KB compared to the 168 KB size of the GRNN due to the size of the training file defining the number of nodes contained in the GRNN.

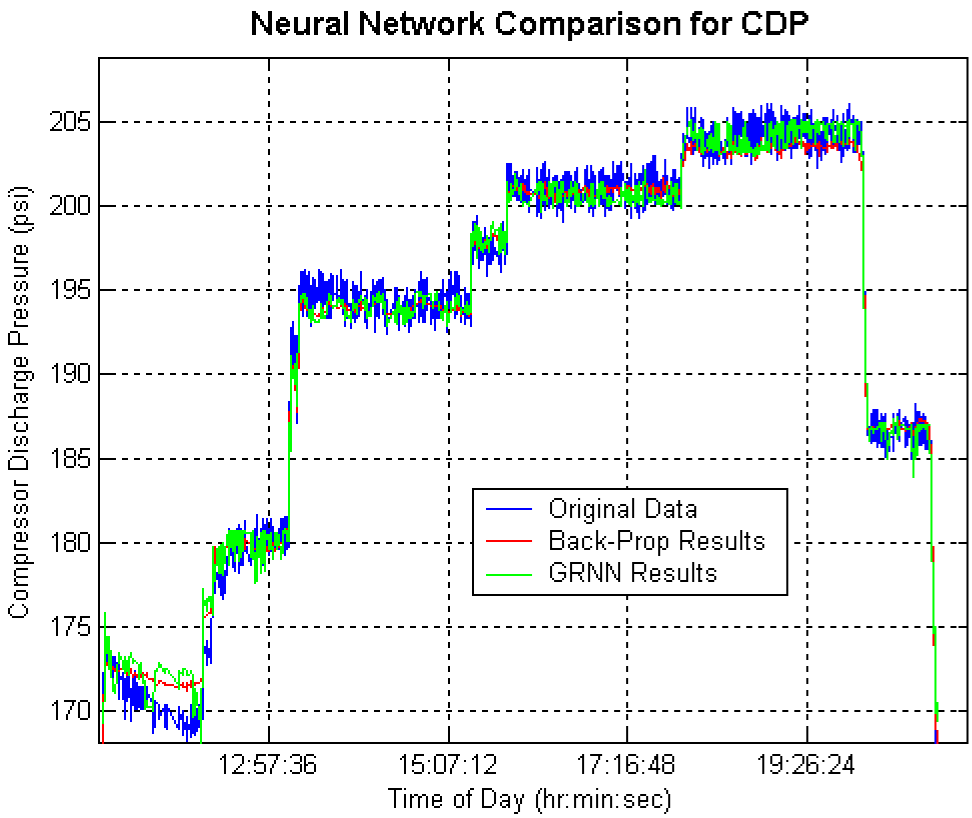

Figure 5 – Results Obtained from Test Case Submitted to GRNN Designed for Compressor Discharge Pressure

Data Flow Modifications

The identification of data recovery as a desired feature of the sensor validation module has necessitated changes in the handling of the data obtained from the PI Historian. Generic signal processing techniques do not require pre-processing steps, only the presentation of data. However, model-based approaches, which capture the underlying physics of the CT unit's operation, require pre-processing steps to eliminate the variability encountered, which is not attributable to the unit's physical operation. Supporting parameters, 'AFPAP', 'AFPCS', 'CMHUM' and 'CTIM', necessary for correcting the desired parameters to standard day conditions are queried and uploaded first for utilization in the pre-processing step of the model-based evaluation. Prior to the addition of the neural networks, parameters being evaluated by the model-based approach were queried, missing data replaced, corrected to standard day conditions before finally being validated utilizing the operating signature curves. Each step was done to completion, for each parameter, before the next parameter was queried.

The introduction of neural networks as a replacement to the operating signature curves has required that the data handling approach utilized within the model-based validation algorithm be re-written. Due to the change in input requirements of the neural networks, each one requiring up to four inputs, all the parameters to be validated will be obtained prior to calling the actual validation algorithm. Subsequent steps will then replace values lost during compression via an interpolation process and correct all parameter values to standard day conditions. Corrected parameter values are then utilized as input to the neural networks to determine the expected values of the parameter being validated. A comparison is given below outlining the differences in the data flow between the signature curve based approach and the neural network based approach.

Signature Curve Model-Based Pre-Processing:

- Support data uploaded from PI Historian
- Individual parameters being validated are obtained from the PI Historian
- Values lost during compression are replaced via interpolation
- Individual parameter's values are corrected to standard day conditions
- Parameter values validated utilizing operating signature curves

Neural Network Model-Based Pre-Processing:

- Support data uploaded from PI Historian
- All Parameters being validated are uploaded from PI Historian
- Values lost during compression are replaced via non-linear interpolation
- All parameter values are corrected to standard day conditions
- Parameter values are input to the neural networks and the parameter in question is predicted and validated utilizing the neural networks

Neural Network Revisions

The development of neural networks was revisited in an effort to modify the parameters designated as inputs to the networks. Selection of network inputs can be based on many different criteria, such as sensitivity, efficiency, robustness or a priori knowledge of the system, so long as a correlation exists between the inputs and outputs. The new approach chosen for selection of the inputs to the networks is based on knowledge of the system.

Table 1 contains a list of the networks which have been developed for implementation in the sensor validation/recovery module. The inputs listed below represent the voted value obtained from the PI Historian. Each network has five input parameters with the exception of the exhaust gas temperature network which utilizes six inputs and the NOX water flow network which uses four. It is also noteworthy that all the networks being developed, with the exception of the compressor inlet pressure and temperature networks are using inputs corrected to ISO standard day conditions with corrections for temperature, pressure and humidity. The compressor inlet neural networks utilize data before it is corrected. We know correcting data to ISO standard day conditions removes the effects that ambient conditions have on parameter values during operation of the unit. Correcting the data to ISO standard day before inputting it to these networks would remove the very effects embedded in the data which must be exploited to reliably predict the compressor inlet conditions.

Table 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
COMPRESSOR INLET PRESSURE	• COMPRESSOR DISCHARGE PRESSURE • COMPRESSOR DISCHARGE TEMPERATURE • GENERATOR OUTPUT POWER • GAS OR LIQUID FUEL FLOW • EXHAUST GAS TEMPERATURE
COMPRESSOR INLET TEMPERATURE	• COMPRESSOR DISCHARGE PRESSURE • COMPRESSOR DISCHARGE TEMPERATURE • GENERATOR OUTPUT POWER • GAS OR LIQUID FUEL FLOW • EXHAUST GAS TEMPERATURE
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.

SVRM Architecture

Here we will attempt to address any remaining questions concerning the architecture of the SVRM. The discussion will start with the manner in which the sensor validation and recovery module queries the PI Historian and move on to how it subsequently deals with the data.

As a result of discussions held with personnel at the Asheville sight, the module is being set up to run at 1:00 A.M. during off-peak hours of the computer network at the Asheville site. A timer is set off to initiate the PI Historian querying process. The process of data gathering begins with a command to query the tag *DWATT* (Generator Output Power) over the preceding twenty-four hour period. The *L1X* results are scanned for the "PERMISSIVE" string. A subsequent command is placed to query the values for the tag *STATUS_FLD* (Status Field) during the same time period. Here, the sought after result is "ON COOLDOWN". Results obtained from these two queries are combined in determining the starting and stopping times for the periods during which the CT units were operational. This is accomplished by sorting the "PERMISSIVE" and the "ON COOLDOWN" values based upon their associated timestamps. If possible, each occurrence of a "PERMISSIVE" is paired with an "ON COOLDOWN" such that the timestamps are sequential. These values are then used to define periods of operation, basically from the start of rotation to the end of rotation. In the event that the operating period exceeds the twenty-four hour window and thus no corresponding "ON COOLDOWN" is obtained for a current and active permissive, the sensor validation and recovery module will perform its analysis on the data available provided the unit has achieved a sufficient level of operation. Here "sufficient level of operation" means the CT unit is running at full speed and the power output level of the generator is at or exceeds 65MW.

With the useful periods during which the CT units were operational determined, two queries are made of the *STATUS_FLD* within each period found. The first query is for "COMPLETE SEQ" which signals completion of the starting sequence. Second is a query for "MANUAL SHUTDOWN". This value flags initiation of shutdown. These two events bound the regions in the data where the CT unit has attained the "sufficient level of operation" defined above and are used to refine the search interval by replacing the previous start and stop times. In its current state the sensor validation and recovery module algorithms do not address 'start-up' and 'shutdown' operating modes. Data generated during these operating modes is simply overlooked at this time.

Once the search interval has been refined, tags of interest are queried and all the available data from the new time interval are attained. This data is then validated utilizing the techniques discussed in previous reports. Table 3 summarizes the capability of the current version of the sensor validation and recovery module.

Table 3 – Sensor Validation and Recovery Summary

Tag	Description	Validated	Recovered
AFPAP	Ambient Pressure	X	X
AFPCS	Inlet Filter Pressure Drop	X	
CMHUM	Specific Humidity	X	
CPD	Compressor Discharge Pressure	X	X
CSRGV	Variable Inlet Guide Vane	X	
CTD	Compressor Discharge Temperature	X	X
CTIM	Ambient Temp/Compressor Inlet Temperature	X	X
DWATT	Generator Output Power	X	X
FQG	Gas Fuel Flow	X	X

Tag	Description	Validated	Recovered
FQLM1	Liquid Fuel Flow	X	X
FTG	Gas Fuel Temperature	X	
RHUM	Relative Humidity	X	
TNH	Speed	X	
TTXD1_1	Exhaust Gas Temperature (position in array)	X	X
TTXD1_10	Exhaust Gas Temperature (position in array)	X	X
TTXD1_11	Exhaust Gas Temperature (position in array)	X	X
TTXD1_12	Exhaust Gas Temperature (position in array)	X	X
TTXD1_13	Exhaust Gas Temperature (position in array)	X	X
TTXD1_14	Exhaust Gas Temperature (position in array)	X	X
TTXD1_15	Exhaust Gas Temperature (position in array)	X	X
TTXD1_16	Exhaust Gas Temperature (position in array)	X	X
TTXD1_17	Exhaust Gas Temperature (position in array)	X	X
TTXD1_18	Exhaust Gas Temperature (position in array)	X	X
TTXD1_19	Exhaust Gas Temperature (position in array)	X	X
TTXD1_2	Exhaust Gas Temperature (position in array)	X	X
TTXD1_20	Exhaust Gas Temperature (position in array)	X	X
TTXD1_21	Exhaust Gas Temperature (position in array)	X	X
TTXD1_22	Exhaust Gas Temperature (position in array)	X	X
TTXD1_23	Exhaust Gas Temperature (position in array)	X	X
TTXD1_24	Exhaust Gas Temperature (position in array)	X	X
TTXD1_25	Exhaust Gas Temperature (position in array)	X	X
TTXD1_26	Exhaust Gas Temperature (position in array)	X	X
TTXD1_27	Exhaust Gas Temperature (position in array)	X	X
TTXD1_3	Exhaust Gas Temperature (position in array)	X	X
TTXD1_4	Exhaust Gas Temperature (position in array)	X	X
TTXD1_5	Exhaust Gas Temperature (position in array)	X	X

Tag	Description	Validated	Recovered
TTXD1_6	Exhaust Gas Temperature (position in array)	X	X
TTXD1_7	Exhaust Gas Temperature (position in array)	X	X
TTXD1_8	Exhaust Gas Temperature (position in array)	X	X
TTXD1_9	Exhaust Gas Temperature (position in array)	X	X
TTXM	Exhaust Gas Temperature voted value	X	X
WQ	NOX Water Flow	X	X

All sensors are made available to the generic signal processing techniques. The methodologies involved work irrespective of the current operating mode of the CT unit within the range of operation currently being targeted, i.e. turbine running at full speed and the generator outputting a load between 65 MW and 170 MW. The hysteretic effects of rapidly occurring transients have been determined to be a secondary consideration currently not requiring special attention within the scope of sensor validation and recovery. Please refer to Status Report #4 for the complete discussion of the work done examining hysteretic effects. The digital high pass filter has been developed such that only physically impossible transients are able to pass through and be evaluated. This allows the effectiveness of the high-pass filter technique to work regardless of the operating mode.

Implementation of the model-based techniques is also independent of the operating mode of the CT unit within the operating range defined above. 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 and the operating signature curves 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 6 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 7 and Figure 8 illustrate magnified views of two transient events encountered during operation. Figure 7 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 8 illustrate a sharp transient. Again, the neural network does an excellent job of approximating the desired compressor discharge temperature values.

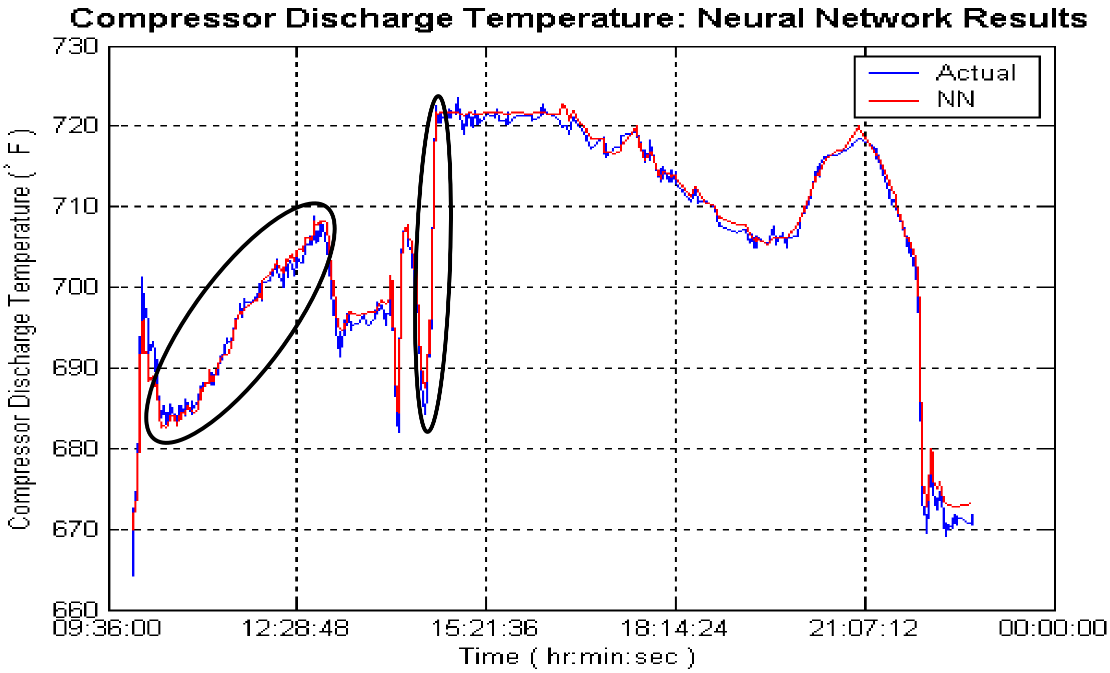

Figure 6 – Sample Neural Network Results for Compressor Discharge Pressure

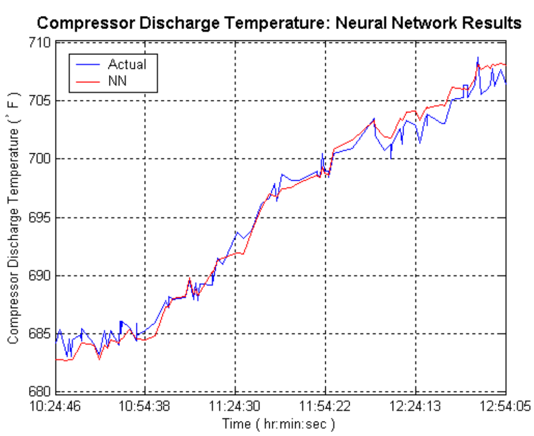

Figure 7 – Neural Network Results Tracking a Gradual Transient

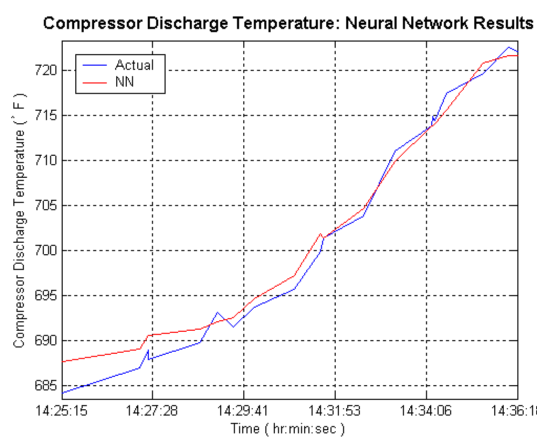

Figure 8 – Neural Network Results Tracking a Steep Transient

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 differ between the two fuel types (see Status Report #12). 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.

SVRM Beta Release

The Sensor Validation and Recovery Module has been completed and delivered. The main screen the user sees when activating the module is shown in Figure 9. Each of the sensors are listed along with fields for sensor condition, 'COND:', number of errors found, 'ERR(#):, severity of the errors found, 'ERR(sev):' and a viewing option in the form of a pushbutton (see February 2003 Status Repot for a detailed discussion of each of these).

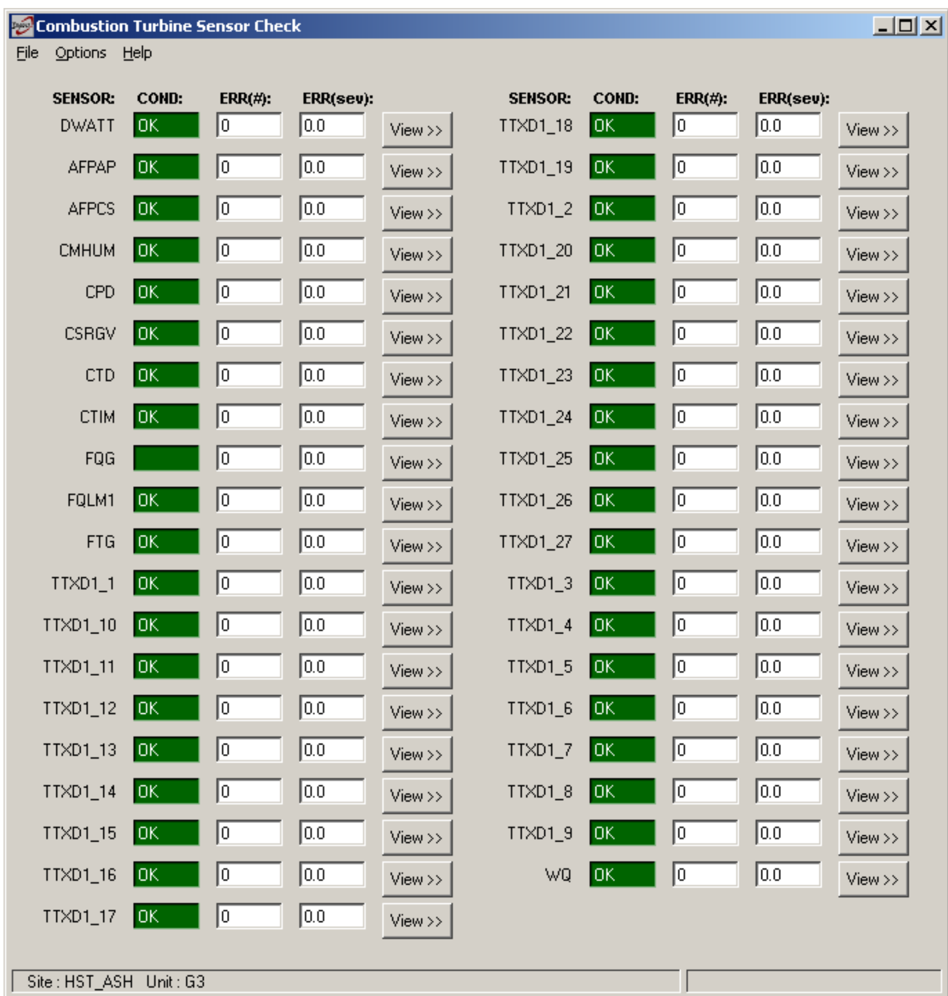

Figure 9 – SVRM Main Screen

User-defined Analysis Period

The Sensor Validation and Recovery Module is now has two modes of operation. First, the default automated mode which executes daily at midnight and analyzes the previous twenty-four hours of data. Second, the ‘User Defined Time Period’ mode which allows the user to specify any time interval at least one hour long and not exceeding twenty-four hours long. The period must also lie within the past seven days from the current user time. A dialogue box, shown in Figure 10 is supplied to assist the user in defining the interval. To validate and recover sensor readings from a selected period of time the user merely specifies the starting time and ending time using the dialogue box shown in Figure 10. The Historian is queried and data is provided at 1 Hz, the sampling frequency over the range of the desired time period. The methodology described here greatly simplified the procedure for obtaining the data, however, issues arose relevant to the limitations of Excel in handling larger amounts of data. The limitations of Excel were overcome by retrieving the data is several pieces of a manageable size.

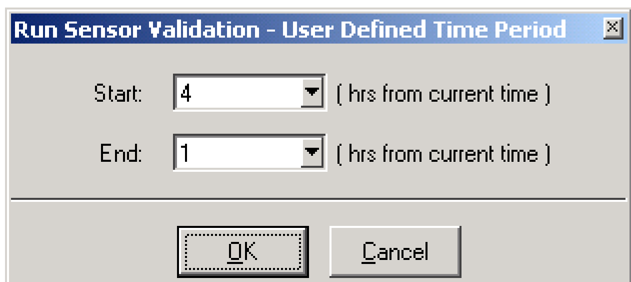

Figure 10 -- User Defined Time Period Dialogue Box

VPN Timeout

The eventual end-user of the CT Diagnostic Health Monitoring program will likely be accessing the plant’s PI Historian from within an internal network. However, access is also available to external sources utilizing a Virtual Private Network, VPN, connection established between the off-site computer and the on-site host computer. One of the issues facing developers was that the VPN disconnected itself, ‘*timed-out*’, after extended periods of no activity. This is not an issue if the only operating mode is the ‘User Defined Time Period’ mode. However, when the module runs in its pre-defined mode of querying the previous twenty-four hour period starting at midnight this becomes a problem. The ‘timed-out’ issue was resolved by setting up a timer within the SVRM which ‘pings’ the host’s IP address periodically. This is sufficient to keep the VPN active.

E-mail Notification

The SVRM has e-mailing capabilities in the event that anomalous data values are detected. In response to discussion with operators on-site, the SVRM has been equipped with an operating mode which enables it to run in the background, without requiring any attention. In the event that faulty data has been detected, the SVRM can be configured to e-mail an exception report to up to ten pre-selected addresses automatically alerting the recipients to the faulty values. At that time these individuals can make an assessment of the proper course of action. The e-mailing option is configured as follows:

1. Open ***Windows Explorer***
2. Locate the file, ***C:\Program Files\SVRM\win32-ix86\bin\svm.ini***
3. Ensure that file reads *'EMAIL_RESULTS 1'*, setting this to *'EMAIL_RESULTS 0'* disables the e-mailing capability.
4. Specify the e-mail addresses using the format: *'EMAIL_X Address'* where "X" is address number and "Address" the associated e-mail address as shown in the following example: *EMAIL_1 john.smith@abc_co.com*.
5. The SVRM module must be restarted for changes to take effect.

Example Results

Upon completion of an analysis the user has the option of viewing the underlying time series' of the various parameters. Figure 11 illustrates this capability. The user can also *zoom in* on a region for closer examination of the data as shown in Figure 12.

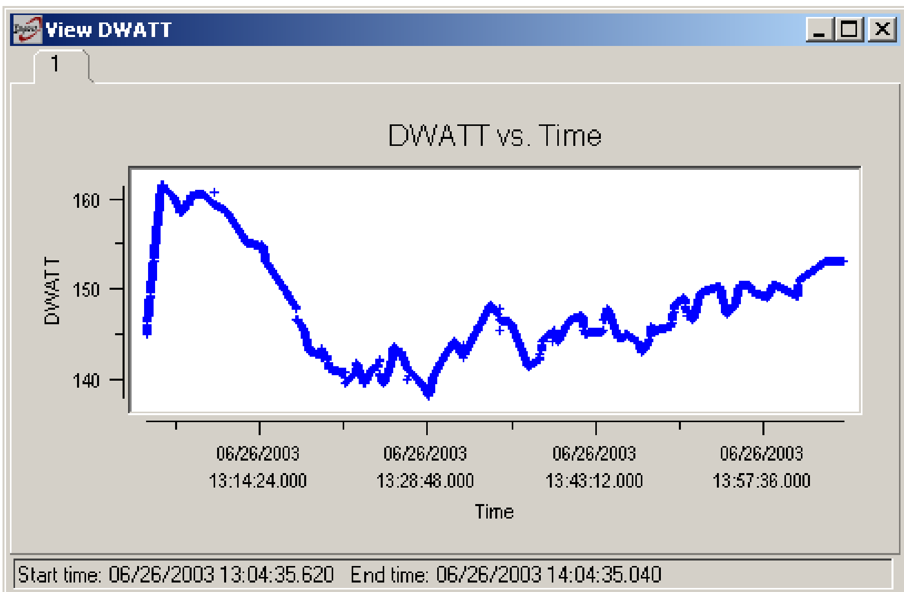

Figure 11 – Generator Output Time Series Viewed from SVRM

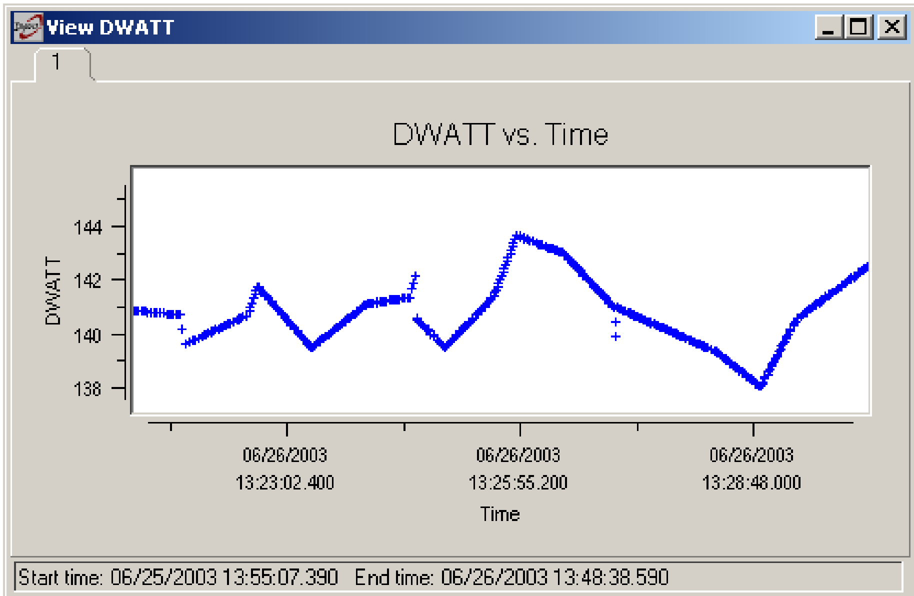

Figure 12 – Zoom Feature of the SVRM

In the event that a fault is found the erroneous point will be highlighted in red and if available a suggested replacement value will be shown in green. Numerous tests have been conducted and an example sensor fault is presented. Erroneous points have been detected in one of the thermocouple's data. The figures below illustrate the capabilities of the SVRM in detecting the noisy signal. The frame of reference is given in Figure 13 and Figure 14. They show that the CT unit is not actually going through the undulations depicted in the TTXD1_12 thermocouple output illustrated in Figure 15 and Figure 16.

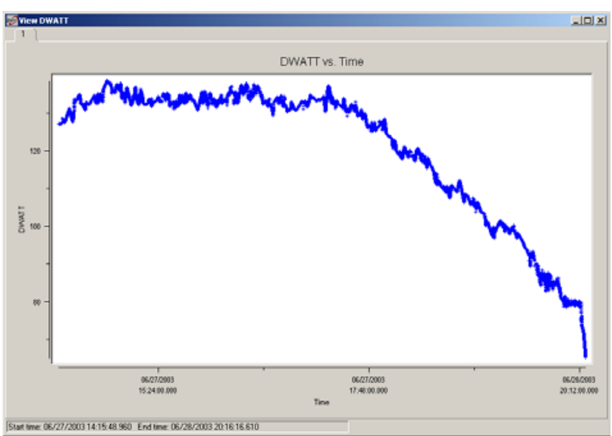

Figure 13 – Healthy Generator Output Sensor Data

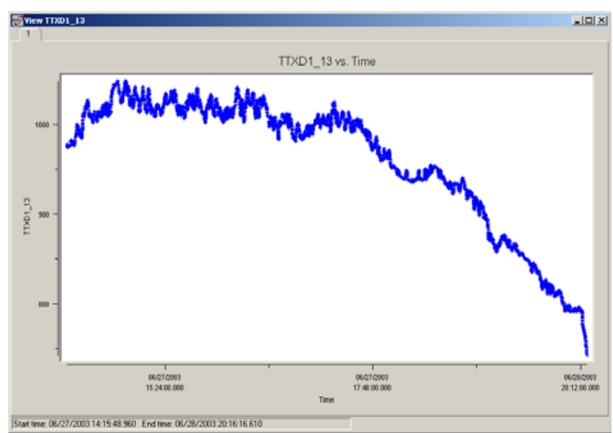

Figure 14 – Healthy Thermocouple Data for an Adjacent Thermocouple

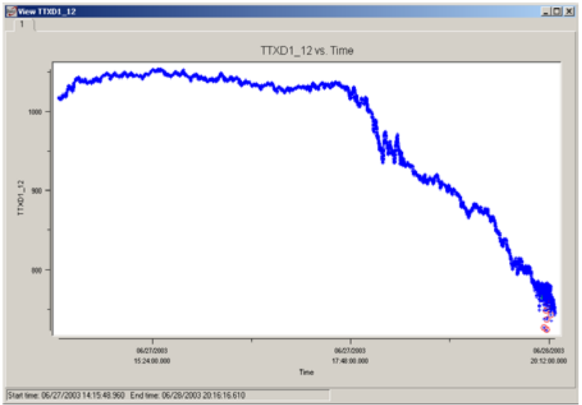

Figure 15 – Faulty Thermocouple Data Shown at the End of the Series

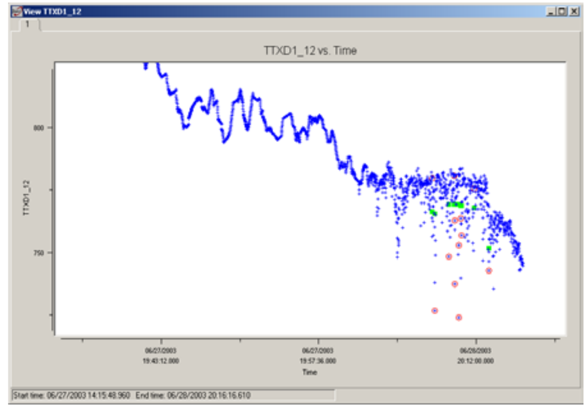

Figure 16 – Magnified View of Anomalous Thermocouple Data

The scatter of the data shown clearly increases to limits beyond reasonable values. The deviations are relatively small, but the generic signal processing algorithms detect several problems, and the recovery module provides proxy values. For larger deviations, more of the points would be identified as invalid by the neural networks and recovered, but we currently have the tolerance set fairly high to avoid false alarms. After more testing, the tolerance will be reduced to achieve even higher sensitivity.

SVRM/PDM

The Sensor Validation and Recovery Module in combination with the Performance Degradation Module (PDM) will provide personnel a comprehensive tool for assessing and monitoring CT and CC performance. Scheduled, periodic monitoring of the unit's performance will facilitate maintenance scheduling and aid in operational optimization.

The Sensor Validation and Recovery Module has been developed as a pre-processor for the performance module. The SVRM can accommodate either a user specified time period or will run in an automated mode which queries the previous day's data at a predefined time, currently midnight. The SVRM will query the plant historian for a predefined set of data obtained from key parameters. This data is then analyzed to determine if any anomalous values exist in the set. In the event an erroneous value has been detected, neural networks are utilized to obtain a replacement value more accurately reflecting the current state of operation of the CT unit. The data can then be passed to the CT performance module for evaluation.

The PDM Excel spreadsheet, which has been developed as a user interface to the PDM.DLL, can also accommodate a user-input mode as well as an "on-line", real time mode acquiring data directly from the CT plant's PI historian via OSIsoft's DataLink Excel add-in. Upon completion of the analysis, results are compiled on the supporting "*Results*" worksheet and shown on a series of graphs illustrating the many performance metrics calculated by the PDM within the Excel environment.

At this stage in the CT Diagnostic Health Monitoring program the objective is to combine the data querying and validating capabilities of the SVRM with performance analysis and trending ability of PDM to form a comprehensive analysis tool. Figure 17 illustrates the interaction of the plant instrumentation, the PI historian, SVRM and PDM. To accomplish the desired data exchange the appropriate cells of the "*Inputs*" spreadsheet within the PDM workbook will be populated with values represented the mean value exhibited by a parameter over some pre-defined period.

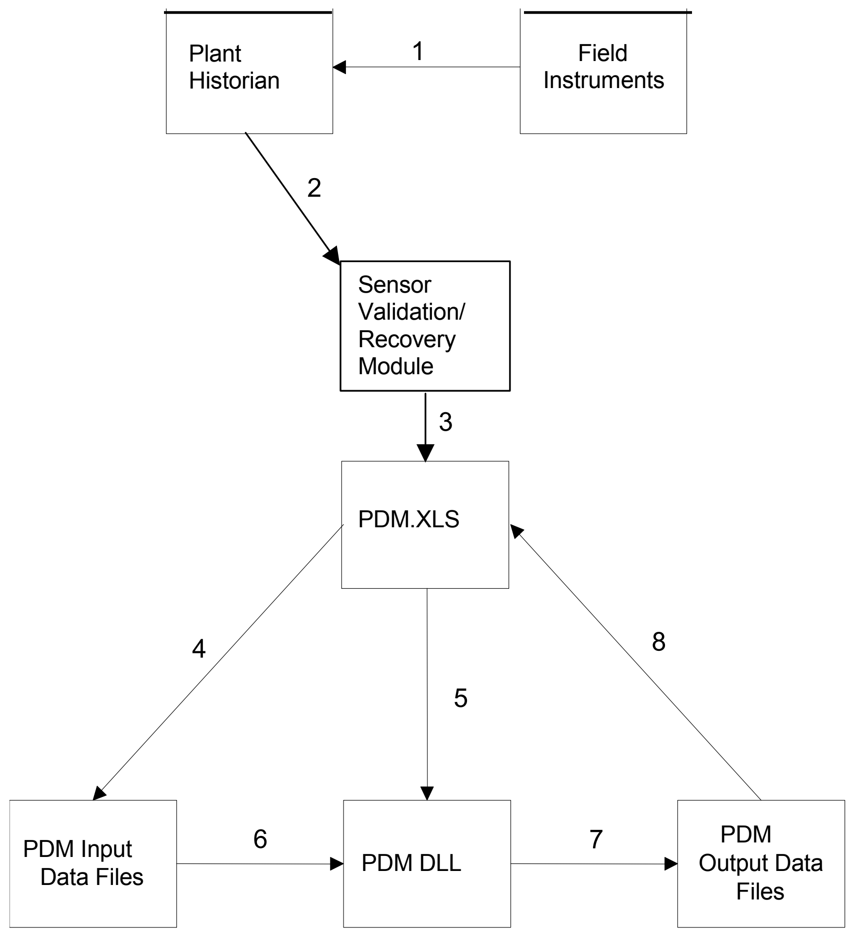

Figure 17 - Functional Flowchart Showing Interaction Between the SVRM, PDM DLL, the PDM.xls Excel Spreadsheet, and Combustion Turbine Instrumentation (Adapted from PDM Spreadsheet, Version 3, Computer Manual, Figure 1-1)

SVRM/PDM Integration

The functionality of the SVRM/PDM integration is designed to emulate a combination of the original PDM input methods, manual and on-line, in an automated fashion. When utilizing the "manual" input mode the user inputs values that characterize a period of performance directly into the appropriate cells of the "*Inputs*" worksheet. The performance analysis is initiated with a button press (*Click to Run PDM*). Results of the analysis are compiled on the "*Report*" worksheet. Upon review of the results the user can save them for trending purposes with another button press (*Save Results*). The results are then saved to the "*Results*" worksheet and subsequently the *Results.csv* file. The "on-line" mode of the worksheet was set up to initiate an analysis every ten minutes on the previous ten minutes of data in real-time. The OSIsoft DataLink querying functions (PICalcVal) embedded in the "*Inputs*" worksheet were configured to query the PI historian for ten minutes of data and subsequently calculate the mean value of the data just obtained. This mean value is then utilized by the .DLL in its performance analysis. The results are then automatically saved to the "*Results*" worksheet and subsequently the *Results.csv* file. A timing function advances the analysis starting time by ten minutes. When the clock reaches the new starting time a new analysis is initiated.

The PDM carries out five main functions when it is called by another program: data checking, actual performance, expected performance, corrected performance, and inlet cooling performance. The data checking function entails an evaluation of whether a complete set of input data is available and, if so, whether the data values make physical sense. (For example, if the compressor discharge temperature is colder than the compressor inlet temperature, an error message is issued and the calculation is not carried out.) However, the checks in place within PDM are very basic and are limited to determining whether values exceed possible physical thresholds and relative temperature and pressure checks.

The Sensor Validation and Recovery Module has been developed to act as a pre-processor for the data being submitted to PDM. To improve upon the basic "sanity check" of the data currently done by PDM, the SVRM validates the data values presented to the performance module are within expected levels given the current state of operation of the CT unit. In the event an anomalous value is detected, the SVRM provides a replacement value for use in the performance calculations.

The process begins with the definition of the time period being evaluated. As previously stated, the SVRM is capable of supporting a user-defined time period or an analysis of the previous twenty-four hours in its automated mode which is initiated by an internal timer. The selection of which sensors to query is based on the sensors required by the PDM.DLL. Figure 18 shows the PDM "Inputs" worksheet containing the parameters required to complete the analysis.

Table 4 has been included to clarify the source of the data that will be used, i.e. the parameter is a measured value with an actual sensor or it is a calculated parameter whose value is determined based on other parameter values or the parameter uses a default value.

Integration of the SVRM with PDM utilizes functionality from both input modes to form an automated hybrid. The sensor validation and recovery module will run on the desired set of data verifying that the parameter values are reasonable. This will result in a matrix of data, decompressed to the original sampling frequency of 1 Hz, with each row containing the "snapshot" of data for the corresponding instant in time and each column representing a particular sensor's output. In each spot where an anomalous value was detected a replacement value is substituted based on results from the appropriate neural network.

Following completion of signal validation, analysis of the resultant matrix of data is completed utilizing blocks of values corresponding to ten–minute intervals. Ten minutes is the default configuration but the user has the option of specifying a different interval from a configuration file. The mean value is then obtained for each parameter from the ten–minute block of data and plugged into the appropriate cell of the "*Inputs*" spreadsheet as illustrated in Figure 18. Analysis is initiated automatically once all necessary cells have been populated, the equivalent of clicking on the *Click to Run PDM* button shown in Figure 18. Upon completion of evaluating the current set of data the results are written to the "*Results*" spreadsheet and the various graphs maintained by PDM are updated. Following this the analysis continues with the mean values obtained from the next ten-minute block of data and so on until all the data has been evaluated. At this point the results may be viewed on the updated graphs and an evaluation of the results can be made.

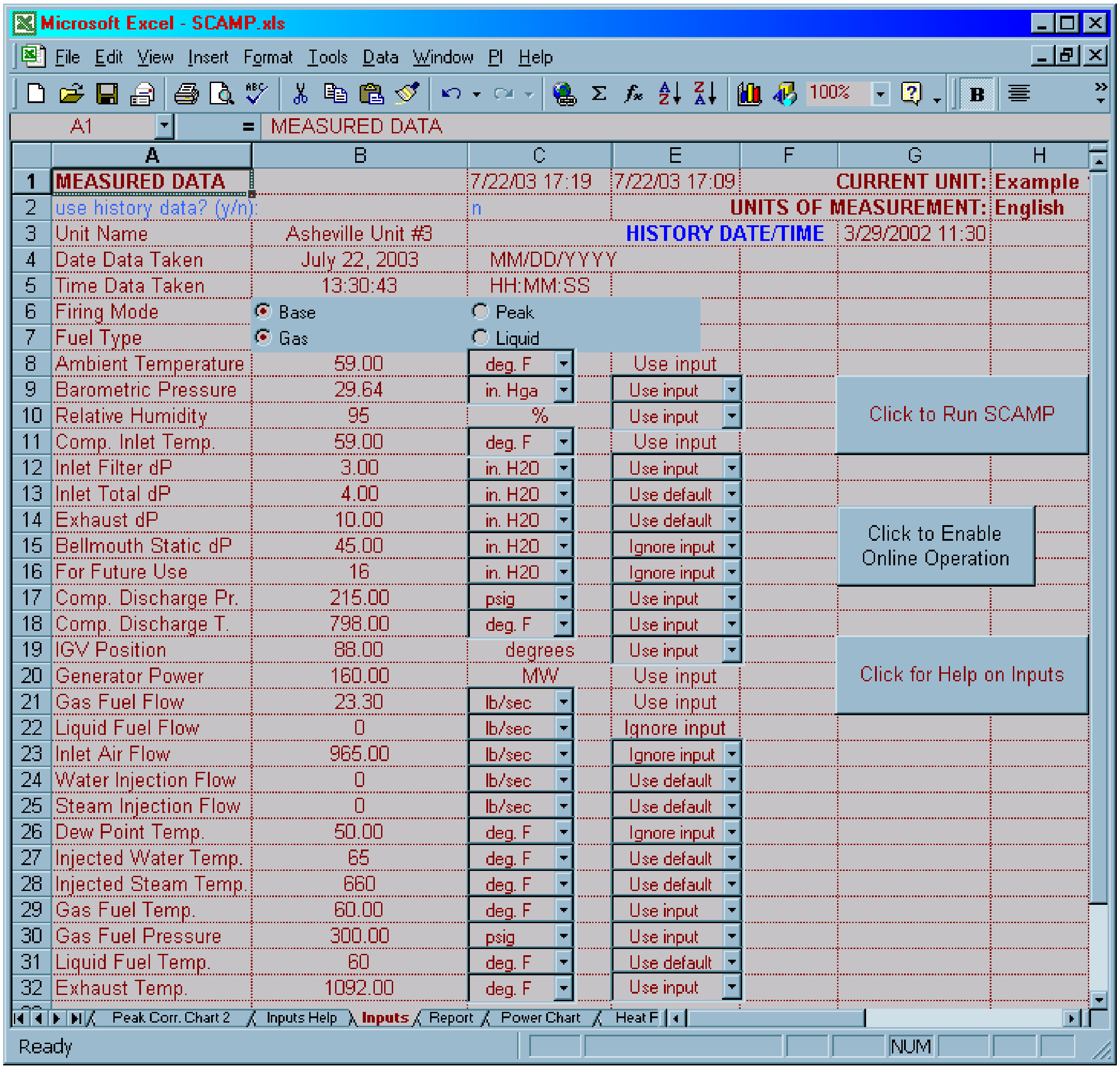

Figure 18 – PDM "Inputs" Worksheet

Table 4 – PDM Inputs Data Source (Adapted from PDM 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
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 available

Inputs Row #	Description	English Units	SI Units	Comments
26	Dew Point Temperature	°F	°C	Measurement Available
27	Injected Water Temperature	°F	°C	Default available
28	Injected Steam Temperature	°F	°C	Default available
29	Gas Fuel Temperature	°F	°C	Measurement Available
30	Gas Fuel Pressure	psig	barg	Default available
31	Liquid Fuel Temperature	°F	°C	Default available
32	Exhaust Temperature	°F	°C	Measurement Available

SVRM Modifications

Several feature refinements had been identified in the latter stages of development and also in the beta testing conducted by Progress personnel for improvement. All of the items, listed in Table 5, have been addressed.

Table 5. Identified Action Items

#	Items	Status
1	Put at the top of display the site name and unit number	Modifications in place
2	Put TCs in numerical order 1,2…10…15,16..27	Modifications in place
3	On the display different colors for status in the bottom right corner	Modifications in place
4	Need E-mail ability for User Defined Time Period	New functionality in place
5	Ability to add or subtract sensors	Ability to add and subtract sensors is available within the limits of those sensors listed in the configuration window
6	User Configurable Batch Analysis.	New functionality in place
7	Change User defined period so it is similar to PI where you can enter a date and time	New user interface facilitates definition of time period
8	Change minimum power to 5 MW instead of 65MW	Not currently feasible due to insufficient data at low power
9	Able to run batches for many units at same time, last night system crash when Units 3 & 4 were running together	This item is still being addressed
10	Error when leaving program run overnight?	Not currently able to reproduce any errors and are investigating issues with Windows XP sleep mode
11	Users guide for exception report e-mails says to use c:\program files\combustion turbine sensor check\win32-ix86\bin\svm.ini. It is actually: c:\program files\SVRM\win32-ix86\bin\svm.ini.	Revisions pending receipt of a current version

Improving the Appearance of the Main SVRM Screen

In response to feedback obtained from beta testing a few modifications have been made to the main window that appears when the SVRM is launched to draw attention to and clarify key information. First, the thermocouples (TTXD1_1 – TTXD1_27) have been re-ordered to appear in numerical order. Respondents also suggested that it would be more lucid to identify which site and unit were being analyzed at the top of the window. Finally, color panes have been implemented to emphasize the status of the current analysis. These modifications are all illustrated in Figure 19.

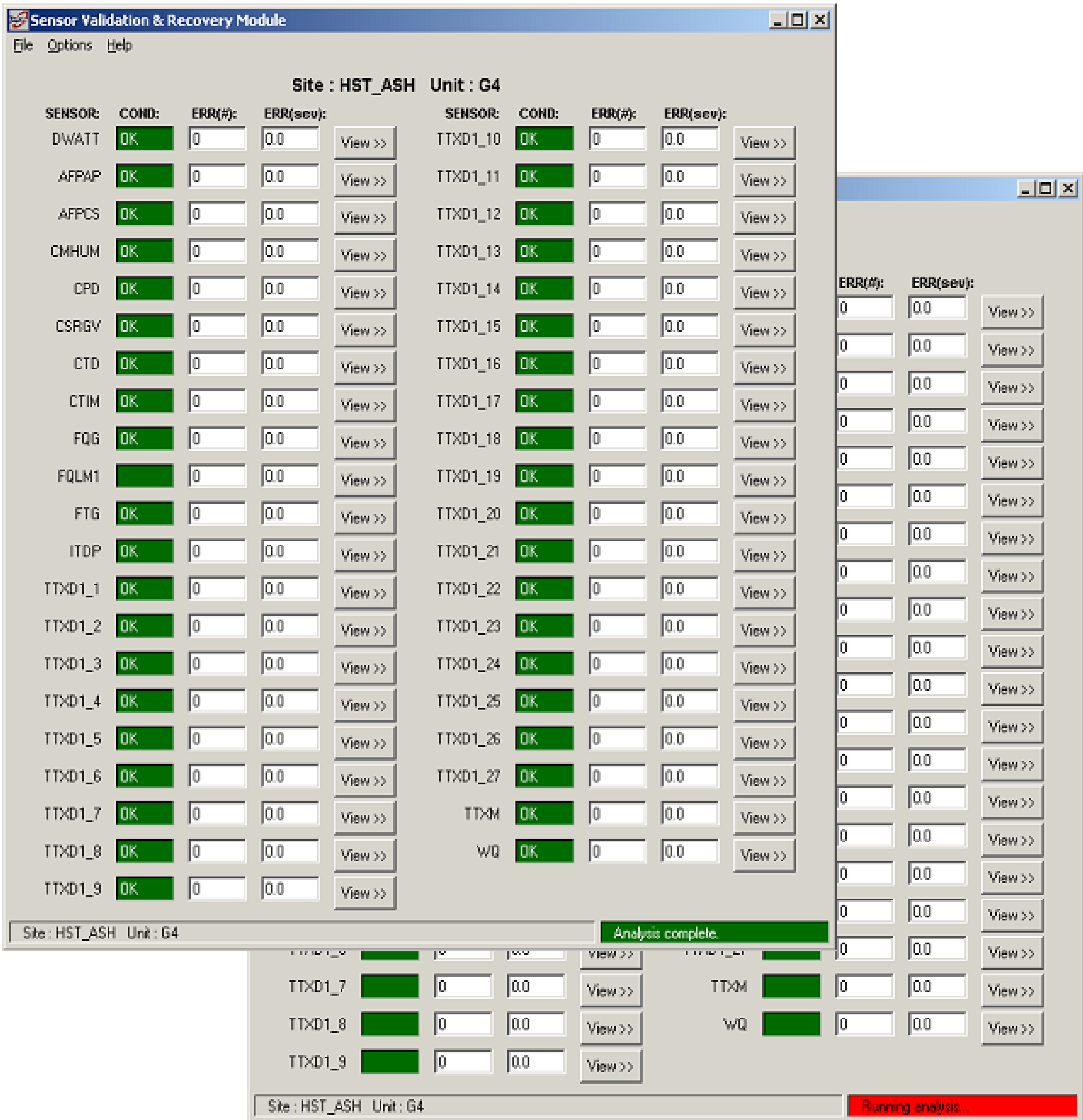

Figure 19. Modifications Made to the SVRM Main Window

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.

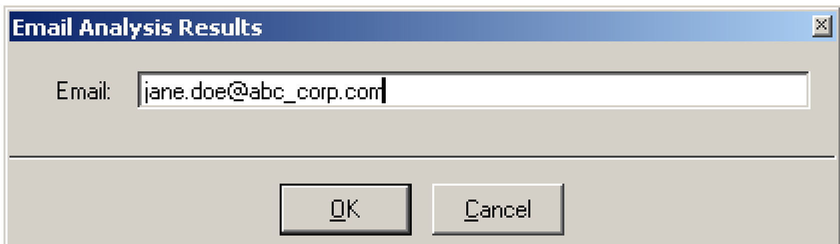

Figure 20 – Dialogue Box Enabling Entry of E-mail Recipient's Address

Improved Configuration Capabilities

Improvements in 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 features have been added or modified will aid the user in setting up the SVRM to analyze and present the desired data.

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 PDM module is run.

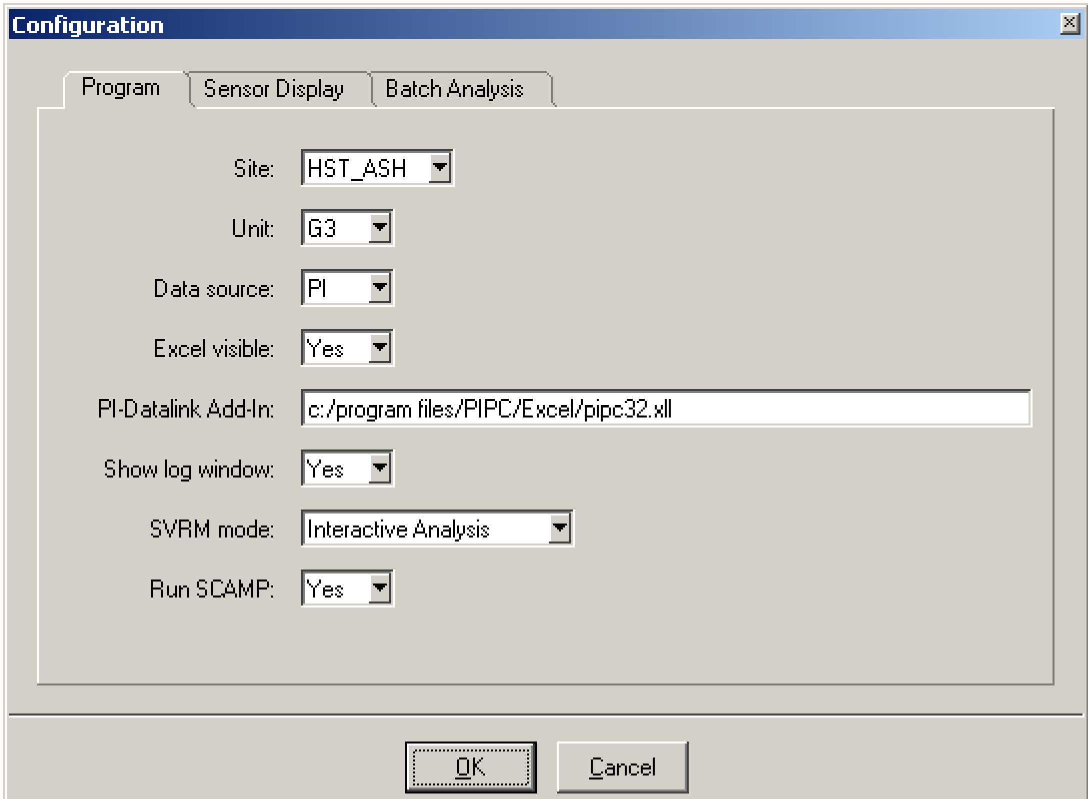

Figure 21. *Program* Tab of the *Configuration* Dialogue Box

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.

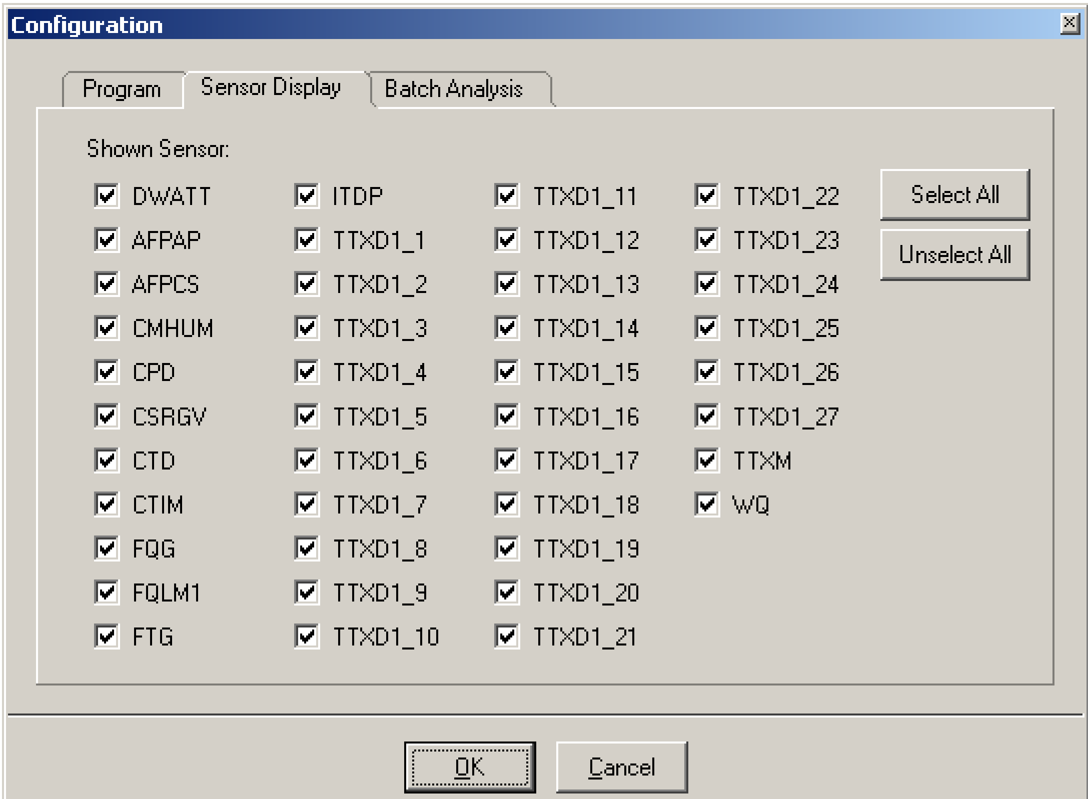

Figure 22. *Sensor Display* of the *Configuration* Dialogue Box

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 23 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.

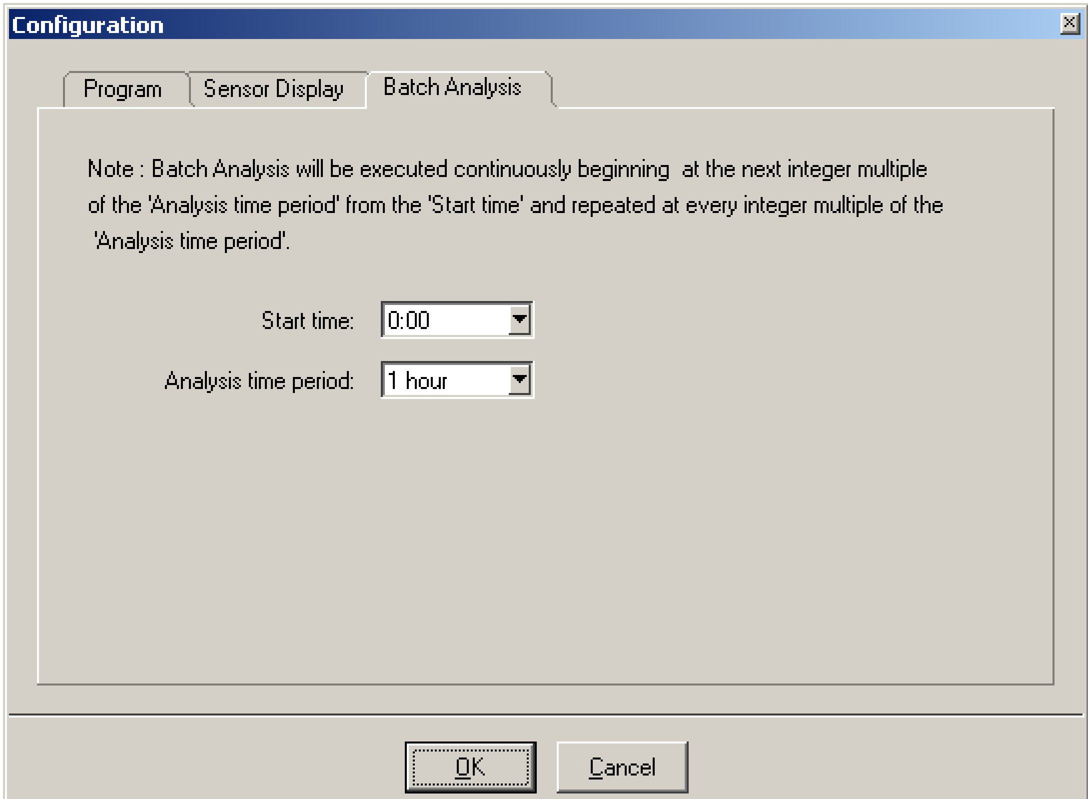

Figure 23. *Batch Analysis* Tab of the *Configuration* Dialogue Box

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 24 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.

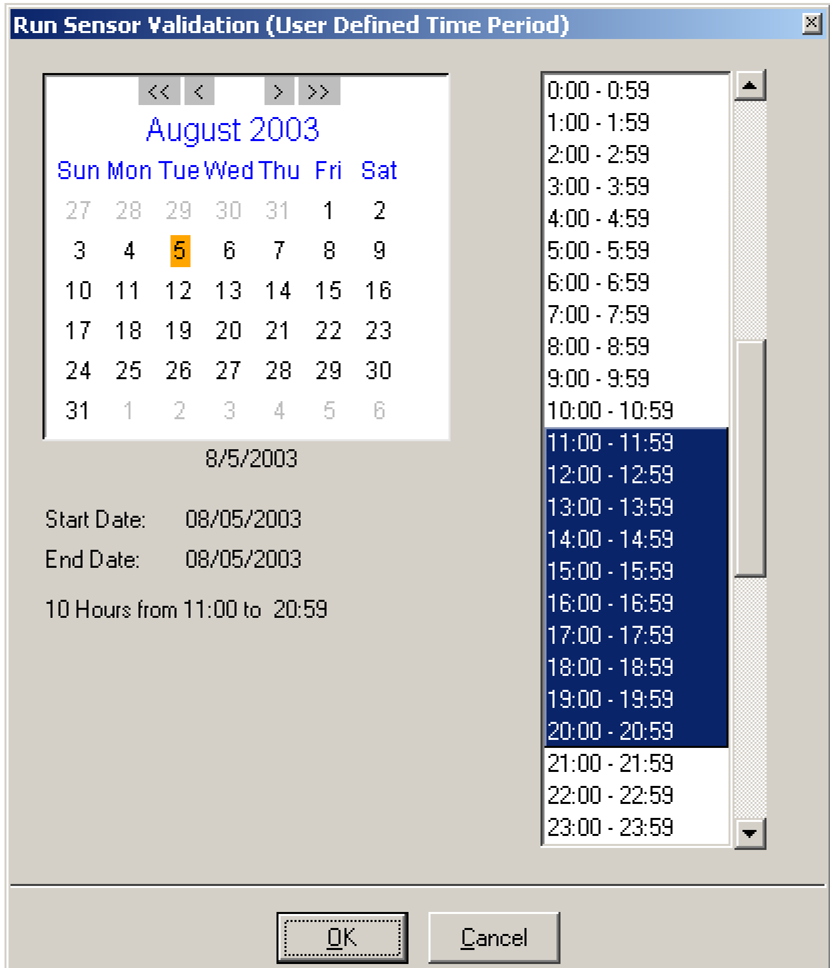

Figure 24. Dynamic Dialogue Box for Specifying *Interactive Analysis* Time Periods

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.

Final Issues

A suggestion was made during beta testing to lower the generator output range the SVRM considers from 65 MW to 5 MW allowing sensor validation to take place during start-up. This would be a very good idea and would be implemented if enough data was available at low output levels to properly develop and mature the model-based approach utilized by the SVRM.

A revision will be made to the Sensor Validation and Recovery Module User's Guide which highlights and explains all the features detailed in this report.

Future Work

Over the next report period the SVRM will be integrated with the performance module and fault diagnostic capability will be added to both CT-PDM and CC-PDM. The fault diagnostics will be based on rules developed for compressor fouling, inlet air filter clogging, damaged compressor blade, clogged fuel nozzle, cracked combustion liner, combustor cross-over tube failure, damaged turbine section blade, high turbine blade temperature, and turbine section fouling.

Future activity will also focus on developing the implementation of the hot section lifing analysis and automating inspection and maintenance interval calculations.

References

1. Demuth, H., & Beale, M., (2002) Neural Network Toolbox: For Use with MATLAB®, Vers. 4 (pp. 7-3 – 7-5, 7-9 – 7-10) The MathWorks, Inc.