MULTIPLE FAULTS DETECTION USING ARTIFICIAL NEURAL NETWORK

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In the Name of Allah, Most Gracious, Most Merciful.

All praise and thanks are due to Allah Almighty and peace and blessings be upon His Messenger.

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ABSTRACT

This thesis investigated issues on the development of efficient fault detection scheme for detection of single and multiple faults due to sensor failure and leakage in the process stream. The proposed scheme consisted of two stage mechanism constructed using artificial neural network (ANN). The first stage was a process estimator that was designed to estimate the normal and unfaulty behaviour of the plant. In order to produce reasonably accurate estimation without including the history data of the output, two types of model have been studied. A group of multi input single output (MISO) Elman network and a multi input multi output (MIMO) Feedforward network have been used, and results revealed that MISO model had better generalisation ability compared to MIMO model. The difference between the actual plant signal and this estimated 'normal' plant behaviour, termed as residual was fed to the second stage for fault classification. In the development of fault classifiers, the MISO models had been proven to be better than MIMO model. The effect of adding input with time delayed signals to the network had also been studied. In both cases, successful implementations were obtained. Finally, the proposed fault detection scheme was applied for detection of sensor faults and stream leakage in the Precut column of a fatty acid fractionation plant. The proposed scheme was successful in detecting both single and multiple faults cases imposed to the process. The strategy was also successful in detecting leakage in the process stream even when the percentage of the leakage was as little as 0.1%. The results obtained in this work proved the potential of neural network in detecting multiple faults and leakage in chemical process plant.

ABSTRAK

Tesis ini telah mengkaji isu-isu berkaitan dengan pembangunan skema pengesan kesilapan yang cekap untuk mengesan kesilapan tunggal dan berbilang ekoran dari kegagalan penderia and kebocoran dalam aliran proses. Skema yang dicadangkan ini terdiri daripada dua peringkat mekanisme yang dibina menggunakan rangkaian saraf buatan (ANN). Peringkat pertama ialah peramal proses yang direkabentuk untuk meramal keadaan loji yang normal dan tidak mempunyai kesilapan. Untuk menghasilkan ramalan yang betul-betul tepat tanpa menggunakan data keluaran masa lalu, dua jenis model telah dikaji. Rangkaian berbagai masukan keluaran tunggal (MISO) Elman dan rangkaian berbagai masukan berbagai keluaran (MIMO) telah digunakan, dan keputusan-keputusan yang diperolehi menunjukkan yang model MISO mempunyai keupayaan meramal yang baik berbanding dengan model MIMO. Perbezaan di antara isyarat loji yang sebenar dengan ramalan keadaan normal ini, disebut baki dimasukkan ke dalam peringkat yang kedua untuk pengkelasan kesilapan. Dalam pembangunan pengesan kesilapan, model-model MISO telah terbukti lebih baik keupayaannya berbanding model MIMO. Kesan penambahan masukan yang terdiri dari isyarat masa lampau terhadap kebolehan rangkaian juga telah diselidik. Dalam kedua-dua kes ini, pelaksanaannya telah mencapai kejayaan. Akhir sekali, skema cadangan pengesan kesilapan ini telah dilaksanakan dalam mengesan kesilapan sensor dan kebocoran dalam loji penyulingan minyak asid lelemak. Untuk mengesan kesilapan penderia, skema yang dicadangkan ini telah berjaya mengesan kesilapan tunggal dan berganda yang berlaku dalam proses. Strategi yang dicadangkan ini juga telah berjaya mengesan kebocoran di dalam saluran proses walaupun peratusan kebocoran itu terlalu kecil sehingga 0.1%Keputusan-keputusan ya ng didapati dari kerja selidik ini telah membuktikan keupayaan rangkaian saraf buatan dalam mengesan kesilapan berganda dan kebocoran yang berlaku dalam loji proses kimia.

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NOMENCLATURE

A_w	-	van der Waals area
a_{ij}	-	non-temperature dependent energy parameter between components *i* and *j* (cal/gmol)
B	-	connection matrix from the input layer to the hidden layer
b_{ij}	-	temperature dependent energy parameter between components *i* and *j* (cal/gmol-K)
b_h	-	bias vector for the hidden layer
b_o	-	bias vector for the output layer
C	-	the unit conversion constant
C	-	*connection matrix* (matrix of weights)) from the hidden layer to the output layer
F	-	tray feed
$f(\cdot)$	-	a nonlinear mapping
$g(\cdot)$	-	a nonlinear mapping
h	-	the step size
h	-	the specific enthalpy (J/mol)
h	-	the height of liquid above the weir
h_n^L	-	the liquid enthalpy for each tray
h_n^V	-	the vapour enthalpy for each tray
k	-	the conductance
L_n	-	the liquid flowrate leaving tray *n*
L_{n+1}	-	liquid enters through the downcomer of the tray from the above
M_n	-	the material on the *n*th tray
l_w	-	the weir length
MW	-	the molecular weight
N_c	-	the number of components in the system
N_{c-1}	-	differential material balances
N_{om}	-	number of manipulated (input) variables with no steady-state effect
N_{oy}	-	number of output variables that need to be controlled

N_m	-	dynamic degrees of freedom
N_{ss}	-	steady-state degrees of freedom
n	-	total number of components
q_i	-	van der Waals area parameter
r_i	-	van der Waals volume parameter
$s(k)$	-	an intermediate variable at a discrete time *k*
T	-	temperature (K)
T_b	-	the boiling point temperature
T_n	-	the temperature for each tray
u_i	-	input vector at a discrete time *i*
$u(k)$	-	input vector at a discrete time *k*
V_n	-	the vapour flowrate leaving tray *n*
V_{n-1}	-	vapour enters the tray from the tray below
V_w	-	van der Waals volume
W^u	-	the interconnection matrices for the input-hidden layer
W^y	-	the interconnection matrices hidden-output layer
X	-	the actual input before scaling
$X_{\max}$	-	the maximum value of the inputs
$X_{\min}$	-	the minimum value of the inputs
X_s	-	scaled input
$x(k)$	-	state vector at a discrete time *k*
x_i	-	mole fraction of component *i*
$x_{i,n}$	-	liquid compositions for each tray
$x^h(k)$	-	a hidden unit at a discrete time *k*
y_i	-	output vector at a discrete time *i*
y_i	-	vapour mole fraction
$y_{i,n}$	-	the vapour compositions for each tray
$y(k)$	-	output vector at a discrete time *k*
Z	-	10.0 co-ordination number
z^{-1}	-	time delay
z_i	-	the feed composition (mole fraction)

Greek Symbols

δ	-	surface tension
γ_i	-	activity coefficient of component *i*
η	-	viscosity
ρ	-	density
$\varphi_h(\cdot)$	-	the vector valued functions corresponding to the *activation* (transfer) *functions* of the nodes in the hidden layer
$\varphi_o(\cdot)$	-	the vector valued functions corresponding to the *activation* (transfer) *functions* of the nodes in the output layer
$\Delta P_{friction}$	-	the dry hole pressure drop

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CHAPTER I

INTRODUCTION

1.1 Motivation

Continuous and batch processes are two important modes of operations in the chemical industry and play an important role in the production and processing of high quality, specialty materials. Monitoring these processes is very important to ensure their safe operation and consistent production of high quality products. Since the manufacturing environment requires higher degrees of automation, fault diagnosis of automated manufacturing systems is becoming a critical issue in production control. Success in detecting and diagnosing faults will decrease system downtime, production delay, and overall production cost.

Research on fault detection has received increased attention in recent years as a result of fatal accidents such as those at Chernobyl and Bhopal, some of which have been traced to sensor failure. Sensors reading provide controllers and operators with a view of the process status and impact the plant operations significantly. Failures in providing correct measurement at the desired frequency can cause process disturbances, loss of control, profit loss, or even catastrophic accidents. In process control, up to 60% of the perceived malfunctions in a plant are found to stem from the lack of credibility of sensor data (Yang and Clarke, 1999). In the interest of maintaining safe and profitable operations, process plant must therefore be equipped with all the required features to provide or maintain reliable measurement.

Major or catastrophic changes are often easy to detect. Unfortunately when such events occur, irreversible damages due to the magnitude of the impact are often incurred. On the contrary, although smaller or non-catastrophic failures may not result in serious immediate damage, detection of these failures is often difficult. Sensor and measurement system failures are examples of the latter. Some of these failure events can result in undesirable process performances. For example, off-calibration instruments provide wrong measurement that will, in turn, result in wrong control action. To alleviate such problems, reliable fault detection mechanisms should be established.

Fault detection is essentially a pattern recognition problem, in which a functional mapping from the measurement space to a fault space is calculated. A wide variety of techniques have been proposed to detect and diagnose faults. Generally speaking, there are three different options available to approach a fault diagnosis problem: state estimation methods, statistical process control methods, and knowledge-based methods. A neural network, a type of knowledge-based system, possesses many desirable and preferred properties for chemical process fault diagnosis. These properties include its abilities to learn from example, extract salient features from data, reason in the presence of novel, imprecise or incomplete information, tolerate noisy and random data, and degrade gracefully in performance when encountering data beyond its range of training (Venkatasubramanian and Chan, 1989). Reviewing the development of neural network fault detection and diagnosis systems, the general trend in research is to increase the robustness of the system to unmodelled patterns, realise fast and reliable diagnosis in dynamic processes, and dynamically filter noisy data used for detection.

In this study, a model-based fault detection system proposed by Ahmad and Leong (2001) will be further developed. Figure 1.1 displays the overall structure of the system. Here, a model-based fault detection system consisting of a process predictor and a fault classifier is proposed. The process predictor is used to predict the normal fault-free operating condition of a Precut column in the Fatty Acid Plant. The deviation of the actual condition from the output of this predictor, termed the residual, is then fed to the classifier, which identifies the residual signal from the process predictor and classifies the cause of faults. The development of both models utilises the nonlinear mapping capability of neural networks.

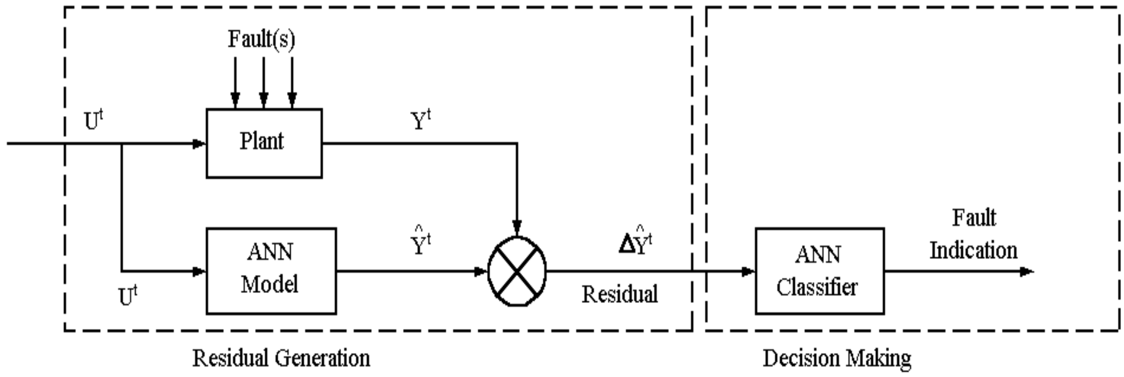

Figure 1.1 The model-based fault detection system

The residual signal plays a central role in the proposed fault detection. It is a measure of process departure from the expected normal operating condition. The idea of utilising the residual signal in fault detection originated from the concept of analytical redundancy. According to Patton et al. (1994), analytical redundancy is a procedure of using model information to generate additional signals to be compared with the original measured quantities.

In their work, Ahmad and Leong (2001) concentrated on the detection of sensor failure in the Tennessee Eastman (TE) plant. Their work revealed the associated problems in implementing the detection scheme. One major difficulty is the training of recurrent network used in the predictor. The proposed system was only capable of detecting single fault. Since various faults can in practice occur simultaneously, there is a need for multiple faults detection scheme.

1.2 Problem Statement and Importance of Study

Artificial neural networks (ANNs) have made rapid developments in the fault diagnosis of chemical processes and related fields. Process fault detection by artificial intelligence techniques have been studied by Venkatasubramanian et al. (1990), Rengaswamy and Venkatasubramanian (2000), Himmelblau (2000), Ungar et al. (1990), Watanabe et al. (1989), Wang et al. (1998), Scenna (2000), Tarifa and Scenna (1999), Pareek et al.(2002), Ferentinos (2003), Sharma et al. (1999, 2004) and others. However, most of the research has been limited to rather 'simple' systems that are systems which can be ably simulated by mathematical models. These models are derived from the various functions that relate the system process variables. Further, most of the work is directed towards identifying operating faults with the focus on safety/reliability aspects rather than process faults; perhaps, except for Sharma et al. (2004).

In this work, the potential of the ANNs to diagnose process faults in a commercially important Precut column in the fatty acid fractionation plant has been explored. These process faults only cause fluctuations in the product quality and yields; they do not lead to failures or operational hazards that might lead to equipment damage and/or plant shutdown. The system investigated operates at dynamic. In addition to the single fault detection and diagnosis, the ability of ANNs to extrapolate and detect leakage and multiple faults is also shown. Relative importance of the various input variables on the output variables plays a vital role in selecting the input/output nodes of ANN architecture.

The main contributions of this work to the fault detection and diagnosis techniques, which also represent the new developments in this field, are the following:

1. The proposed scheme can be applied in detection of single fault or simultaneously multiple faults.
2. The proposed scheme can also be applied to detect leakage in the stream.

3. In the development of process estimator and fault classifier, the MISO model has better generalisation ability compared to MIMO model.
4. The proposed scheme capable to detect single and multiple faults as well as leakage in the light noisy environment.

1.3 Objective and Scope of Work

The main aim of this study is to develop a multiple faults detection scheme using artificial neural networks. The proposed fault detection scheme will able to detect single or multiple faults and also leakage in the selected case study. The selected case study is a Precut Column in the Fatty Acid Plant (FAP). In order to achieve the above objective, the following scopes have been drawn.

1. Simulation of case study – Precut Column.
   Simulation of the plant was carried out within HYSYS.Plant version 2.4.1 process simulator using a flowsheet provided by a local industry. In doing so, a number of modifications were implemented to successfully represent the behaviour of the FAP process especially in the Precut Column.
2. Development of process predictor.
   Process predictor is used to predict the normal behaviour of the process. The development of the process predictor involves selecting an appropriate ANN architecture to differentiate the abnormal behaviour of the process and the normal condition to enable the generation of residual signal. Here, Matlab 6.1 software is used.
3. Development of fault classifier.
   Fault classifier is a decision making system used to detect process faults. Residual signals generated from the process predictor serve as an input to the classifier. Structure selection and training method are the criteria that must be taken into consideration. Matlab 6.1 was used to develop the fault classifier.

4. Implementation of the proposed fault detection strategy.
   Here, the proposed model-based fault detection strategy is implemented to detect faults in the Precut column. The work illustrates the detection of sensor failures and leakage in pipelines.

1.4 Thesis Organisation

In general the thesis was organised as follows:

Chapter II presents the literature overview about different approaches to the fault detection problem. Early diagnosis of the process faults while the plant is still operating in a controllable region can help avoid event progression and reduce the amount of productivity loss during an abnormal event. Due to the broad scope of the process fault diagnosis problem and the difficulties in its real time solution, various computer-aided approaches have been developed over the years. They cover a wide variety of techniques such as the early attempts using fault trees and diagraphs, analytical approaches, and knowledge-based systems and neural networks in more recent studies. The chapter also discusses neural networks that have been used for the fault detection purposes.

Chapter III elaborates the Fatty Acid Plant (FAP) in detail especially Precut column. Description of typical packed column with pumparound system was also mentioned. Simulation methodology of this case study using HYSYS.Plant dynamic simulator was described and validation of the flowsheet with the real data was presented. The mathematical modelling of the distillation operation also presented in this chapter.

Chapter IV presents in details the development of process estimation for fault detection purposes. The process estimator was used to predict the ‘fault free’ operating condition of the process. The model was constructed using a class of recurrent neural network known as Elman network. Procedures for development of process estimator were explained. In this chapter, network structure and training algorithm were studied. Issues of residual generation and prediction accuracy are central to the chapter. The outputs from the process estimator are used as inputs for fault classifier.

Chapter V elaborates the development of fault classifier. This fault classifier is also based on an artificial neural network. In this chapter the study of two types of fault was discussed in details, they are corrupted sensor measurement and leakage in the pipeline. At the end of this chapter, description of the performance of the proposed fault detection scheme tested in the presence of the noise-corrupted measurements and without noise-corrupted measurements was discussed.

Chapter VI is the conclusions and recommendation section. For conclusion, the researcher proposed an effective artificial neural networks fault detection scheme that was able to detect single and multiple faults simultaneously as well as leakage in the light noisy environment. Recommendations were proposed to enhance its efficiency, application and robustness.

6.4 Recommendations for Future Work

The study undertaken here is preliminary towards providing a complete solution to the fault detection and fault diagnosis problem in complex plants. Although this study proved the capability of proposed fault detection scheme, there are still more works required to study various aspects of the approach. To enhance its efficiency, application and robustness, the following works are recommended:

1. Online implementation was not applied in this study. Through online implementation, robustness and efficiencies of the scheme can be evaluated.

2. Capability of the proposed scheme to work effectively in the very noisy environment. In actual process condition, significant process noise can affect the performance of fault detection.

3. Integration of the “fault detection and diagnosis” and the process control system would be most beneficial to the process industries. Investigations should include the efficiency of the fault detection scheme in assisting process control and safety issues. The aim is towards providing a complete package for fault-tolerant control system.

REFERENCES

Ahmad, A., and Leong, W.H. (2001). Model-based Fault Detection Using Hierarchical Artificial Neural Network. *Regional Symposium on Chemical Engineering,* Bandung, 29-31 Oct.

Bankhedda, H., and Patton, R.J. (1996). Fault Diagnosis Using Quantitative and Qualitative Knowledge Integration. *Proceeding of UKACC International Conference of Control'96*, 2-5 Sept, Exeter, UK. Vol. 2: 849-854.

Baughman, D., and Liu, Y. (1995). *Neural Networks in Bioprocessing and Chemical Engineering*, Academic Press, San Diego, CA.

Changkyu Lee , Sang Wook Choi and In-Beum Lee (2004). Sensor Fault Identification Based on Time-Lagged PCA in Dynamic Processes. *Chemometrics and Intelligent Laboratory Systems,* 70(2): 165-178.

Chen, J., and Liao, C.M. (2002). Dynamic Process Monitoring Based on Neural Network and PCA. *Journal of Process Control* 12: 277-289.

Chen, Y.M. and Lee, M.L. (2002). Neural Networks-Based Scheme for System Failure Detection and Diagnosis. *Mathematics and Computers in Simulation*, 58: 101-109.

Demuth, H., and Beale, M. (2000). *Neural Network Toolbox: For Use with MATLAB User's Guide Version 4*, The MathWorks, Inc.

Downs, J.J., and Vogel, E.F. (1993). A Plant-wide Industrial Process Control Problem. *Computer and Chemical Engineering*, vol.17, no.3: 245-255.

Elman, J., (1990). Finding Structure in Time. *Cognitive Science*, 14: 179-211.

Ferentinos, K.P., and Albright, L.D., (2003). Fault Detection and Diagnosis in Deep-trough Hydroponics using Intelligent Computational Tools. *Biosystems Engineering*. 84 (1): 13-30.

Ferrada, J.J., M.D. Gordon and I.W. Osborne-Lee (1990). Application of Neural Networks for Fault Diagnosis in Plant Production, AIChE Mtg, San Francisco.

Frank, P.M. (1990). Fault Diagnosis in Dynamic System Using Analytical and Knowledge-based Redundancy: A Survey and Some New Results. *Automatica*, 26: 459-474.

Frank, P. M., Ding, S. X., & Marcu, T. (2000). Model-based Fault Diagnosis in Technical Processes. *Transactions of the Institution of Measurement and Control,* 22 (1): 57-101.

Fuat Doymaz, James Chen, Jose A. Romagnoli and Ahmet Palazoglu (2001). A Robust Strategy for Real-Time Process Monitoring. *Journal of Process Control,* 11(4): 343-359.

Fuente, M. J. and P. Vega (1999). Neural Networks Applied to Fault Detection of a Biotechnological Process. *Engineering Applications of Artificial Intelligence,* 12(5): 569-584.

Gomm, J.B. (1996). On-line Learning for Fault Classification Using an Adaptive Neuro-fuzzy Network. *Proceeding of 13th IFAC World Congress,* 30 June-5 July, San Francisco, USA Vol. N: 175-180.

Himmelblau, D.M. (2000). Applications of Artificial Neural Networks in Chemical Engineering. *Korean Journal of Chemical Engineering,* 17(4): 373-392.

Himmelblau, D.M. (1978). *Fault Detection and Diagnosis in Chemical Engineering and Petrochemical Processes*, NY: Elsevier.

Himmelblau, D.M. (1992). Use of Artificial Neural Networks to Monitor Faults and for Troubleshooting in the process Industries. Delaware, USA: *IFAC On-line Fault Detection and Supervision in the Chemical Process Industries*,: 201-206

Hoskins, J.C, and Himmelblau, D.M. (1988). Artificial Neural Network Models of Knowledge Representation in Chemical Engineering. *Computer and Chemical Engineering*, 12: 881-890.

Hoskins, J.C., K. M. Kaliyur and D.M. Himmelblau (1989). The Application of Artificial Neural Networks of Fault Diagnosis in Chemical Processing, *AIChE Spring Mtg*, Houston.

HYSYS.Plant User's Manual. (2002), Hyprotech Ltd., Calgary, Canada.

Isermann, R. (1984). Process Fault Detection Based on Modelling and Estimation Methods: A Survey. *Automatica*, 20: 387-404.

Kramer, M.A. and Leonard, J.A. (1990). Diagnosis using Backpropagation Neural Networks – Analysis and Criticism, *Computers and Chemical Engineering,* 14(12): 1323-1338.

Kramer, M.A., and Leonard, J.A. (1991). Radial Basis Function Networks for Classifying Process Faults. *IEEE Control System Magazine,* 11(3): 31-38.

Laser, M. (2000). Recent Safety and Environmental Legislation. *Trans IchemE* 78 (B): 419-422.

Lennox, B., P. Rutherford, G. A. Montague and C. Haughin (1998). Case Study Investigating the Application of Neural Networks for Process Modelling and Condition Monitoring. *Computers & Chemical Engineering,* 22(11): 1573-1579.

Lees, F. P. (1996). *Loss Prevention in Process Industries: Hazard Identification, Assessment and Control.* London: Butterworth-Heinemann.

Leger, R. P., Wm. J. Garland and W. F. S. Poehlman (1998). Fault Detection and Diagnosis using Statistical Control Charts and Artificial Neural Networks. *Artificial Intelligence in Engineering,* 12(1-2): 35-47.

Li, R., Olson, J.H., and Chester, D.L. (1990). Dynamic Fault Detection and Diagnosis Using Neural Networks, *Computer and Chemical Engineering,* 14(10): 957-971.

Lou, S.J., Budman, H., and Duever, T.A. (2003). Comparison of Fault Detection Techniques, *Journal of Process Control,* 13: 451-464.

Luyben, W.L., B.D. Tyreus and M. Luyben. (1998). *Plantwide Process Control*, McGraw-Hill.

Maki, Y., and Laparo, K.A. (1997). A Neural Network Approach to Fault Detection and Diagnosis in Industrial Processes, *IEEE Transactions on Control System Technology,* 5(6): 529-540.

Manish Misra, H. Henry Yue, S. Joe Qin and Cheng Ling (2002). Multivariate Process Monitoring and Fault Diagnosis by Multi-Scale PCA. *Computers & Chemical Engineering,* 26(9): 1281-1293.

McAvoy, T. (2002). Intelligent "Control" Applications in the Process Industries. *Annual Reviews in Control,* 26(1): 75-86.

McDurff, R.J., and Simpson, P.K. (1990). An Adaptive Resonance Diagnostic System, *Journal of Neural Network Computing*, 2: 19-29.

McGraw-Hill Economics (1985). *Survey of Investment in Employee Safety and Health*. NY: McGraw-Hill Publishing Co.

Naidu, S.R., Zafiriou, E., and McAvoy, T.J. (1990). Use of Neural Networks for Sensor Failure Detection in Control System. *IEEE Control System Magazine*, 10: 49-55.

National Safety Council (1999). *Injury Facts 1999 Edition*, Chicago: National Safety Council.

Nimmo, I. (1995). Adequately Address Abnormal Situation Operations. *Chemical Engineering Progress* 91 (9): 36-45.

Nomikos, P., and MacGregor, J.F. (1994). Monitoring Batch Processes Using Multiway Principal Component Analysis. *AIChE Journal,* 40(8): 1361-1373.

Pareek, V.K., M.P. Brungs, A.A. Adesina, and R. Sharma (2002). Artificial Neural Network Modelling of a Multiphase Photodegradation System, *J. Photochem. Photobiol. A: Chem*. 149: 139-146.

Parthasarathy Kesavan and Jay H. Lee (2001). A Set Based Approach To Detection and Isolation of Faults in mMultivariable Systems. *Computers & Chemical Engineering,* 25(7-8): 925-940.

Patton, R.J., Frank, P.M., and Clark, R.N. (1989). *Fault Diagnosis in Dynamic Systems: Theory and Applications*. Prentice Hall, London.

Patton, R.J., Chen, J., and Siew, T.M. (1994). Fault Diagnosis in Nonlinear Dynamic Systems via Neural Networks. *Proceeding of IEEE International Conference of Control'94,* 21-24 March, Coventry, UK 2: 1346-1351.

Qin, S.J., and McAvoy, T.J. (1992). Nonlinear PLS Modelling using Neural Networks, *Computers and Chemical Engineering,* 16(4): 379-391.

Qin, S.J., and Li, W. (2001). Detection and Identification of Faulty Sensors in Dynamic Processes. *AIChE Journal* 47(7): 1581-1593.

Ralston, P., DePuy, G., and Graham, J.H. (2001). Computer-based Monitoring and Fault Diagnosis: A Chemical Process Case Study. *ISA Transaction* 40: 85-98.

Rengaswamy, R., and Venkatasubramanian, V. (2000). A Fast Training Neural Network and Its Updation for Incipient Fault Detection and Diagnosis. *Computers and Chemical Engineering* 24(2-7): 431-437.

Rengaswamy, R., Dinkar Mylaraswamy, K. -E. Årzén and V. Venkatasubramanian (2001). A Comparison of Model-Based and Neural Network-Based Diagnostic Methods. *Engineering Applications of Artificial Intelligence,* 14(6): 805-818.

Rich, S.H., and Venkatasubramanian, V. (1987). Model-Based Reasoning in Diagnostic Expert System for Chemical Process Plants. *Computers and Chemical Engineering*, 11: 11-22.

Rozier, D. (2001). A Strategy for Diagnosis Complex Multiple-fault Situations with a Higher Accuracy/Cost Ratio. *Engineering Applications of Artificial Intelligence* 14: 217-227.

Ruiz, D., Nougues, J.M., and Puigjaner, L. (2001). Fault Diagnosis Support System for Complex Chemical Plant, *Computers and Chemical Engineering,* 25: 151-160.

Russell, E. L., Chiang, L. H., and Braatz, R. D. (2000). *Data-driven techniques for fault detection and diagnosis in chemical processes*. London: Springer.

Samanta, B., K. R. Al-Balushi and S. A. Al-Araimi (2003). Artificial Neural Networks and Support Vector Machines with Genetic Algorithm for Bearing Fault Detection. *Engineering Applications of Artificial Intelligence,* 16(7-8): 657-665.

Scenna, N., S. Benz, B. Drozdowicz, and E. Lamas (2000). A Diagnosis System for Fault Diagnosis in Batch Distillation Columns, ESCAPE10, *Computed Aided Process Engineering*. 8: 805-810.

Scenna, N. J. (2000). Some Aspects of Fault Diagnosis in Batch Processes. *Reliability Engineering and System Safety*, 70(1): 95-110.

Seongkyu, Y., and J.F. MacGregor (2001). Fault Diagnosis with Multivariate Statistical Models Part I: Using Steady State Fault Signatures, *Journal of Process Control,* 11(4): 387-400.

Sharma, R., D. Singhal, R. Ghosh, and A. Dwivedi (1999). Potential Applications of Artificial Neural Networks to Thermodynamics: Vapor-Liquid Equilibrium Predictions. *Computers and Chemical Engineering*, 23: 385-390.

Sharma, R., Kailash Singh, Diwakar Singhal, and Ranjana Ghosh (2004). Neural Network Application for Detecting Process Faults in Packed Towers, *Chemical Engineering and Processing,* 43(7): 841-847.

Skoundrianos, E. N., and S. G. Tzafestas (2002). Fault Diagnosis via Local Neural Networks. *Mathematics and Computers in Simulation,* 60(3-5): 69-180.

Sorsa, T., and Koivo, H.N. (1993). Application of Artificial Neural Network in Process Fault Diagnosis. *Automatica,* 29(4): 843-849.

Sorsa, T., Koivisto, H., and Koivo, H.N. (1991). Neural Networks in Process Fault Diagnosis. *IEEE Trans. System, Man & Cybernetics.,* 21: 815-825.

Sourabh Dash and Venkat Venkatasubramanian (2000). Challenges in the Industrial Applications of Fault Diagnostic Systems. *Computers & Chemical Engineering,* 24(2-7): 785-791.

Tarifa, E., and N. Scenna (1999). A Methodology for Fault Diagnosis in Batch Reactor. *Computers and Chemical Engineering*, 6: 223-226.

Thomas, P., and Lefebvre, D. (2002). Fault Detection and Isolation in Non-linear System by Using Oversized Neural Networks, *Mathematics and Computers in Simulation* 60: 181-192.

Tsai, C.S., C.T. Chang, and C.S. Chen (1996). Fault Detection and Diagnosis in Batch and Semi Batch Processes using Artificial Neural Networks. *Chemical Engineering Comm.,* 143: 39-71.

Tsuge, Y., Hiratsuka, K., Takeda, K., and Matsuyama, H. (2000). A Fault Detection and Diagnosis for the Continuous Process with Load-fluctuations using Orthogonal Wavelets. *Computer and Chemical Engineering* 24: 761-767.

Tzu-Ming Yeh, Ming-Chieh Huang, and Chi-Tsung Huang (2002). Estimate of Process Compositions and Plant-wide Control from Multiple Secondary Measurements using Artificial Neural Networks. *Computer and Chemical Engineering* 00: 1-18.

Ungar L.H., B.A. Powell and S.N. Kamens (1990). Adaptive Networks for Fault Diagnosis and Process Control, *Computers and Chemical Engineering,* 14: 561-573.

Vachhani, P., Rengaswamy, R., and Venkatasubramanian, V. (2001). A Framework for Integrating Diagnostic Knowledge with Nonlinear Optimization for Data Reconciliation and Parameter Estimation in Dynamic Systems. *Chemical Engineering Science*, 56(6): 2133-2148.

Venkatasubramanian, V., and Chan, K. (1989). A Neural Network Methodology for Process Fault Diagnosis. *AIChE Journal,* 35(12): 1993-2002.

Venkatasubramanian, V., Vaidynathan, and R., Yamamoto, Y. (1990). Process Fault Detection and Diagnosis Using Neural Networks-I: Steady-state Processes. *Computers and Chemical Engineering*, 14: 699-712.

Venkatasubramanian, V., R. Rengaswamy, K. Yin and S. N. Kavuri (2003). A Review of Process Fault Detection and Diagnosis: Part I: Quantitative Model-Based Methods. *Computers & Chemical Engineering,* 27(3): 293-311.

Venkatasubramanian, V., R. Rengaswamy, K. Yin and S. N. Kavuri (2003). A Review of Process Fault Detection and Diagnosis: Part III: Process History Based Methods. *Computers & Chemical Engineering,* 27(3): 327-346.

Wang, H., Y. Oh, and E. Yoon (1998). Strategies for Modelling and Control of Nonlinear Chemical Processes using Neural Networks. *Computers and Chemical Engineering,* 22: 823-836.

Watanabe, K., I. Matsuura, M. Abe, M. Kubota and D.M. Himmelblau (1989). Incipient Fault Diagnosis of Chemical Processes via Artificial Neural Networks, *AIChE Journal,* 35: 1803-1812.

Watanabe, K., Hirota, S., and Hou, L. (1994). Diagnosis of Multiple Simultaneous Fault via Hierarchical Artificial Neural Networks. *AIChE Journal,* 40(5): 301-308.

Yang, J. C. and David W. Clarke (1999). The Self-Validating Actuator. *Control Engineering Practice,* 7(2): 249-260.

Ye, N., and Zhao, B. (1996). A Hybrid Intelligent System for Fault Diagnosis of Advanced Manufacturing System. *Int. J. Prod. Res.,* 34(2): 555-576.

Yu, D.L., Shields, D.N., and Daley, S. (1996). A Hybrid Fault Diagnosis Approach using Neural Networks. *Neural Computing and Application,* 3(4): 21-26.

Yunbing Huang, Janos Gertler and Thomas J. McAvoy (2000). Sensor and Actuator Fault Isolation by Structured Partial PCA with Nonlinear Extensions. *Journal of Process Control,* 10(5): 459-469.

Zhang, J., A. J. Morris, E. B. Martin and C. Kiparissides (1999). Estimation of Impurity and Fouling in Batch Polymerisation Reactors through the Application of Neural Networks. *Computers & Chemical Engineering,* 23(3): 301-314.