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Fault Diagnosis Based on Improved Bayesian Classier in Power Communication Network

Yang Zhou[1],Juhong Tian[2],Li Yu[2]

[1]*(State Grid Jiangxi Electric Power Corporation Information Communication Branch, No.666, HubinRD east, Qingshanhu District, Nanchang City, Jiangxi Province, 330000, China)*

[2]*(School of Electronic Information and Communication, Huazhong University of Science andTechnology (HUST), Hongshan District, Wuhan, Hubei Province Luo Yu Road 1037, 430074, China)*

Abstract: Fault diagnosis is one of the most important tasks in network fault management. However, the traditionalnetwork fault diagnosis technologies cannot deal with incomplete information. Besides, they don't havegood learning ability and fault-tolerant feature. In this paper, we present a knowledge-based diagnosismethod called selective hidden naive bayesian (SHNB) classifier to diagnose power communicationnetwork fault. It selects parts of strong dependent relations' attributes as hidden parent for each attributeaccording to conditional mutual information. Compared to naive bayes (NB), tree augmented naïvebayesian (TAN), hidden naive bayes (HNB), our experiments show that SHNB algorithm outperformsthree other algorithms in accuracy, and has lower complexity compared to HNB and TAN. In addition,SHNB algorithm possesses good learning ability. As the same time, its fault-tolerant feature can deal with incomplete information very well.

Keywords: fault diagnosis, bayesian classifier, SHNB

I. INTRODUCTION

Power communication network is crucial in maintaining the power grid system functions, reliableoperation and safe production. what is more, it is easy to affect network adjustment and cause thewhole power grid function obstacle when the power communication networks break down. Faultdiagnosis can allow networks to operate reliably and stably by discovering the faults and recoveringfaults. Hence, how to diagnose the power communication network fault fast and accurately isimportant.

The early power communication network fault diagnosis is entirely based on the human operator'sexpertise. However, it proved to be difficult to maintain network in operating reliably andstably. Besides, the amount and complexity of status information generated by the fault makesit impossible to perform fault management efficiently. Therefore, automating fault diagnosisappears very critical in large and complex communication network.

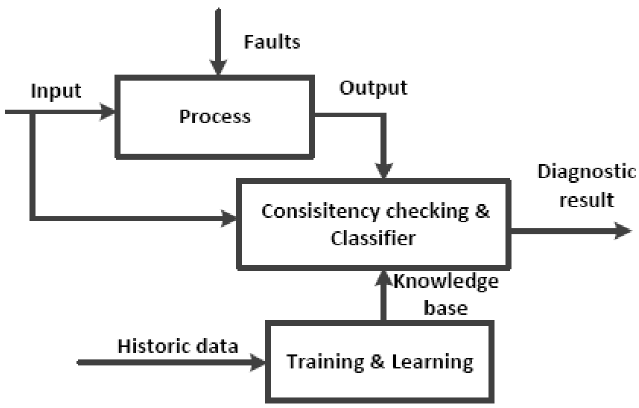

Fig. 1. The schematic of knowledge-based fault diagnosis approaches

Numerous efficient and practical fault diagnosis techniques have been presented in recent severaldecades [1], [2], such as signal-based fault diagnosis, model-based fault diagnosis, knowledge-basedfault diagnosis. Signal-based fault diagnosis methods including frequency-domain signal-basedmethod, time-domain signal-based method, and time-frequency signal-based method have a wideapplication in real-time monitoring and diagnosis [3], [4]. The signal symptom of a system undera healthy status is a priori knowledge and diagnostic decision is made based on the symptomanalysis and prior knowledge. Model-based method is a frequently used diagnosis method in thenetwork diagnosis [5], [6]. For this method, the practical power communication network systemsare required to be available and the models which serves as representation of the real system.The virtue of this method is its straightforwardness, robustness, and ease of use. However, forcomplicated power communication network systems, a large amount of historical data, ratherthan a model or a signal pattern, is available. Hence, it is difficult to acquire the priori knowledgeor known models.

Different from signal-based methods and model-based methods which require either a prioriknown signal patterns or model, knowledge-based fault diagnosis approaches start from where onlya large volume of historic data is available. And its schematic is depicted in Fig. 1. It diagnosesfault by checking consistency between the observed behavior of the system and the knowledgebase. The main knowledge-based methods include rule-based system [7], support vector machines(SVMs) [8], artificial neural networks (ANNs) [9], decision trees [10] and bayesian classifier [12].Their advantages and disadvantages are detailed in the Table 1.

Rule-based diagnosis methods take the form ”IF syndrome, THEN fault” to locate a fault[7]. Obviously, it bases on the abundance of knowledge and doesn’t have good learning ability.Decision trees [10] are an improvement over rule-based methods. This method builds a decisiontree using the most discriminative symptom as its starting point, and final fault are available asthe leaf nodes of the tree. This method is not only easy to use but also shortens the test time.However, specific applications limit its applicability. ANNs [9] have an advanced fault-tolerantability. But its drawbacks are long training periods and off-line training. SVMs [8] is a relativelynew machine learning technique relying on statistical learning theory, which is able to achieve highgeneralization and to deal with problems with low samples and high input attributes. But it isdifficult to handle the problem of multiple classification. Bayesian classifier [15] is a very effectiveclassification method based on probability density function. Naive bayesian (NB) classifier isone of most simplest classifier. And it successfully used in many areas widely [11], [13], [16] dueto its simplicity and effectiveness. However, the conditional independence assumption in NB israrely true in reality. Especially for the power communication network, a fault may cause a setof alarms and many symptoms have strong dependent ralations. What’s more, fault evidencemay also be inaccurate on account of spurious alarms, which are generated by transient problemsor as a result of overly sensitive fault detection mechanisms. Hence, it’s necessary to considerdependent relations between the symptoms at the time of diagnosing fault.

Table 1: Fault diagnosis methods’ advantages and disadvantages.

Fault diagnosis method	advantages	disadvantages
Decision trees	visualized	specific applications
Bayesian classifier	quick, good learning ability	weak in features combination
SVMs	high generalization	complex in multiple classification
Rule-based system	strong logic reasoning ability	poor learning ability
ANNs	advanced fault-tolerant	long training periods

In this paper, we propose an improved bayesian classification algorithm called selective hiddennaive bayesian (SHNB) algorithm to diagnose fault in power communication network. It selectsparts of strong dependent relations’ attributes as the hidden parent for each attribute. Ourmotivation is to develop a novel algorithm to reduce the test time and still has high diagnosisaccuracy compare to other bayesian classification algorithm. We test SHNB in terms of diagnosisaccuracy and test time based on the historical fault case, compared to NB, tree augmented naïvebayesian (TAN) [17], and HNB [14] in the experiment. The experimental results show that ourclassification algorithm has higher diagnosis accuracy and lower diagnosis time. In addition, thisalgorithm embody fault-tolerant feature and can handle missing information.

The rest of the paper is organized as follows. In section II, we introduce bayesian classifier.Then, we present our SHNB model and algorithm. The experiments and results based on SHNBclassifier is described in the section IV. Conclusions are given in the final section.

II. BAYESIAN CLASSIER

Bayesian classifier is a statistical classification method, which classifies an instance by determiningits probability belonging to a class label. Assuming n attributes $A_1, A_2 \dots A_n$ (corresponding toattribute nodes in bayesian model), an example E is represented by a vector$< a_1, a_2 \dots\ a_n >$,where a_i is the value of attribute A_i. We use C to represent the class variable (corresponding tothe class node in a bayesian model), cis the value of C and c ϵC. c(E) denotes the class labelE belonging to. The classifier represented by a general Bayesian network is defined as:.

$$c(E) = \underset{c\epsilon C}{\operatorname{argmax}} P(c)P(a_1 a_2 \dots a_n|c) \qquad (1)$$

Assume that all attributes are independent given the class label, the resulting classifier is callednaive bayesian (NB). It is defined as follows:

$$c(E) = \underset{c \epsilon C}{\operatorname{argmax}}\ P(c) \prod_{i=1}^{n} P(a_i|c) \qquad (2)$$

NB classifier is a popular learning algorithm for data mining applications due to its simplicityand linear run-time. However, the independent assumption is not always invalid in the realworld. The performance become poor when the assumption is violated. HNB [14] is an improvedNB model where each attribute has a hidden parent which considers the influences from otherattributes. Fig. 2 shows the structure of an HNB. In Fig. 2, Cis the class node, and eachattribute A_i has a hidden parent A_{hpi}, expressed by a dashed circle.

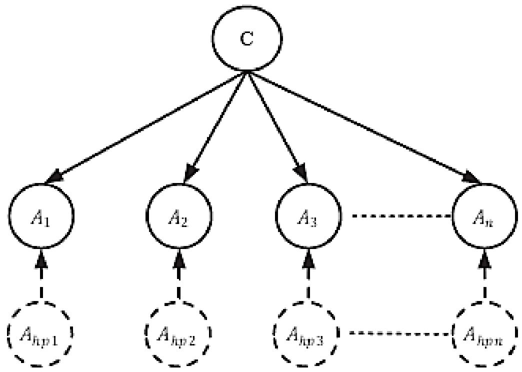

Fig. 2. The structure of HNB

The classifier corresponding to an HNB is defined as follows:

$$c(E) = \underset{c \epsilon C}{\operatorname{argmax}}\ P(c) \prod_{i=1}^{n} P(a_i|a_{phi}, c) \qquad (3)$$

where $P(a_i|a_{hpi}, c)$is the conditional probability of the attribute and its hidden parent definedas:

$$P(a_i|a_{hpi}, c) = \sum_{j=1, j\neq i}^{n} W_{ij} * P(a_i|a_j, c) \qquad (4)$$

We determine the weights W_{ij} by using the conditional mutual information between two attributes$A_i$and A_j in the [14], and Wij is defined as:

$$W_{ij} = \frac{I_p(A_i; A_j|C)}{\sum_{j=1, j\neq i}^{n} I_p(A_i; A_j|C)} \qquad (5)$$

where $I_p(A_i; A_j|C)$is the conditional mutual information and is defined as:

$$I_p(A_i; A_j|C) = \sum_{a_i, a_j, c} P(a_i, a_j, c) log \frac{P(a_i, a_j, c)}{P(a_i|c)P(a_j|c)} \qquad (6)$$

Compared to other improved models for relaxing naive bayesian, HNB has a better performance.However, it costs too much test time on high dimensional data sets. In fact, the numberof correlative attributes is further lower than the number of all attributes. And taking all attributesinto account may increase the noiseand decrease classification efficiency. Our purposeis to propose a practical classifier algorithm which can reduce the complexity and increase theclassification accuracy.

III. SELECTIVE HIDDENNAIVE BAYESIANMODEL

In this section, we put forward a selective hidden naive bayesian (SHNB) model, which can reducethe classification complexity and close to the practical situation compared to HNB. The structureof SHNB is shown in Fig. 3, where C is the class node which points all attribute nodes, andeach attribute A_i has a hidden parent. It is different from HNB model where all attributes areconcerned in hidden parent. However, in SHNB, we only select parts of most correlative attributesas the hidden parent for each attribute. What is more, we use variable $S_i(i = 1,2, \ldots, n)$ to standfor the hidden parent, expressed by a dashed circle in the Fig. 3. In Fig. 3, We can see thateach hidden parent contains m attributes which are most correlative with attribute Ai. The valueof m can be change in accordance with different data set. Generally, we need to experiment todetermine the best value ofm.

For SHNB algorithm, how to select appropriate attributes to a hidden parent is an important issue.This paper we adopt the method by computing the mutual information between the attributes.For example, we calculate the conditional mutual information between the attribute A_1 and otherattribute $A_j\,(j = 2,3, \ldots, n)$, and select m attributes which have great conditional mutualinformation with attribute A_1 as hidden parent S_1. Let $S_1 = \{A_{11}, A_{12}, \ldots A_{1k}, \ldots A_{1m}\}$.

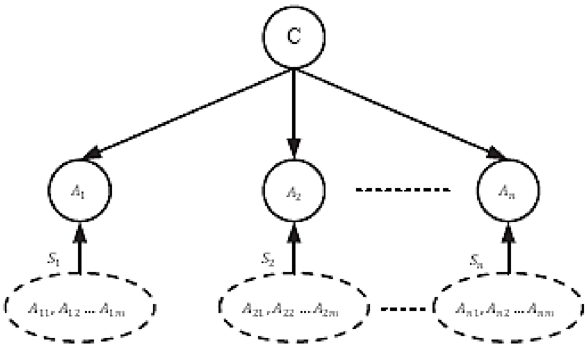

Fig. 3. The structure of SHNB

The classifier corresponding to SHNB on an instance E is defined in (7). The hidden parent $S_i$just contains parts of most correlative attributes.

$$c(E) = \underset{c \epsilon C}{\operatorname{argmax}}\ P(c) \prod_{i=1}^{n} P(a_i | S_i, c) \qquad (7)$$

where $P(a_i|S_i, c)$denotes the conditional probability of the attribute Ai and its hidden parent,defined as:

$$P(a_i|S_i, c) = \sum_{k=1}^{m} W_{i-ik} * P(a_i|a_{ik}, c) \qquad (8)$$

Where a_{ik} is the value of A_{ik} . W_{i-ik} represents the conditional mutual information between twoattributes A_i and its hidden parentA_{ik} $(k = 1,2, \ldots, m)$, which is defined as follows:

$$W_{i-ik} = \frac{I_p(A_i; A_{ik}|C)}{\sum_{k=1}^{n} I_p(A_i; A_{ik}|C)} \qquad (9)$$

where$I_p(A_i; A_{ik}|C)$is the conditional mutual information and is defined as:

$$I_p(A_i; A_{ik}|C) = \sum_{a_i, a_{ik}, c} P(a_i, a_{ik}, c) log \frac{P(a_i, a_{ik}, c)}{P(a_i|c)P(a_{ik}|c)} \qquad (10)$$

At classifier training phase, we need to estimate the parameters and determine the number ofthecorrelative attributes for each attribute. Thus, learning a SHNB algorithm is depicted as:

Algorithm: Selective Hidden Naive Bayesian

for each $c \epsilon C$ **do**
compute *P*(*c*) from *D* ;
end for
for each pair of attributes $A_i$and A_j **do**
each assignmenta_i, a_j and *c* to A_i, A_j and *C*;
compute $P(a_i|a_j, c)$ from *D*;
end for
for each A_i $(i\ \epsilon[0,1])$**do**
compute$I_p(A_i; A_j|C)$;
sort$I_p(A_i; A_j|C)$;
select *m* most relevant attributes;
set $S_i = \{A_{i1}, A_{i2}, \ldots A_{ik}, \ldots A_{im}\}$;
end for
for each value *c* of *C* **do**
compute the *c*(*E*);
end for

In our implementation of SHNB, conditional probability $P(a_i|a_j, c)$ and prior probability $P(c)$ are estimated using the M-estimation as follows:

$$P(c) = \frac{F(c) + \frac{1.0}{t}}{u + 1.0} \qquad (11)$$

$$P(a_i|a_j, c) = \frac{F(a_i|a_j, c) + \frac{1.0}{n_i}}{F(a_j, c) + 1.0} \qquad (12)$$

where F(•) is the frequency with which a combination of terms appears in the training data, *u*is the number of training examples, *t* is the number of classes, and n_i is the number of values ofattribute A_i.

Obviously, when *m* approximates to *n*, SHNB model evolves into HNB model. But if *m* farless than *n*, SHNB algorithm can decrease computational complexity greatly, especially appliedon high dimensional data sets.

IV. EXPERIMENTS AND RESULTS

We run our experiments on Weka by selecting 500 historical faults instance from the powercommunication network historic logs. The performance of each classifier is obtained via 10 runsof 10-fold cross validation. Runs with the various bayesian classification algorithms are carried outon the same training sets and evaluate on the same test sets. In order to construct a feasible faultdiagnosis scheme for power communication network based on bayesian classifier, some steps canbe referred as follows: 1) Acquire data from the fault management database; 2) Discrete numericattribute values, and determine the attribute variables and fault class variables; 3) Choose aappropriate bayesian classification algorithm; 4) Learning the parameter (prior probability andconditional probability) of bayesian classifier through the training sample; 5) Fault diagnosisanalysis according to the result of testing sample. The Fig. 4 presents the detailed flow chart.

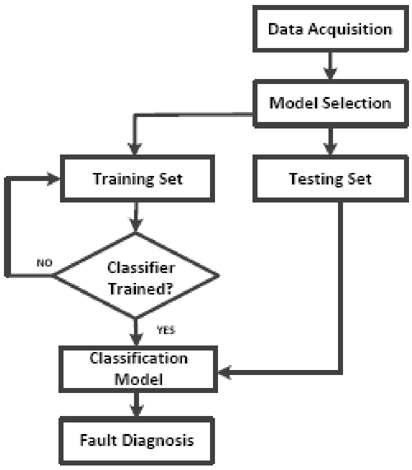

Fig. 4. Fault diagnosis steps based on bayesian classifier.

In the historical faults instance of power communication network. We summarize some symptomsets(attributes) and fault sets (classes), and they are shown in Table 2. The correspondingrelationships between symptoms and fault are shown in Table 3 where $A_1 = 0, A_1 = 1$ respectivelyrepresent the interface manage state UP and DOWN. Attribute $A_2 = 0, A_2 = 1$ respectivelyrepresent interface operating state UP andDOWN. The value of $A_1, A_2, A_3, \dots, A_{10}$ being equal to 0 denote the attribute value in normal range. On the contrary, there are somefaults in the power communication network when attribute value is equal to 1.

Table 2: Power communication network faults and symptoms.

Class	Fault	Attribute	Symptom
C_1	Interface down	A_1	Interface manage state
C_2	Port not match	A_2	Interface operating state
C_3	Line fault	A_3	Input packet loss rate
C_4	Buffer shortage	A_4	Output packet loss rate
C_5	Bandwidth shortage	A_5	Input error rate
C_6	Protocols not compatible	A_6	Output error rate
		A_7	Utilization

A_8	Unknown protocol rate
A_9	Broadcast packets
A_{10}	Connection speed

For simplest NB model, we put power communication network fault as the root node, and attributesas the leaf node. we find the cause of the malfunction by calculating the maximumposterior probability. In this model, all attributes are independent between them. In fact, thereis a relationship between each other in many attributes. For example, the attribute A_4 has strongcorrelation with A_3 in Table 3. The NB model ignore dependencies between attributes A_4 andA_3. Thus the accuracy of NB model is affected by it's conditional independence assumption.However, if all attributes are concerned, such as HNB, some accidental may be involved. It notonly increases the classification time but also bring down the accuracy. Therefore, we put forwardSHNB model combining NB model and HNB model. It can avoid the above problem by selectingparts of most correlative attributes.

Table 3: Training sample set; "*" denotes uncertain attribute value.

Number	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	Class
102	0	1	0	0	0	0	0	0	0	0	C_1
22	0	0	1	1	0	0	1	0	*	1	C_2
105	0	0	*	1	1	*	1	0	0	1	C_3
39	0	1	1	*	0	0	0	0	0	0	C_1
15	0	0	1	1	0	0	1	*	0	0	C_4
78	0	0	1	1	1	1	0	0	0	1	C_3
46	0	0	0	1	*	0	1	0	0	1	C_4
20	0	1	*	1	0	0	*	0	0	0	C_3
35	0	0	1	1	0	0	1	0	0	1	C_5
12	0	0	1	*	0	0	0	1	0	1	C_6
24	0	*	1	0	0	0	1	0	*	0	C_1
2	0	0	1	*	0	0	1	0	0	0	C_5

The accuracy of SHNB model has relation to the value of *m*. Therefore, we need to experimentallytest accuracy on different m in historical instances. Fig. 5 describes the accuracy ofSHNB classifier when *m* increases from 0 to 9. We can see that the accuracy is not increasingas m from Fig. 5, and SHNB classifier has the best accuracy when *m* equal to 2.

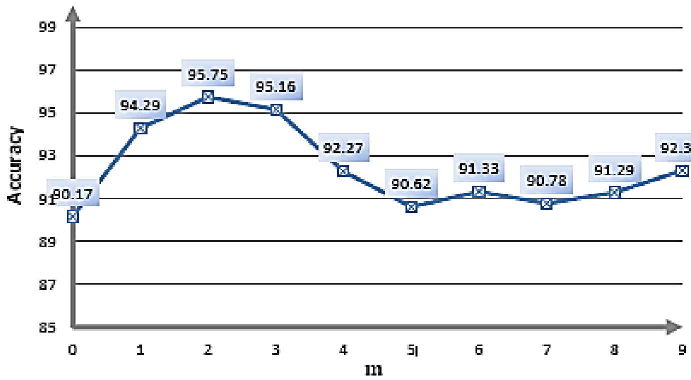

Fig. 5. The accuracy of SHNB algorithm in different *m*.

Hence, *m* = 2 when we introduce the process of establishing a SHNB model.Firstly, for each attribute, we needto compute the mutual information between it and other attributes. Then use the method ofselection sort to choose two attributes with maximum mutual information. For instance, for attributeA_1compute $I_p(A_i; A_j|C)$, then select the attributesA_2 and A_3according to selection sortalgorithm. Thus, the hidden parent S_1 contains attributesA_2 and A_3. The similar way to selecttwo most relevant attributes for other remaining attributes. SHNB diagnosis model is presentedin Fig. 6 where each hidden parent contain two attributes. If we have an order of attributes:$A_1, A_2, A_3, \dots, A_{10}$, we can calculateapproximate of$P(C|A_1, A_2, \dots, A_{10})$ by formula (7)(8)(9)(10) to find root fault.

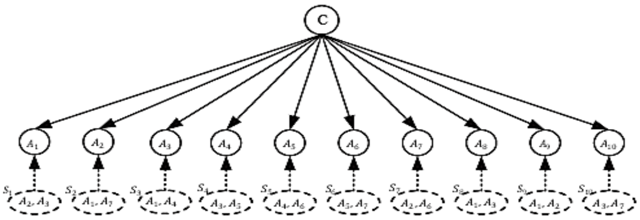

Fig. 6. The SHNB diagnosis model when m = 2

To verify the learning ability of bayesian classifier, we conduct our experiments to test the classifieraccuracy in nine different number of training samples. We establish NB, TAN, HNB, and SHNBclassifiers respectively with the number of training samples gradually increasing from 50 to 500.The accuracy of classifiers is shown in Table 4. We can see from Table 4, with the increaseof training sample sets, each bayesian classifiers' classification accuracy becomes higher. Thisillustrates bayesian classifiers have strong learning ability by constantly improving the probabilitydistribution parameters. In addition, as the training sample sets reach a certain number, the fourclassifiers' classification accuracy tend to be stable. What is more, we test the accuracy of indifferent m values of 1, 2, 3. Obviously, the accuracy of SHNB (m = 2) is overall the best amongother three classifier compared in this paper and it can achieve more than 95% in accuracy aslong as the training samples are enough.

Table 4: The accuracy of different training samples.

Trainingcase	NB	TAN	HNB	SHNB(m=1)	SHNB(m=2)	SHNB(m=3)
50	50.96±0.53	43.67±2.13	53.15±0.91	51.84±0.52	56.78±1.36	52.9±0.71
100	67.42±0.87	63.44±1.33	66.76±1.35	65.43±1.17	69.41±2.53	68.25±0.89
150	73.26±1.65	71.53±1.04	74.98±1.28	75.71±0.95	77.14±0.72	74.36±1.47
200	75.94±1.56	77.16±0.71	80.22±1.14	79.65±0.87	83.51±0.94	82.09±1.03
250	83.26±2.57	85.78±1.35	86.53±1.57	86.94±2.21	88.54±1.76	87.66±1.97
300	88.63±0.65	89.87±2.03	90.14±1.19	90.56±2.15	92.16±1.76	92.04±0.55
350	90.09±0.78	91.46±1.27	93.31±1.44	92.44±0.97	95.13±0.81	94.77±1.21
400	90.21±0.75	92.52±1.15	94.58±0.79	94.29±1.22	95.75±0.99	95.16±1.54
500	90.26±0.32	93.14±0.95	94.77±0.59	95.01±0.96	95.92±0.85	95.22±1.17

As we know, the practical sample attribute information is often incomplete. In order to simulatethe situation of attribute missing, we randomly take out 0-6 attributes of sample sets. Theclassification accuracy is shown in Table 5. We know from Table 5, all bayesian classifiers havehigher classification accuracy when attribute value is not missing. With the number increasing ofmissing attribute, classifiers' classification accuracy decrease gradually. Specially, the accuracy ofTAN decrease rapidly, because missing attribute value affect its' structure learning process. Whenmissing attribute value is less than 3, all bayesian algorithm's classification accuracy maintainhigher level and SHNB is the best one. Hence, SHNB has the advantages of flexible and faulttolerance, and can better deal with incomplete information.

Table 5: Accuracy of diagnosis with missing attribute samples.

Attributemissing	NB	TAN	HNB	SHNB(m=1)	SHNB(m=2)	SHNB(m=3)
0	90.21±0.75	92.52±1.15	94.58±0.79	94.29±1.22	95.75±0.99	95.16±1.54
1	89.42±0.64	86.89±2.94	89.36±2.35	90.53±1.46	91.65±1.27	91.14±1.85
2	88.24±1.36	84.52±1.24	88.25±0.22	89.76±0.73	90.53±0.85	88.92±1.43
3	86.89±1.87	80.78±1.76	84.74±1.63	85.55±0.97	85.79±1.1.2	86.32±0.87
4	73.16±3.47	70.28±2.83	72.72±2.17	78.14±2.19	88.54±1.76	78.75±1.98
5	69.31±2.29	61.68±3.03	70.24±3.19	69.26±3.48	79.35±2.16	70.06±2.24
6	60.44±2.71	52.33±3.24	64.18±3.85	65.21±2.55	66.71±2.37	64.16±3.57
Mean time/s	0.09	0.92	0.25	0.11	0.16	0.19

Although SHNB significantly outperforms NB, it slightly outperforms HNB in accuracy. Inorder to prove that SHNB has better performance than HNB, we compare the mean time of fourbayesian classifiers. And the details are shown in last line of Table 5 where NB classifier costsleast time and TAN classifier costs most. Compared to HNB, we can find that the test time ofSHNB is shorter.

V. CONCLUSIONS

In this paper, we propose a high-efficient and knowledge-based diagnosis method called selectivehidden naive bayesian (SHNB) classifier to diagnose the power communication network fault. Ouralgorithm selects the most relevant attributes as hidden parent for each attribute according toconditional mutual information. It not only consider the attribute correlativity, but also reducehigh complexity. The experiment results show that SHNB classifier outperforms other classifiersin accuracy and test time. Our classifier' classification accuracy reaches more than 95% at thecase of $m = 2$, and it costs less than HNB and TAN with same sample sets. Even if the attributevalue is incomplete or inaccurate, our classifier still has high accuracy. Thus, it can be seen SHNBclassifier has good learning ability and fault tolerance.

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