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Model-Based Diagnosis Using Qualitative Causal Model and Set-Covering

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Abstract

In this paper we propose a model-based diagnostic system for continuous physical devices such as a thermal power plant. The aim of model-based diagnosis is to find faulty components in the model from observations (symptoms). The model-based diagnosis is well formalized as the diagnosis from first principle by Reiter [6]. Reiter proposed a method to calculate diagnoses from first principle using a theorem prover. In the continuous physical domain it is difficult to obtain proper theorem prover. Set-covering is another approach to get diagnosis when the causal relations between symptoms and disorders is clearly defined. Our new method combines the model-based approach and set-covering approach. We introduce the Qualitative Causal Model(QCM) and define symptoms and qualitative disorders in QCM. The qualitative propagation on QCM and the BIPARTITE algorithm based on set-covering calculates all the diagnoses. Finally the proposed method is proved to realize the diagnosis from first principle in the continuous physical domain.

AI Topic:	Model-Based Diagnosis; Qualitative Causal Model; Set-Covering
Domain:	Plant Diagnosis; Continuous Physical Device
Language:	KL1 (parallel logic programming language)
Status:	The prototype system is successfully developed.
Effort:	4 man-years
Impact:	The system can realize the *diagnosis from first principle* in the continuous physical domain efficiently.

1 Introduction

The aim of the model-based diagnosis is to determine which part of the model of a system has gotten out of its normal functions or behaviors. Reiter [6] formalized the model-based diagnosis from first principle, and he defined a *diagnosis* in a *system* as follows.

definition A *system* is a triple $(SD, OBS, COMP)$ where

SD	is the system description.
OBS	is a set of observations.
$COMP$	is a set of components.

definition A *diagnosis* of $(SD, OBS, COMP)$ is a minimal hitting set for the collection of all the conflict sets for the system.

A conflict set for $(SD, OBS, COMP)$ is a subset $\{c_1, c_2, .., c_n\}$ of $COMP$ at least one component of the subset is abnormal, i.e.

$$SD \cup OBS \cup \{\neg AB(c_1), ..., \neg AB(c_n)\}$$

is inconsistent. $AB(c)$ is a sentence suggesting that component c is abnormal.

Let $S_i (1 \leq i \leq n)$ be a conflict set and $S = \{S_1, .., S_n\}$ be a collection of all the conflict sets. A minimal hitting set H for S is a set such that

$$H \in \bigcup_{i=1}^{n} S_i$$

and,

$$H \cap S_i \neq \{\} \text{ for all } i$$

A *diagnosis* corresponds to a minimal set of components which has become abnormal simultaneously, so it represents multiple faults. Reiter proposed the procedure to calculate a *diagnosis* according to the definitions above. First, all the conflict sets for $(SD, OBS, COMP)$ are calculated by using a theorem prover as a consistency checker. Next, all the minimal hitting sets for the collection of all conflict sets are calculated using the H-P tree method. These procedures are shown in the left side of Figure 1(Reiter's approach). Because the calculation for all conflict sets is so costly, Reiter proposed the DIAGNOSE algorithm to obtain the minimal hitting sets by building a search tree, called a pruned H-P tree, with a frequent queries to the theorem prover in order to check consistency.

In order to apply Reiter's diagnosis from first principle to continuous physical devices, an appropriate model and theorem prover are necessary to describe

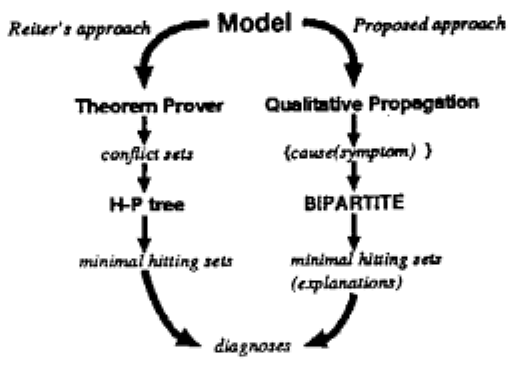


Figure 1: Model-Based Diagnosis

system behaviors. The qualitative representation is one way to make such a model, but it is difficult to get a practical theorem prover for qualitative representation. H.T.Ng [4] used Kuiper's qualitative simulator QSIM [5] as the theorem prover, and obtained the minimal hitting sets using the pruned H-P tree method as Reiter did with frequent queries to QSIM as a consistency checker. However building a search tree with frequent queries to QSIM is too costly to deal with real time problems.

Set-covering is another approach to calculate the *diagnosis* from the symptoms when the causal relations between the symptoms and the disorders are clearly defined. We apply this approach to model-based diagnosis in qualitative representation. We introduce a Qualitative Causal Model (QCM), define the symptoms and qualitative disorders in QCM, and define the system behavior in the qualitative causal constraints between plant parameters in QCM.

Our system has two sub-modules to calculate the *diagnosis* from symptoms. The qualitative propagation module calculates the causal relations between the symptoms and the qualitative disorders. The BIPARTITE module based on set-covering generates all the *diagnoses* using these relations. These procedures are shown in the right side of Figure 1.

In the following sections, we will explain the model definitions, qualitative propagation, set-covering, and the diagnostic strategy. The applicability of our system is estimated in section 7 and 8.

2 Model Definitions

2.1 Qualitative Causal Model

The Qualitative Causal Model (QCM) represents the physical behavior of the target system qualitatively. The QCM consists of the qualitative parameters and the qualitative causal constraints.

- Qualitative parameters
  All the parameters in the plant are classified in three types as follows.
  - *Input parameters* have direct relations to external environment or system design. (*e.g.* the temperature of sea water.)
  - *Sensored parameters* have sensors implying that there exists qualitative variation on that parameter. (*e.g.* the level of the tank.)
  - *Pathological parameters* are neither *input parameters* nor *sensored parameters*.

  We define the qualitative parameters and the symptoms.

  definition $< p, v >$ (p is parameter, $v \in \{[+],[-],[0]\}$) is a qualitative parameter which represents that the parameter p has qualitative variation v compared to normal value.

  definition A symptom is a qualitative sensored parameter which has $[+]$ or $[-]$ for its qualitative value.

- Qualitative causal constraints
  A qualitative causal constraint represents the qualitative causal relation between one parameter and other parameters. All the parameters are related to other parameters by the constraints. Each constraint has a direct mapping to the component of the target plant. If the constraint is violated, it implies that the component is in fault. We define the qualitative causal constraints.

  definition A qualitative causal constraint r for parameter p is expressed as follows,

  $$r : p \Leftarrow \{\{+ : p_1, .. p_n\}, \{- : p_{n+1}, .., p_m\}\} \quad (1)$$

  The left arrow is the causal direction. The constraint (1) means that the p and $p_i (1 \leq i \leq m)$ have a causal connection via constraint r. The qualitative effects on p by $p_j (1 \leq j \leq n)$ are monotonic increase, and the effects on p by $p_j (n+1 \leq j \leq m)$ are monotonic decrease.
  The qualitative causal constraint is a directed relation from cause parameters $(p_1, ..., p_m)$ to an effect parameter p. There are no constraints for an input parameter and there is no constraint which has a sensored parameter as its cause parameters. A simple example of the qualitative causal constraints is shown in Figure 2.

$$r_1 : a \Leftarrow \{\{+ : b\}, \{- : c\}\}$$
$$r_2 : c \Leftarrow \{\{+ : d\}, \{- : e\}\}$$
$$r_3 : f \Leftarrow \{\{+ : c\}, \{- : \}\}$$

Figure 2: An example of Qualitative Causal Constraints

2.2 Qualitative Disorder

Disorders are classified in the following two types.

Type 1 Abnormal variation of the input parameters.
This disorder represents an external change in the plant. (*e.g.* the temperature of sea water is high.)

Type 2 Fault in plant devices.
This disorder represents an internal change in the plant. (*e.g.* a pump has broken down.)

In QCM, a disorder corresponds to the qualitative variation [+] or [−] on a parameter. We define two types of qualitative disorders (q) and (r, q) according to above classification.

definition (q) where $q =< p, v >$ is a qualitative disorder which represents an input parameter p has qualitative value v and v is [+] or [−]. The value is caused by an external change in the plant. ($e.g.$ $d_1 = (< t_{water}, [+] >)$)

definition (r, q) where $q =< p, v >$ is a qualitative disorder which represents a pathological or sensored parameter p has v which is [+] or [−]. The value is directly caused by a violation of the constraint r which is relevant to an internal fault in a device.
($e.g.$ $d_2 = (r_{pump}, < p_{out}, [-] >)$)

3 Qualitative Propagation

Each symptom is related to a set of qualitative disorders which have causal relations to the symptom via relevant qualitative causal constraints. The qualitative propagation on QCM calculates these qualitative disorders for a given symptom. The propagation mechanism is based on that of a search.

The propagation mechanism has three features.

- Reverse propagation
  Unlike usual qualitative propagation mechanisms such as QSIM, the direction of propagation is from effect to cause.
- Qualitative calculation rule
  The qualitative value on one effect parameter of a constraint is propagated to cause parameters whose values are calculated by qualitative constraints. In general, plural possible combinations of qualitative value for cause parameters can be calculated. As the propagation goes on, these combinations on each constraint lead to combinatorial explosion.
  To avoid this difficulty, we adopt a new rule for qualitative calculation. This rule does not consider any combinations. In the example shown in Figure 2, the cause of $< a, [+] >$ on r_1 is calculated as either $< b, [+] >$ or $< c, [-] >$. The rule implies that at least one of $< b, [+] >$ or $< c, [-] >$ is occurring to cause $< a, [+] >$ as long as r_1 is not violated.
- Qualitative disorders
  The aim of propagation is to find all the qualitative disorders which are related to a symptom. As defined in section 2, the qualitative disorders are classified into two types.
  The qualitative input parameter is found when the propagation reaches the input parameter which has no next constraint.
  The pair of a qualitative pathological or sensored parameter and a constraint is found when the propagation passes through the constraint.

A propagation starts with one symptom s and expands its search tree on QCM until each branch reaches an input parameter, and as a result returns $cause(s)$ as a set of qualitative disorders which could cause the symptom. A function PROPAGATE in Figure 3 is a pseudo algorithm which calculates $cause(p)$ for given symptom p.

For example, in Figure 2 the $cause(< f, [-] >)$ is

$$cause(< f, [-] >) = \{(r_3, < f, [-] >), (r_2, < c, [-] >), (< d, [-] >), (< e, [+] >)\}$$

function PROPAGATE(p, QCM)
 $D := \{\}$;
begin
 if p is not an input parameter **then**
  $cnstr$:= Constraint for p;
  $Para$:= Causes for p on $cnstr$;
  while $Para \neq \phi$ **do**
   p' := NextCause from $Para$;
   D' := PROPAGATE(p', QCM);
   $D := D \cup D'$;
  endwhile;
  $D := \{(cnstr, p)\} \cup D$;
 else $D := \{(p)\}$;
 endif;
 return D;
end.

Figure 3: PROPAGATE

4 Set-Covering to Generate Minimal Hitting Set

4.1 Qualitative Propagation and Diagnosis from First Principle

The set-covering is another approach to get the minimal hitting sets when the relations between the symptoms and their possible disorders are clearly defined. The relation between $cause(s)$ and the symptom s calculated in qualitative propagation module satisfies the relation in set-covering.

The $cause(s)$ is also a conflict set in QCM because if all the qualitative disorders included in $cause(s)$ did not occur, the existence of symptom s cannot be explained. In set-covering the explanations(minimal hitting sets) are calculated from the collection of $cause(s)$ by the BIPARTITE algorithm, whereas in the diagnosis from first principle, the minimal hitting sets are calculated from the collection of the conflict set by the H-Ptree method.

4.2 Basic Idea of Set-Covering

The basic idea of set-covering is as follows.

If $cause(s_i)$ and $cause(s_j)$ have the same qualitative disorder d then it is possible that both symptoms s_i and s_j were caused by d. All the symptoms can be classified into several groups according to whether they have same qualitative disorder or not.

Let $C_i = \{S_1, S_2, ..., S_n\}$ $(S_j \cap S_k = \phi, j \neq k)$ be one classification of all the symptoms S. Each $S_j \in C_i$ corresponds to one fault occurring which causes S_j. The number of groups in C_i corresponds to the number of faults occurring simultaneously.

There may exist more than one possible classification which can explain all the symptoms. For example, a problem with three symptoms $\{s_1, s_2, s_3\}$ is shown in Figure 4. It is possible that all the symptoms relate to one common group of disorders (classification C_1 in Figure 4: one group classification), or it is possible that all the sensors are abnormal (classification C_4 in Figure 4: three group classification). In this example, the number of the possible classification is four [1].

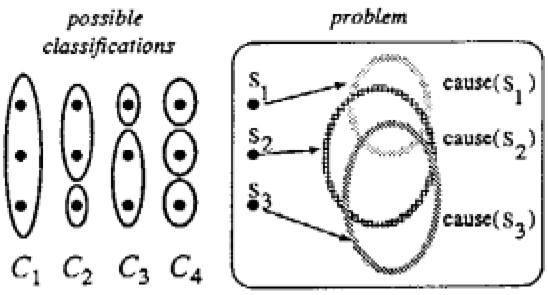


Figure 4: Possible Classifications

Set-covering calculates all these possible classifications examining whether each $cause(s)$ has some common qualitative disorders or not.

4.3 Formalization by Peng and Reggia

Peng and Reggia justified the idea of set-covering in "*Parsimonious Covering Theory*" [8]. In their formalization, set-covering deals with diagnostic problem (D, M, C, M^+) which is defined as follows.

- M: manifestations
- M^+: symptoms (observed manifestations)
- D: disorders
- C: relationship between M and D
  C consists of 2 functions
  $cause(m) \subset D$ $\quad m \in M$
  $effect(d) \subset M$ $\quad d \in D$

The *solution* for a diagnostic problem (D, M, C, M^+) is defined as follows.

[1] Because $cause(s_1) \cap cause(s_3)$ is a subset of $cause(s_2)$, the two group classification which implies that s_1, s_3 is one group and that s_2 is another, is impossible.

definition The ***solution*** of a diagnostic problem (D, M, C, M^+) is the set of all ***explanations*** of M^+.
An ***explanation*** of M^+ for (D, M, C, M^+) is a set $\{d_1, .., d_n\} \subset D$ where

$$\bigcup_{i=1}^{n} effect(d_i) \supset M^+$$

and no subset of $\{d_1, .., d_n\}$ can explain M^+ (minimal).

An *explanation* corresponds to a minimal hitting set in Reiter's formalization. Figure 5 shows an *explanation* for (D, M, C, M^+).

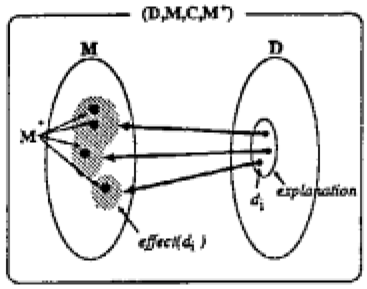


Figure 5: An *explanation* for (D, M, C, M^+)

The correspondence between the definitions above and our model definition in QCM is listed below.

Reggia's definition	QCM
M	sensored parameter
M^+	symptom
D	qualitative disorders
C	$\{cause(s_i) \mid s_i \text{ is symptom}\}$

4.4 BIPARTITE Algorithm

Peng and Reggia proposed an algorithm to calculate all the *explanations* for (D, M, C, M^+) [8]. All the *explanations* are classified in the form of a *generator-set* as shown in Figure 6.

A *generator* G_i is a combination of the groups of qualitative disorders D_j and corresponds to one possible symptom classification via causal relations. Each $D_j \in G_i$ is $D_j = \cap cause(s_k)$ $s_k \in S_j$, where S_j is one group of symptoms in the classification. The class generated by G_i is defined to be $[G_i] = \{\{d_1, d_2, d_3, .., d_n\} | d_j \in D_j, D_j \in G_i\}$. The *explanations* related to the symptom classification are the class $[G_i]$.

Set-covering calculates all the possible classifications of the symptoms, so it calculates all the possible *generators*. A *generator-set* is the set of all the possible *generators* and contains all the *explanations* for the symptoms.

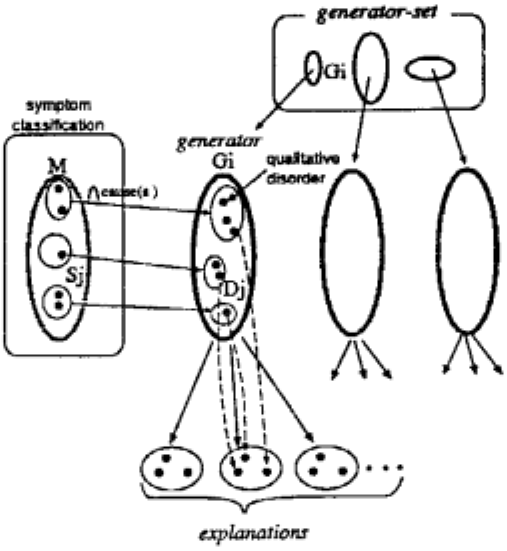


Figure 6: A generator-set

```
function BIPARTITE(D, M, C, M+)
  begin
    Gs := {[ ]};
    while M+ ≠ φ do
      m := Nextman from M+;
      Gs := revise(Gs, cause(m));
    endwhile;
  return Gs;
end.
```

Figure 7: BIPARTITE

The BIPARTITE algorithm calculates a *generator-set* for the symptoms M^+ incrementally by using $cause(s_i)$ ($s_i \in M^+$). Function *revise*/2 updates old *generator-set* with $cause(s_i)$ for newly input symptom s_i.

The advantages of this BIPARTITE method are listed below.

- The incremental diagnosis can easily be realized. Function *revise*/2 can update the *generator-set* for newly found symptom.
- All the *explanations* (minimal hitting set) can be obtained systematically.

5 Diagnostic Strategy and Characteristic Disorder

We adopt a diagnostic strategy to select the most probable *generator* with a single group of the qualitative disorders from the *generator-set*. This strategy, called the *single fault strategy*, is based on the fact that in real world problems, independent multiple faults scarcely occur. In many cases, multiple faults have some causal relations. If there is no *generator* with a single group, then a *generator* with the least number of groups is selected.

Though the most probable *generator* is selected using the *single fault strategy*, this *generator* can generate plural *explanations*. The selection of one disorder from D_j is necessary in order to select a single *explanation* from the *generator*.

We introduce the characteristic disorders to deal with this difficulty. The qualitative disorders in D_j also have causal relation with each other. There exists one qualitative disorder $(r, d_j) \in D_j$ which satisfies following condition.

$$cause(d_j) \cap \{(r, d_j)\} = D_j$$

The characteristic disorder d_j is the most probable disorder in D_j because there are no other symptoms which narrow the D_j and yield another characteristic disorder on the cause side of d_j.

In this way, we can select one qualitative disorder from D_j, and can select one *explanation* for one *generator*.

6 Implementation

Our system has been implemented by using the parallel logic programming language KL1 [1] on the parallel inference machine Multi-PSI which has 16 processing elements.

The QCM is implemented as the qualitative causal network. The network consists of s-nodes, p-nodes, i-nodes, and arc. A s-node represents symptom, a p-node represents one qualitative causal constraints, and an i-node represents one input parameter. The nodes have their own data base for the constraint and communicate with each other via arc. Figer 8 is the network for the QCM of the example shown in Figure 2.

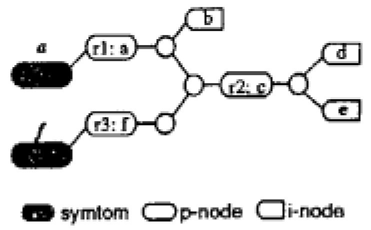


Figure 8: Qualitative Causal Network

The qualitative propagation is realized by the communications between the nodes in the network.

The BIPARTITE module calculates the *generator-set* Gs using the relations obtained by the propagation module.

The system selects a *generator* G from Gs using the *single fault strategy*. Finally the system selects the most probable *explanation* (*diagnosis*) from G using the characteristic disorders.

7 Experiments

We applied our diagnostic system to a thermal power plant, and through experimentation, we estimated its applicability.

The scale of the model for the plant was as follows:

plant devices	:	20
parameters	:	175
constraints	:	100
sensors	:	30

The qualitative causal network of the condenser and its qualitative causal constraints are displayed in Figure 9.

We made some experiments with this QCM under the condition that *(a)* the causes of the symptoms were known in advance and *(b)* the number of symptoms were variable.

The explanation obtained in experiment 1 which dealt with one symptom is the error in the sensor of the symptom. In experiment which dealt with 4 with four symptoms, we were able to get an explanation which corresponded to the cause known in advance.

In order to analyze the dependence of processing time and diagnostic efficiency on the number of sensors (symptoms), we summarized the results into Table 10. This table contains the number of symptoms (S), the number of combinations of the qualitative disorders ($\|Gs\|$), the number of the qualitative disorders in the most probable combination ($\|G\|$), and the processing time ($Time$).

	S	$\|Gs\|$	$\|G\|$	$Time$ (sec)
experiment 1	1	1	151	210
experiment 2	2	2	139	212
experiment 3	3	4	110	215
experiment 4	4	10	105	215

Figure 10: Experiments in the thermal power plant

The relation between $\|G\|$ and S is monotonic-decreasing. It shows that the number of the fault candidates decreases as the number of the available sensors increases. $Time$ does not depend on S, which shows that the processing time does not increase even though the number of the available sensors is increased to narrow the range of the fault candidates.

8 Discussion

We can estimate the diagnostic efficiency of the system using both the processing time ($Time$) and the number of fault candidates in G ($\|G\|$).

$Time$ does not depend on S, although the calculation cost of the BIPARTITE module depends on S on the order of e^S. This result shows that the calculation of the present implementation of the system is not yet optimized, for the following reasons:

1. The processing time in the qualitative propagation module does not depend on S, because in present implementation all the sensor data including normal value ($< p, [0] >$) are propagated in QCM.
2. The processing time of the qualitative propagation module is much longer than that of the BIPARTITE module.

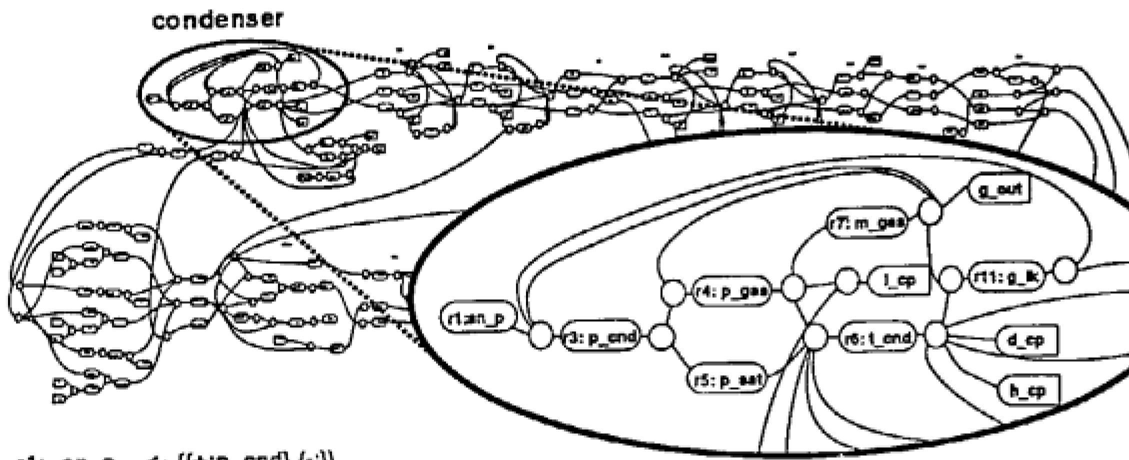
For these reasons, the total processing time does not depend on S. In order to give our system a real-time facility, we should improve the processing time in both modules. We are developing a parallel processing mechanism with the parallel inference machine Multi-PSI. The qualitative propagation of each symptom can be executed in parallel, and the set calculation in the BIPARTITE module can be executed, not only in parallel, but also in a pipeline manner.

The diagnostic efficiency can be measured by the narrowing rate of the fault candidates. This range of the fault candidates is $\|G\|$. Comparing the results of experiment 1 and experiment 4, the range of the fault candidates in experiment 4 is narrowed about 1.5 times that of experiment 1. Although this result proves that our diagnostic system can be improved by using more symptoms, the improvement so far is not enough, because the causal relations in a target plant with circulating flows often make a large loop as a whole in the QCM. In this plant, the intersection of $cause(s_i)$ and $cause(s_j)$,$(i \neq j)$ covers almost the whole of the QCM. In order to resolve this problem, it is necessary to narrow the region of the propagation.

As for related works, although H.T.Ng [4] proposes a diagnostic system which is based on Kuipers's QSIM [5] and Reiter's Π-P tree method [6], the queries to QSIM are costly and it is difficult to realize a real-time diagnosis. ODS [3] is one typical diagnostic system using the qualitative causal model. The system generates fault candidates by decision tree at first, and these candidates are verified in the qualitative simulation module. The consequences of the qualitative simulation are compared with the observations to check the validity of the fault candidates. ATMS[2] is used to manage different diagnostic hypotheses. This approach is based on the *generate and test* method. Our approach is the reversal of this approach, because the qualitative propagation starts with the symptoms (observations) to get the faults while QSIM starts with the faults and calculate observations. Our approach is more efficient because the propagation mechanism is much simpler than the qualitative simulation approach with ATMS. Peng and Reggia [8] propose a causal net for the problem, but in QCM the pathological causal relations could become disorders themselves. Wu's [7] symptom clustering is equivalent to set-covering. The idea of symptom clustering corresponds to symptom classification. The main difference is the algorithm to reach the goal. Set-covering has a much simpler algorithm, and because it is defined declaratively, the implementation in logic programming is much easier.

9 Conclusion

In this paper we proposed a new model-based diagnostic system which combines the techniques of qual-



r1: an_p <- {{+:p_cnd},{-:}}
r3: p_cnd <- {{+:p_gas,p_sat},{-:}}
r4: p_gas <- {{+:m_gas,l_cp,t_cnd},{-:}}
r5: p_sat <- {{+:t_cnd},{-:}}
r7: m_gas <- {{+:p_gas,g_lk},{-:g_out,.p_cnd}}
r6: t_cnd <- {{+:g_cndi,h_cndi},{-:g_lk,d_cp,h_cp,h}}
r11: g_lk <- {{+:g_cndi},{-:p_cnd}}

Figure 9: The Qualitative Qausal Network for the.Condenser

itative propagation and set-covering. This method proved to realize the *diagnosis from first principle* in continuous physical devices. The qualitative propagation module and the BIPARTITE module are implemented by using parallel logic programming language KL1, and the applicability to real world problems has been verified in the thermal power plant.

The improvement of the parallel processing mechanism to deal with a real-time problem and the improvement of the diagnostic efficiency by narrowing the region of the propagation are left for future work.

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