Solutions for Information Overload from Process Control Systems: *Real-Time Process & Enterprise Information Validation for Making Plants Smarter and Safer.*

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ABSTRACT

Engineers and operators today have access to enormous amounts of information from their control systems. In most cases, they experience information overload or just don't have the time and resources to use all of this information effectively, if at all. Specifically, the control systems and data historians of today's plants generate enormous quantities of data from the process instrumentation that needs to be interpreted at multiple levels within an organization. At the lowest level this raw sensor data is used to directly operate and control the given process in a plant. At the higher levels, this information is used to monitor operations so that they can be optimized at the overall highest or enterprise level. Ultimately, the reasons for collecting and analyzing this information are to improve the plant's profitability and safety.

Smart plant technologies are being developed to address this situation. However, current solutions often focus entirely on lower level diagnostics, just monitoring individual sensors or individual pieces of equipment (that many have multiple IO points). A complete, more robust solution requires higher level monitoring, combining the lower level individual smart diagnostics with process or enterprise wide smart diagnostics. Also, even though this information from the process control system is available at the enterprise level, it is typically not being formally validated prior to being used at that level. Obviously, if the raw sensor data is not first validated as being accurate, the information derived from it is not always truly meaningful.

Process-wide and even enterprise-wide real-time monitoring, validation and predictive fault analysis can be accomplished using models of normal process operation, which provide a means for determining that the particular sensor measurements referenced in those models are valid and correct or at least consistent with each other. These models thus provide a means of deriving additional information from the control systems in an efficient and meaningful manner. This approach directly allows much of the engineering knowledge used to design and operate a given process to be leveraged to create higher-level information necessary to make enterprise wide decisions for optimization, profitability and safety. This smart plant technology greatly improves the fundamental quality of and confidence in those decisions. Several applications of this technology over a range of industries will be presented.

I. INTRODUCTION

Engineers and operators today have access to enormous amounts of information from their control systems. In most cases, they experience information overload or just don't have the time and resources to use all of this information effectively, if at all. Specifically, the control systems and data historians of today's plants generate enormous quantities of data from the process instrumentation that needs to be interpreted at multiple levels within an organization. At the lowest level this raw sensor data is used to directly operate and control the given process in a plant. At the higher levels, this information is used to monitor operations so that they can be optimized at the overall highest or enterprise level. Ultimately, the reasons for collecting and analyzing this information are to improve the plant's profitability and safety.

Young engineers coming into the industry need to be exposed to and to develop the skills and tools to work effectively in this environment. A critical responsibility for new engineers and plant engineers is daily operations assessment, planning, adjustment and, too often, troubleshooting or "fire fighting". Information overload is also often a routine experience that goes with this responsibility.

Ideally, a continuous performance monitor system can help to assess the performance within a plant in real-time identifying areas (instrumentation, control loops, equipment, unit operations, etc.) that are both underperforming and performing properly – essentially sifting through the information overload to find the business "gems" or benefits. The key benefits of a performance monitoring system are a more efficient plant, improved reliability & safety, and increased profitability. The most immediate benefit comes from predictive and preventative actions based on performance monitoring results. Identifying non-optimal conditions as they begin to occur or faults and failures as they are about to happen will allow for rapid corrective action that may prevent or mitigate the economic, environmental, and safety consequences. Longer-term benefits are obtained through improved process & equipment performance after corrective actions based on the performance monitoring results. Troubleshooting time is reduced. Difficult problems, or multiple cause problems, are more readily diagnosed.

Smart plant technology solutions are being developed to address this situation, but have some deficiencies. Current solutions often focus entirely on lower level diagnostics, just monitoring individual sensors or individual pieces of equipment (that many have multiple IO points). A complete, more robust solution requires higher level monitoring, combining the lower level individual smart diagnostics with process or enterprise wide smart diagnostics. For example, 65% of perceived transmitter problems are with other equipment or the process and

75% of control valve preventative maintenance is unnecessary[1] as the root cause(s) of the symptoms are due to equipment or process conditions issues. Also, even though this information from the process control system is available at the enterprise level, it is typically not being formally validated prior to being used at that level. Obviously, if the raw sensor data is not first validated as being accurate, the information derived from it is not always truly meaningful.

II. REAL-TIME PROCESS MONITORING & VALIDATION

Process-wide and even enterprise-wide real-time monitoring, validation and predictive fault analysis can be accomplished using models of normal process operation, which provide a means for determining that the particular sensor measurements referenced in those models are valid and correct or at least consistent with each other. These models thus provide a means of deriving additional information from the control systems in an efficient and meaningful manner.

FALCONEER Technologies has developed smart plant software that continuously performs real-time process performance monitoring and validation once these models have been specified. This approach directly allows much of the engineering knowledge used to design and operate a given process to be leveraged to create higher-level information necessary to make enterprise wide decisions for optimization, profitability and safety. This smart plant technology greatly improves the fundamental quality of and confidence in those decisions.

The smart plant software accomplishes this improvement by combining process state identification, sensor and process condition validation, continuous statistical process control monitoring, and predictive fault analysis using a master control module or gatekeeper. In this manner, the plant has a single source means for complete, high level monitoring and analyzing all manufacturing & environmental process data in real time to predict future process performance and optimize current process performance to help improve reliability, yield and quality, avoid failures and accidents, and reduce costs. Below is a summary of the purpose and operation of the different modules that add intelligence to the control systems and instrumentation.

II.A. Process State Identification

The smart plant software program first determines whether the process is operating within standard conditions or not, using a State Identification (State ID) Module. Initially, the smart plant program “knows” to be idle if the process is not operating. The program begins its analysis of sensor measurements once the correct process state is occurring; i.e. startup is complete. It continues this analysis until the process is shutdown and then is idle again until the next startup completes. The process condition monitoring suite thus runs continuously and adjusts its analysis to current process operations accordingly.

II.B. Validation and Predictive Fault Analysis

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[1] www.emersonprocess.com

The Sensor Validation and Predictive Fault Analysis (**SV&PFA**) software module monitors current process sensor measurements to determine if they are either valid or incorrect. It also determines if certain processing faults (leaks, pump failures, controller malfunctions, etc.) are occurring or not. It does this by evaluating engineering models that describe normal process operation. Briefly, when the process system is operating normally (i.e., fault free), the engineering models describing normal process operation should all close. When they don't this is evidence that something is going wrong in the process system. By looking at the patterns of all this evidence it is possible to infer the underlying fault(s) in the process that could cause such behavior. These results are then given as alerts to the users. Multiple fault situations are also detected and communicated using this method. If not found to be faulty, the sensor measurements are considered validated (i.e., trustworthy).

The evidence determined by evaluating the engineering models is combined together using a Fuzzy Logic calculation. The fuzzy logic based real-time method is called the Method of Minimal Evidence. This algorithm is general enough to validate current instrumentation, equipment operation and process conditions AND to diagnose both single and multiple faults directly. It uses first principle or statistical models, correlations and experiential heuristics to define relationships between particular measured sensor data and assumed unmeasured process variables that describe normal process operation. It continuously evaluates those relationships with real time data to determine which close or not. It also exhaustively combines those relationships together to form additional but novel relationships, which are also continuously evaluated. The resulting patterns of these evaluations are interpreted with the general-purpose fuzzy logic diagnostic rule to determine the certainty associated with each sensor's validation and each of the potential fault hypotheses. For the fault hypotheses, these certainty factors can range from 0 (at least some evidence does not support that fault hypothesis) to 1.0 (that fault hypothesis is a highly plausible explanation of the current process behavior). Appropriate alerts are given if these certainty factors for the faults exceed the chosen alert thresholds. Else the instrumentation and process are logged and documented as being validated.

II.C. Statistical Process Control

The **V**irtual **S**tatistical **P**rocess **C**ontrol (**VSPC**) software module augments the SV&PFA module, providing an independent but complementary analysis of sensor measurements. The VSPC module uses Exponentially Weighted Moving Averages (EWMA's) to determine in real-time if individual process sensors and process conditions are in control, are going out of control, or are definitely out of control. It directly flags out of control sensors and process conditions in real-time rather than after-the-fact. These alerts can also occur at levels that may allow the process operators to take appropriate control actions to reduce or eliminate disruptions to process operations or product quality. This method is considered virtual because the analysis is done automatically without the need for the operators to collect and chart any process sensor readings.

Statistical Process Control (SPC) is a tool used to assess whether a process is currently under or out of control. Various techniques exist for doing this analysis depending upon the nature of the process being monitored. In continuous processes (as opposed to the manufacture of discrete, individual units), process data collected at a particular moment in time is not completely independent of its previous data. This phenomenon is referred to as auto-correlation between the data. SPC techniques for continuous single point samples that handle auto-correlation in the data include Cumulative-Sum (CUSUM) as well as EWMA. These techniques can better handle the effects of auto-correlation and allow small but statistically significant shifts in an observed variable's value to be readily detected. With this process monitoring suite, the EWMA calculation is the preferred method because of its ability to not only monitor current process operations but to forecast where the process is headed. There are two classes of sensor variables that can be used by this module: sensors that are being directly controlled and those that are not.

III. REAL-TIME PROCESS MONITORING & VALIDATION CASE STUDIES

The following three cases will elaborate how this tool can cut through information overload to help plants improve operations (smarter through improved information use!) and safety.

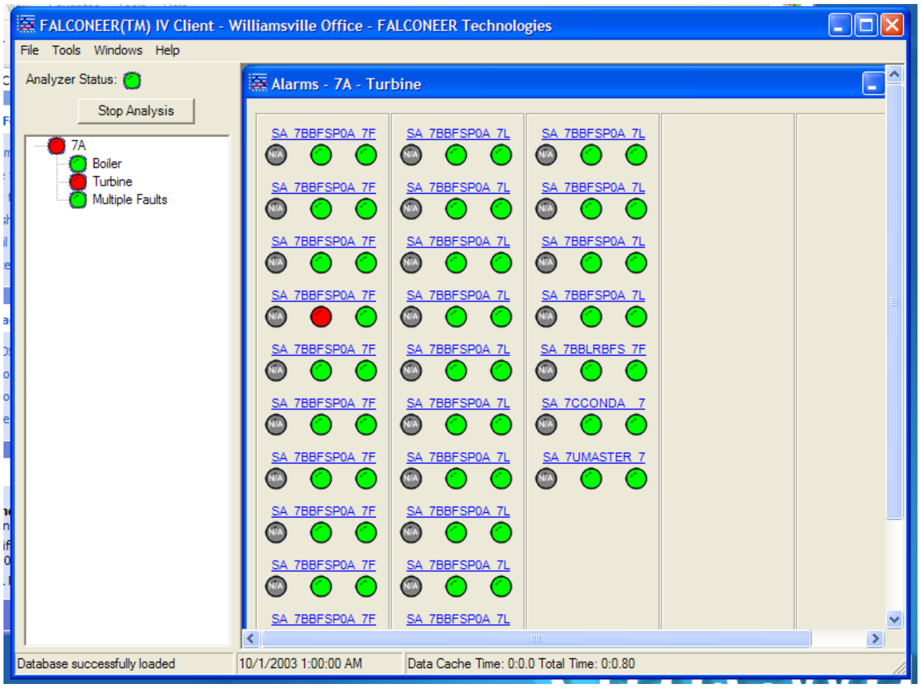
III.A. THE POWER-GENERATION INDUSTRY

A large power utility was interested in real-time validation and fault detection for both equipment and instrumentation condition monitoring and ensuring that process information used in their enterprise systems (financial, production planning, etc.) was accurate and correct. A dataset containing known equipment and process issues was provided for a "blind" evaluation to assess the smart plant software's validation and fault analysis performance as well as how easily and quickly a system could be developed and operational.

The system developed for this evaluation incorporated 44 sensor measurement inputs, no unmeasured process condition (i.e. assumptions, leaks, etc.) inputs, 7 material & energy balance primary independent models and 40 statistically-based models and correlations. The program automatically generated and compiled ~575 additional secondary or dependent engineering models, ~90 potential determinable fault hypotheses, ~ 7700 single & multiple fault diagnostic rules (things that could go wrong at any one time) and 44 virtual EWMA statistical process control charts. It performed process state identification before applying the data validation and fault analysis rules. These FUZZY Logic / certainty factor calculations used by this smart plant technology ensure confidence in its conclusions using an algorithm anticipating all possible levels of diagnostic resolution between faults. The whole configuration required about 4 day to develop, implement and complete the testing.

Over the 6 month period comprising the dataset, the condition monitoring technology correctly validated that ~99% of the time information from the instrumentation was correct and the equipment operation in control ~96% of the time. Half of all the instrumentation was validated for 100% of the period of operation. It identified the significant faults, failures and abnormal operation occurring during this period as well, primarily caused by a handful of the process conditions and equipment sensors.

Below is an example snapshot of a customized alarm page that is automatically generated and available via webservice to multiple users for this instrumentation validation and equipment condition monitoring application. In essence, all the green buttons are providing real-time validation that the instrumentation is reading correctly and operating under control within normal operating conditions. In this example, there is one point or sensor in the turbine system that is alarming and requires attention. The actual value of this sensor appears to be at a normal condition and so this fault or failure would have either been missed or mis-diagnosed.



Database successfully loaded | 10/1/2003 1:00:00 AM | Data Cache Time: 0:0.0 Total Time: 0:0.80

FIGURE 4: ALARM SCREEN AVAILABLE VIA WEBSERVICE TO WINDOWS CLIENTS

III.B. THE PULP & PAPER INDUSTRY

A well-instrumented paper machine provides abundant measurements about the paper making process to help control the process. Much of the information provided by these measurements is never used and the lost opportunity can be worth a significant amount of money in terms of downtime prevention, operating cost savings, waste reduction, improved safety or environmental compliance. Consistency monitors are an important measurement in the paper process to insure uniformity, quality, and process stability. In addition to typical reliability problems with these meters such as fouling, drifting and mechanical failures, consistency sensors are sensitive to routine process variations such as stock velocity and changes to furnish.

In this system, there are 10 measured variables typically;

- The flow, the temperature and the consistency measurement into the stock chest,
- The level of the stock chest that is used to control flow in,
- The temperature of the stock chest,
- The flow, the temperature, and the consistency of the stream out of the stock chest,
- The header pressure of the dilution water for the stream coming out of the stock chest.

There is also a dilution controller output, which reads the outlet consistency meter and adjusts the control valve on the water line and hence the flow of water for dilution. In addition, the tank level is controlled by adjusting the chest inlet flow. A typical system is shown schematically below.

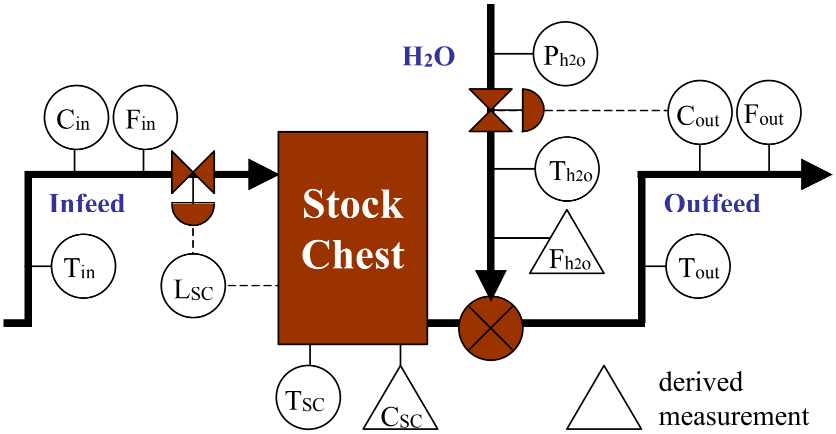


FIGURE 3: SCHEMATIC OF A PULP & PAPER PLANT STOCK CHEST

Smart plant software was used to created two soft sensors that are virtual sensors used to monitor and possibly control the process without having to purchase additional sensors. These soft sensors, or derived measurements, are:

- The flow of the dilution water and
- The consistency meter in the stock chest.

The solution developed for this process incorporated the 10 sensor measurement inputs, 5 unmeasured process condition inputs (mixing pump suction pressure, dilution water temperature, and three potential leaks), 4 material & energy balance primary independent models and the 2 soft sensors or performance equation models. The smart software automatically generated and compiled 15 additional secondary or dependent engineering models, ~30 potential determinable fault hypotheses, ~ 1000 single & multiple fault diagnostic rules (things that could go wrong at any one time in just this simple process) and 12 virtual EWMA statistical process control charts. It performed process state identification before applying the data validation and fault analysis rules.

The real-time monitoring and validation system detected 4 fault or failure situations that are common with this process.

1. A failure of the consistency meter on the outlet together with a drastic change or fluctuation in the dilution water header pressure.
2. A failure of the outlet consistency meter with now a change in the outlet flow rate (stock velocity) because of a change in the furnish.
3. A bias in the inlet consistency meter due to drift, miscalibration, instrument malfunction without any accompanying perturbations to the system.
4. A combination of the failure of the outlet consistency meter coupled with another typical furnish change that is reflected by change in the inlet consistency meter.

These situations, when undetected, can lead to breaks in the paper-making process resulting in paper machine downtime and restart-up, plus additional broke (waste). Since the most cost effective operation for a paper machines is continuously for the entire batch run, downtime can cost $5,000 to $10,000 per hour per machine, depending on the value of the paper. Paper making is also very energy-intensive, so reducing broke can save significant energy and chemical costs.

The process performance monitoring system also successfully demonstrated that when the sensors are reading properly and are validated, real swings or disturbances in the process can be tolerated by this software and will not trigger fault or failure detection alarms - just out of control alerts or alarms as should be expected.

III.C THE CHEMICAL INDUSTRY

FMC manufactures a wide range of industrial and specialty chemicals. FMC has been using FALCONEER Technologies' smart plant software since its earliest version in 2001. The FMC system for this case is a continuous electrolytic process. A generalized schematic of this complicated recycle process is shown below. The main unit operations in the plant are the electrolytic cells and the crystallizer. In addition a series of feed and mixing tanks are used to maintain the correct chemistry. A Honeywell TDC 3000 is the distributed control system that runs the electrochemical plant.

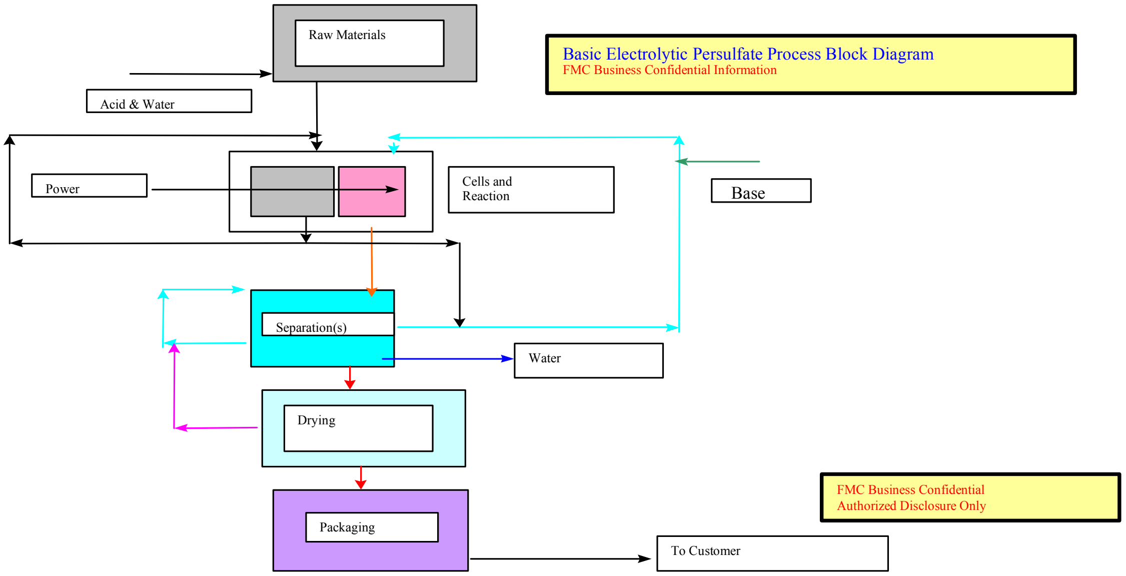


FIGURE 1: SCHEMATIC OF INDUSTRIAL CHEMICAL PROCESS

FMC was looking for several types of improvements by making better use of the information being collected by its process control system. They were interested in validating their safety instrumentation systems and reducing the costs associated with this requirement, optimizing certain under-performing unit operations, improving process on-stream time & reliability, reducing operating expenses associated with manpower and raw material usage and finally, capturing existing process knowledge in an organized and usable manner.

The smart plant software application developed for FMC's complex process system incorporated ~100 sensor measurement inputs, ~ 40 unmeasured process condition inputs (such as leaks, solution compositions, assumed flows, etc.), 24 material & energy balance primary or independent models and 3 performance equation models. The program automatically generated and compiled ~100 additional secondary or dependent engineering models, ~250 potential determinable fault hypotheses, ~ 60,000 single & multiple fault diagnostic rules and ~100 virtual EWMA statistical process control charts. In essence, with this particular chemical process, there are around 60,000 things that could go wrong at any one time. Whereas multiple faults are less common, when they do occur the consequences are significant. It is these situations that, when undetected or ignored, lead to costly downtime, accidents, releases, and worse. The smart plant software thus makes this plant inherently safer as it continuously monitors for such situations.

During the testing & validation phase prior to transferring this smart technology over to operations full-time, the following upsets & disturbances were identified:

- Abnormal temperature conditions were detected due to changing ambient temperature conditions and mode of operation, which was subsequently adjusted sooner than may have occurred just based on operator experience.
- Micromotion meter density & flow components failures were detected 12 to 18 hours prior to TDC alarms. The micromotion temperature component was unaffected and remained validated.
- During validation, a condenser unit was detected as location for crystallizer vacuum leak about 3-4 months before plant personnel finally found the leak in this unit. (Unscheduled downtime to fix = 37.5 hours). The search could have begun during earlier scheduled outages and required less time, manpower, and cost to locate.
- Correct diagnosis was provided for a crystallizer overflow pump's two failures over a six-month period and for a raw material pump flow failure. The addition of pump diagnostic models in installed version may have provided some level of predictability, depending on the nature of failures.
- Four controlled variables were detected operating in manual control.
- Several process changes were detected. The normal operation parameters for three primary models were quickly reevaluated and easily adjusted. These include:
    - Energy Balance on Heat Exchanger – The temperature rise across solution side almost doubled after an outage.
    - Tank pH Balance – A pH meter that had been wrong for over a year was finally recalibrated or repaired during a scheduled outage and now reads properly.
    - Energy Balance around Cells - The thyristor bus voltage meter had been faulty for a considerable period of time and was finally repaired or recalibrated.
- Three newly installed sensors were identified with extreme variability due to tuning, operation, or sensor problems. These sensors had been operating in this mode (and ignored) for a period of time since their installation, but the operators thought they just had to live with the poor quality sensors.

IV. CONCLUSIONS

Manufacturing companies over a range of industries have identified significant value to be gained with real-time process monitoring systems operating in conjunction with their control systems. Accessing under-utilized process information for validation, optimization & control, fault analysis and detection can improve plant profitability and safety without expending significant additional resources (time, money, and people). Process-wide and even enterprise-wide real-time monitoring, validation and predictive fault analysis can be accomplished using models of normal process operation, which provide a means of deriving additional information from the control systems in an efficient and meaningful manner. This approach directly allows much of the engineering knowledge used to design and operate a given process to be leveraged to create higher-level information necessary to make enterprise wide decisions for optimization, profitability and safety. This smart plant technology greatly improves the fundamental quality of and confidence in those decisions.

V. REFERENCES

Dhurjati, P.S., Lamb, D.E., and Chester, D.L., “Experience in the Development of an Expert System for Fault Diagnosis in a Commercial Scale Chemical Process”, Proceedings of the 1st International Conference on Foundations of Computer-Aided Process Operations, ed. by G.V. Reklaitis and H.D. Spriggs, New York, Elsevier Science Publishers Inc., 1988, pp. 589-617.

Rowan, D. A. and Taylor, R. J., "On-Line Fault Diagnosis: *FALCON* Project," Artificial Intelligence Handbook, Instrument Society of America 1989, Vol. 2, pp. 379-399.

Fickelscherer, R. J., "Automated Process Fault Analysis," Ph.D. Thesis, University of Delaware, Newark, DE, 1990.

Rowan, D.A, “Beyond FALCON: Industrial Applications of Knowledge-Based Systems”, IFAC Symposium – On-line Fault Detection and Supervision in the Chemical Process Industries, ed. by P.S. Dhurjati, Newark, DE, 1992, pp. 215-217.

Dhurjati, P.S., ed., “On-Line Fault Detection and Supervision in the Chemical Process Industries,” Proceedings of the International Federation of Automatic Control Symposium, Newark, Delaware, USA, 1992.

Fickelscherer, R.J., “A Generalized Approach to Model-based Process Fault Analysis”, Proceedings of the 2nd International Conference on Foundations of Computer-Aided Process Operations, ed. by D.W.T. Rippin, J.C. Hale, J.F. Davis, Austin, TX, CACHE, 1993, pp. 451-456.

IFAC 1995, “IFAC Workshop on On-Line Fault Detection and Supervision in the Chemical and Process Industries”, Proceedings of the International Federation of Automatic Control Symposium, Seattle, Washington, USA, 1995.

Skotte, R., Lenz, D.H., Fickelscherer, R.J., An, W., Lapham, D.L. IV, Lymburner, C.J., Kaylor, J.M., Baptiste, D.L., Pinsky,M., Gani, R. and Jørgensen, S.B. "Advanced Process Control with Innovation for an Integrated Electrochemical Process," AIChE Spring National Meeting, Houston, TX, April, 2001.

Venkatasubramanian, V., “A Review of Process Fault Detection and Diagnosis: Past, Present and Future” submitted to Computers and Chemical Engineering, 2003

Fickelscherer, R.J., Ambrusko, J.R., Lenz, D.H., Lymburner, C.J., Rovison, J.M., Chester, D.L., Dhurjati, P.S. “Optimal Automated Process Fault Analysis: MOME Methodology and Implementation”, University of Delaware Process Control & Monitoring Consortium Meeting, Newark, DE, January 24, 2002

Fickelscherer, R.J., Lenz, D.H., Chester, D.L., “Intelligent Process Supervision via Automated Data Validation and Fault Analysis: Results of Actual CPI Applications”, AIChE 2003 Spring National Meeting, New Orleans, LA, April 2003