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A machine learning bayesian network for refrigerant charge faults of variable refrigerant flow air conditioning system

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ABSTRACT

An intelligent fault diagnosis network for variable refrigerant flow air conditioning system is proposed in this study. The network is developed under the foundation of bayesian belief network theory, which comprises two main elements: the structure and parameters. The structure obtained by machine learning and experts' experiences illustrates the relationships among faults and physical variables from the qualitative prospective, and its parameters (including prior probability distribution and conditional distribution) describe the uncertainty between them quantitatively. Once the structure and parameters are determined, the posterior probability distribution which can be used to complete fault diagnosis and isolation will be calculated by some algorithms. In comparison with other fault diagnosis approaches, the proposed approach can make full use of performance information. Moreover, it is more reasonable and precise to express the relationship between faults and variables rather than Boolean variables. Evaluation was conducted on a variable refrigerant flow air conditioning system, which demonstrated that this strategy is effective and efficient.

1. Introduction

Because of the demands for thermal and humidity comfort in residential and commercial buildings, the heating, ventilation, and air conditioning (HVAC) system accounts nearly half of overall building energy [1,2]. As a consequence, it is necessary to achieve energy saving in such systems. And in recent years the conception of air conditioning system has gradually developed from one unit for one house to independent units from separated zone in the same house along with the rising demands for comfortable environment [3]. Thus variable refrigerant flow (VRF) air conditioning system which is a multi-split type of HVAC system has been arisen and applied in practice due to its flexible form, compacted structure, high part-load efficiency and individual thermal control strategy [4]. It is made up of one outdoor unit and several indoor units. In essence, the VRF system is a system which maintains the indoor temperature at different set temperatures by controlling compressor frequency and the opening of electronic expansion valves to varying refrigerant flow rate. However, as a result of the intrinsic complexity of VRF system it easily suffers from various kinds of faults, which may lead to energy waste, shortened life span of the mechanical parts and deterioration of its performance. Meanwhile, it is a difficult task to detect and diagnose faults timely merely relying on manual work. Therefore, the artificial intelligent diagnosis methods for VRF system attract more attention. FDD (fault detection and diagnosis) tools have provided robust and effective approaches to ensure performance of various air conditioning systems from the perspective of artificial intelligence. What is more, they are also been applied into many HVAC components. Comstock et al. [5], Reddy et al. [6], Katipamula and Brambley [7,8] have used FDD in chillers. Besides, faults in air handling units (AHU) [9], variable volume terminals (VAV) [10] are detected and diagnosis by different FDD tools.

Although FDD has been applied into heating, ventilation, air-conditioning (HVAC), chiller plants, air handling units (AHU), variable air volume terminals and other refrigeration systems, there are few researches in fault detection and diagnosis of multi-split air conditioning system during the latest decades. As is known, a suitable and excellent FDD tool is essential for achieving timely detection and precise diagnosis in the FDD period. In terms of previous researches significant breakthroughs have been made, but there are more aspects that should be taken into consideration in such process. Firstly, there are many uncertainties among faults and symptoms which extant rule-based approaches hardly cope

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with. In other word, a fault may result in different symptoms at different probabilities. Thus it may be more rational to express FDD results by reasonable probabilities instead of the Booleans (i.e. Yes or no). Secondly, it is rewarding to notice that the more information used in FDD process, the more accurate the results are. It means that not only data collected by sensors but also other additional information, i.e., service history, maintenance records and components performance data, should be used to complete such a process. Thirdly, when it comes to conflicting or incomplete information as a result of sensors faulty or unavailable measurements, the traditional FDD methods will be incapable of such situations. Aimed at those defects, bayesian belief network has been gradually applied into FDD fields.

Since Pearl [11,12] coined the terminology "Bayesian network" in the 1980s, it has been successfully applied in the domain of knowledge discovery and probabilistic inference. Because of its powerful ability to cope with diagnosis of complex systems with uncertain, incomplete and even conflicting information, bayesian network has been used in many fields, such as medical diagnosis [13], faults identification in aircraft engine [14], nuclear power system [14], power system [15] and so forth. Besides, it has also been used in economics field [16] and other areas for decision support. What's more, recently it has been applied in the heating, ventilating, air conditioning (HVAC) systems [17], chiller systems [18], air handling units [19,20] and variable air volume system terminals [21]. Among these researches, Najafi [19] has proposed diagnostic algorithms based on bayesian network for air handling units that can address those three constrains systematically by machine learning techniques. This algorithm is implemented by analyzing the observed behaviors and comparing them with a set of behavior patterns generated based on various fault symptoms. Then under the foundation of pattern matching, the bayesian network can be constructed. However, this work may require full data sets (including normal data and fault data) for machine learning, which makes it difficult to achieve. In 2015, Zhao [20] developed a bayesian network for air handling units (AHU) according to experts' experience to stimulate experts' diagnostic thinking, which is more feasible. But there are a few of bayesian network for VRF system which has been widely applied in buildings. Therefore, in this study a BBN for VRF system will be constructed to stimulate the experts' thoughts to diagnose system faults. FDD tools often divide the whole process into two parts– fault detection and fault diagnosis. In general, before fault diagnosis there is a need to complete fault detection to judge if the system is operating deviating normal conditions. This study tends to pay more attention to fault diagnostic systems with bayesian belief network (BBN). Two significant elements for BBN is its structure and probabilities. First of all, there are so many physical features, some of which have more effect on faults, so they are selected to construct network before machine learning, which makes the structure easier and more effective. Then, regarding to probabilities of BBN, there are two main methods. One is relying on experts' experience and professional knowledge; and statistical analysis [22] is also an effective approach. History data and performance data are often applied into statistical analysis. Zhao [18] has applied these methods into chiller plants and demonstrated that its diagnostic results were satisfying. Thus in this study machine learning combined with experts' knowledge and experience is used to obtain the prior probability and conditional distribution. After those two elements are decided, some data sets will be used to validate the BBN for VRF system.

2. The preliminary for bayesian belief network

Bayesian belief network (BBN) introduced by Judea Pearl [23] is a graphic model representing the joint probability distributions among different variables. BBN has provided a convenient and coherent way to represent the uncertainty between variables, and it has been increasingly applied into probability knowledge. In general, BBNs are directed graphs which reflect the relationships between variables, such as conditional independence and causal relationship, by its structure and the uncertainty between them with joint probability distributions. In other word, an integral BBN comprises a reasonable structure and precise probability distributions among variables. Besides, the theory foundation of BBNs is probability and Bayes' theorem. In the following part of this section, its theory foundation and two significant elements will be explicitly explained.

2.1. Theoretical foundation for BBNs

2.1.1. Probability theory

With respect to what probability means, there are several interpretations. These can be simply summarized into three classes: the frequency interpretation, the propensity interpretation and the subjective interpretation. For the definition of frequency interpretation, it can be seen as the proportion of the specific outcome when the number of repetitive experiments is large under the same conditions. For example, if you throw the dice, the probability of a specific point can be calculated as the frequency of corresponding outcome. In the propensity interpretation, the probability is seen as the physical feature of some system. Similarly, in the dice game because the dice is homogeneous from either density or shape. Thus the chance of every point's appearance is same and equals to 1/6. It is rewarding to note that when the number of experiment is large, the probability in frequency interpretation will approach to the probability of propensity interpretation. And they are can be categorized as objective probability because that their definitions obey objective law. The last one, from the subjective perspective, probability is mainly retrieved from personal belief. Different person will assign an outcome a different probability under different consideration and related information, and they may change their probability assignment in the course of observation. Sometimes when the information is not complete or even conflicted, the probability in former two definitions is difficult to obtain. As a consequence, the subjective probability will be effective. The subjective probability here mainly refers to the probability under expert's knowledge, technicians' experience. As an objective verification of this type of probability assignment is impossible, the frequentist view of probability does not seem to be suitable to support such decisions and is restricted to events that are repetitive in nature. The subjectivist view allows for a meaningful treatment of such events. It is worth noting that if the events are repetitive in nature, in the long run, the subjectivist and the frequentist views will tend to agree on the assignment of probabilities.

2.1.2. Bayes' theorem and inference

Bayes' Theorem is a theorem of probability theory originally stated by the Reverend Thomas Bayes. It is often used to describe the probability of an event, based on the relevant events. For example, A and B are two random relating events, the probability of them are donated by$P(A)$and $P(B)$ separately. And the probability of the event B is larger than zero. When given the event B, the conditional probability of the event A can be expressed as Eq. (1):

$$P(A|B) = \frac{P(AB)}{P(B)} = \frac{P(A)P(B|A)}{P(B)} \tag{1}$$

where$P(AB)$ is the joint probability, $P(A|B)$ is the conditional probability of event A given the event B and $P(B|A)$ is the conditional probability of event B given the event A. Supposing that B_1, B_2, $B_3 \cdots B_n$ represent a set of random variables and they are mutual exclusive. Besides they satisfy: (1)$P(B_i) > 0, i = 1, 2, 3 \cdots n$; (2)

$\Sigma_{i=1}^{n} B_i = S$; S is a certain event. In this case, the marginal probability of event A can be calculated as:

$$P(A) = \sum\nolimits_{i=1}^{n} P(B_i) P(A|B_i) \tag{2}$$

The item $P(A)$is the prior probability, which is known in advance. Thus the posterior probability $P(Bi|A)$, which is often used to diagnosis, can be formulated as follows:

$$P(B_i|A) = \frac{P(AB_i)}{P(A)} = \frac{P(B_i)P(A|B_i)}{\Sigma_{i=1}^{n} P(B_i)P(A|B_i)} \tag{3}$$

This principles can be demonstrated on a simple case. One of the requirements for obtaining a marriage license in the state of Pennsylvania is undergoing a blood test for syphilis. Assuming the sensitivity and specificity of such a procedure are 98% and 95%. The prevalence rate of syphilis in the population of marriage license applicants is nearly 0.001. If S denotes presence of syphilis, $\bar{S}$ means its absence. Meanwhile, assuming that the positive test result is T, and the negative result is $\bar{T}$. According to the known information, we can get some mathematical equations:

$$\mathrm{P}(S) = 0.001$$

$$\mathrm{P}\left(\bar{S}\right) = 0.999$$

$$\mathrm{P}(T|S) = 0.98$$

$$\mathrm{P}\left(\bar{T}|\bar{S}\right) = 0.95$$

Thus with respect to Eq. (3), we can calculate $\mathrm{P}(S|T)$.

$$\mathrm{P}(S|T) = \frac{P(T|S)P(S)}{P(T)} = \frac{P(T|S)P(S)}{P(T|S)P(S) + P\left(T|\bar{S}\right)P\left(\bar{S}\right)}$$

$$= (0.98 * 0.001)/(0.98 * 0.001 + 0.999 * 0.05)$$

$$= 0.1924$$

From the above calculation process, it is clear that one of important properties is the belief updating. The initial belief, known prior probability distributions and conditional probability distributions accumulate to complete the unknown belief named posterior probability distributions. Once such distributions are obtained, it also can be seen as the evidence input of another event. Alternatively, the posterior probability can be used as the prior probability of the next step. Thus in order to get probability distributions of complicated event, it is allowed to take every evidence into consideration, which means that evidence can be imported into the bayesian belief network stepwise.

In summary, the bayesian theorem provides theory basis for the calculation of posterior probability, which can be used for bayesian inference. In this study, when bayesian belief network is applied into fault diagnosis, the bayesian theorem Eq. (3) can be comprehended as follows. A represents the observed symptoms and B_i represents faults of the system. The prior probability of a certain faults is known and the conditional probability distributions among variables can be obtained from experts' knowledge or some probability analysis results based on the performance data. Thus the posterior probability distributions of the certain fault can be calculated using Eq. (3).

2.2. Significant elements of BBNs

The structure and probability distributions are two key elements of the Bayesian network presenting the relationships among the faults, symptoms, performance qualitatively in the process of fault diagnosis. On the other hand, the structure needs probability distributions to weigh the relationships between variables quantitatively, which is also the essential difference between bayesian network and other fault diagnosis methods. The other methods often adopt boolean variables to express the relationships between variables. Unlike them, the BBN method uses probabilities to express relationships between variables, which will be more reasonable and precise.

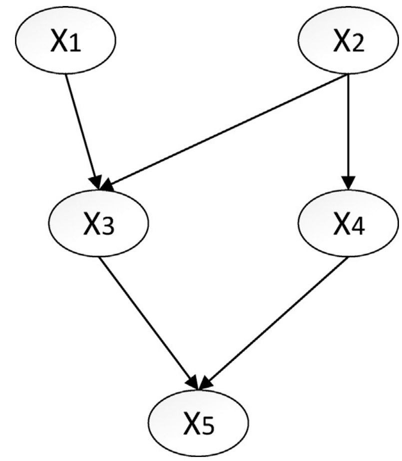

Fig. 1. General scheme of BBN.

2.2.1. Structure

From the foregoing, it can be known that it is a directed acyclic graph (DAG) as the structure of BBN. It is allowed to describe the relationships among variables. In the structure, there are two main compositions: nodes and arrows. The nodes denotes variables or other important indexes, while the arrows descript the directed relationships between nodes. In other words, the arrows between nodes show the relationships between them. The general scheme for BBN is illustrated as Fig. 1. It is clear to that there are two different kinds of nodes. One is root nodes without parental nodes, and the other one is child nodes. The arrows between them are always used to depict their relationships, such as causal relationships, qualitatively.

Once the construction of its structure is known, the following work is to decide how to obtain the BBN structure for a specific network. Two approaches are provided to complete such a task. One is manually developed by experts and technicians relying their knowledge and experience which are in compliance with objective laws and regulations; the other one is machine learning method based on data mining with full data sets, including normal data and fault data. For the VRF system studied in this paper, it is hardly possible to gather the exhaustive and full data because of measurement and technical limits. Thus, only using the second approach to construct its structure is apparently impractical. Meanwhile, the study on the VRF system is rare and the reference materials that can provide information for the structure is not easily available. So it is not suitable to merely relying on the first approach for construction of the structure.

Consequently, these two methods are adopted jointly to avoid their disadvantages in this study. Firstly, the known experts' knowledge and related experience are used to choose some typical characteristic variables (features), which can simplify the network and avoid the interruption of some irrelevant variables. The first step gives a coarse preparation for feature selection. Secondly, some data analysis methods are used to complete a rigorous feature selection process. After features are determined, the structure of bayesian network can be learned by some algorithms. And during the machine learning process, it is allowed to input the known relationships and limits between nodes to avoid the appearance of discrepancy between the learned network and the known common sense in the field. Thus the structure of the VRF system can be constructed with the combination of two methods. And it is also can be revised manually.

2.2.2. Probability distributions

Probability is the most distinct attributes of BBNs, which illustrates relationships among nodes quantitatively as a supplement of the qualitative illustration of BBN structure. The uncertainty is embedded into the BBN in the form of probability distributions other than boolean variables in traditional FDD tools. What is more, the states of nodes are not binary and they may include various states. For an example, the states of temperature can be roughly divided into three classes: higher, normal and lower. And its domain can also be divided finer. So it is more suitable and precise to convey uncertainty.

Similarly, the probability distributions of nodes are obtained by combining the experts' knowledge and machine learning methods. The probability distributions of BBNs comprise prior probability of each nodes and the conditional probability between nodes. The prior probability is simple, which can be obtained by simple data analysis or experts' knowledge and experience. However, the conditional probability is more difficult and complicated. Because the conditional probability distributions of child nodes should consider all of the possible combination of different states of its parent nodes, which makes the number of parameters in the conditional table grow exponentially with the number of the parental nodes' states. For instance, if a child node with two states has n parental nodes whose states number is also two, the number of parameters in its conditional probability table will be up to 2^{n+1}. Especially when the numbers of the parental nodes and their states increase, the number of the parameters which are need to specified in the conditional probability table will grow more rapidly. An ingenious practical solution to this problem has been the application of parametric conditional distributions, such as the noisy-OR and noisy-MAX [20]. Taking the advantage of the assumption of independence of casual interaction (ICI), Noisy-MAX can be adopted to reduce the number of parameters needed to specify the conditional probability tables. In a noisy-MAX model, multiple causes independently influence the effect and their combination is specified by the max factor [21]. According to these two axioms, if anode is considered as a Noisy-MAX node, the number of parameters is reduced from exponential to linear. Under the assumption that all the nodes are boolean, the number of parameters will reduce from 2^{n+1} to $2 * (n+1)$. Furthermore, there will be LEAK parameters to represent the probabilities when all the parents are false.

3. The specific BBN for VRF system

3.1. Description of VRF system and data preparation

A generic framework is established for the VRF system in this section. Schematic diagram of the VRF system is shown in Fig. 1. It can be divided into two parts: the ODU (outdoor unit) and five IDUs (indoor units). The ODU mainly consists of some necessary components and several sensors. What's more, it has two liquid storage devices: an accumulator at low pressure side and a subcooler with EEV (electronic expansion valve) at high pressure side. When refrigerant is overcharged, the two devices act as containers to store it. The IDUs compose of five indoor DX (direct exchanger) coils. More detail specification and characteristics of this two parts can been seen in Table 1. Because there are five indoor units, the rated cooling capacity in the Table 1 is the sum of those indoor units' capacities which are 2.8, 3.6, 5.0, 7.1 and 11.2 separately.

Table 1
Specification and characteristics of IDUs and ODU of VRF system.

		Outdoor Unit	Indoor units
Rated cooling capacity(KW)		28.0	29.7
Refrigerant	Type	R410A	
	Nominal charge(kg)	9.9	
Compressor		Hermetically sealed scroll type	

Table 2
Nine charging levels of VRF system.

Test Groups	Refrigerant Charging Level (%)
1	63.64
2	75.45
3	79.80
4	84.45
5	95.76
6	103.74
7	111.72
8	120.00
9	130.00

All experiments that will be used to evaluate the proposed bayesian network are carried out on standard psychrometer testing room which is made up of an indoor room and an outdoor room. According to Chinese testing standards: GB/T 18837-2002, GB/T 1778–2010, performance standards: GB/T 18837-2002, GB/T7725-2004 and GB/T 17758-2010, enthalpy potential method is applied to investigate the performance of VRF system. The studied fault is about RCL (refrigerant charging level), the performance data under 9 refrigerant charging level are used to develop a bayesian model. And these refrigerant charging levels can be divided into three sorts: leakage, normal and overcharging. The detail charging levels range from 63.64% to 130.00%, as shown in Table 2.

And for each refrigerant charging level, VRF system operated under three different cooling conditions. These conditions presented in Table 3 can also be classified into three groups: low, medium and high temperature cooling modes. Therefore, there would be 27 kinds of working conditions. Besides, due to repeatability of experiments, each working condition would perform at least three times. Thus at least 81 groups of data would be produced. Each experiment lasted for at least 45 min, so the whole experiments would last for almost a month. When it comes to data acquisition, data were measured every 15 s and collected by data logger. And the data recording software showed the cooling capacity for each 5 min. When the data did not fluctuate widely, mean values of them which were collected to be the steady-state data sets could be used for model evaluation. On the other hand, control mechanism of the system is as follow. In order to satisfy such corresponding operating mode, two air handling units are employed to adjust the air temperature and relative humidity of outdoor unit and indoor units. As for approaches to adjustment, the proportion integration differentiation (PID) control algorithms were adopted. Furthermore, the enthalpy potential method ensured that inlet air temperature deviation of indoor units and outdoor unit was no more than 0.5 °Cand 1.0 °C, respectively. Consequently all coils received same signal about inlet conditions. Although the speed of all fans were almost same, compressors and EEV would need to be adjusted separately to adapt to different refrigerant flow rate as a result of different indoor DX coils' cooling loads. As regards to its rated charge situation, enthalpy potential method required that the error of the mean results (e.g. cooling capacity for three experiments) of the tested system compared with that of standard unit were between −5% and 5%.

Table 3
Specific temperature setting of three cooling conditions.

Test modes		Low temperature cooling mode	Medium temperature cooling mode	High temperature cooling mode
Indoor room inlet conditions	Dry-bulb temperature (°C)	22	26	31
	Wet-bulb temperature (°C)	15	19	24
outdoor room inlet conditions	Dry-bulb temperature (°C)	31	35	40
	Wet-bulb temperature (°C)	23	24	26

3.2. Process of constructing BBN

When the system is specific and the operation data are collected, the next step will be fault diagnosis. In this research, BBN is used to do fault diagnosis. The detail process can be seen from Fig. 2. The whole process can be divided into four parts: data collection, data preparation, model construction and model evaluation. Data collection is mainly completed relying on sensors. Moreover, some data should be calculated based on the measure data. As for the second part, it has a great impact on fault diagnosis results. The aim of data preparation is to eliminate the unsteady data and outliers during operation which will make diagnosis result inaccurate. Then the data remained can be divided into two groups: training data which are be used to construct the model and test data which are used to evaluate the diagnosis results. After preparation, the main work is to construct BBN based on training data. The network includes two elements: structure and parameters. By combining experts' knowledge and machine learning methods, the structure can be confirmed. As regards to parameters, they are prior probabilities and conditional probabilities, which are calculated by machine learning methods. The last part (model evaluation) is to compare the diagnosis results with the actual results, which can be used to check the rationality of this specific BBN.

3.3. Structure for BBN of VRF system

In order to construct fittest bayesian model, it is necessary to know to relationships between faults and variables. In this study, feature selection is used to achieve such a function. Thus feature selection will be the first step that should be done, which decides the accuracy of such network in diagnosis to some extends. Feature selection is an important problem for pattern classification systems. It is aimed at selecting good features according to the maximal statistical dependency criterion based on mutual information. When it comes to the VRF system, there are too many variables, such as physical variables and operation parameters, which made feature selection difficult and time-consuming. Therefore, in this case, fourteen measured variables were selected manually under the foundation of experts' knowledge and related references. More information about such fourteen variables can be seen from Table 4. Besides, some significant physical variables which cannot be measured directly are often calculated by known variables. Although they need to be computed, they sometimes can be a perfect token of certain fault. For example, when refrigerant is overcharged in the system, temperature difference of heat exchanger fluctuates conspicuously. Because the superfluous refrigerant can decrease heat transfer efficiency between heat exchanger and environment, consequently temperature difference of heat exchanger declines. As is stated above, it is necessary to employ such variables like temperature difference of heat exchanger as important factors of bayesian network structure. Combined with characteristics of VRF system, three indirect variables which can be calculated using other observable variables are chosen, whose detail definition are illustrated in Table 5.

After manual selection, there will be feature selection algorithms to help select some variables which reflect faults more sensitively. Five algorithms are employed to do feature selection, and the selection results are listed in Table 6. By referring to experts' knowledge, variables (T_{trans}, $T_{sh,com,suc}$, $T_{sc.cond.out}$, EXV, T_{cond}, T_{evap}) may form direct relationships with fault nodes in the construction of BBN. Under the foundation of feature and experts' knowledge, the bayesian network for VRF system can be form by machine learning approach. Thus the bayesian network is constructed as Fig. 3.

Table 4
Abbreviation of Measured Physical Variables.

NO.	Measured variables	Abbreviation
1	Outdoor Temperature	T_{out}
2	Compressor Frequency	f_{com}
3	Condensing Saturation Temperature	T_{cond}
4	Evaporating Saturation Temperature	T_{evap}
5	Compressor Discharge Temperature	T_{dis}
6	Compressor Shell Temperature	T_{shell}
7	Condenser Out pipe temperature	$T_{cond,out}$
8	Liquid Refrigerant Temperature at the Subcooler Outlet Pipe	$T_{subc,out,l}$
9	Vapor Refrigerant Temperature at the Subcooler Outlet Pipe	$T_{subc,out,v}$
10	Accumulator Inlet Pipe Temperature	$T_{accu,in}$
11	Accumulator Outlet Pipe Temperature	$T_{accu,out}$
12	Electronic Expansion Valve Opening	EXV
13	Compressor Current	I_{com}
14	Compressor Module Temperature	$T_{com,mod}$

Table 5
Abbreviation of Indirect Measured Variables.

Calculated Physical Variables	Definition	Abbreviation
Degree of heat transfer	temperature difference of condenser saturation and outdoor temperature	T_{trans}
Degree of superheat	temperature difference of compressor suction temperature and evaporator saturation temperature	$T_{sh.com,suc}$
Degree of supercool	temperature difference of condenser saturation temperature and condenser outpipe temperature	$T_{sc,cond.out}$

Table 6
Feature selection results.

Algorithms	Selected features
Gain Ratio Attribute Evaluation	$T_{sc,cond,out}$, EXV, $T_{sh.com,suc}$, f_{com}, T_{cond}, T_{trans}
Correlation Attribute Evaluation	$T_{sc,cond,out}$, $T_{sh.com,suc}$, $T_{accu,out}$, EXV, T_{trans}, T_{cond}
Cfs Subset Attribute Evaluation()	T_{cond}, f_{com}, EXV, $T_{sc,cond,out}$, $T_{sh.com,suc}$, $T_{accu,out}$
Symmetrical Uncert Attribute Evaluation	$T_{sc,cond,out}$, $T_{sh.com,suc}$, $T_{sc,cond,out}$, T_{cond}, f_{com}, T_{evap}
Info Gain Attribute Evaluation	f_{com}, EXV, $T_{sc,cond,out}$, $T_{sh.com,suc}$, $T_{accu,out}$, T_{cond}

3.4. Probability distributions for BBN of VRF system

In this proposed BBN, the probability distributions include prior probability distributions and conditional probability distributions.

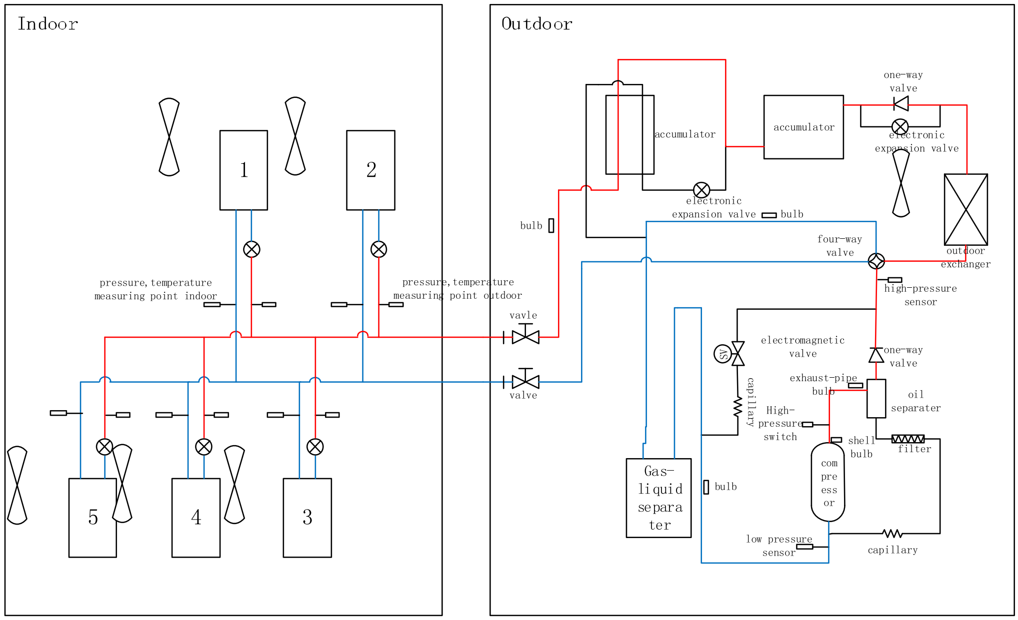

Fig. 2. The Scheme of VRF air conditioning system.

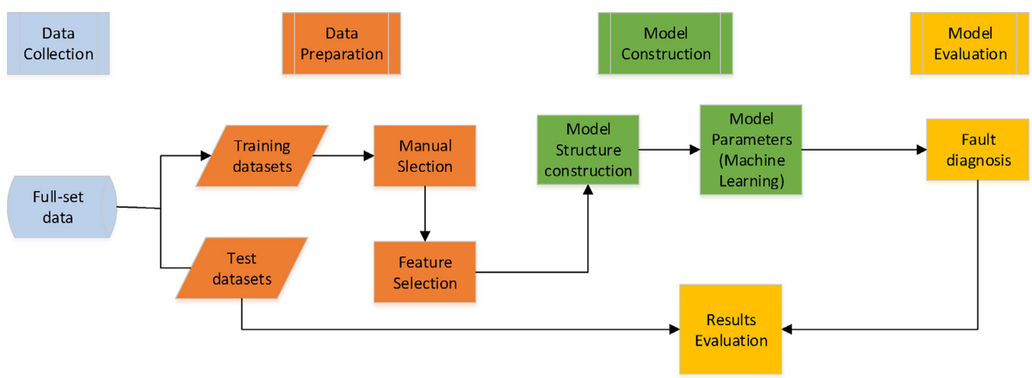

Fig. 3. Bayesian diagnosis flowchart.

It is clear that prior probability is necessary for root layer and conditional probability is needed to explain direct probabilistic dependence among different nodes. As for conditional probabilities of some nodes, they might be too complicated to express. The nodes with many parental nodes can be set as Noisy-Max nodes, and the others are set as general nodes. For general nodes, parameters comprise only conditional probability table. But for Noisy-MAX nodes, their parameters are made up of conditional probability table, sometimes the leak parameters are needed.

The prior probability distributions are mainly obtained on the basis of the frequency of different faults. Obviously a fault with higher prior probability is suspected to be more possible to occur than those with lower prior probability. As to the conditional probability distributions, statistical analysis and machine learning is adopted to obtain conditional probability distributions because of the lack of experts' experience and previous research on VRF system. And in this study, situations with multiple faults are not taken into consideration. Thus in each diagnosis process only single fault is suspected. It is worthwhile to note that the states of different variables are no longer boolean variables. For an instance, the fault symptoms, such as degree of superheat and degree of supercooling, can be set as three different level–lower, medium and high. And such setting is also reasonable, because according to different faults, temperature may fluctuates away from normal values in different directions. Thus boolean variables are not enough to describe such trends. In this study, only faults on refrigerant charge are taken into consideration. Among the data, 2/3 experiment data are used to obtain parameters of BBN, and the left 1/3 are used to evaluate the model. The calculated prior probabilities of the two faults can be set as Table 7. Meanwhile, the conditional probability tables among different nodes are computed by machine learning. As the conditional probability tables are complicated, for example, conditional probabilities of Noisy-MAX node $T_{sh,com,suc}$, T_{evap} are shown as in Table 8 and Table 9, while the conditional probability distributions of general node T_{cond} are shown in Table 10.

Table 7
Priori probability distributions of faults.

Faults	Refrigerant overcharge	Refrigerant leakage
Prior probability	0.23	0.38

4. Fault diagnosis results and discussion

It is clear that a certain fault may result different change trends of physical variables. And sometimes faults may leads to the same symptoms during the incipient stage of faults. Perhaps when the faults developing, the corresponding symptoms are different. But at that time the fault diagnosis may be not timely so that the VRF systems have been operating for quite a long period of time. In

Table 8
Conditional probability distribution of Noisy-Max node $T_{sh.com,suc}$ given variables.

$T_{sh.com,suc}$	Refrigerant overcharge	Refrigerant Leakage	T_{cond}		Leak
			Lower	Higher	
Lower	0.74	0	0.247	0	0.01
Higher	0.23	1	0.583	1	0.01
Normal	0.04	0	0.190	0	0.98

Table 9
Conditional probability distribution of Noisy-Max node T_{evap} given variables.

T_{evap}	Refrigerant Overcharge	Refrigerant Leakage	$T_{accu,out}$		T_{trans}		Leak
			Lower	Higher	Lower	Higher	
Lower	0.01	0	0.01	0	0.55	0	0.12
Higher	0	1	0.99	1	0.31	1	0.74
Normal	0.99	0	0	0	0.14	0	0.14

order to establish a fault diagnosis system to achieve timely and precise diagnosis, not only physical variables but also system operation information including operation records and collected data of control systems are combined to develop a bayesian network.

After the network is completed, it is necessary to validate it. In this study five cases are involved in validation. In the process, evidence is imported stepwise. The posterior probability distributions computed after importing the former piece of evidence can be seen as the initial probability distributions before the next one evidence is introduced. It is the belief update attribute of bayesian network, which is benefit for the importing of different pieces of evidence. The detailed orders of importing evidence are shown as Table 11 and the concrete explanation are as follows (Fig. 4).

4.1. Case 1

At the step one, T_{evap} was observed to fluctuate in the abnormal domain. It can be imported as the first evidence: cis lower. Then the posterior probability of refrigerant leakage (73.5%) is largest. Such probability distributions can be seen as the prior probability distributions. Next $T_{sh,com,suc}$ and T_{trans} are set as higher and lower respectively step by step. The posterior probability of refrigerant leakage increases from 88.6% to 95.0%, which trends can assure that the system fault is refrigerant leakage. From the expert knowledge, when the refrigerant is less than the normal charge amount in cooling mode, the saturation evaporation pressure and the saturation evaporation temperature $\left(T_{evap}\right)$ will become lower than that in normal conditions. After the refrigerant flows out of the evaporator, the superheat process is more thorough because of less refrigerant in the system, so the $T_{sh,com,suc}$ increases to deviate the normal domain. Then since the outdoor temperature is constant, the condenser saturation temperature is lower, thus the heat exchange temperature difference (T_{trans}) is naturally lower than normal value. As a consequence, the diagnosis results are in accordance with the experts' knowledge and experience.

4.2. Case 2

Assuming that physical variable is only T_{trans} and the compressor frequency (f_{com}) is also recorded as additional information. When T_{trans} is set as lower in the network, the posterior probability distributions illustrate that the fault is nearly refrigerant leakage. But if the network is more complicated, the fault isolation will be not as easy as now. So it is necessary to import additional information to ensure the fault diagnosis results. Then f_{com} is set as lower, the new posterior distribution are shown as Table 9. It is clear that probability of refrigerant leakage has shown an upward trend. According to the experience that if the refrigerant leaks, the operation of compressor will be affected. As a result, the compressor operation data can be imported as additional evidence into to bayesian network.

Table 10
Conditional probability distributions of general node T_{cond}.

T_{cond}	Refrigerant Overcharge	Refrigerant Leakage
Lower	0.99	0.99
Higher	0	0
Normal	0.01	0.01

4.3. Case 3

If T_{trans} is set at higher level firstly, it can be seen that the posterior probability of refrigerant overcharge is the biggest. Then $T_{subc,out,v}$ is set at higher level, it has grown from 85.5% to 91.9%. At last when T_{evap} is ascertained to be higher than normal value, it can be concluded that the system fault is refrigerant overcharge because of it high posterior probability (96.5%). It also can be understood from the experience that the overcharged refrigerant may lead to imperfect heat exchange in condenser that the refrigerant temperature in the system is higher than that in normal conditions.

4.4. Case 4

Assuming that indirect variables ($T_{sh,com,suc}$,$T_{sc,cond,out}$) and compressor operation variable (f_{com}) are taken into account in the diagnosis process. When that $T_{sh,com,suc}$ is higher is input as the first evidence, the diagnosis result is refrigerant leakage which is accordance with the diagnosis result in case 1. Following, the evidences that $T_{sc,cond,out}$ is lower and f_{com} is lower are imported into the system stepwise. The calculated posterior probability distributions confirm that the fault is refrigerant leakage, which is also accordance with case 2.

4.5. Case 5

The first piece evidence that $T_{sh,com,suc}$ is higher is the same as first step of fault diagnosis process in case 4. Obviously, the posterior probability distributions are the same, which can be seen from Table 9. But when T_{trans} is set as higher, the posterior probability of refrigerant overcharge becomes bigger than refrigerant leakage, which is accordance with case 3. From the diagnosis results, it needs patience to collect data and additional information to avoid bad judgment. Sometimes, the data collected may not corrected because of faulty sensors or conflicted as a result of incomplete data sets. Consequently, generally speaking, the more information you collect and input, the more precise the diagnosis results are.

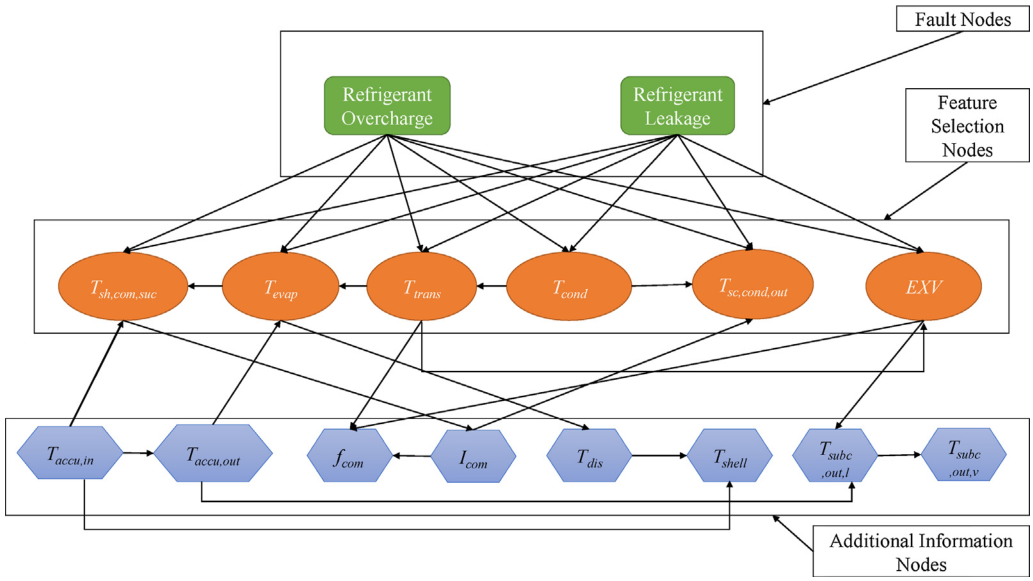

Fig. 4. The BBN for VRF system.

Table 11
Fault diagnosis posterior probability distributions.

Fault	Node	State	Fault diagnosis result		
			Refrigerant overcharge (%)	Refrigerant leakage (%)	Normal (%)
Refrigerant leakage	T_{evap}	lower	7.7	73.5	18.8
	$T_{sh,com,suc}$	higher	2.4	88.6	9
	T_{trans}	lower	0.5	95.0	4.5
–					
Refrigerant leakage	T_{trans}	lower	3.1	82	14.9
	f_{com}	lower	0.9	91.7	7.4
Refrigerant overcharge	T_{trans}	higher	85.5	0.1	14.3
	$T_{subc,out,v}$	higher	91.9	2.1	0.8
	T_{evap}	higher	96.5	0.7	3.4
Refrigerant leakage	$T_{sh,com,suc}$	higher	6.7	74.5	18.8
	$T_{sc,cond,out}$	lower	2.6	85.8	11.6
	f_{com}	lower	0.6	89.5	9.9
Refrigerant overcharge	$T_{sh,com,suc}$	higher	6.7	74.5	18.8
	T_{trans}	higher	72.6	26.6	0.6

5. Conclusions

This paper has proposed an intelligent fault diagnosis network for VRF systems using bayesian belief network. Because of its special attribute, the BBN accounts for relationships between variables with probability and distributions. Thus the most important and significant thing for BBN is to obtain the suitable network structure and probability distributions. The subject in this study is VRF system which has seldom been studied. As for its BBN structure, manual setting based on experience and experts' knowledge and data mining combining feature selection and machine learning are united, which is different from previous researches. On the other hand, the probability distributions are obtained mainly by statistical analysis. Prior probability distributions are often on frequencies in training data set, while the conditional probability tables are calculated by algorithms under some independence assumptions. Besides, the constructed network has been evaluated by test data set. The diagnosis results has evaluated using the part of experiment data, which demonstrates that such a BBN is an excellent tool for fault diagnosis. It is noticeable that it is difficult to separate refrigerant overcharge from normal condition especially when the fault level is not heavy. It is because of the attribute of VRF system. Because there is an accumulator in the system which can accumulate extra refrigerant so that it does not affect performance. But when the surplus exceeds the capacity of accumulator, the fault can be diagnosed. Furthermore, during bayesian inference, the order of input evidence have an impact on fault isolation efficiency in spite of the final posterior probabilities are same.

There are also many strengths for such a network. From the perspective of manual setting, the framework takes full advantage of domain knowledge and useful information hidden beneath the VRF system. Results of previous studies are integrated in the framework as well. Besides, it can merge different types of knowledge and information (i.e. quantitative and qualitative) from diverse sources. What's more, it is capable of dealing with conditions containing incomplete or even conflicting information.

In this study only two typical faults have been taken into consideration, which is not enough to achieve complete fault diagnosis for VRF system. In the future more faults are involved into the BBN. And according to different objective of bayesian belief network, different criteria are taken into consideration to select structure in the structure space.

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