Study On Diagnostic Expert Systems for Power Plant Boilers

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Key Words: Power Plant Boiler, Fault Diagnosis, Flame Imaging, Artificial Intelligence, Real Time Systems, WINDOWS Programming

CONTENT

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ABSTRACT

Diagnostics have been applied to power plant operation monitoring for many years. Much work has been conducted on steam turbine or gas turbine diagnosis with emphasis on vibration or life extending, etc. In recent years, much has been reported on boiler diagnosis, but most has been focusing on thermal parameter monitoring and steam side diagnosis. In combustion research field, deep research work has been carried out on optical measurement and diagnosis technologies. In this paper, we will introduce our recent work on boiler diagnosis with emphasis on combustion fault analysis, measurement methods based on radiative energy of coal combustion, application of artificial intelligence and finally real time diagnosis system development practice.

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1. INTRODUCTION

Successful expert systems have been built to support the operation, diagnosis, maintenance and design in the power industry. Power plant diagnosis is an obvious example of the applications for expert systems [1].

For large scale power generation units, advanced control systems have been facilitating the processing of general faults. However, operators still have to face vast amounts of measurement data even though these data might have been processed and presented in either form of tables or curves. This gives the operators the difficulties in handling an abnormal situation when many alarms occur in parallel, which will probably evolve into a severe accident. One typical example is the explosion of   a 600MW boiler in Beilungang Power Plant in Zhejiang Province in China[2]. Similar cases can be found in nuclear power generation in Three Miles Island (USA) or Chelnobri (Russia) , which have resulted in a much more severe damages and a long-term consequences of both environmental pollution and the residents' suspicion on the safety of nuclear power [3][4]. One way is to use simulators to give the operators more training on how to deal with the possible disorders while the other way is to establish diagnostic system to secure safe and economic operations.

For old power generation units, mainly in the fossil fuel power plants, which have been 20~30 years old—an age when declining reliability might make it more economical to replace them than to repair them, as some have suggested. However, Some investigations foresee the useful life of these units extending as long as 60 years with judicious refurbishing[5]. In China, such units are still playing and will probably have to play an important role in the power industry because of the increasing need for power supply resulting from the fast growth in economy. On-line diagnostic monitoring will be an essential part of the future of these plants.

Diagnostic expert systems present a prospect of performing corrective maintenance rather than the currently adopted predictive maintenance. Preventive maintenance is scheduled periodically, based on the manufacturer's recommendations and the utility's experience regardless of the condition of the equipment when it is recommended for service. Because of the guest work involved, this is truly an expensive approach. According to the study by the Forbes Magazine in 1983, one in three dollars spent on these programs—about $60 billion annually is wasted. However, corrective maintenance simply fixes something when it breaks. This approach is considered cost-effective because repairs are made only when machinery fails, but it risk letting relating minor failures become catastrophic and expensive[5].

Besides the safety considerations and economy considerations of power plant operation, expert systems can help reduce the power production cost by intelligent monitoring of the thermal efficiency and pollutant emissions. This is especially important for the old power plants, which was design in an age when environmental issues were not so much emphasized.

For boiler monitoring and diagnosis, research and development have been widely carried out in USA, Europe, Japan, China and many other countries. For example, ESCATRA is an on-line expert system developed by the Electric Power Research Institute(EPRI) for tube-leakage diagnosis during boiler operation. Besides ESCATRA, 15 projects were listed in EPRI's development plan with about 10 of them is on power plants—mainly on boiler and steam turbine monitoring and diagnosis [6]. North Indiana Public Service Company designed an expert system to optimizes the power plant boilers. Its prototype includes three main parts for 1) boiler and air preheater; 2) air re-circulation system; and 3) exhaust smoke temperature. Back-chaining was employed for inference and Prolog Language was adopted for coding[7]. The Pegasu Technology Company used the neural network as the core for its combustion optimization system in order to achieve the goal of low NOx and high thermal efficiency of the boiler[8]. Lockheed Marting Company and New York Electric Company cooperated to present an expert system named InEC^{TM} to help operators in selecting proper control parameters in order to meet the NOx emission standard issued by CAA (Clean Air Act) at the least expense of combustion losses. Both rule-based technology and neural network were employed in the system[9]. In addition, a diagnosis center has been established by Westinghouse, which can provide services on remote fault diagnosis on boilers, steam turbines and auxiliary equipment in the power plant through an information highway[6].

Japan has also been playing an important role in this field, especially its work on combustion monitoring and diagnosis through image processing technology[10]. Finland has also reported much work in this field. Tuula Ruokonen gives the detailed plan of Imatran Voima Oy (IVO) for expert system applications in the power industry, with much of the work on boiler monitoring and diagnosis[1]. As a matter of fact, this has been a spot of world-wide interests.

In China, great successes have been achieved during the recent years. On the basis of the key project on steam turbine fault diagnosis, researches on boiler fault diagnosis have been conducted in Tsinghua University, Harbin Institute of Technology, Huazhong University of Science and Technology, Southeast University, Zhejiang University and etc., by cooperating with some power plants and instrument company. Based on the former work on power plant simulators, useful diagnostic models in either mathematical or symbolic formality have been reported and practical monitoring and diagnosis systems have been put into practice at thermal power plants.

Our work has been focusing on the fundamental study on combustion faults besides development of diagnostic systems. The main reasons lie on the following four considerations: 1) Some combustion faults (e.g. furnace explosion) can cause severe damages of the boiler or unplanned halts (e.g. due to severe slagging or combustion stability), and some may be the original cause of the steam-water side faults such as tube leakage. 2) Combustion is a complex process involving various physical and chemical changes, therefore, modeling the process is much more difficult than modeling mechanical processes. 3) The currently used control systems are mostly based on signals of the steam side. However, there is a long delay between the disturbance to the system and the response in the steam parameters while there will be a quick response if a disturbance such as the variation in fuel quality or fuel-air ratio is put into the system. According to Reference[11], slagging will have been developed so that it cannot be removed by blowing or combustion adjustments if we only depend on signals provided by the existing control system. 4) much has been done on the steam-water side faults in this field , so the models and knowledge will be easier to acquire. Besides, study on combustion side helps improve integrity of the models for the whole boiler system.

For combustion diagnosis, novel measurement methods and analysis methods will be essential for effective fault detection. Considering some quantities which are beyond current instrumentation capability, studies on theoretical models and state or parameter estimation or prediction methods should be necessary in this area.

The following 5 parts will introduce in detail the work on fundamental research and system development. In part 2, we will analyze the characteristics of combustion faults and diagnosis strategy; in part 3, we will briefly introduce the fundamental research on combustion faults, mainly on combustion stability and slagging, including experimental results and flame imaging technology. In part 4, knowledge processing will be discussed and systems we have finished will be introduced. In part 5, we will introduce in detail the on-line monitoring and diagnostic system developed in Borland C/C++ for WINDOWS.

2. ANALYSIS OF BOILER FAULTS AND DIAGNOSTIC STRATEGY

2.1 General Process of Fault Diagnosis

The purpose of fault diagnosis is to secure a system to function properly under certain conditions for a fixed period of time. Generally speaking, fault diagnosis has two main tasks. The first is to detect the fault(s) arising in the system and the second is to find out the size, location and original causes of the fault(s) and hence to find a proper way to solve the problem. Fault diagnosis can be regarded as a process of pattern recognition because different state spaces can actually be taken as different patterns. By monitoring or observing a given system, characteristic signals can be obtained in either energy form (e.g. pressures, temperatures , vibrations, radiation, etc.) or material form (e.g. Oxygen concentration, coal-in-ash, etc.), through a preprocessing and feature extracting subsystem, the featured pattern can be obtained. Considering the observability of the system, we may have to build system models and system identification methods will be useful for estimation of the non-measurable state variables, non-measurable process parameters and non-measurable characteristic quantities (efficiencies, fuel consumption per production unit, etc.)[12]. Then, the pattern recognition subsystem will try to recognize the state of the system and propose a judgment on what faults have occurred and will probably tell the original causes based on all the information that is available. To locate the fault, both mathematical models and empirical and heuristic knowledge may be used. Fig-1 shows the general process for fault diagnosis of a certain object.

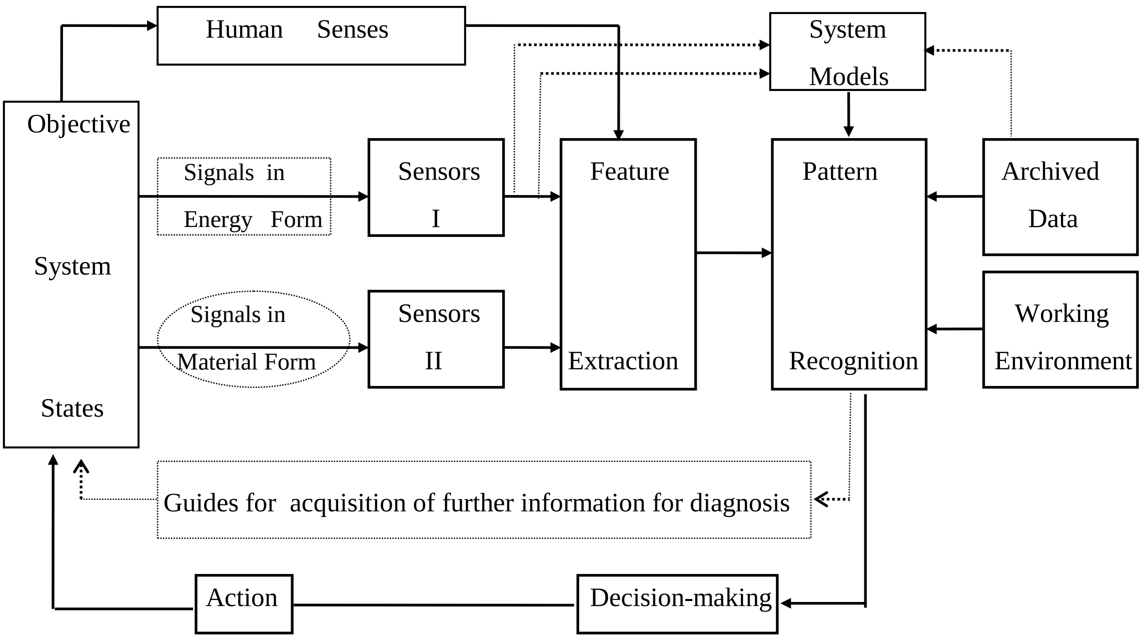


Fig-1 Flow Chart for the General Process of Fault Diagnosis

To establish a fault diagnosis system, discussions should be conducted on the following questions.

a) What faults might arise in the operation of the object? And Which faults are the most important? Or what is required to be the target of the diagnosis system?
b) For each of the main faults, try to understand as much about the mechanisms of its development as possible; find the necessity and possibility of developing mathematical models for its diagnosis; conduct fundamental studies (either theoretical or experimental) for further knowledge for diagnosis.
c) Try to make clear what signals are available for diagnosis and if it is necessary to take additional measurement besides the system already has; what extra parameters are to be be estimated for fault diagnosis purposes.
d) Establish effective measures for signal processing and analyzing , and feature extraction; select proper methods for diagnosis(pure numerical, fuzzy logic, symbolic inference, neural network).

e) Analyze the characteristics of the knowledge and choose a proper way for knowledge representation Collect and summarize the field knowledge, setup the knowledge base (including model set, rules sets, symptom set and fault set) and knowledge management system to facilitate the clarification and management of the knowledge.
f) System analysis and architecture design for the diagnostic system and programming concerns.

2.2 Analysis on the Main Faults of Boiler Combustion

For thermal power generating units, boilers tend to have more faults than steam turbines during operations. In the regulations for the power plant operation, both *fault* and *failure* are defined in order to classify the degrees of severity. Usually, the failures are more serious than the faults. In this paper, we take the failures as one kind of faults and in this way we can reach a conceptual unity.

Generally, boiler faults can be classified into steam-water side faults, combustion side faults. The former includes water shortage, overfeed of water into drum, priming, water beat, steam leakage, tube failure and some other mechanical failures; the later refers to the failures that might occur in the furnace or the gas pass, for example, explosion , implosion or puff in the furnace or in the gas pass, fouling and slagging of the convection heating surfaces (e.g. superheater, reheater, etc.) and radiation heating surfaces (e.g. the waterwall, ceiling superheater, platen heater), flame failure, furnace roar. From the environmental point of view, combustion pollutant emissions beyond the legal standard due to bad combustion adjustment should also be taken as a severe fault. For the steam-water side faults, the characteristic signals can be easily obtained from the control system, and both mathematical models and symbolic models can be employed for diagnostic purposes. For the combustion side faults, each of them has its own different characteristics, which require a careful comparative analysis in order to propose appropriate strategies for diagnosis on it. In fact, The fouling and slagging of the convection heating surfaces can be treated in the way in which the steam side faults are dealt with, i.e. by monitoring the steam temperatures and pressures and then using the quantitative (or qualitative) formula to help detect the fault.

When studying fault diagnosis, we should first notice the corrections among the different faults. In case of boilers, we see that the steam-water side faults can causes combustion side faults, and the different faults in either class are generally correlated in one way or the other. For example, slagging on the water wall might result in tube leakage on the wall; and a fault of tube leakage might eventually result in a positive pressure in the furnace, unstable combustion and even flame failure.

The second consideration in fault diagnosis is the layered nature of the object to be studied. This nature offers a basis for employing Object-Oriented technology. Usually, mechanical systems have clear structures and the layers of faults can be in good accordance with the structural architecture and hence a good diagnosis strategy as well as layered models can be established in order to conduct effective diagnosis. A boiler is a mechanical system, but it is much more complex than those pure mechanical systems because of the flow and combustion processes involved. For the steam-water side, there is a layered feature (though less than a pure mechanical system) and layered models have proved useful [13]. On the other hand, combustion systems are more complicated and in this case layered nature is not so clear.

The third point in analyzing faults is the real-time consideration.. As we can see, some faults may arise abruptly (e.g. as the flame failure, explosion, implosion and priming) while others may experience a long period before an emergency occurs (as in case of slagging, which experiences several stages before reaching a severe situation). For those fast-growing faults, quick detection, quick decision-making and quick action are essential among the considerations in designing the system. The algorithms for pattern recognition or inference should be fast enough. And when anyone of these faults occurs, the system should provide enough information to help the operators handle the situation with the aid of a well established expert knowledge base on these issues. Characterized signals should be selected and effective measurement technology should be developed. Multimedia should be an effective way for information layout. For slow growing faults, there is enough time for carrying out careful analysis and diagnosis inference. The system can be more complex, archived data can be employed and the algorithms for inference can be selected without emphasizing the speed (of course, it cannot be too low to use) while emphasis can be put on the effectiveness. For both types of faults, how to detect the faults in the early stage of their development processes is essential and hence fundamental researches should be conducted in order to understand the fault development mechanisms.

The fourth consideration is the uncertainty in fault diagnosis. For example, there is a probability problem when predict flame failure from the load change , coal quality and combustion stability signals. To make a diagnosis on slagging, there is a fuzzy problem as well as the probability problem[14]. Good handling of the uncertainty problems is the key to achieving successful diagnosis.

3. MEASUREMENT AND SIGNAL ANALYSIS

3.1 Fundamental Work

As stated above, effective measures for on-line signal acquisition have to be established before building an successful real-time expert system for system The existing control systems can provide a large amount of signals for fault diagnosis. These are mainly from the measurements on the steam-water side. At present, what are commonly used for combustion monitoring include the flame monitoring TV and analysis of the gas compositions in the rear pass of the boiler. The gas analysis method is an indirect way for combustion monitoring, which has a comparatively slow response and low reliability and has difficulties in reflecting the general features of the combustion states. The flame monitoring TV is actually not so instrumental as expected since what is shown on the screen is just a fire ball, which can only serve to reflect the existence of firing. In order to get more information that can be used for fault diagnosis, we conducted researches on image processing and feature extraction. Fig-2 shows the research approaches based on the flame radiation characteristics.

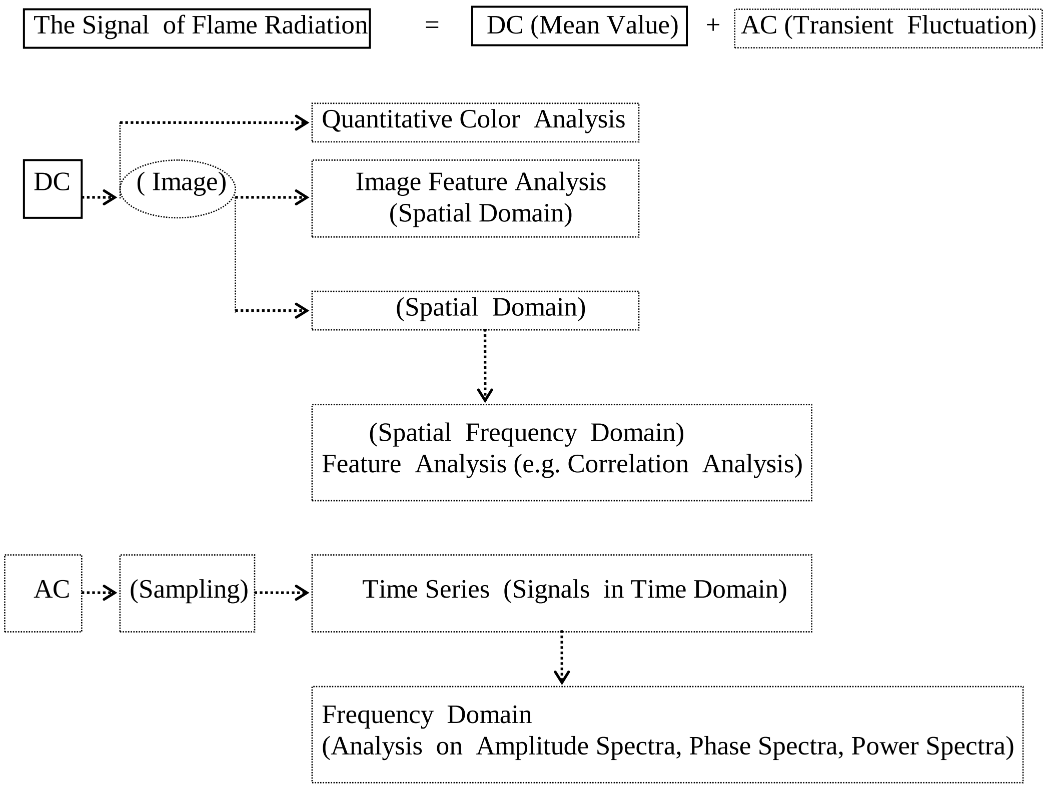


Fig-2 shows the research approaches based on the flame radiation

In reference[15], we introduced two measurement methods for boiler combustion diagnosis. One is based on quantitative color characterization of the combustion flame while the other is based on power spectrum estimation of the flame signals. Experiments and analyses showed that these methods can be introduced to diagnosis systems. Based on these results, Kohonen's self-organized neural network has been employed to carry out feature extraction and combustion instability diagnosis and the results are very satisfactory [15].

By introducing a PC computer with an image board to the flame monitoring system, we established a flame imaging system. Based on Plank's Law on radiation, methods for two-dimensional and three dimensional temperature calculations have been proposed[16][17]. The 2-D method has been tested on a pilot furnace and has been applied to a power plant boiler monitoring system. Careful Analysis were done and detailed experimental plans has been proposed. To make use of the information on combustion temperature distribution, a simplified pattern is established and the Kohonen's self-organized neural network were used again for flame feature extraction.

3.2 A Practical Data Acquisition System

Part of our research achievements has been used in the monitoring and diagnosis system for the Jingyuan Power Plant in Gansu Province in China. Fig-3 shows the structure of the data acquisition system. The system consists of an imaging subsystem and a data acquisition system for getting parameters on working conditions. A 486 computer is used for data processing and analysis. The imaging subsystem is based on the DZHJ/II type flame monitoring TV system manufactured by the Eastern Boiler Company in China. To get monochromatic images, a monochromatic filter (λ=632nm) has been installed onto the CCD camera. The images, being in digital form, can be easily processed and then displayed on both CRT and monitoring TV.

Combustion Flame Image Aquision   Data Aquisition of Thermal Parameters of the Operating Boiler

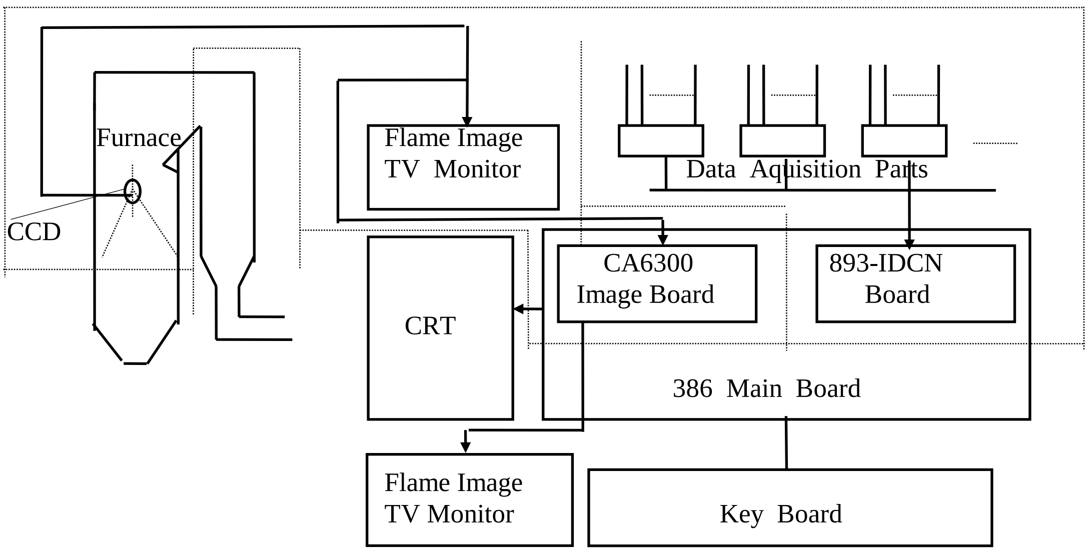


Fig-3 Diagram of the Hareware for Boiler Monitoring and diagnosis

The software for data acquisition were composed in C language. The library files(*.lib) for both CA6300 image board and the 893-IDCN distributed data acquisition board were combined with the standard C library files and used for system development.. Similar was done with the head files (*.h).

The original images have a resolution of 512×512. When they are used for calculating the temperature distribution, there is no need to select such a high resolution, which will make the calculations a very time-consuming process and hence cannot meet the real-time requirement. Therefore, we selected a resolution of 60×60. For data archiving, we adopted bigger grids (5×5). In addition, mean temperatures were calculated (1×1) for direct furter analysis on dynamic characteristics using the radiation singnal series in time domain.

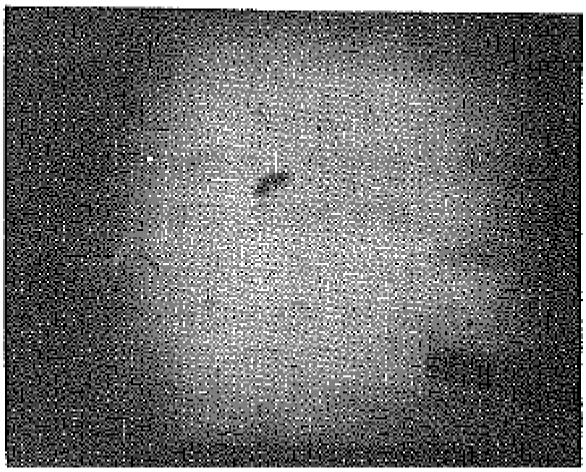
For 893-IDCN data acquisition, the mean values for every 20 samples were save to the data file as one record.

One of the programs we have composed is named AQUIS. It is designed to perform data acquisition, calculation and recording every 30 seconds. The temperature distribution is calculated based on a resolution of 60×60 and storing the data of 5×5. For every 3 hours, a temperature field of 60×60 as well as detailed data from 893-IDCN will be archived. The program was designed to keep an hour's latest records and establish a data file per hour. The file is defined as month-day-hour-minute with an extension of SMP (eg. 07-12-12-07.SMP).

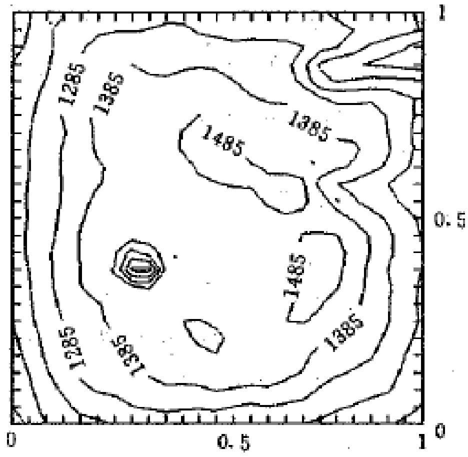
In order to get the flame signal within shorter intervals, a program named RES was composed. RES was also designed to calculate the mean value of the gray scale in stead of performing temperature calculation, and at the same time, it also processes the data from 893-IDCN. The interval for acquisition, calculation and storage is 4.44s. The file name is defined as in AQUIS with an extension of DYN.

ONTIME is another program designed for the user to acquire, calculate and store a series of 10 continuous data at any time. The extension name is CNT.

Fig-4 shows the data acquired in the lab at HUST in July 1995. Fig-4(a) is the original flame image. Fig 4-b is the temperature contour calculated from a single flame image[16].



(a) The Temperature Contour



(b) The Bar Chart of the Series (10 times)

Fig-4 Combustion Flame Image and Temperature Profile

Analysis on the acquired data shows that proper relations can be established between the steam pressure and the combustion radiation energy (the gray scale value of an image) when the CCD camera is properly adjusted.

Fig-4 is based on the on the data acquired by RES on July 24,1995. The time started from 11:50 and ended on 15:37. The sampling interval T_0 is 4.44s. The figure shows the changing trends of the mean gray scale value of the flame image (having been filtered) and the measured pressure in the drum (which is in accordance with the main steam pressure with just a pure delay). It can be seen from the test data that the pressure has a similar trend as the gray scale with a delay of about $70T_0$. This suggests an approach to perform control and diagnosis based on the combustion radiation. In reference[18] we established an model for fuel control based on signals of radiation energy from furnaces. And based on this model, a two-loop fuel control strategy was proposed and simulations were carried out after some coefficients and variables in the model had been identified using in-situ data. From the curves in Fig-4, we can see that this has greatly reduced the delay and fluctuation in the control process. From the angle of diagnosis, this suggests a good resource of featured signals of combustion.

4. KNOWLEDGE SYSTEM

Diagnostic knowledge refers to all that can be used in a certain field including the principles, models, experiences and etc. rather than just the rules, which are commonly used. Accurate models are preferred if they are available. However, for a complex system such as a power plant, pure mathematical models might be established but it will not serve as an effective measure for diagnosis because the working mechanisms of the system or some a key problem in fault developing and spreading are highly beyond our current understanding. A strategy that can be recommended to solve this problem is to establish a hierarchy of the object to be diagnosed based on analyses on the physical processes and try to incorporate the detailed knowledge in either explicit or implicit forms.

4.1 Object Oriented Knowledge Representation

One way that has proved efficient in fault diagnosis of complex mechanical systems or electronic equipment is the Object Oriented Knowledge Representation. Work has also been done on fault diagnosis of power plant boilers[13][19].

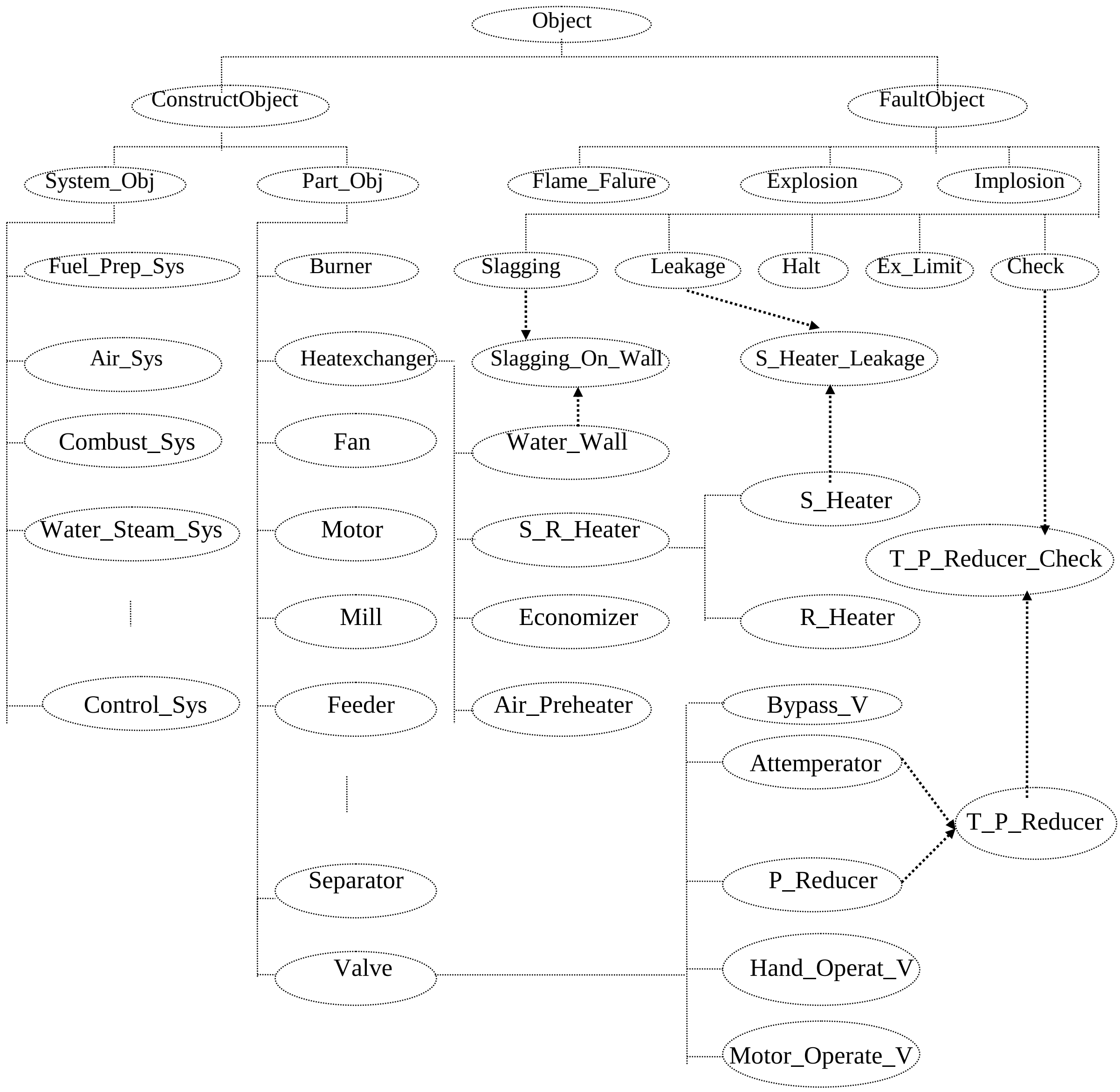


Fig-5 The Hierarchy of Classes of a Boiler Used for Diagnostic Purposes

In Fig-5, we present a class hierarchy. The basic class is named Object, in which class examination and encapsulation, message transfer and link between two objects are defined. ConstructObject and FaultObject are two subclasses based on class Object. In class ConstructObject the general features and corresponding behaviors, based on which two subclasses are defined to describe system objects and part object respectively. And in this way, more subclasses are defined with more specific features added to the superclasses, and finally a complete hierarchy for fault diagnosis can be established. Note that multiple inheritance from two superclasses (e.g. Slagging, Waterwall) will also result in a new subclasses (e.g. Slagging_on_Waterwall) as illustrated in the diagram. Another way of adding new features and behaviors is to define a friend class.

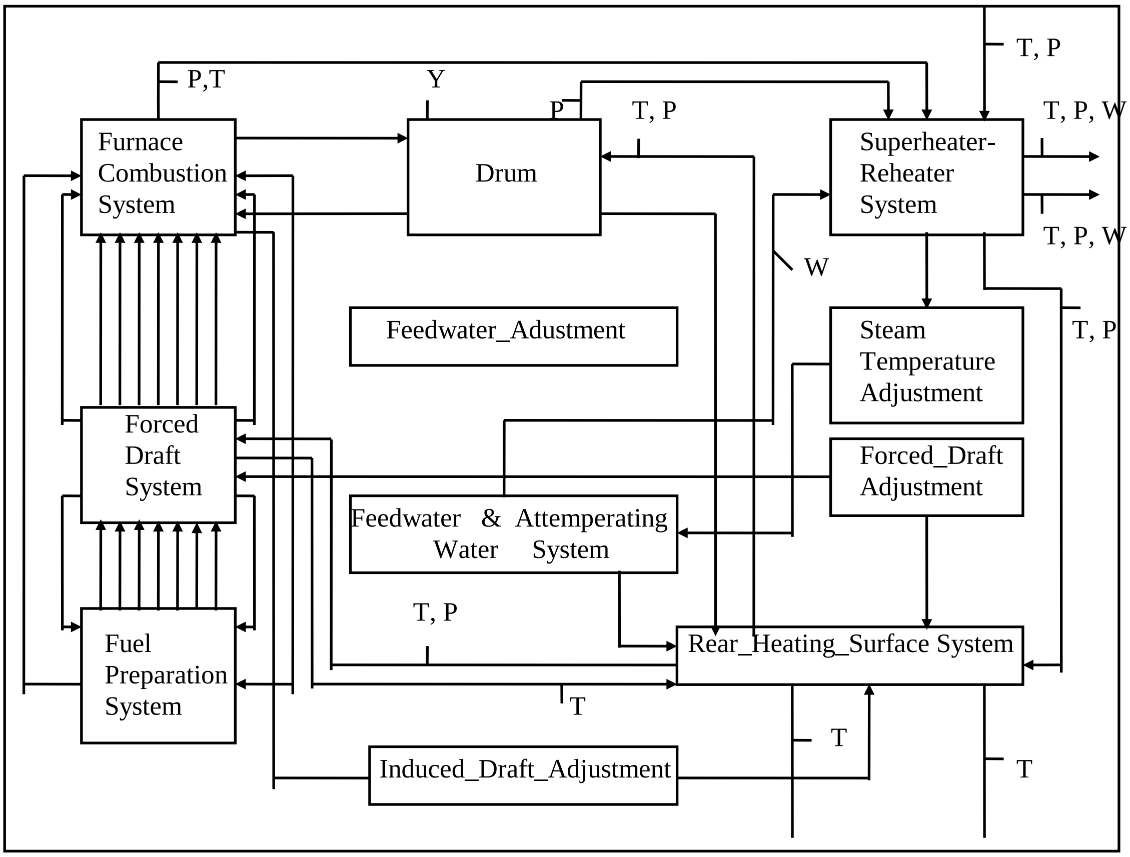


Fig -6 Decomposition of t he Boiler Object

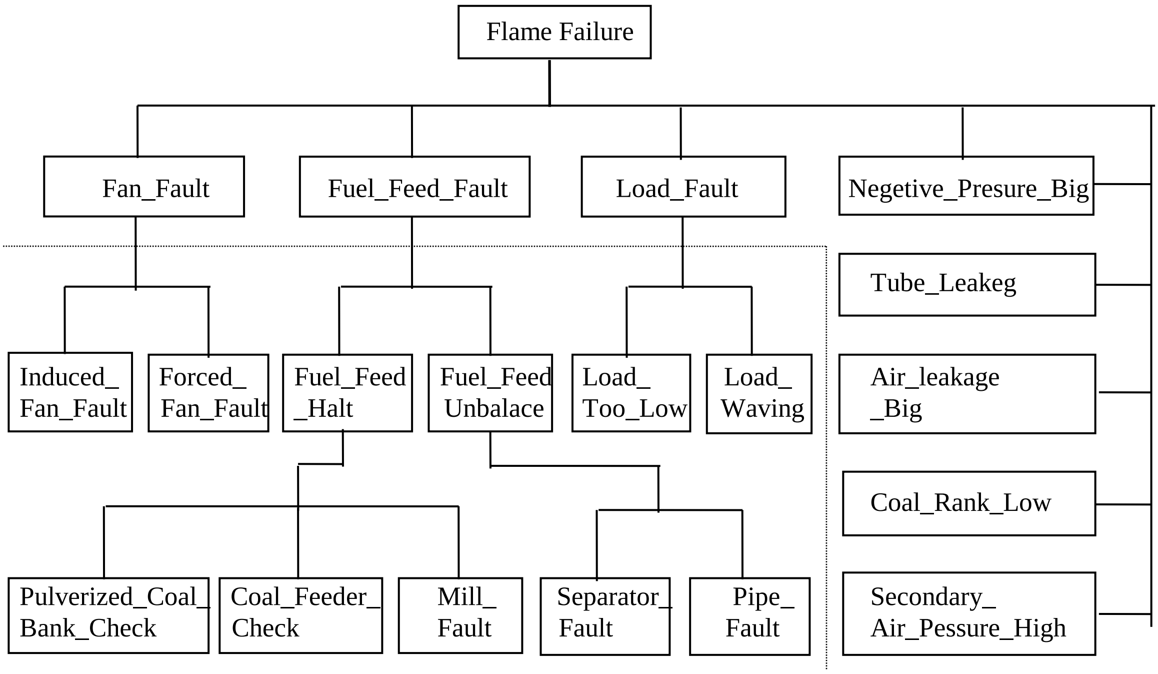


Fig-7 Fault Objects relations used for Flame Failure Diagnosis

Based on the class hierarchy, the boiler object can be depicted as fig-6. And Fig-7 gives the diagram of fault objects .for flame failure diagnosis. This is similar to a fault tree, however, since each node corresponds to an object, which can include rules or methods for inferencs and calculations, this will greatly facilitate the searching operations and it will be much easier to change the searching methods rather than the limited ways in fault tree searching.

4.2 Models

Mathematical models with emphasis on the whole power plant system based on those models for simulators can be modified into diagnosis oriented models. For combustion fault diagnosis, we focus on combustion stability and slagging.

In Reference[20], we established a mathematical model based on the concept of Firing Chain proposed by Dr. Zhang Mingchuan[21]. The control theory was introduced to the establishment of the model as shown in Fig-8. The model might be too simple to express in detail the complex progress of combustion. However, it introduces a novel approach to the establishment of dynamic models for diagnosis as well as control purposes. Numerical simulations were performed and the results show that it can largely simulate the trends of the dynamic process under an disturbance of the fuel feed rate.

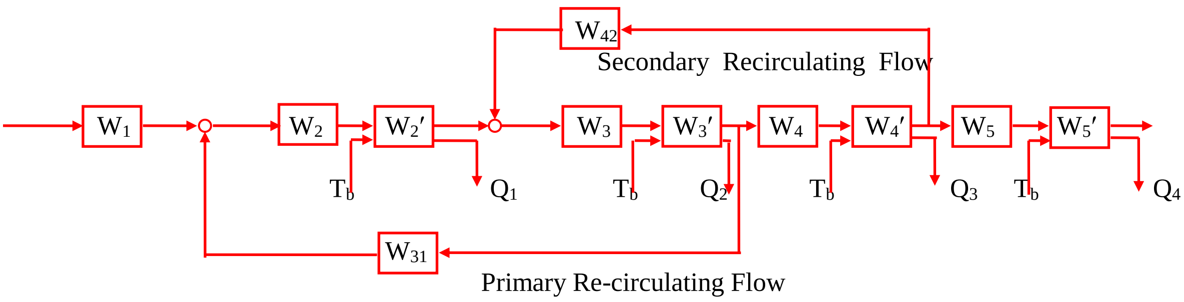


Fig-8 Modular Structure based on Ignition Chain

Besides the theoretical models, modeling based on transient data have also been conducted[Report,Contrl].

To incorporate the latest achievements into a practical model, more work is being carried out.

As for slagging study, fuzzy mathematics has been employed to predict the possibility of a certain type of coal and mixture of various kinds of coal(this is the most effective method in slagging-free technology)[14]. We also proposed a novel approach to diagnose the slagging from the combined effects of coal quality, furnace structure and working conditions using artificial neural network as shown in Fig-9.

4.3 Expert Knowledge

Empirical knowledge and heuristic knowledge are very important in fault diagnosis. Contrast to the deep knowledge such as mathematical models, it is called shallow knowledge. Acquisition of the shallow knowledge and its proper use are among the key problems in establishing a successful expert system. Among the symbolic methods, rule-based knowledge representation and inference are widely used. Most of the successful expert systems are built using rules. The main problems involved in using rule based systems are bottle neck and combination explosion.

On the other hand, neural networks has the advantages in overcoming these difficulties and are good at generalization in inference. However, They are usually weak in explaining the inference process, and successful hardware for parallel neural computation cannot be foreseen in the near future. A good compromise is to develop a hybrid expert system which combines both technology. The Object Oriented method is a good way to integrate the two methods. To achieve this goal , the first step we t have taken is to conduct researches on each of these aspects.

Up to now, both rule based and neural network based methods have been studied and two knowledge management system for each method have been developed receptively. In the Object Oriented knowledge system being developed, the codes for both methods will be incorporated.

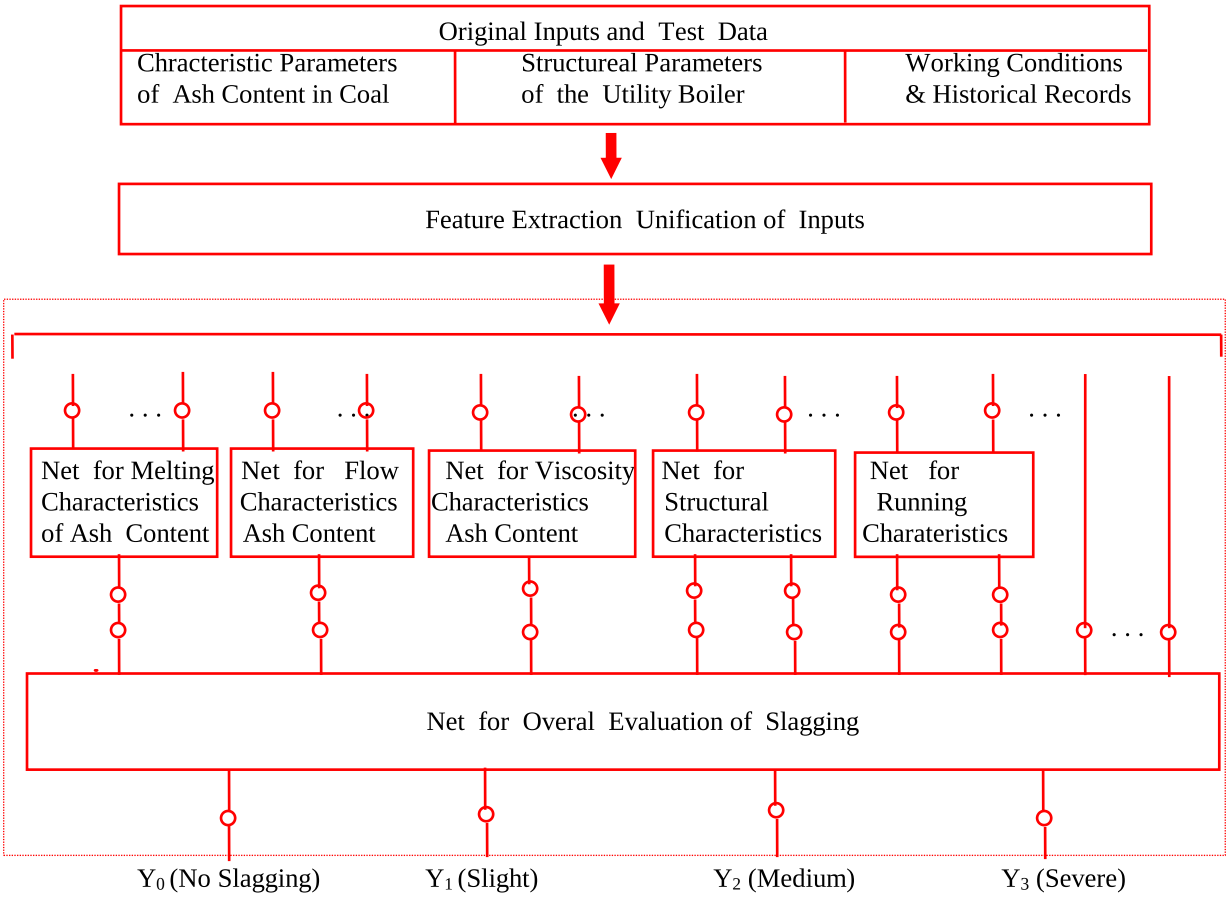


Fig-9 A Schematic of a Neural Networks Based Slagging Evaluation Model

4.3.1 Rule Based Knowledge System

<u>4.3.1.1 Defining a Rule</u>

Considering the uncertainty involved in the diagnostic knowledge, a rule can be defined in such a form:

IF <A> THEN <B> : f (B, A) ,

Where, A={ A_i } , the premise section of a rule while Ai refers to the i-th premise, C (A_i) is used to express belief of premise A_i;

B={ B_i } , the conclusion section of a rule while Bi refers to the i-th conclusion or action; C(A_i) is used to express the belief of action B_i;

f (B, A) expresses the rule's uncertainty, ie. the effect of A=TRUE on B=True.

For example, we may have such a rule for diagnosing the slagging fault in boiler operation.

IF (1) The heat resistance of wall is too big (0.8) AND
(2) Exhaust gas temperature increases (0.75) AND
(3) Furnace Temperature level increases (0.75) AND
(4) The Load is steady (0.85)
Then Slagging occurs on the water wall.
Belief = 0.85

<u>4.3.1.2 Form an Evidence (Symptom)</u>

In a real-time diagnosis system, the beliefs of the rules in the knowledge base have to be given by the experts and the knowledge engineers. But it is a different case for the beliefs of the evidences acquired for diagnosis. In fact, there are two kinds of evidences. One is offered by the operators or users, who have observed some abnormal phenomena; the other is automatically acquired from the parameters on the system states. The former is usually certain, or even if uncertain, the belief will be input when the evidence is key in (or selected by a mouse). For the later, with fuzzy problems involved, it requires proper functions for automatic acquisition of evidences.

The functions should not be sensitive toward the noises arising in the measured parameters and are expected to weaken the effects of the waving of the parameters. On the other hand, if an evidence value is bigger enough to flood the noises, it should be sensitive enough and the sensitivity should increase with the increase of the waving so as to strengthen the evidence. A set of second order functions are recommended to achieve such a goal [92]:

Suppose X_c is the normal value, X_{sl} and X_{sr} are the left and right thresholds respectively. Bel (x) refers to the function for calculating the belief, where x is the on-line measured data.

In case of a single right threshold, we have,

$$C(x) = \begin{cases} [(x - x_c) / (x_{SR} - x_{c})]2, & x_c \le x \le x_{SR} \\ 1, & x > x_{SR} \end{cases} \qquad \textbf{(1)}$$

In case of a single left threshold, we have,

$$C(x) = \begin{cases} [(x - x_c) / (x_{SL} - x_c)]^2, & x_{SL} \le x \le x_c \\ 1, & x < x_{SL} \end{cases} \qquad \textbf{(2)}$$

In case of a double threshold, we have,

$$C(x) = \begin{cases} [(x - x_c) / (x_{SL} - x_c)]^2, & x_{SL} \le x \le x_c; \\ [(x - x_c) / (x_{SR} - x_c)]^2, & x_c \le x \le x_{SR}; \\ 1, & else. \end{cases} \qquad \textbf{(3)}$$

These Functions can be used limit checking of on-line signals and can also be used for trend checking limit checking of estimated parameters, states and characteristic quantities, depending on what X represents in physical meaning.

<u>4.3.1.3 Rules Matching and Belief Calculation in Diagnostic Inference</u>

In a diagnosis system, the inference machine performs rule searching and matching based on the acquired evidences and their beliefs, and calculate the beliefs of the conclusions using a certain algorithm.

<u>1. rule matching</u>

In a diagnosis system, rules can be expressed as:

IF A_1 (b_1)^A_2(b_2)^...^A_n(b_n), THEN B (λ, CF) ,

Where, A_i is the i-th premise while b_i is the belief of A_i , i. e. b_i=C(A_i); B is the conclusion; λ is a given limit value for activating the rule, and CF is the belief of the rule.

Suppose there are a set of acquired evidences, $A_1'(b_1')$, $A_2'(b_2')$, ... , $A_n'(b_n')$, where Ai’ is the i-th evidence, b_i' is its belief, then the following two ways can be used to realize rule matching.

(i) General method for rule matching

If $\max\{0, b_1 - b_1'\} + \max\{0, b_2 - b_2'\} + ... + \max\{0, b_n - b_n'\} \leq \lambda$,

Then, the rule is matched.

(ii) Weighted rule matching

Let $w_1 + w_2 + ... w_n = 1$, if

$(w_1 * \max\{0, b_1 - b_1'\} + w_2 * \max\{0, b_2 - b_2'\} + w_n * \max\{0, b_n - b_n'\}) \leq \lambda$,

then the rule is matched.

In the first method, each premise is treated equally important; but in the second method, weights are introduced to clarify the degrees of the importance. In fact, each of the evidences usually varies in importance in fault diagnosis problem. Therefore, the second method should be more reasonable. Then, the rule can be expressed as:

$$\text{IF } A_1(b_1, w_1) \wedge A_2(b_2, w_2) \wedge ... \wedge A_n(b_n, w_n) \text{ THEN } B(\lambda, CF)$$

<u>2. Belief Calculation</u>

Belief calculation is among the key problems in the inaccurate inference. Improper choice of the belief calculation algorithm will result in incorrect conclusions or loss of correct answers.

There are many algorithms based on the probability theory or the fuzzy theory. What we have used is one that imitates the way in which field experts solve problems. Take one rule for combustion diagnosis for example:

IF

Coal volatile content is low (0.8, 0.45) AND
Boiler load fluctuates with big amplitudes (0.75, 0.55)

Then

Flame failure will occur
(0.6, 0.8) .

The field experts usually use the rule in this way:

When the evidences " Coal volatile content is low" and " Boiler load fluctuates with big amplitudes" and the beliefs for them are not less than 0.8 and 0.75 respectively, then the experts draw such a conclusion " Flame Failure will occur " and assign a belief of 0.8 to this conclusion. When either of the two beliefs is less than its set limit value, the experts will modify the belief of the conclusion based on the beliefs of the premises and the rule itself and those of the acquired evidences.

On the basis of the above analysis , we have such a belief calculation algorithm based on fuzzy theory as follow:

$$((1 - \max\{b_1 - b_1', 0\} * w_1 + (1 - \max\{b_2 - b_2', 0\} * w_2 + ... + (1 - \max\{b_n - b_n', 0\} * w_n) * CF;$$

For the rule given for combustion diagnosis, if the beliefs of the two evidences are 0.82 and 0.73 respectively, the belief of the conclusion will be

$$((1 - \max\{(0.8 - 0.82), 0\} * 0.45 + (1 - \max\{0.75 - 0.82), 0\} * 0.55) * 0.8 = 0.62$$

3. The data structure for rule representation

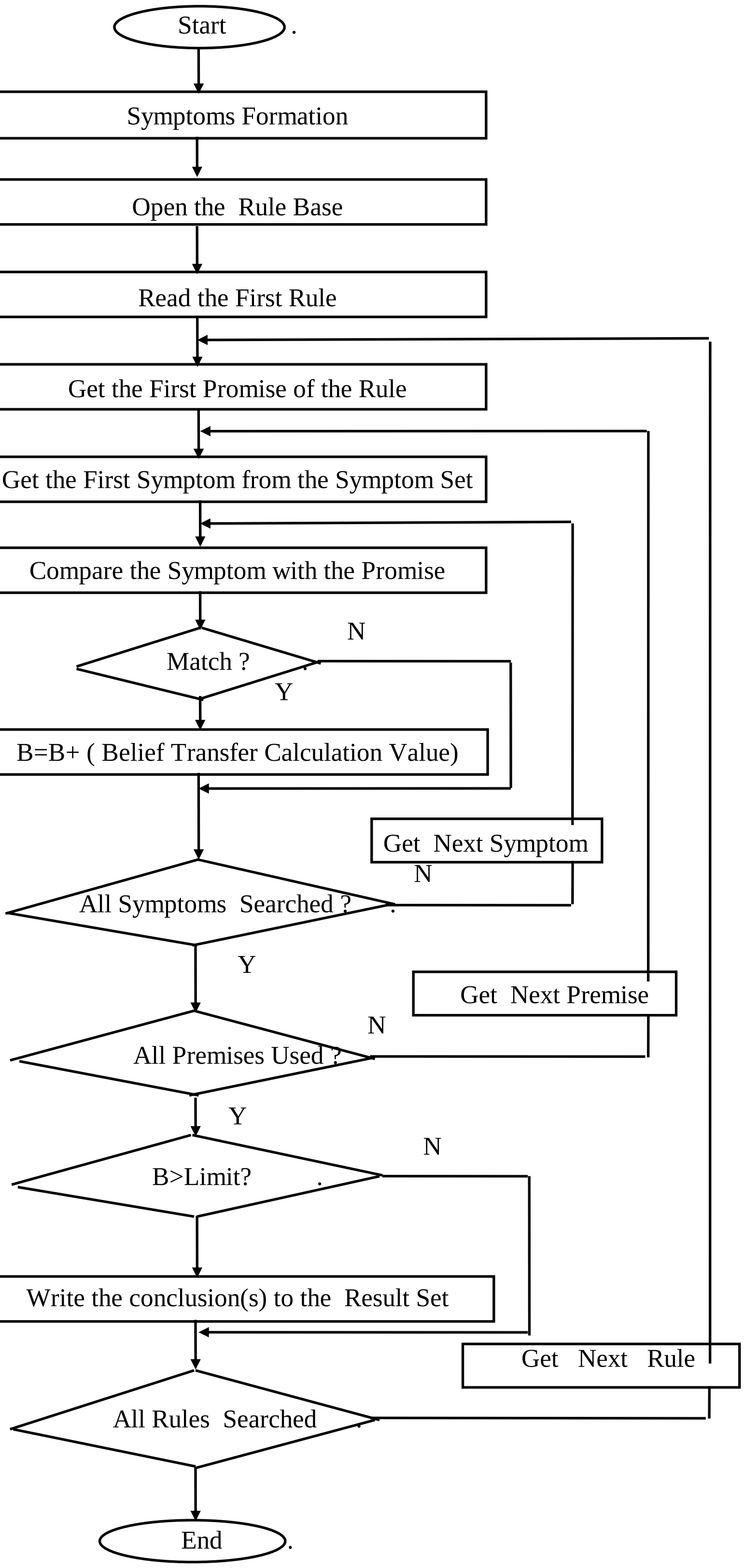


Fig-10 The Flow Chat of Forward Inference Based on Closed Chain Data Structure

The basic data structure we used for rule representation is the closed chain list.

In C language, we first define such a closed-chain list to represent the facts (the evidences, the premises or the conclusions):

```
Struct fact{
        Char content [ MAX_LENGTH];          // the content of the fact
        float  belief;                       // the belief of the fact
        float weight;                        // to express the weight of the premise in a rule
        struct fact * next;                  // pointer to the next node in the chain
        };
```

Then, we define the data structure for rules:

```
struct rule {
        Char  name[MAX_LENGTH];              //rule name
        float  belief;                       // rule belief
        int counter;                         // used to count the times the rule is used
        int  p_num;                          //number of the premises
        int  c_num;                          // number of  the conclusions
        struct fact * premise;               // pointer to the head of the chain of  premises
        struct fact * conclusion;            // pointer to the head of the chain of  conclusions
        struct rule * next;                  // pointer to the next node in the rule chain
        };
```

when the data structure is established, if only the chain list is not empty, the following algorithm can be used for searching :

```
p=head;            // Let p point to the head pointer of  a chain list
do {
   process p;             // do some processing on the node to which p points, eg. matching operations
                          //          between an  evidence and rule promises
   p=p->next;             // let p point to the next node
   } while (p!=head);     // loop until p goes back to the head
```

Based on the simple searching mechanism, matching operations can be realized for inferences. When a rule is activated, the belief calculation algorithm can be used to give the belief of the conclusions and hence we can realize inaccurate inference. Fig-FR gives the flow chat of forward inference based on the above data structure.

4.3.1.4 Rule Based Knowledge Management System

The rule based knowledge management system has an architecture as shown in fig-x. Some Demonstrations of the system can be found in Appendix I

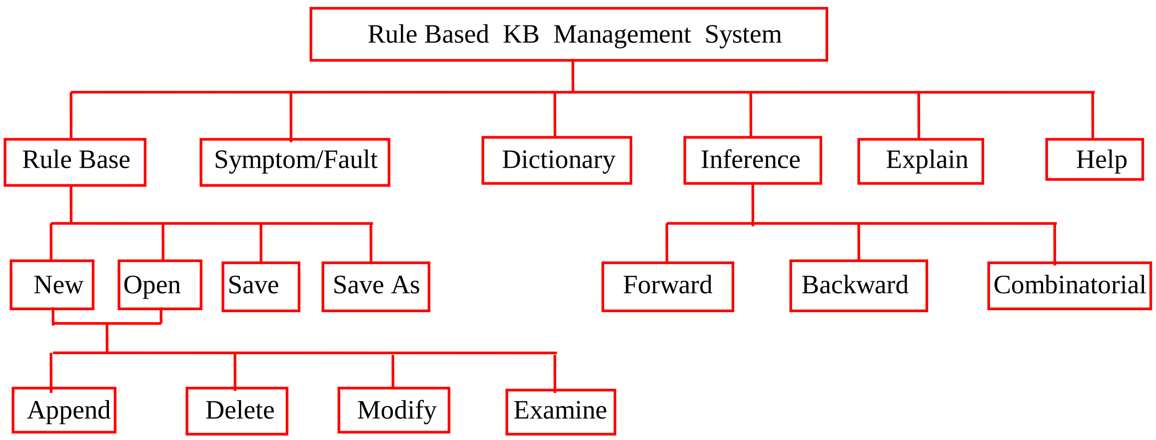


Fig-11 The Architecture of the Rule Based Knowledge Management System

4.3.2 Neural Net based Knowledge System

4.3.2.1 Knowledge Representation Using Neural Network

Rule based knowledge processing method has achieved great successes on both design and diagnosis areas. However, there are still some key problems involved in the traditional method such as the bottleneck involved in knowledge acquisition, matching collision and combinatorial explosion in inference operations and low capability in learning. Contrast to the typical symbolic approach in knowledge processing, connectionists are advocating more applications of neural networks, which are characterized by interconnected neurons and weight matrices. Studies show that this method does have advantages in knowledge acquisition, generalization and self-learning as well as representing complex relations such as fuzzy consequences.

Among the theoretically proposed artificial neural networks, BP (Back Propagation) network is among the most commonly used and successful examples though it has some drawbacks compared with those self-organizing networks such as ART -I, II, II and ARTMAP, which are featured by non-supervision learning.

A BP neural network is usually composed of an input layer, one or more hidden layers and an output layer. Connections are set up between the neighbor layers. During the working process, an input vector is given to the input layer and is then forward propagated to the hidden layer(s) and finally to the output layer. The learning process consists of forward and backward propagation.

Owing to the input - output structure of BP network, it can be easily adapted for diagnostic knowledge representation. For a certain diagnostic problem, we can have a symptom set and a fault set. In rule based knowledge system, combination of the set elements may result in a number of rules for diagnosis. On the other hand, when employing BP neural network, each symptom can correspond to an input node and each conclusion to an output node. Based on the already existing rule collection, we can have a group of samples for net training. In this way, the existing rules are re-organized and stored in the form of weight matrices. Suppose we have new knowledge regarding a certain diagnostic problem, we may modify the sample (and the net structure when necessary) and retrain the neural network. In this way, we can update the knowledge base at any time. This gives more flexibility in knowledge processing.

Table-1 Registration Table

Input Nodes	Output Nodes
a. Mean gray scale value of flame is low b. Sudden increase in negative pressure in furnace c. Water-level in drum increases d. Boiler Load decreases e. Main Steam Pressure decreases	a. Flame failure in Furnace
Other Parameter List	
Hidden Layer No.: 1 Hidden Nodes: 8 Accuracy: 0.001	

Table-2 Samples for net learning

Sample No.	Input	Output
1	0.9 0.8 0.8 0.6 0.2	0.90
2	0.8 0.7 0.6 0.8 0.7	0.80
3	0.7 0.9 0.7 0.5 0.2	0.82
4	0.6 0.9 0.7 0.4 0.4	0.75
5	0.5 0.8 0.2 0.3 0.3	0.65
6	0.4 0.7 0.4 0.3 0.8	0.65
7	0.6 0.5 0.4 0.4 0.4	0.60
8	0.4 0.4 0.4 0.3 0.5	0.40
9	1.0 1.0 1.0 1.0 1.0	1.00
10	0.0 0.0 0.0 0.0 0.0	0.00

One concern in using BP network is the fact that we have to retrain the whole network even if there is a small change in the sample while the training is usually a time -consuming process due to the following factors:

(1) Local minimum problem arising from non-linear optimization; (2) selection of hidden node numbers; (3) Initialization of the weight Matrices. Referring to the non-linear programming theory, by using interpolating steps and inexact line search, an important conjugation gradient method was found, by which the training speed of the BP network was improved by hundreds of times and the rate of failures in training was decreased significantly.

Take the flame failure fault as an example for demonstration purposes. To facilitate net learning, we use the following two tables, Table-1 for registering the input/output node names and parameters for net training, and Table-2, which contains the samples for learning.

Using the samples in Table-2, it took 218 iterations to reach the required accuracy. Using an input vector (0.7, 0.6, 0.8, 0.7, 0.2) to do an inference test, forward propagations of the net gave an output of 0.69628, a result which is approximately the case in operations.

Since more rules are already available ding to much more fundamental work in this area, this method was introduced to a real-time system, in which a rule based system had been installed. Generally, the number of symptoms of each fault is not too large (4~20), therefore, we built a single net for each fault. Over 20 faults are concerned in fault diagnosis system and totally 1400 rules are adopted to form training samples. The trained networks were incorporated into a practical diagnostic system, which is working at Yangluo Power Station in Wuhan, China. Tests on the system show that in some cases the neural net based system gives better results than the rule based one [report].

4.3.2.2 An Neural Network Based Knowlegde Base Management System

To facilitate the operations on neural network based acquisition and knowledge base maintenance, a knowledge base management system has been developed based on the structure of rule based KB management system. The architecture is shown in Fig-x.

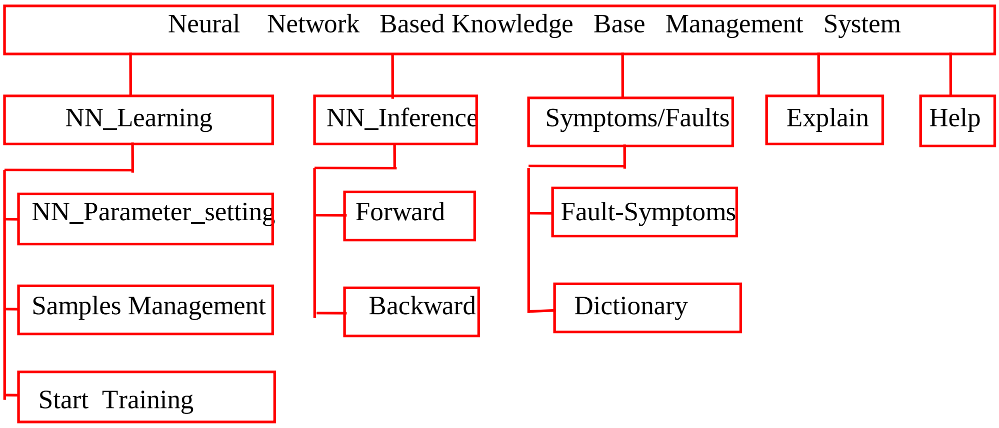


Fig-12 The Architecture of the Neural Network Based Knowledge Management System

The *NN_learning* fuction is intended for general usages of BP network. Running under the Windows environment, standard dialogue boxes make easy operations for the users. NN_inference is designed for both general BP inference tests and specific fault oriented diagnostic inferences for it provides the selection of faults or symptoms for inference testing. Under the Symptoms/Faults submenu, users can build or modify the fault-symptoms tables and corresponding English-Chinese dictionaries. Explanation is not so easy for neural network systems, what we have used is a deign which allows users to access the data on samples and weight matrices and some other possible information available about the working network. Some running demonstrations are given in Appendix II.

5. SOFTWARE DESIGN OF THE MONITORING AND DIAGNOSIS SYSTEM

5.1 Outline of the System

The whole system was developed in Borland C/C++ for Windows 3.1 in order to make advantage of the multitask environment of Windows. In the system, MDI(Multiple Document Interfaces), DDE (Dynamics Data Exchange) and DLL (Dynamic Link Library) were employed to achieve friendly interfaces and to optimize the utility of computer system resources.

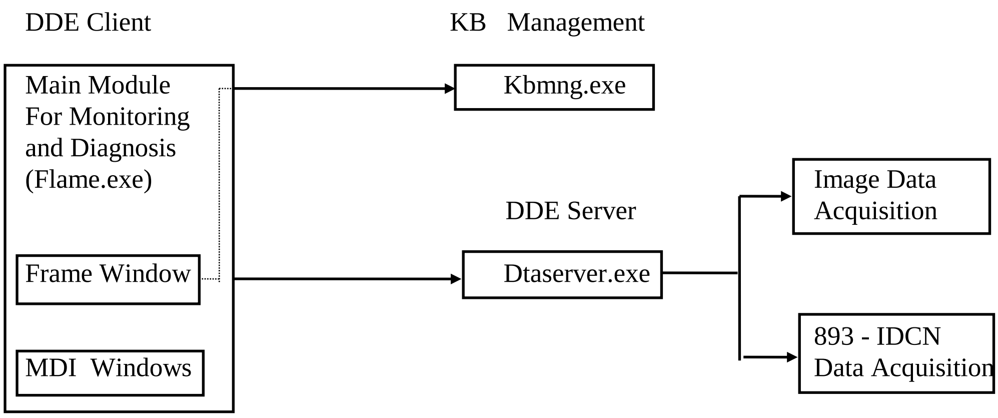


Fig 13. The Schematic of the Boiler Operation and monitoring and Diagnosis System

As shown in Fig-10, the whole system is mainly composed of three executable files -- Flame.exe, the main module to perform monitoring and diagnosis and also acts as the DDE client; Dataserver.exe, which is responsible for data acquisition and transmission to the client; and Kbmang.exe, the module for maintaining the knowledge base. When in operation, the main module sends requests for data transmission to DDE server according to the message released by the timer. On receiving the requests from the main module (DDE Client), the server will read data from the 893-IDCN board and at the same time, start image acquisition and processing programs, and eventually transmits the data to the client through the allocated block of memory for dynamic data exchange. The knowledge maintenance module is what we have introduced in the former part of the paper. It is intended for management of diagnosis knowledge and inference test. The module that is currently being used is a rule based knowledge base system. Further work will be done to incorporate the neural net based knowledge base maintenance module and object-oriented knowledge module. Work is being done on summarizing the specialized knowledge using the neural net method and the OO method.

Since the inference machines are actually the same for knowledge base maintenance as for the main diagnosis module, we have built a DLL file, which can export the required functions by the main application module. In this way, the code can be shared by the two application modules and the memory it occupies can be freed when its tasks are terminated. This technique was also used for data analysis, image processing and transformation.

5.2 The Structure and Function of the system

Fig-10 shows the architecture of the software system for monitoring and fault diagnosis.

For a MDI application module, there are a frame window and a group of subwindows, both of which are standard in the windows style. On the frame window, usually several pop-up submenus serve to provide the choices for various operations. In our system, there are five pop-up submenus on the main frame window, namely, Monitoring & **Diagnosis**, Parameter **Setting,** Emergency Recall & **Analysis,** **K**nowledge **B**ase Maintenance and **Help** Information. They serve to perform different functions as described below.

(a) Monitoring and Diagnosis

Since the system was designed to perform both on-line diagnosis and off-line analysis, will be at an interactive frame window stage, whence the system has not stated to perform on-line monitoring and diagnosis. If t he user choose the “Initialize” menu item in the “Diagnosis” submenu, then the MDI subwindows for monitoring and Diagnosis will pop out.

(b) Parameter Setting

The upper and /or lower limits are required in order to form symptoms for diagnostic inference. Besides, as discussed in the former parts, coal quality as well as the structural parameters of the furnace and burners have direct effects on fault development. These parameters vary in different boilers and even for the same boiler, they may vary under different situations, especially in case of varying coal resources. These data are stored in a data base with a properly designed data structure. In the Object Oriented knowledge base system, they are regarded as the static knowledge and incorporated into the diagnostic knowledge architecture, as can be easily understood if taking a look at the text on Object Oriented analysis of the boiler diagnosis problems.

(c) Emergency Recall and Analysis

This is used for off-line analysis in case of an emergency has taken place. Recorded data can be shown in tables and figures and analysis tools including diagnostic inference are available for searching the causes of the accidents.

(d) No further explanations are necessary for the Knowledge Base Maintenance and Help information modules.

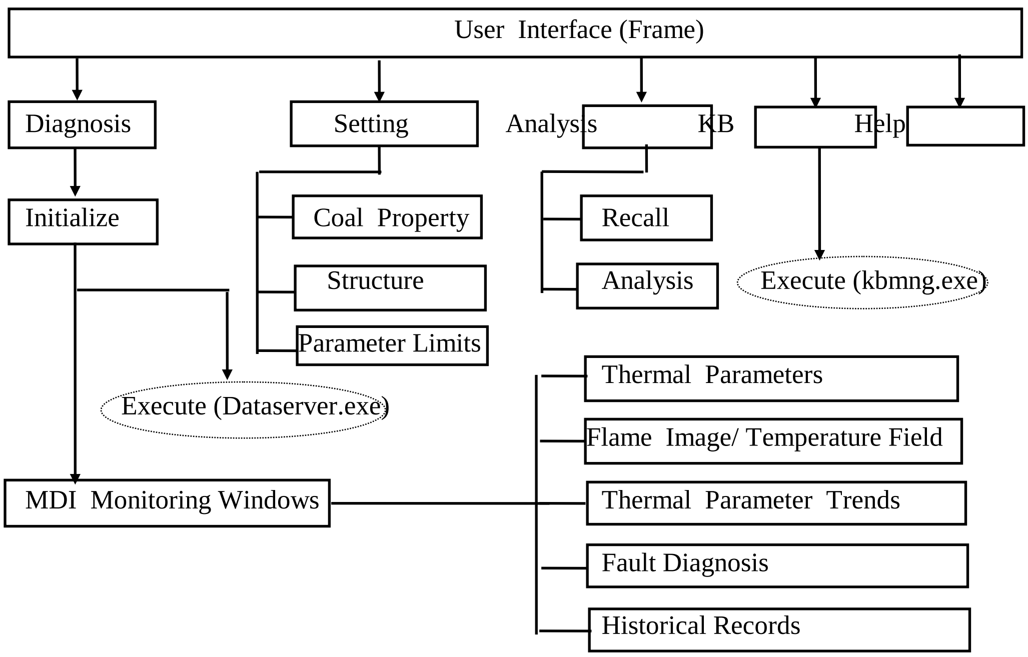


Fig-14 The Architecture of the Software System for Monitoring and Fault Diagnosis

6. CONCLUSIONS

Diagnostic expert systems have been successfully applied to industrial process monitoring. In the above text, We have presented in detail the studies that we have carried out on combustion fault diagnosis for power plant boilers, summarized as follows:

1) Based on the analysis of the general process of fault diagnosis, careful discussions were conducted on boiler fault concepts and the characteristics of the faults from the angle of diagnostics.

2) As an important part relating measurements in combustion fault diagnosis, a radiant signal analysis strategy was presented based on the component characteristics of the flame radiations; image based measurement methods for 2-D and 3-D diagnostic temperature distributions are proposed as an important measure for diagnostic signal analysis and in-situ test results show this is an effective way.

3) Since knowledge systems are the core of a diagnostic expert system, we have done a great deal on knowledge processing. In this paper, we give a detailed analysis on the diagnostic object -- the boiler by using the Object Oriented methodology, and proposed a hierarchy of the classes of a boiler intended for diagnosis purposes followed by the structures of the flame failure fault and the structural objects of a boiler, which serve to give further explanations of the method.

4) Mathematical models are instrumental for fault diagnosis, especially for fault sizing and location, which requires knowledge in depth. In this paper, we have introduced two models. The first is a dynamic model for combustion stability analysis, which is built on the basis of the concept of Firing Chain and by employing the thought of control theory. This model is simple so that it might not serve to reflect the complex processes of combustion, but it provides a novel way for combustion simulations intended for fault diagnosis purposes. The second model is what we have designed for slagging evaluation and prediction using artificial neural networks. This is still a theoretical model, which requires much more experimental work in order to make it a practical model for real-time slagging diagnosis. This model has been adopted and in fact work is actually being done at our lab.

5) Rule based systems are among the most successful experts systems. We have studied the methods for rule based combustion fault diagnostic knowledge representation, symptoms extraction methods based on fuzzy mathematics, inference machine design and finally a rule based knowledge base management system were developed under the Windows environment.

6) The BP neural network was employed for fault diagnosis in our work. The way of using it for diagnosis knowledge representation and inference was studied with an example of flame failure fault. To facilitate the usage of BP network in knowledge acquisition and maintenance, a neural network based knowledge base management system were also composed under the Windows environment

7) Based on the above described fundamental work, a monitoring and diagnosis system was developed to aid power plant boiler operation. Designed in the Windows environment, the system makes advantages of the multitask working environment. In addition, the use of MDI, DDE and DLL techniques in Windows programming has helped achieve friendly interfaces and optimization of the utility of the computer system resources. The system has been put into practice in the Jingyuan Power Plant and further improvement in the knowledge base will make it a more practical one.
Further work will be conducted on:

1) More studies on the fault mechanisms through both experimental and computational approaches. The aim is to better our understanding of the physical processes of fault development.

2) Introducing system dynamics and advanced control theory in analysing the high non-linear dynamic process of combustion. Theoretical as well as practical system models are among the main targets. Chaotic nature regarding combustion processes are expected to be studied because it may help better our understanding of the uncertainty involved in the diagnostic problem and will be useful for diagnostic strategy design, namely, measurable parameters choosing, estimation of quantities which are non-measurable but required for diagnosis, etc.

3) Further the work on object Oriented knowledge systems and try to incorporate it into the current monitoring and diagnosis system.

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