FAULT DIAGNOSIS USING ARTIFICIAL INTELLIGENCE IN THERMAL DESALINATION SYSTEMS

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Contents

Summary

The basic concepts for process diagnosis are outlined and the principal reported works using signed directed graph (SDG) are covered. A specific introduction to the subject is made focusing on the theoretical background needed for the application to thermal desalination processes. Artificial intelligence application and the computational implementation of a diagnosis system for complex desalination processes is considered. The final product is an expert system that uses fuzzy logic and blackboard architecture.

1. Introduction

Fault diagnosis is the problem of finding out the root causes of process faults. However, due to the complex dynamics existing in most chemical processes (i.e. time delay, complicated interconnection between mass, momentum and energy flows, and the high dimension involved) it is very difficult to detect and diagnose faults in a limited time. Moreover, even with the help of the computer, diagnosis and supervision are difficult tasks.

The set of all the symptoms caused by a fault is the *pattern* of this fault. Symptoms analysis can be done by checking if particular measurable variables are close to a certain tolerance to the normal value. If this check is not passed, a fault message is displayed. The functions up to this point are usually called monitoring or fault detection. This is followed by fault diagnosis: the fault is located and the fault origin is found. The next step is the fault evaluation, which means an assessment is made of how the fault will affect the process. After the effect of the fault is known, a decision (the action to be taken) can be made (Isermann 1984).
Generally, the diagnosis methodologies are based on the following strategy: first, appropriate measurements are made, the results of which are termed measurement space. The measurements can be represented as a vector in which the elements: X_1, X_2, …, X_n represent numerical values (measured process variables). A computer-data acquisition system must be connected to the process. A statistical procedure checks if they are normal or faulty values comparing them with a predetermined normal range for each variable. In this way, qualitative values can be assigned to each component - measured or estimated variables - determining the State Vector (SV). Possible values for SV_j are (+1), higher than the normal value, (-1), lower than the normal value, and (0), normal value. The SV changes according to the evolution of the measured variables.

The analysis of the system is done by monitoring a set of process variables - which can be measured - but this "measured space" is not complete. Thus, the resolution for the diagnosis procedure is limited. Generally, it is common to find a set of faults that corresponds to the same observed *pattern*. This set of faults is defined as a *cluster* of faults corresponding to this pattern. Then, to individualize the actual fault from the cluster, more resolution must be achieved using knowledge of the process, the operator expertise, etc.

2. Model Based Approaches. Qualitative vs Quantitative Approaches

There have been developed different strategies to carry out the diagnosis process, such as quantitative algorithms (Isermann 1984), fault tree methods (Lapp and Powers 1977), qualitative model approach like directed signed graphs (Iri et al. 1979), expert system based approach (Kramer 1987), statistical pattern recognition strategies (Kvalhein 1988), and more recently, neural network approach (Venkatasubramanian et al. 1990). In general, these methodologies can be divided in empirical and model based approaches. The first, are based on the expertise; that is, the expert knowledge of the process, while the latter are based on a process model. Again, we can divide process modeling in quantitative and qualitative approaches.

For large real scale plants like desalination processes, it is very important for the diagnosis implementation to take account of the specific advantages of each method. The model based approach is the best because it represents a structured knowledge about the processes. In fact, model based approaches are based on theoretical principles. Nevertheless, sometimes model building may be very difficult. Then, in these cases, it is necessary to use empirical knowledge, that is, expert knowledge. This kind of knowledge is lesser structured and may contain some mistakes. Besides, the result strongly depends on an adequate communication between the expert and a knowledgable engineer.

In general, the knowledge of expert operators is elaborated because they usually try to capture (not often successfully) the underlying causal structure of the plant behavior. As a result, expert interview is a complex task since knowledge obtained has to be analysed more deeply to discover the formal articulation of theoretical concepts and physical phenomena used by them. Thus, knowledge elicitation typically requires several cycles in which the expert operator is systematically guided through "abnormal" process scenarios and motivated to provide an explanation. In this way, tools of the Reliability Engineering like CCA (Cause and Consequence Analysis), HAZOP (HAZard and OPerability analysis) and FMEA (Failure Mode and Effect Analysis) can be applied (Himmelblau 1978; Henley and Kumamoto 1981).

Clearly, the model approach must be used when possible. In this sense, there are two options to consider: quantitative and qualitative approach. Quantitative approaches involving filtering and estimation have been reviewed by Isermann (1984). Qualitative approaches involving fault trees and related diagrams have been reviewed by Lees (1983). Another qualitative approach, involving the signed directed graph (SDG), has been developed by O'Shima and coworkers (Iri et al. 1979; Shiozaki et al. 1985; Tsuge et al. 1985).

Quantitative fault diagnosis algorithms use a rigorous process model and on-line measurements to back-calculate unmeasured process variables and model parameters. This kind of approach can accurately find out the sources of process upsets and the deviation size, but generally requires extensive engineering manpower and computation horsepower. In the last decade many approaches for variable estimation have been developed. However, the application of quantitative models for complex processes is often complicated by many characteristic problems, requiring a continual on-line examination of the validity of the underlying mathematical models, re-identification of the model parameters, and a repeated test for numerical stability of the employed algorithms (Isermann 1984).

On the other hand, qualitative models are very successful in different applications in chemical processes. They have many advantages over the quantitative models: model building is easier, they are more generals, and time processing is lower. However, the cost of these advantages is the ambiguity. In fact, if a variable is affected by two opposite effects, the model information is not enought to detect which will be the dominant effect.

Many qualitative models are based on the Signed Directed Graph (SDG). The seminal work in this area was the paper of Iri et al. (1979), in which an algorithm for fault diagnosis using SDGs was presented. Variations involving multiple time stages and delay times have been proposed by Umeda et al. (1980) and Tsuge et al. (1985). Kokawa et al. (1983) present an algorithm considering delays, gains, and fault propagation probability, but the method is limited to processes without feedbacks.

3. Process Modeling using Signed Directed Graphs (SDGs)

In a SDG each node represents the qualitative state of each variable (normal (0), high (+1) or low (-1)). Each arc represents the influence of one variable (initial node) on the other (final node). The direct relation (both nodes changes in the same direction) is showing by (+1) gain, the inverse by (-1) and (0) shows no relationship. In other words, in a digraph the gain (G_{ij}) corresponding to the arc from the node *i* to node *j* is a qualitative indicator of the net effect on *j* due to a perturbation on *i*.

Considering the process mathematical model, which usually consists of ordinary differential equations and algebraic equations, generally rewritten in the following form:

$$\frac{\mathrm{d}X_j}{\mathrm{d}t} = f_j(X_1, X_2, \ldots, X_n) \qquad (1)$$

The general expression for G_{ij} given by Iri et al. (1979) is:

$$G_{ij} = Sign\left(\frac{\partial f_j}{\partial X_i}\right) \qquad (2)$$

where the Sign function is used to obtain the qualitative values. For a survey of different methodologies for gain determinations see the work of Oyeleye and Kramer (1988). When the system is strongly nonlinear, some gains become a function of the state variable values, the perturbation size and the duration of it (Tarifa 1995; Tarifa and Scenna 1998).

4. Diagnosis using SDGs

Digraph-based methods are attractive because relatively little information is needed to set up the digraph and do the diagnosis. The SDG represents pathways of causality in the fault-free process. Nodes of the SDG correspond to state variables, alarm conditions, or failure origins. It is assumed that a single fault, which affects a single node in the SDG (the root node), is the source of all disturbances. It is also assumed that the fault does not alter other casual pathways in the digraph. The fundamental premise of digraph techniques is that cause and effect linkages must connect the fault origin to the observed symptoms of the fault. The diagnosis involves locating all possible disturbance sources (root nodes), given on-line sensor data.

4.1. The Compilation of the SDG

Kramer and Palowitch (1987) have pointed out that the SDG, derived as was suggested above, has certain limitations. In fact, in these algorithms, the correct diagnosis can only be guaranteed if each variable undergoes no more than one transition between qualitative states during fault propagation. This is because the SDG only represents the initial response to a given disturbance. In this way, when compensatory responses (CR), inverse responses (IR), noise, or out of order events (OOE) produce qualitative changes more than once during the fault propagation, a continuous causal pathway from the source node to each disturbed node may not exist. To solve this, the authors have stated the need to work only with the *first change* of each node. This means that if some variable has a CR or an IR, only the first *observed* qualitative value (first change) must be considered. In others words, it must be used a sort of snapshot capturing the first changes during the fault evolution.

The SDG compilation was the principal idea introduced by the Palowitch and Kramer work. Thus, in on-line mode only the compilated knowledge is used. Kramer and Palowitch have given a method to obtain a set of rules from the SDG. This set comprises one rule for each possible fault.

Nevertheless, the CR-IR detection problem subsists. Rules are strongly sensitive to the symptom sequence (the order of detection). To overcome this situation, Oyeleye et al. (1990) introduced a new model based on the idea of events (transitions of qualitative states) instead of state variables. The whole idea was implemented by Finch et al. (1990) in MIDAS - model integrated diagnostic analysis system. Nevertheless, for industrial problems, the previous steps before the use of MIDAS (determination of IV and CV, building of the ESDG and the event model), are very time consuming (Rose 1990).

4.2. Fault Diagnosis using Qualitative Simulation

As pointed out by Kramer and Palowitch, the diagnosis problem is the inverse or dual of a much simpler problem, namely that of *fault modeling*. Diagnosis uses a set of observed symptoms to generate a hypothesis, while dual modeling predicts the response of the plant, given the operating faulty state. The last problem is more easy to solve.

Fault simulation using SDG implies the deduction of all the *interpretations* (directed trees branching from a given root node, considering only measured nodes). The simulation tree represents a prediction of the dominant pathways of fault propagation, and yields information about events' order (*the sequence*) and the deviation sign of each node connected to the fault origin (*the fault pattern*). Each simulation tree represents one set of routes from the root node to each causally connected node. For a given digraph and a given fault origin, there may be many interpretations of the fault propagation, but only one or a small set of these interpretations reflects the real behavior of the plant. Finally, Kramer and Palowitch (1987) remark that for practical cases it is a combinatorial explosive problem.

In fact, the number of interpretations depends on the number of nodes where the fault propagation-pathway converges, and the number of control loops. The full set of interpretations comes from invoking all combinations of these choices. To avoid a combinatorial explosive problem, they propose an implicit representation of the combined interpretation set by making explicit the choices, instead of enumerating each interpretation. However, in this way an important part of the interpretation information is lost: the fault patterns.

An alternative to eliminate the explosion risk is to avoid the use of fictitious arcs (for controllers, CV, and/or IV variables) and working, if it is necessary, with a part of the SDG. (Tarifa 1995; Tarifa and Scenna 1998) proposed a method that is based on the previous one proposed by Palowitch and Kramer (1987). Its main features are:

- A set of rules is generated from the SDG. This is an off-line step, as in Kramer and Palowitch's algorithm. However, in this case it is not necessary to add new fictitious arcs for RV or IV variables.

- The incorporation of the fault to the model can modify the SDG. This fact allows the usage of more realistic process models.
- For complex SDGs, the explosion is avoided limiting the searching process into the surroundings of the origin node (root node corresponding to the analysed fault).
- An on-line expert system evaluates the set of rules by means of the process data and the use of fuzzy logic. The last tool enables to overcome the negative effects introduced by the spurious signals and the potential out-of-order detection of the first changes.

Summarising, from this point of view, to build the expert system it is necessary to implement the fault modeling or qualitative simulation step, in which for each fault a new node is added to the SDG (which is build according to was pointed out previously). Afterwards, all the interpretations are generated by qualitative simulation. Finally, they are transformed in rules (*compilation*). There is one rule for each fault. These rules are simplified using logic calculus laws. They are transformed in production rules (IF-THEN format).

Formally, the rule set (RS) have the following form:

$$RS = \{R_1, R_2, \ldots\ldots R_{NR}\} \tag{3}$$

$$R_i \equiv \{A_i \Rightarrow C_i\} \tag{4}$$

So, RS is a set of rules R_i (corresponding each of them to a potential fault cluster of the system). Each rule has an antecedent A_i and a consequent C_i. This consequent represents the cluster (a set of faults characterized by the same fault pattern) assigned to this rule. The antecedent A_i is formed by two propositions:

$$A_i = EZ_i \wedge NAZ_i \tag{5}$$

where $\wedge$ is the AND operator.

The proposition EZ_i (explored zone) verifies the observed symptoms agreement with the expected state for the part of the SDG explored by the qualitative simulation. The second, NAZ_i (no affected zone), verify that the observed symptoms do not affect the part of the sub SDG that should not be affected by the fault (cluster C_i).

On the other hand, EZ_i is true if at least one possible propagation route $I_{i,j}$ (interpretations) is satisfied by the process data. That is:

$$EZ_i = \bigvee_{j=1}^{NI_i} I_{i,j} \tag{6}$$

where $\vee$ is the OR operator.

While the NAZ_i must verify only one special interpretation (the subSDG non-affected by the fault):

$$NAZ_i = Io_i \tag{7}$$

The verification of one propagation route (I_{ij} in EZ_i - Eq. 6) implies that all its elements must be observed. In I_{ij} two elements will be considered, as was pointed out above:

$$I_{i,j} = P_{i,j} \wedge S_{i,j} \tag{8}$$

where P_{ij} are patterns and S_{ij} are sequences.

On the other hand, patterns and sequences are defined as:

$$P_{i,j} = \bigwedge_{k=1}^{NX} X_{i,j,k} \tag{9}$$

$$S_{i,j} = \bigwedge_{k=1}^{Nb} b_{i,j,k} \tag{10}$$

In this way, the pattern satisfaction implies that each variable evolves according to its expected value (indicated by the proposition $X_{i,j,k}$) and the sequence satisfaction implies that the sequence is verified in each arc (it is expressed by the proposition $b_{i,j,k}$). These propositions are calculated by:

$$X_{i,j,k} \equiv (\mathrm{d}X_k = \mathrm{d}X^0{}_{i,j,k}) \tag{11}$$

$$b_{i,j,k} \equiv (\mathrm{d}b_k = \mathrm{d}b^0{}_{i,j,k}) \tag{12}$$

where $\mathrm{d}X_k$ are the qualitative values given by the detector module. The $\mathrm{d}b_k$ values indicate the observed qualitative sequence of arcs (b_k), (+1 if the sequence is right, and -1 if it is inverse). $\mathrm{d}X^0$ and $\mathrm{d}b^0$ are the qualitative simulation predictions for node values and arc sequences respectively. In other words, the evaluation is done by comparing the actual state of the process with the predicted one.

Finally, the special interpretation *Io* is defined in the similar way; but considering that the qualitative predictions ($\mathrm{d}X^0$ and $\mathrm{d}b^0$) belonging to *NAZ* are zero (non affected variables). Moreover, it is convenient to define a rule for the normal state of the process (#Normal). This rule is true if the process is operating normally. Here, the whole SDG is considered into the *NAZ*.

4.3. The Use of Fuzzy Logic for Qualitative State Determination

In general, fuzzy logic is used to deal with the problem of CR, IR, OOE and noise. Several works report the use of non Boolean logic (the Boolean logic uses only two values of truth: TRUE and FALSE) in fault diagnosis. For instance Dohnal (1983) uses fuzzy logic for the construction of CONFUCIUS (CONcentrated FUzzy CIcerone of USer) implemented in Pascal. Kramer (1987) presents a method that uses the violation and the satisfaction of the qualitative pattern generated by equation residues (Mah et al.

1976). It is proved that the fuzzy logic increment the stability and sensibility in presence of noise. Petti and Dhurjati (1991) also analyse the sensibility of the evidence on the diagnosis process. Yu and Lee (1991) combine quantitative and qualitative approach using digraphs presented by Chang and Yu (1990). Finally, the quantitative fuzzy set manipulation during diagnosis was introduced by Han et al. (1994).

In the method proposed by (Tarifa and Scenna 1998) fuzzy logic is used to avoid the rigid evaluation of the causal order of events. In this way, OOEs are tolerated because only a smooth degradation is produced in the fault ranking.

The detector mission is to transform the process measurements in qualitative values. It was pointed out in previous sections that it is not always easy to detect the first change. Fuzzy logic can be used to handle the difficulty associated with this problem.

Fuzzy logic, proposed by Zadeh (1965), uses the concept of membership grade to express partial degrees of inclusion of items in sets. A fuzzy set X is a set of ordered pairs:

$$X = \{[x, \mu_x(x)] / x \in U_x \wedge \mu_x : U_x \rightarrow \in [0,1]\} \qquad (13)$$

where $\mu_x(x)$ is a number comprised in the interval [0, 1] representing the grade of membership of x in X, with the ends of this interval representing no membership and full membership, respectively.

Then, we can combine both ideas: The first change and fuzzy symptoms. To reach this goal, the detector must calculate the membership degree of the variables to the fuzzy sets High (+1), Normal (0) and Low (-1). ΔX (*quantitative deviation* of X) is the difference between the real value of X and its normal value. The value μ_{Normal} (*membership degree*) reflexes the pertaining degree of the value ΔX to a given fuzzy set Normal. $\mu_{Normal} = 1$ means full pertaining to the set Normal, while $\mu_{Normal} = 0$ means the opposite concept. In the same way μ_{Low} and μ_{High} can be defined.

5. The Computational Implementation

As was mentioned, the diagnosis system uses qualitative values. Thus, the detector module transforms quantitative information (the process data of measured variables) in fuzzy qualitative values (Dohnal 1983). Once an anomaly is detected, the diagnostic module is charged in the computer memory.

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Bibliography and Suggestions for further study

Aly G (1983) Computer simulations of multiple-effect (FFE-vue). systems for water desalination. *Desalination J*. 45, 119-131.

Barr A, Cohen P R, Feigenbaun E A (1989) *The Handbook of Artificial Intelligence*. USA: Addison Wesley.

Beery M., Wozny G., Repke J.U. (2010), Sustainable Design Of Different Seawater Reverse Osmosis Desalination Pretreatment Processes ,ESCAPE-20 ,Ischia,Naples,Italy

Berenblut B J and Whitehouse H B (1977) A method for monitoring process plant based on a decision table analysis. *The Chem. Engng.(London)* 318, 175-181.

Chang C C and Yu C C (1990) On-line fault diagnosis using the signed directed graph. *Ind. Engng. Chem. Res*. 29, 1290-1299.

Dohnal M (1983) Linguistics and fuzzy models. *Computers in Industry* 4, 341-345.

El-Dessouky H, Shaban H and Al-Ramadan H (1995) Steady-State analysis of multi-stage flash desalination process. *Desalination* 103, 271-287.

F. Chu, H. Ouyang, V. Silberschmidt, L. Garibaldi, C.Surace, W.M. Ostachowicz and D. Jiang(2009), A Steam Turbine Fault Diagnostic System Based on the Web and Database Technologies , Key Engineering Materials (Volumes 413 - 414)

Finch F E and Kramer M A (1988) Narrowing diagnostic focus using functional decomposition. *AIChE J*. 34(1), 25-36.

Finch F E, Oyeleye O O and Kramer M A (1990) A robust event-oriented methodology for diagnosis of dynamic process systems. *Comput. Chem. Engng*. 14(12), 1379-1396.

Gani R, Ruiz C A, Cameron I T (1986) A generalized dynamic model for distillation columns, Part I: Model description and applications. *Comput. Chem. Engng.* 10(3), 181-198.

Han C C, Shih R F, Lee L S (1994) Qualitative signed directed graph with the fuzzy set for fault diagnosis resolution improvement. *Ind. Eng. Chem. Res.* 33, 1943-1954.

Helal A, Medani M S, Soliman M A and Flower J R (1986) *Comput. Chem. Engng*. 10(4), 327-342.

Henley E J and Kumamoto H (1981) *Reliability Engineering and Risk Assessment*. USA: Prentice-Hall.

Himmelblau O M (1978) *Fault Detection and Diagnosis in Chemical and Petrochemical Process*. Amsterdam: Elsevier.

Huang Y L and Fan L T (1993) A Fuzzy-logic-based approach to building efficient fuzzy rule-based Expert Systems. *Comput. Chem. Engng*. 17(12), 181-192.

Husain A, Hassan A, Al-Gobaisi D M K, Al-Radif A, Woldai A and Sommariva C (1993) Modelling, simulation, optimization and control of multistage flashing (MSF). Desalination Plants. Part I: Modelling and simulation. *Desalination* 92, 21-41.

Husain A, Woldai A, Al-Radif A, Kesou A, Borsani R, Sultan H and Deshpandy P (1994) Modelling and Simulation of a multistage flash (MSF). Desalination Plant. *Desalination* 97, 555-586.

Iri M, Aoki K, O'Shima E and Matsuyama H (1979) An algorithm for diagnosis of system failures in the chemical process. *Comput. Chem. Engng.* 3, 489-493.

Isermann R (1984) Process fault detection based on modeling and estimation methods - A survey. *Automatica* 20(4), 387-404.

Kokawa M, Miyazaki S and Shingai S (1983) Fault location using digraph and inverse direction search with application. *Automatica* 19(6), 729-735.

Kramer M A (1987) Malfunction diagnosis using quantitative models with non-Boolean reasoning in expert systems. *AIChE J*. 33, 130-140.

Kramer M A and Palowitch B L (1987) A rule-based approach to fault diagnosis using the signed directed graph. *AIChE J.* 33(7), 1067-1078.

Kvalheim O M (1988) A partial-least-squares approach to interpretative analysis of multivariate data. *Chem. Intell. Lab. Sys.* 3, 189-197.

Lapp S A and Powers G J (1977) Computer-aided synthesis of fault trees. *IEEE Trans. Reliab.* R-26, 2-13.

Lees F P (1983) Process computer alarm and disturbance analysis: review of the state of the art. *Comput. Chem. Engng.* 7(6), 669-694.

Mah R S H, Stanley G M and Downing D M (1976) Reconciliation and rectification of process flow and inventory data. *Ind. Eng. Chem. Process Des. Dev.* 15, 175-183.

Marcovecchio M.G., Aguirre P.A., Scenna N.J., Mussati S.F. (2010),Global Optimal Design Of Mechanical Vapor Compression (Mvc) Desalination Processes ,ESCAPE-20 ,Ischia,Naples,Italy

Oyeleye O O and Kramer M A (1988) Qualitative simulation of chemical process systems: Steady-State Analysis. *AIChE J*. 34(9), 1441-1454.

Oyeleye O O, Finch F E and Kramer M A (1990) Qualitative modeling and fault diagnosis of dynamic processes by MIDAS. *Chem. Eng. Comm.* 96, 205-228.

Petti T F and Dhurjati P S (1991) Object-based automated fault Diagnosis. *Chem. Eng. Comm.* 102, 107-126.

Rautenbach R and Buchel H (1983) Simulation of thermal desalination process. Some results. *Desalination J*. 45, 37.

Rose P (1990) *A Model Based System for Fault Diagnosis of Chemical Process Plant*. M.S. Thesis, Massachusetts Institute of Technology.

Ruiz C and Gani R (1986) Simulation and design of distillation column. Part I: Hydraulic model and dynamic behavior. *Lat. Am. S. Chem. Eng. Appl. Chem.* 16, 277-305.

Ruiz C, Basualdo M and Scenna N (1995) Dynamic simulation. Reactive distillation. *Trans I Chem* part A, 73, 363-377.

Said S.A., Mujtaba I., Emtir M. (2010),Modelling And Simulation Of The Effect Of Non-Condensable Gases On Heat Transfer In Msf Desalination Plants Using Gproms Software ,ESCAPE-20 ,Ischia,Naples,Italy

Sassi K., Mujtaba I. (2010) ,Simulation And Optimization Of Full Scale Reverse Osmosis Desalination Plant ,,ESCAPE-20 ,Ischia,Naples,Italy

Scenna N (1987) *Simulación y síntesis de procesos químicos. Su aplicación a procesos de desalación por métodos térmicos*. PhD Thesis, Universidad Nacional del Litoral, Santa Fe, Argentina.

Shiozaki J, Matsuyama H, O'Shima E and Iri M (1985) An improved algorithm for diagnosis of system failures in the chemical process. *Comput. Chem. Engng.* 9(3), 285-293.

Tarifa E E (1995) *Fault Diagnosis in Chemical Processes*. PhD Thesis, U.N.L (Universidad Nacional del Litoral), Santa Fe, Argentina.

Tarifa E E and Scenna N (1998) A methodology for fault diagnosis in large chemical process and an application to a multistage flash desalination process. Part I and Part II. *Reliability Engineering and System Safety*, in press.

Tsuge Y, Shiozaki J, Matsuyama H, O'Shima E, Iguchi Y, Fuchigami M and Matsushita M (1985) Feasibility study of fault diagnosis system for chemical plants. *Int. Chem. Eng.* 25, 660-667.

Umeda T, Kuriyama T, O'Shima E and Matsuyama H (1980) A graphical approach to cause and effect analysis of chemical processing systems. *Chem. Engng. Sci.* 35, 2379-2388.

Venkat Venkatasubramanian , Raghunathan Rengaswamy , Surya N. Kavuri ,Kewen Yin ,(2003),A review of process fault detection and diagnosis Part III: Process history based methods,Computers and Chemical Engineering 27 , 327-346

Venkatasubramanian V, Vaidyanathan R and Yamamoto Y (1990) Process faults detection and diagnosis using neural networks - I. Steady-state processes. *Comput. Chem. Engng.* 14(7), 699-712.

Yu C C and Lee C (1991) Fault diagnosis based on qualitative/quantitative process knowledge. *AIChE J.* 37(4), 617-628.

Zadeh L A (1965) Fuzzy Sets. *Info. Control* 8, 338-352.