'89 KACC 1989. 10. 27~28

A Real-Time Operation Aiding Expert System Using the Symptom Tree and the Fault-Consequence Digraph

Jeon Keun Oh, En Sup Yoon, Byung Nam Choi*

Department of Chemical Engineering, Seoul National University.

**Information and Control Department, Yukong Lmtd.*

Abstract - An efficient diagnostic approach for real-time operation aiding expert system in chemical process plants is discussed. The approach is based on the hybrid of the simplified symptom tree(SST) and the fault-consequence digraph(FCD), representation of propagation patterns of fault states. The SST generates fault hypothesis efficiently and the FCD resolve the real fault accurately. Frame based knowledge representation and object-oriented programming make diagnostic system general and efficient. Truth maintenance system enables robust pattern matching and provides enhanced explain facilities. A prototype expert system for supports operation of naphtha furnaces process , called OASYS, has been built and tested to demonstrate this methodology. Utilization of diversified process symbolic data, produced using dynamic normal standards, overcomes the problem of qualitative Boolean reasoning and enhance the applicability.

Introduction

Recently AI(Artificial Intelligence) has been regarded as a promising approach to a number of chemical process engineering problems. Traditional computer control systems perform monitoring and controlling activities. But knowledge based expert systems make extend the computer application domains in a process operation to process trend analysis, decision making and advicing, and troubleshooting activities. It is now under study very actively on the development of the expert system for maintenance support, scheduling, optimization, supervisory control, and as well as troubleshooting.

Especially knowledge based expert systems for process supervisory control on fault occurrences are the most active research domain among the problems. The chemical process plants are large and complex, moreover the installed sophisticated digital control system makes them more complicated. Diagnosis of the complex process fault is a difficult task for the process operator. Although well experienced in various process operational situations, the operator may have difficulty in diagnosis of inexperienced and rare faults. Accordingly the operation aiding expert system can help the operator with complicated conditions. The system increases safety by preventing accidents, reduces the loss of raw materials and downtime by preventing shutdowns, and finally maintains product quality by early detection, diagnosis and correction of process faults.

Real-Time Diagnostic Expert System

The process of fault occurrence and its treatment during operation forms a cyclic loop. If a fault occurs, the trend or value process variables change. In order to detect the fault, the on-line real-time system should monitor the trend and the value of process variables and continuously compare them with certain criteria. Continuous analysis and detection is one of the essential functions required in the real-time system. When abnormality is detected, the causal origin should be found. Fault diagnosis is the search process for the causal origin of the abnormality by using the pattern of process variables. According to the severity of the event, automatic/manual interlocking is conducted, otherwise the operation condition is changed not to invoke shutdown or not to produce bad products. During the fall back operation or downtime the fault is eliminated. Then the supervisory system monitors the influence of the corrective action and repeats the process of detection, diagnosis, evaluation, and corrective actions.

Monitoring and fault detection

On-line real-time expert system requires capabilities such as automatic and continuous process data analysis and conversion to significant symbols or symptoms. But the off-line system makes them rely on the human operator's manual input based on his analysis and decision making. Also, automation of these processes is a difficult task. However theses processes determine the quality of diagnosis in the on-line system.

In most of the studies about real-time diagnostic expert systems, normal standard values on the process variables are fixed and the bands of normal operation or alarm bands are also fixed. But occasionally the actural normal process conditions are changing in chemical process plants. It is due to the changeover of operation conditions, the transition of the automatic computer control set-point by supervisory control logic, and the process performance degradations which from time to time go through the whole operational progress. Therefore, the normal standard values should be changed accordingly. Figure 1. shows an example of the transition operation limits. The operation limit moves according to normal operation conditions within alarm limit and constraints. Therefore, the band of operation limit becomes narrower than the alarm band, so the more abudant and the more sensitive symbolic symptoms are generated earlier. These symptoms are useful information to resolve the real fault among the fault candidates in diagnostic tasks. Normal standard values can be determined by using some criteria such as set points, average values during a definite period, and constraints.

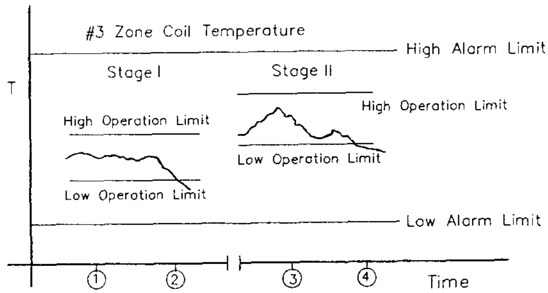


Figure 1. Transition of operation limit.

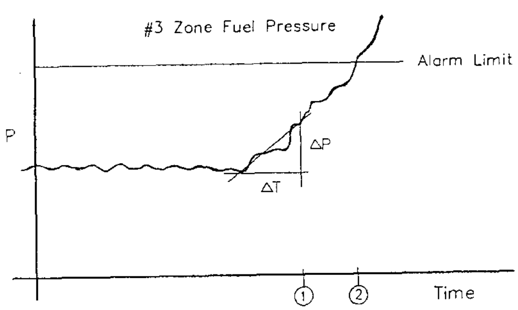


Figure 2. Rate of change and variiance.

The period, when effects of a fault come out conspicuously, is different to the nature of the fault. So the normal standard value calculation should be adjusted to the nature of the fault in order to obtain useful symptoms. Faults can be classified according to the period of biginnig to come out its effects. The term is used not only for normal standard calculation, but also for the diagnosis frequency determinations.

Simple conversion of quantitative data to qualitative data such as high, low may invite loss of information. To minimize the loss and to make multilateral use of informations, many-sided analysis and reduction activities, such as increased/decreased deviation from normal standard criteria, ascending/descending dynamics, and high/low violation of normal operation bands, should be accomplished. Use of these symbolic data raise the quality of diagnosis in the aspect of speediness and accuracy. As shown in the Figure 2, the deviation information, although it is in the normal operation band, is very useful for diagnostic resolution.

Diagnosis

Fault diagnosis is a abduction process in nature like medical diagnosis. If a fault takes place, the symptom patterns are generated. Diagnostic task is the opposite directional search process to a causal origin using the come out symptom patterns. Logically this diagnostic abduction process is incomplete. In other words, the result of the diagnosis may have uncertainties. But peculiar symptom pattern for each fault makes it diagnosable.

The expert system strategies have two basic approaches. One is experiential or "surface(shallow)" knowledge approach and the other is model-based or "deep" knowledge approach. Each approach has its advantages and disadvantages. Therefore, there are hybrid approaches which take advantages of both approaches. Typically in the experiential approach, the knowledge categories are in the form of trees or networks. This approach uses the existing experiential knowledge of operational experts and has efficient diagnostic capabilities. However it is inflexible with respect to various events of the symptom patterns and has limited generality with other process application. On the other hand, model-based approach has generality through modularized models. The models, used in the expert system, are generally qualitative causal models. They can have various or unanticipated event of symptoms. Therefore, the model-based approach is more flexible and general than the experiential approach in the case when combinations of dynamic and various symptoms take place. Diagnostic results may be more accurate, but it is slower than the experiential method. However, diagnostic efficiency is very important in the real-time system. In order to increase efficiency, the hybrid strategy of experiential and model-based approach should be established and compromised with each other.

Formalization of Diagnostic Knowledge

In this study, diagnostic efficiency and accuracy are gained through hybrid use of symptom tree and fault-consequence digraph(FCD) that bear analogy with both experiential and model-based approaches. The symptom tree is a opposite representation of cause-effect relationship. On the other hand, the FCD model is a qualitative digraph along the fault propagation path. It starts from a hypothesized fault and propagates through the causal path of influencing process states.

Symptom tree

The symptom tree is a fault tree like representation of causal relations(Yoon, 1984). Top node is a symptom that represents the change of process variables. Also the intermediate node is a symptom, and the bottom node is basic event, represents a cluster of physical faults that have direct effect on the above symptom. Figure 3 is a imaginary cause-effect directed graph. Node X represents a boundary state. the boundary state node, established between a loosely coupled subsystem, makes the symptom trees manageable. Figure 4 represents a simplified symptom tree(SST) for symptom node B, C, D and for boundary state node X. Basic event of SST, located in the left, has the shorter path to the top node.

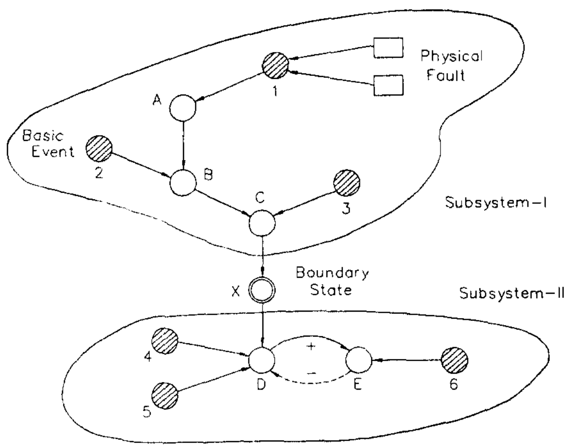


Figure 3. Cause-effect digraph.

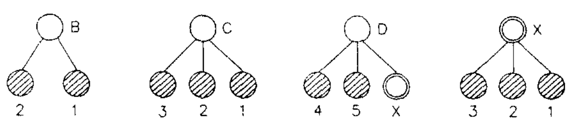


Figure 4. Simplified symptom tree.

Symptom tree is used for hypothesizing fault candidates more efficiently. So to speak, it reduces search space in order to find the real fault. If there are more than one symptom, intersection of symptom trees for each symptom, provides fault candidates of which number is drastically reduced. However, the intersection operation is not allowed to across the subsystem. If a symptom like D is generated and there is no other in the subsystem-I, then the fault candidates are only events 4, 5. In fact, events 1, 2, 3 are excluded from candidates until any other symptom in the subsystem-I appears. In consideration of the symptom tree, it is proper and efficient for classification task in the fault diagnosis. The process is very similar to medical diagnosis. Firstly, a physician will categorize a few diseases by using significant symptoms of a new patient. Then, he will examine more closely for the proposed diseases with more detailed symptoms.

Fault-consequence digraph(FCD)

The signed directed graph(SDG) model has been developed by O'Shima and co-workers(Iri et al., 1979; Shiozaki et al., 1985). Diagnostic expert system methodology, using the SDG model, has been developed and enhanced by Kramer and co-workers(Kramer and Palowitch, Jr., 1987; Oyeleye and Kramer, 1988). SDG is a qualitative representation of the cause-effect relationship between process variables. The cause-effect relationship is based on causality between two individual process variables. The digraph model is the integrated representation of those causal relations. Also the SDG model is relatively easy to develop for new process. Figure 5 shows a simple buffer system. There are four sensors in the process. Figure 6a is SDG for the process. However, the SDG model often can not simulate symptom pattern for a certain fault. For example, suppose a fault occurs in a part of the downstream pipe, then the simulated digraph is like Figure 7a. But pipe faults like leaking in pipe p1 or pipe p2 and pipe blockage can not be simulated. Especially SDG, represented with observable process variables or measured process variables compactly, has a few more problems. It is because the event node, which is process variable, can not contain various multiple fault state at times. So to speak, some faults, though its primary symptom and state are same, they may have different secondary symptom patterns.

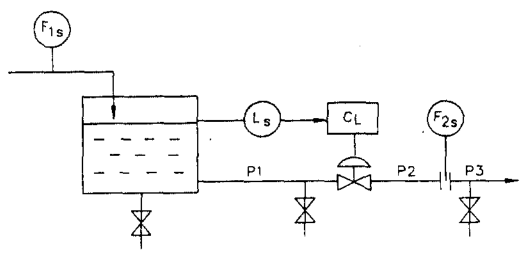


Figure 5. Buffer tank system.

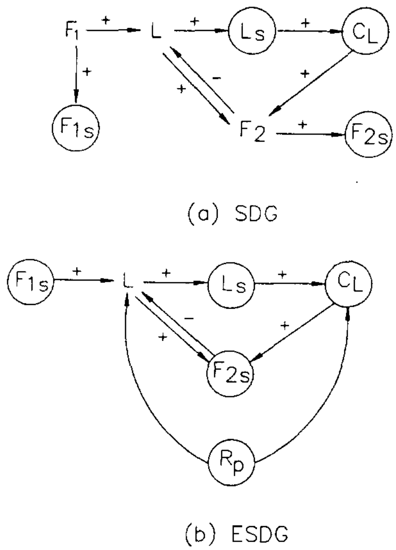


Figure 6. SDG and ESDG for buffer tank system.

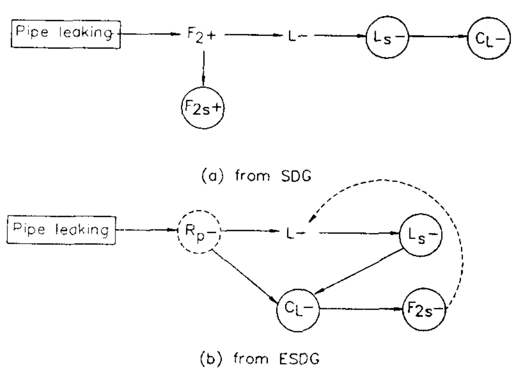


Figure 7. Cause-effect graph derived from SDG and ESDG.

Fault-consequence digraph(FCD) is a representation of effective symptoms through the causal path. Individual faults, which have same primary event state and secondary patterns, constitute a basic event. On each basic fault event, fault propagation behavior is represented as a digraph. The FCD model does not focus on slight dynamic changes. It only represents symptoms that are significant in order of magnitude. If a fault occur, there is some latent phenomena or mechanism at times. Some symptoms, which have a causal relationship with respect to a occurred fault, will not appear until latency is saturated. Occasionally, some discontinuous actions are taken when a certain condition occurs during the propagation of a fault. The FCD can handle latency and discontinuity problems easily. Such behavior can be expressed by using conditional gates in FCD. These conditional gate inhibit propagation of fault

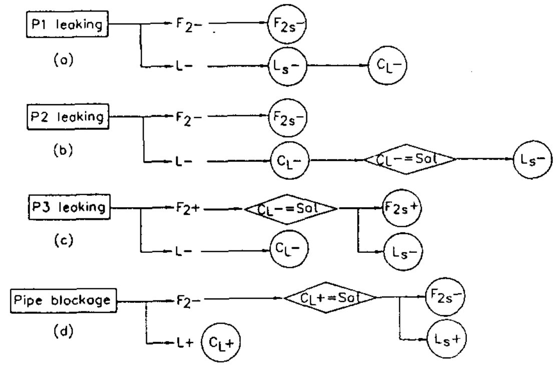


Figure 8. FCD for pipe failures.

to the condition whether it is satisfied or not. Figure 8 represents FCD for pipe failures. It shows that four similar kind of faults have different propagation patterns. Such unique patterns for each fault make it diagnosable. So to speak, FCD has more unique and diagnosable fault propagation patterns than the traditional digraph model.

FCD is based on the simple principle that fault propagation is made through causality between states rather than causality between process variables. In the SDG approach, SDG may be extended with more state variables to express more various kind of faults. Through the introduction of adequate state variables as a basic event, it is possible to explain more fault cases. Oyeleye and Kramer have suggested extended signed graph(ESDG) model (Oyeleye and Kramer, 1988). As shown in Figure 6b, pipe resistance state variable R_p and the bold solid arrow added to SDG, shown in Figure 6a. Cause-effect digraph for pipe p1 leaking failure, derived from ESDG, is shown Figure 7b. It shows the almost same pattern with FCD for p1 leaking, displayed in Figure 8a. However, the cause-effect digraph derived from SDG or ESDG contains many unnecessary feedback loops and unrealistic patterns. Such less unique patterns for the faults brings out decrease of diagnostic resolutions. So to speak, there are too many fault candidates, which adjust to a process symptom pattern. However, in the FCD model, the unrealistic symptom pattern is eliminated through the conversion of feedback loop to the one way arrow and condition gate by using the order of magnitude analysis. So FCD contains more realistic patterns and it is more unique to each other. Therefore diagnostic resolution is enhanced through real, and unique pattern of FCD for each fault events.

However, the FCD model is a more compiled form than the SDG model. Consequently, large space of memory is used for its storage and it takes longer to develop and debug the FCD model than the SDG model based approach.

On the other hand the FCD model is used directly in running diagnostic environments without any pre-compilation processing.

The FCD model is constructed along the path of propagation for a hypothesized fault. The process is a kind of mental simulation by using process engineers' structural and experimental knowledge. However, there are active studies on qualitative simulation. Especially Oyeleye's work (Oyeleye and Kramer, 1988) is an attractive approach for automatic derivation of our fault propagation model.

Automatic derivation of propagation models should be accomplished on off-line basis and during development stage. Because diagnostic speed and efficiency is important in runtime environments of a real-time diagnostic expert system. However, in order to take merits of a model-based approach, such as explaining fault propagation mechanisms and utilizing propagation sequence, efficient models should be exploited in runtime environments. The FCD model is adequate for a runtime environment without any pre-compilation processing and there is no loss of knowledge about a fault and its dynamics. Though the FCD model is not derived automatically, it has flexibility in expressing experimental knowledge, causal knowledge, latency, discontinuity, and constraints. So that the FCD model can be the target model, generated in the qualitative model activities.

Integration of the both models

Typical diagnosis strategy is a cycle of hypothesis and test process. As mentioned above, symptom trees are used for hypothesizing fault candidates and reduces search space drastically. FCD is used for testing the hypothesized fault with more detailed symptoms. This testing procedure is a kind of pattern matching operation between a real context and a hypothesized context of process status. There are assertive and contradictory symptoms, which are used for pattern matching. Contradictory symptoms, opposite symptoms between the world of reality and hypothesis, are opposing evidence of the hypothesis. Assertive symptoms, exact match eaches of other, become supporting evidence for the hypothesis. In the SDG approach, the symptom patterns from simulation tree are generated based on the assumption of the sequential appearance of symptoms. So in a cause-effect relation, if a symptom at the origin does not appear then the consequent symptoms do not appear. However there is a possibility that consequent symptoms appear although causal symptoms do not appear. Especially when quantitative values are converted to qualitative values, the symptoms may disappear due to insignificant change in order of magnitude.

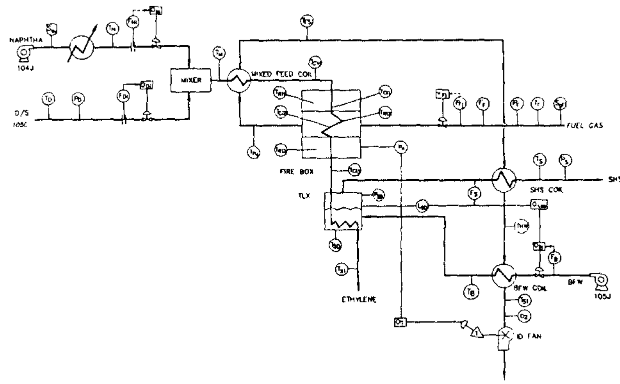


Figure 9. Conceptualized furnace model.

Hybrid use of symptom tree and FCD request maintenance of integrity between two models. Loss of integrity may invoke diagnostic failure. So to maintain integrity, it is better to derive a simplified symptom tree from the FCD model.

Development of OASYS

OASYS(Operation Aiding Expert System) is developed for fault diagnosis and operation support of five naphtha cracking furnaces in an ethylene plant. One of the furnace processes, modeled as heat exchanger network, is represented in Figure 9. In this model each stream for naphtha, dilution steam, and fuel are represented as one stream, but real system have three streams respectively. So there are eleven digital control loops for each furnace. Set points of three naphtha flow rates, three steam flow rates, and three fuel flow rate controllers are determined automatically by dynamic matrix control(DMC) logic. These complex control structures and large process structures make the operator obscure when operational abnormalities take place. Thus OASYS is developed in order to support the operator in troubleshooting of process malfunctions, misoperations, and performance degradations.

Knowledge representations

The strategies for knowledge representation in OASYS are based on frame-based knowledge base, object-oriented programming(OOP), and truth maintenance system(TMS). Frame-based representation makes knowledge base systematic and structured. Especially, the hierarchical representation of frames makes reasoning knowledge and diagnostic knowledge more abstract and general. OOP causes the frames to become active. This paradigm makes reasoning efficient. Active demons and active images make event-driven programming possible. TMS is applied to the simulation of hypothesized fault behavior using FCD in order to maintain conceptual dependency between cause-effect relations along the path of propagation of the fault. First of all, contradiction tests which use TMS supply a new pattern matching strategy. Moreover, the utilization of TMS for fault simulation in a hypothesized context provides good explaining facilities for symptom patterns, propagation paths, and cause of contradictions.

Knowledge and data base structure - There are five frame type knowledge bases in OASYS. One of them is process variable frames. This knowledge base manages symbolic data such as violation of operation limits, deviation from normal standards, dynamical changes to the previous value, and violations of constarints. There are information about sensor failure. Also informations about symptom trees can be stored.

There is another knowledge base which is composed of hardware unit frames. Informations about equipment or process unit failures are stored in this knowledge base. These frames are connected to a graphic frame for process malfunction display. Both of the above knowledge bases have hierarchical structures. So general and abstract diagnostic knowledge representation are enabled.

Knowledge bases about failure modes contains FCD models. Failure mode frames also have hierarchical structures. Faults, which have same FCD or nature, are integrated as one failure mode frame.

Cause-effect frames are included in another knowledge base. Cause-effect frames are causal relationship between two variables. In this case, frames are represented as general as possible in order to express a causal relation of n:n or 1:n or n:1.

There is a knowledge base about process graphics, and there are relational maps which connect knowledge bases.

On these above knowledge bases, the dynamic data or knowledges can be added on-line or off-line basis. These knowledge base structure are shown in Figure 10.

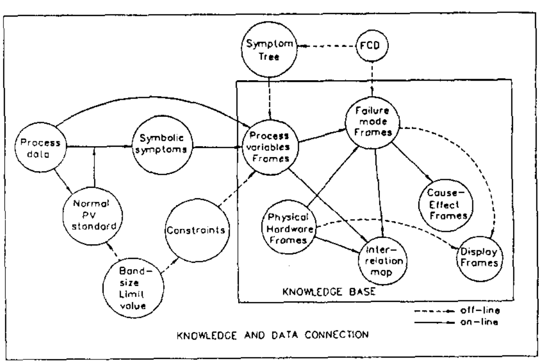


Figure 10. Knowledge base structure.

Architecture of OASYS

OASYS is divided into two modes. One is the monitoring/detection mode and the other is the diagnosis mode. Each mode is composed of many various functional modules.

Monitoring/detection mode - This mode consists of three major modules. Real-time data sending module does rolls of real-time data that send from process computer or intermediate computer to the workstation, in which the expert system is installed. This module manages data storing them in or take them out from memory to make the data usable at next modes. Another module is for symbolic symptom generation. Symptoms such as deviation, dynamics, violations are generated, and normal standard criteria are changed dynamically. The other module is for unstable variables display. In this module, the process variable symptoms, deviated from a normal standard, and its trends are displayed.

Diagnosis mode - This mode is composed of assignation/activation module, reduction/hypothesis module, resolution module, and display/explain module. Figure 11 shows the whole process of diagnosis using these modules. Assignation/activation module gets symbolic data from the detection mode, checks abnormal symptoms, activate the diagnosis module if abnormality exists, and displays abnormal symptoms by using active images. The reduction/hypothesis module reduces fault candidates by using symptom trees. All of the proposed fault candidates should explains the severe abnormal symptoms. The resolution module is a detailed pattern matching process. In this module, assertive and contradictive symptoms are used for resolving the real fault cause. Primary symptoms and important symptoms are used for assertive pattern matching. Secondary symptoms are used for contradictive pattern matching. The pattern

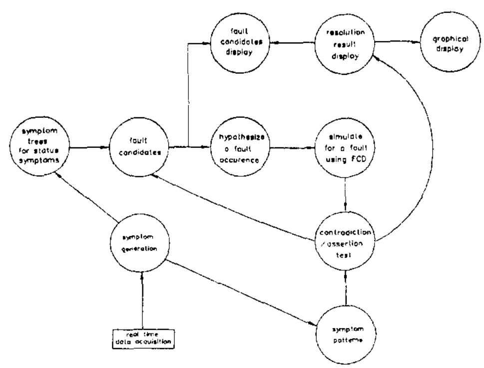


Figure 11. Diagnostic process of OASYS.

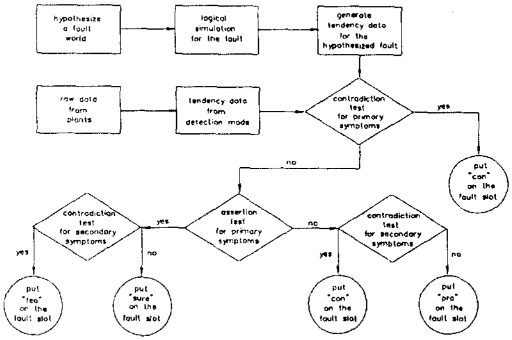


Figure 12. Pattern matching logic.

matching logic is shown in Figure 12. Display/explain module displays diagnostic results using active image, and provides a description for the diagnosed faults. TMS provides explain facilities, so that the propagation path, reason for contradiction, and simulation results can be referred at the off-line basis.

Implementation of OASYS

OASYS was developed on SUN 3/260 workstation by using the LISP, C language, and the KEE shell. The overall structure of OASYS is shown in Figure 13. Data acquisition and analysis/detection mode are implemented with C language and graphic utility. The diagnosis mode is implemented with LISP and KEE shell.

OASYS is connected to process computer, which accomplish data acquisition on the 30 seconds basis. So the diagnostic period is set on every 30 seconds. The number of diagnosable faults, related to only one furnace, is 314. The numbei of symptoms for each furnace is 226. Knowledge bases of process variables, hard ware units, failure modes, and cause-effect relations are composed of 164 frames, 189 frames, 165 frames, and 255 frames.

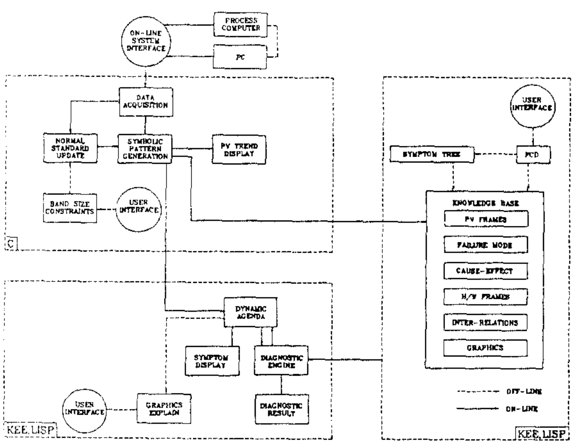
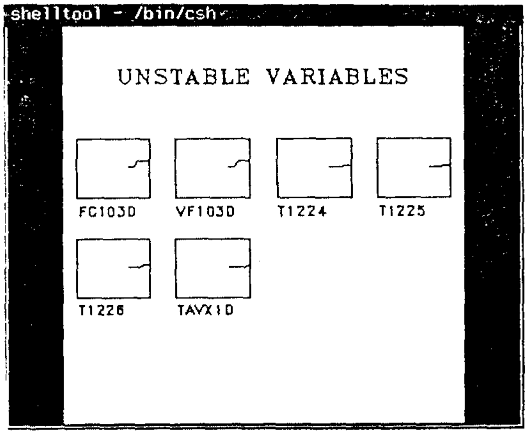


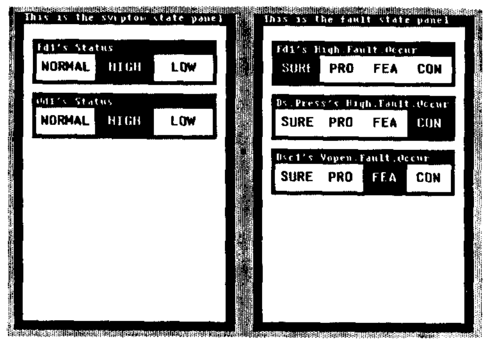
Figure 13. Overall structure of OASYS.

Diagnostic results

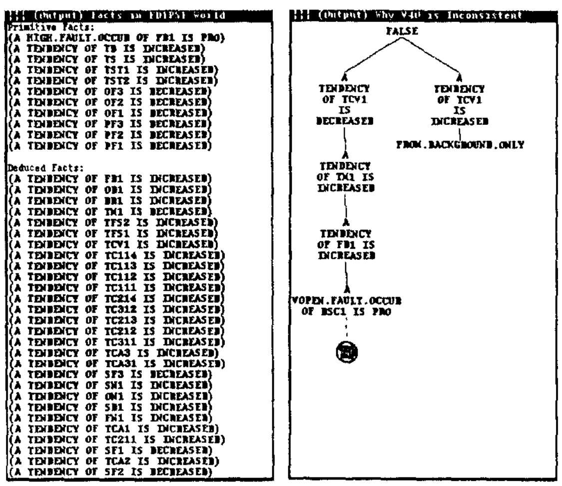
Diagnosis is accomplished for demonstration by using process abnormal data, which are sent continuously every 30 seconds in real-time from another computer. Figure 14.



(a) Tendency of unstable variables.



(b) Symptom states panel. (c) Diagnostic results of fault candidates



(e) Fact from simulation. (f) Logical explain for inconsistency.

Figure 14. Various displays of OASYS.

represents varicus displays, which OASYS offers, for the case of dilution steam flow rate sensor failure. Figure 14a shows tendency of unstable variables, which have a deviation some measure from normal standard Figure 14b displays symptom variables of which operational limits are violated. Figure 14c shows fault candidates, explaining abnormal symptoms, and displays results of diagnosis. It shows that the most plausible fault candidate is that no. 1 dilution steam flow rate is high. Figure 14d and 14e are explaining displays. Figure 14d shows the symptoms when high failure of FD1 sensor takes place. Figure 14e explains why the opening fault of number 1 dilution steam controller is in conflict with the real symptoms.

Table 1 is about the results of 20 case studies. It shows that OASYS diagnose real fault accurately. In all of the cases, diagnosed faults are in accord with hypothesized real faults. Especially, the diagnostic resolution of OASYS is prominent.

Conclusion

OASYS, a real-time diagnostic expert system based on symptom tree and FCD, provides distinguished diagnostic capability with respect to accuracy, resolution, and efficiency. The representation strategies are hierarchical frame bases knowledge bases, OOP, and TMS. These strategies not only increase generality and efficiency of the system but also enables implementation of new pattern matching logic and explaining facilities.

Table 1. Diagnostic results for 20 faults.

Cases	Real Failure Cause	Dianostic Results
Case 1	Naphtha Pump Failure	Naphtha Flow Decrease
Case 2	BFW Pump Failure	BFW Pump Low Fault or BFW Control Valve Close
Case 3	ID Fan Trip	ID Fan Low Fault
Case 4	LSD Sensor Failure	LSD Sensor Low Fault
Case 5	PF3 Sensor Failure	PF3 Sensor High Fault
Case 6	Bias Temp. Input Error	TB31 High Set-Point Fault
Case 7	D/S Ratio Input Error	D/S High Set-Point Fault
Case 8	TLX Fouling	#1 TLX Fouling or #1 Coil Coking Fault
Case 9	TCV1 Sensor Failure	TCV1 Sensor High Fault
Case 10	PSD Sensor Failure	PSD Sensor Low Fault
Case 11	Fuel Gas Leaking Failure	Fuel Gas Leaking or #3 Fuel Control Sensor Fault
Case 12	#2 Naphtha Control Valve Stuck	NFC2 Valve Close or Naphtha Feed Leaking
Case 13	#2 D/S Valve Open	#2 D/S Valve Open or FD2 Sensor High Fault
Case 14	SHS Silencer Valve Close	Steam Make-up Control Valve Close
Case 15	1 Zone 7th Coil Plugging	1Zone 7th Plugging Fault
Case 16	1 Zone 8th Coil Plugging	1Zone 8th Plugging Fault
Case 17	BFW Controller Upset	BFW Controller High Output Fault
Case 18	#1 Naphtha Controller Upset	NF#1 Low Output Fault
Case 19	BFW Inlet Temp. High	BFW Inlet Temp. High Fault
Case 20	Naphtha Preheating Failure	Naphtha Inlet Temp. Low Fault

Acknowledgement

The authors thank the Yukong Limited for their support of this work and providing the necessary hardware and software. The authors are grateful to the process operators and engineers at the NCC plant, system engineers in information and control department, and others of Yukong who provided their working knowledges and devotions.

Reference

Hoskins, J. C., and D. M. Himmelblau, "Artificial Neural Network Models of Knowledge Representation in Chemical Engineering," *Comput. Chem. Eng.*, **12**, 881(1988).

Kramer, M. A., "Expert System for Process Fault Diagnosis: a General Framework," *FOCAPO-87*, (Park City,1987).

Kramer, M.A., "Malfunction Diagnosis Using Quantitative Models with Non-Boolean Reasoning in Expert Systems," *AIChE J.*, **33**, 130(1987).

Kramer, M. A., "A Rule-Based Approach to Fault Diagnosis Using the Signed Directed Graph," *AIChE J.*, **33**, 1067(1987).

O'shima, E., "Computer Aided Plant Operation," *Comput. Chem. Eng.*, **7**, 311(1983).

O'shima, E., and M. Iri, "An Improved Algorithm for Diagnosis of System Failures in the Chemical Process," *Comput. Chem. Eng.*, **9**, 285(1985).

Oyeleye, O. O., and M. A. Kramer, "Quantitative Simulation of Chemical Process Systems:Steady-State Analysis," *AIChE J.*, **34**, 1441(1988a).

Oyeleye, O. O., and M. K. Kramer, "The Role of Causal and Non-causal Constraints in Steady State Qulitative Modeling," submitted to *Artificial Intelligence, Simulation and Modelling*, (1988b).

Ramech, T. S., S. K. Shum, and J. F. Davis, "A Structured Framework for Efficient Problem Sloving in Diagnostic Expert Systems." *Comput. Chem. Eng.*, **9/10**, 981(1988);

Rich, S. H., and V. Venkatasubramainan, "Model-Based Reasoning in Diagnostic Expert Systems for Chemical Process Plants", *Comput. Chem. Eng.*, B, 111(1987).

Rich, S. H., and V.Venkatasubramanian, "Causality-Based Failure-Driven Learning in Diagnostic Expert Systems," *AIChE J.*, **35**, 943(1989).

Shum, S. K., J. F. Davis, F. Punch, and B. Chandrasekaran "An Expert System Approach to Malfunction Diagnosis in Chemical Plants," *Comput. Chem. Eng.*, **12**, 27(1988).

Venkatasubramanian. V., "An Object-Oriented Two-Tier Architecture for Integrating Compiled and Deep-Level Knowledge for Process Diagnosis. *Comput. Chem. Eng.*, **12**, 903 (1988).