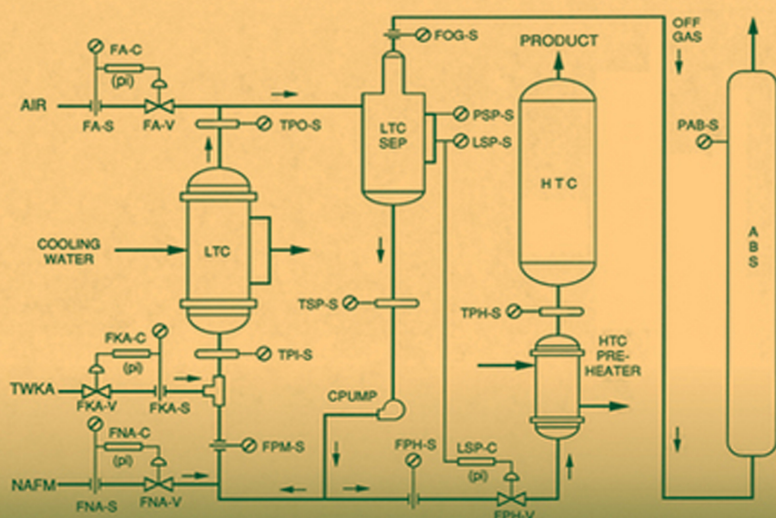


Optimal Automated Process Fault Analysis

Richard J. Fickelscherer and Daniel L. Chester



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R.J.F.: I dedicate this book to my loving wife, Pat, for all her encouragement and help, and for always believing in me. I am very fortunate to have found her and to have her at the center of my life.

D.L.C.: I dedicate this book to my parents, Fred and Della, for all the guidance they gave me over the years, and for making it possible for me to get the training and develop the skills that led to my contributions to this book. Their encouragement has always been appreciated.

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FOREWORD

It is an honor to be asked to write the foreword to Rich and Dan's book on diagnostic reasoning for process plants. The story of the FALCON diagnostic system goes back to when I first joined MIT as a young faculty member in the early 1980s. In those days computing meant numerical computation in Fortran or C, mainframes and minicomputers ruled, and personal computers were underpowered novelties. Process control had begun a slow transition from pneumatic to digital instrumentation, but the first digital controllers were modeled unimaginatively after the PID loops they were replacing.

But Metcalfe's law was in full exponential ascent, and the world was rapidly changing, not only in terms of faster numerical methods. New ideas from artificial intelligence were flooding across the MIT campus, upending the very foundation of computing by means of an entirely new synthesis of symbolic, object-oriented, neural, and rule-based computing. Touching off a great intellectual ferment in chemical engineering, virtually every aspect of process operations was being transformed. Gauges transformed into graphical operator interfaces, fixed threshold alarms into intelligent monitoring and diagnosis, and steady-state operation into dynamic economic optimization.

The University of Delaware was one of the leaders in this exploration, especially in the area of process monitoring and fault diagnosis. Undertaking a joint project with Foxboro and DuPont in the early 1980s, Delaware spearheaded the first industrial application of an expert system, FALCON (fault analysis consultant), for online fault diagnosis of the DuPont adipic acid plant in Victoria, Texas. A key idea, expounded further in this book, was the synthesis of logical (pattern or rule) analysis and quantitative mathematical modeling.

This period of creative experimentation reached its zenith in 1995, at the First International Conference on Intelligent Systems in Process Engineering in Snowmass, Colorado. By that time, I had moved to an MIT spin-off, Gensym Corporation, developers of the G2 real-time expert system development environment. G2 was that generation's ultimate synthesis of graphical UI, structured natural language, object-oriented programming, and rule-based

processing. The conference showcased innovative knowledge-based systems ranging from product design to intelligent control, optimization, and diagnostics. Flush with the success of building and deploying hundreds of expert systems to solve real industrial problems, few of us realized just how quickly another revolution, the Internet, was going to overturn everything, yet again.

Throughout these many changes, some determined individuals have persevered to bring the vision of intelligent operations closer to reality. In this book, Rich and Dan explain how they transformed the art of the diagnostic expert system into a practical and reproducible system, implemented in FALCONEER™ IV to increase the operating safety and reliability of process systems. Their system captures many lessons learned during the rapid and often convulsive change of the past 25 years. I wish them the very best.

MARK A. KRAMER, PH.D.

*Winchester, Massachusetts
February 2012*

PREFACE

Process fault analyzers are computer programs that can monitor process operations to identify the underlying cause(s) of operating problems. A general method for creating process fault analyzers for chemical and nuclear processing plants has been sought ever since the incorporation of computers into process control. The motivation has been the enormous potential for improving process plant operations in terms of safety and productivity. Automated process fault analysis should help process operators (1) prevent catastrophic operating disasters such as explosions, fires, meltdowns, and toxic chemical releases; (2) reduce downtime after emergency process shutdowns; (3) eliminate unnecessary process shutdowns; (4) maintain better quality control of process products; and (5) ultimately, allow both higher process efficiency and higher production levels.

A wide variety of logically viable diagnostic strategies now exist for automating process fault analysis. However, automated fault analysis is currently still not widely used within the processing industries. This is due mainly to the following limitations: (1) the prohibitively large development, verification, implementation, or maintenance costs of these programs; (2) an inability to operate a program based on a given diagnostic strategy continuously online or in realtime; and (3) an inability to model process behavior at the desired level of detail, thus leading to unreliable or highly ambiguous diagnoses. Subsequently, a method for efficient production of automated process fault analyzers is still being actively sought. It is our contention that evaluating engineering models of normal process operation with current process data is the most promising and powerful means of directly identifying underlying process operating problems. Doing so generates an unimpeachable source from which to logically infer the current state of the process being modeled. Performing this inference automatically online enables these programs to perform *intelligent supervision* of the daily operations of their associated process systems. It makes possible a fundamental understanding of a given process system's design and operation to be utilized in evaluating its current operating conditions.

The *method of minimal evidence* (**MOME**) is a model-based diagnostic strategy for developing optimal automated process fault analyzers. It was derived at the University of Delaware while developing the **FALCON** (fault analysis consultant) *system*, a real-time online process fault analyzer for a commercial-scale adipic acid plant formerly owned and operated by DuPont in Victoria, Texas. It provides a uniform framework for examining both models of normal process operation and their corresponding associated modeling assumptions that are required to build such fault analyzers. MOME can be used directly to correctly diagnose both single- and multiple-fault situations, to determine the strategic placement of process sensors to facilitate fault analysis, and to determine the shrewd division of a large process system for distributing fault analyzers.

The MOME diagnostic strategy was again demonstrated to be effective in a commercial-scale persulfate plant owned and operated by FMC in Tonawanda, New York. Versions of two *knowledge-based systems* (**KBSs**) developed using MOME have been running online at this plant since February 2001. In the current implementation, these KBSs [a.k.a. **FALCONEER™ IV** (**FALCON** via engineering equation residuals IV)] diligently perform automated sensor validation and fault analysis of both FMC's electrolytic sodium persulfate and liquid ammonium persulfate processes in realtime. The development effort for these two FALCONEER IV applications was more than two orders of magnitude less than that required for the original FALCON system, with even better performance to date. This impressive improvement in the development and maintenance effort required was possible because FALCONEER IV contains a compiler program that automatically generates the *sensor validation and proactive fault analysis* (**SV&PFA**) *diagnostic logic* required to perform competent fault analysis directly from the underlying engineering models of normal process operation. Since the MOME diagnostic strategy is a systematic procedure, creating an algorithm based on it and then codifying that algorithm proved to be straightforward. This treatment describes both the underlying logic of MOME and the fuzzy logic algorithm based on it. It is meant to be a study guide for those who wish to develop such fault analyzers for their own process systems.

Motivations for automating process fault analysis are described in detail in Chapter 1. Our patented methodology for automating process fault analysis (MOME and its associated fuzzy logic algorithm) is then discussed in detail in Chapters 2 to 5. The logic behind model-based reasoning in general and MOME in particular is described in Chapter 2. The MOME logic for performing single- and multiple-fault diagnosis is described in Chapter 3. Also discussed in Chapter 3 are the motivations behind the creation of process fault analyzers based on MOME automatically via the SV&PFA diagnostic rule logic compiler program contained in FALCONEER™ IV. The fuzzy logic

algorithm automating MOME as implemented in this compiler is described in Chapter 4. In Chapter 5 the criteria for shrewdly distributing process fault analyzers throughout a large processing plant are described. Some general guidelines for the strategic placement of process sensors for directly facilitating fault diagnosis are also discussed.

Chapter 6 covers the need to augment process fault analysis with trend analysis of the various process sensor measurements and *key performance indicators (KPIs)* via the *virtual statistical process control (virtual SPC)* technique of calculating and analyzing *exponentially weighted moving averages (EWMA)*s).

The need to first determine the current overall operating state of the process undergoing automated fault analysis is discussed in Chapter 7. Such determinations provide the proper context required for the fault analyzer to make legitimate diagnoses.

Chapter 8 summarizes the benefits derived and lessons learned when employing FALCONEER™ IV in actual process applications. A systematic procedure to follow when creating such applications is also described. The chapter concludes by summarizing the advantages of distilling the raw information contained in typical process sensor data continuously into value-added knowledge concerning the current state of process operations and having that knowledge be instantaneously available for *intelligent supervision* of those operations.

For completeness, four appendixes have been added to this treatment as background information. A number of the other various possible diagnostic strategies also used to automate process fault analysis and their limitations are reviewed briefly in Appendix A. Appendix B describes DuPont's adipic acid plant and the original automated process fault analyzer (i.e., the FALCON system) developed for it. The lessons learned from the development of this real-world fault analyzer are discussed in detail. The advantages of using the knowledge-based system paradigm for solving problems, especially those that led directly to the creation of the MOME diagnostic strategy, are also discussed. As described throughout the book, this strategy has since been codified into FALCONEER™ IV. Appendix C outlines the logic that was used by the original hand-compiled FALCONEER system to determine the current process state in FMC's electrolytic sodium persulfate plant. This logic has since been simplified, generalized, and codified in the current implementation of FALCONEER™ IV. Finally, Appendix D describes two downloadable FALCONEER™ IV demos provided to accompany this treatment.

RICHARD J. FICKELSCHERER
DANIEL L. CHESTER

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Feel free to contact either of us if you would like to find out more about the FALCONEER™ IV software and our company's services. Following is the contact information:

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MOTIVATIONS FOR AUTOMATING PROCESS FAULT ANALYSIS

1.1 INTRODUCTION

Economic competition within the *chemical process industry* (CPI) has led to the construction and operation of larger, highly integrated, and more automated production plants. As a result, the primary functions performed by the process operators in these plants have changed. An unfortunate consequence of such changes is that the operators' ability to perform process fault management has been diminished. The underlying reasons for this problem and the methods currently used to counteract it are discussed here.

1.2 CPI TRENDS TO DATE

The CPI constitutes one of the largest and most important segments of the global economy. While developing into its current, relatively stable position, competition for market share among the various chemical producers has greatly intensified. This competition has, in turn, created continuously downward pressure on the market price, and hence the associated profit margin, of most commodity chemical products. Several major trends within the CPI in the operation of production plants have resulted.