Research on fault diagnosis method based on Temporal Bayesian Network

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Abstract. This paper is based on the traditional network of bayesian, introducing the concept of the time window, to construct the Temporal Bayesian Network (TBN) model. In addition, optimizing TBN model reasoning algorithm to process system data which has the temporal haracteristic. Then we can obtain the posterior probability of each node in the TBN and use importance ranking method to determine the fault retrieval sequence, optimize of fault diagnosis process.Combined with the state power line fault diagnosis example to verify the correctness of this method.

Introduction

With the continuous development of the complex system, we need to know the real-time state of the complex system. When the system occurs the failure, we can identify the failure location and maintain as soon as possible, but the traditional fault diagnosis methods have been unable to meet the need. The bayesian network has the ability to deal with uncertain information, coupled with the introduction of the concept of time window, real-time monitoring system status and when the system failure occurs, we can determine the fault location at the first time, and provide efficient fault retrieval sequence, to optimize the fault diagnosis process.

Time window

In the TBN, the nodes are intertwined, and the observation of any node or the interference to any node observations will affect the other nodes in the bayesian network. The short distance of the recent evidence has a greater impact on the reasoning results of the time slice, and vice versa. Thus, if you want to compute a posterior probability of a hidden variable or multiple hidden variables on a time slice, you can use the evidence of the time slice, the evidence before the time slice, and the evidence after the time slice to calculate its posterior probability. Because it is not using all the evidence of observation, the result is an approximate reasoning.In TBN, the reasoning is carried out only using TBN composed of successive time slices and the，forward information propagating to the network, the time window consist of multiple time slices.

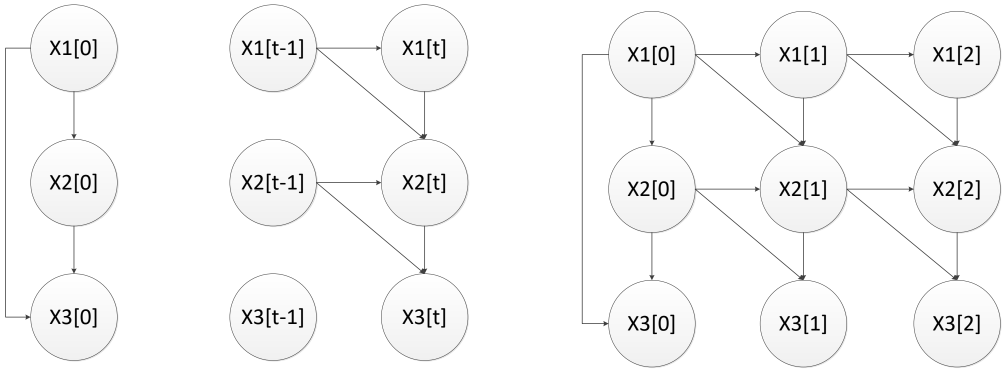
TBN model

The TBN is developed from the static bayesian network, where each factor in the environment is represented by a random variable, and the ever-changing system environment is modeled in this way. The relationship between these variables can describe how the state of the system changes slowly over time. The process of the system state changing can be regarded as a set of random states of the system at each discrete point in time, and each time point is called a time slice, and each time slice can be regarded as a static bayesian network. In order to avoid assigning different conditional probability tables to each time slice, it is assumed that the environmental state of the system is evolved by a steady-state process, that is, the process of system changing is caused by the system itself, not dominated by the the regular pattern of the time factor. Under the assumption of steady state, the network structure in each time slice is same. Therefore, the research process only needs to specify the condition probability for the variable of a representative time slice, so as to study the TBN model.

So the TBN can be defined as $B(B_0, B_{\rightarrow})$, where B_0 means the TBN of the initial time and $P(Z_0)$ is defined as the probability distribution of the initial time. $B_{\rightarrow}$ is a bayesian network containing two time slices, meaning the conditional distribution between two adjacent time slices.the conditional distribution is defined as follows:

$$P(Z_t \mid Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i \mid \pi(Z_t^i)) \quad (1)$$

Where Z_t^i means the node i of the time slice t, $\pi(Z_t^i)$ means the parent node of Z_t^i. Z_t^i and $\pi(Z_t^i)$ can lie in the same time slice or the previous time slice. The edges that lie in the same time slice can be understood as transient effects, and the edges that cross the time slice can be understood as temporal changes, that is reflecting the pass of the time. In the figure 1, (a) shows a TBN of the initial time, (b) shows a a bayesian network containing two time slices, (c) shows an expanded TBN.



(a) (b) (c)

Figure 1 TBN representation

The TBN consists of two basic assumptions:

(1) First-order Markov hypothesis: the edges between the nodes are either in the same time slice, or between adjacent time slices, and can not cross the boundaries of the time slice.

(2) Homogeneity: parameter in $B_{\rightarrow}$ does not change with time occurs, according to the initial probability and the conditional probability distribution between adjacent time slices, TBN can be expanded into the time slice T, the result is we can obtain a joint probability distribution over a plurality of time slices as follows:

$$P(Z_{1:T}) = \prod_{t=1}^{T} \prod_{i=1}^{N} P(Z_t^i \mid \pi(Z_t^i)) \quad (2)$$

It can be seen from the above ,the time series of the TBN does not mean that the structure and parameters of the bayesian network are constantly changing over time, but the sample data (or the observed data) is changing over time. It is necessary to fully describe a TBN that needs three aspects: one is to determine the structure of the TBN, the second is to determine the TBN parameters, the third is to determine the inference algorithm.

TBN inference algorithm

Each time slice is composed of a hidden variable X and an observation variable Y. $X_t(t=1,2,...,T)$ means hidden variable of time slice t, $Y_t(t=1,2,...,T)$ means observation variable of time slice t. y_t means observation value of time slice t. a_{ij} means state transition matrix. $\gamma_t(i)$ means the posterior probability of the hidden node.

$$\eta = \frac{1}{P(y_{t+1},...,y_T \mid y_1, y_2,..., y_t)} \tag{3}$$

$$\alpha_t(j) = \eta P(Y_t = y_t \mid X_t = j)\sum_{i=1}^{n} a_{ij}\alpha_{t-1}(i) \tag{4}$$

$$\beta_t(i) = \sum_{j=1}^{n} \beta_{t+1}(j) P(y_{t+1} \mid X_{t+1} = j) a_{ij} \tag{5}$$

$$\gamma_t(i) = \eta\alpha_t(i)\beta_t(i) \tag{6}$$

Then we can reason TBN following the steps below:

Step 1: Initialization: Enter a priori probability, posterior probability, time window width l and time slices total T_0.

Step 2: Inputting the time slice T to the time window. If $T \le l$, using the recursion formula of the forward algorithm to calculate α_T, using the recursive formula of the backward algorithm to calculate $\beta_T^l, \beta_{T-1}^l, ..., \beta_1^l$, and then calculate $\gamma_1^l, \gamma_2^l, ..., \gamma_T^l$, and updating the reasoning result of the TBN in the time window.

Step 3: Enter a new time slice to the time window, make $T = T+1$. If $T \le l$, repeated step 2, if $T > l$, go to step 4.

Step 4: Output the approximate reasoning result from the time window

Step 5: Using the forward algorithm to calculate α_T, using the backward algorithm to calculate $\beta_T^l, \beta_{T-1}^l, ..., \beta_{T+1-l}^l$, updating the reasoning result of the time window.If $T+1 \le T_0$, go to step 6, otherwise it will end.

Step 6: Outputting the approximate reasoning result γ_{T+1-l}^l from the time window, inputting the next time slice to the time window, and make $T = T+1$, go to step 5.

Importance ranking method

According to the reasoning results of the TBN, the following formula is used to determine the rank of the root node of the TBN. The higher the value is, the node has the priority to carry out the fault retrieval in order to complete the fault diagnosis of the system.

$$V_i = \frac{1}{T-1}\{\sum_{i=1}^{T}\gamma_t(i) + \frac{T}{2} - 1\} \tag{7}$$

Where T means the number of the time slice, $\gamma_t(i)$ means the posterior probability of the hidden node.

Simulation and analysis

The overall operating state of the state power line is affected by the working conditions of the unit equipment, and the status of each unit is determined by different factors. Determining these influence factors and the influence of these factors on the unit and line conditions is the basis for constructing the TBN fault diagnosis model. Therefore, it should select those nodes that are easy to observe, influence large and have a strong independence, so according to the above rules, combined with the actual situation, we determine the factors which influence the state power line are pole, cable, insulator and fitting. It is assumed that each factor has three failure modes. The TBN of the state power line is established as follows.

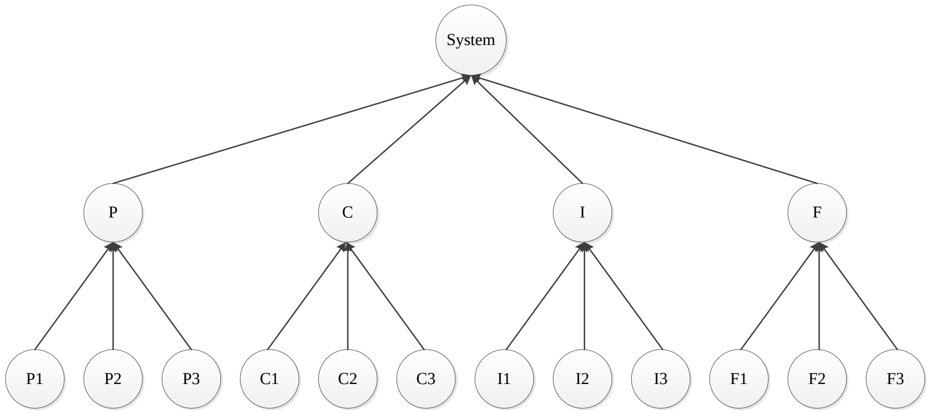


Figure 2 State power line TBN

Table 1 assumes the initial-time prior probabilities, conditional probabilities and the state transition probabilities of the root nodes.

Table 1 initial-time prior and conditional probabilities

Failure unit	Failure cause	Prior Probabilities	Conditional probabilities	state transition probabilities
Pole	P1	0.3	0.6	0.2
	P2	0.3	0.2	0.4
	P3	0.4	0.2	0.4
Cable	C1	0.3	0.5	0.3
	C2	0.3	0.4	0.6
	C3	0.4	0.1	0.1
Insulator	I1	0.3	0.3	0.5
	I2	0.3	0.4	0.2
	I3	0.4	0.3	0.3
Fitting	F1	0.3	0.8	0.4
	F2	0.3	0.1	0.5
	F3	0.4	0.1	0.1

According to the recursive formula of the forward algorithm and the backward algorithm mentioned above, we can calculate the posterior probability $\gamma_t(i)$ of each root node in each time slice. In order to verify the validity of this method, setting the number of time slices to 10. The simulation results can be obtained as shown in the table 2, then using the importance ranking formula (7) to get the importance of each root node as shown in the table 3.

Table 2 posterior probabilities of the root node

	1	2	3	4	5	6	7	8	9	10
P1	0.728	0.766	0.708	0.575	0.44	0.343	0.247	0.174	0.132	0.16
P2	0.199	0.195	0.238	0.32	0.343	0.446	0.44	0.352	0.315	0.314
P3	0.073	0.039	0.054	0.105	0.217	0.211	0.313	0.474	0.553	0.526
C1	0.62	0.716	0.61	0.396	0.228	0.125	0.079	0.054	0.029	0.036
C2	0.26	0.23	0.309	0.382	0.444	0.387	0.278	0.19	0.071	0.092
C3	0.12	0.054	0.081	0.222	0.328	0.488	0.643	0.756	0.9	0.872
I1	0.667	0.73	0.63	0.419	0.247	0.15	0.093	0.063	0.069	0.037
I2	0.204	0.158	0.247	0.445	0.489	0.365	0.387	0.478	0.542	0.618
I3	0.129	0.112	0.123	0.136	0.264	0.485	0.52	0.459	0.389	0.345
F1	0.124	0.261	0.238	0.331	0.284	0.195	0.119	0.152	0.215	0.249
F2	0.376	0.278	0.375	0.561	0.452	0.456	0.309	0.334	0.461	0.135
F3	0.5	0.461	0.387	0.108	0.264	0.349	0.572	0.514	0.324	0.616

Table 3 The importance of each root node

Node	P1	P2	P3	C1	C2	C3
V_i(%)	91.9	79.6	72.9	76.6	73.8	94.0
Node	I1	I2	I3	F1	F2	F3
V_i(%)	78.9	88.1	77.4	68.5	86.0	89.9

According to Table 3, we can obtain the fault retrieval sequence as follow:

$$C3 > P1 > F3 > I2 > F2 > P2 > I1 > I3 > C1 > C2 > P3 > F1$$

From the last fault search sequence, it can be seen that the probability of occurrence of these three failure modes which contains C3, P1, F3 is high. Therefore, when the system fails, giving a priority diagnosis to the cable can improve the fault diagnosis efficiency and optimize the fault diagnosis process.

Conclusion

This paper is based on the traditional bayesian network, introducing the concept of the time window, combined with the forward-backward reasoning algorithm and importance ranking method, constructing the TBN model to handle with the complex overtime changing system. From the fault retrieval sequence ranking result, the method proposed in this paper can improve the fault diagnosis efficiency and optimize the fault diagnosis process. So the method has a certain value in time-series system field.

References

[1] Soderlan, S. Learning Information Extraction Rules for Semi-Structured and109[Pea01] J. Pearl, "Bayesian Networks, Causal Inference and Knowledge Discovery", UCLA Cognitive Systems Laboratory, Technical Report (R-281), March2001.

[2] Leonid Peshkin and Avi Pfeffer. Bayesian information extraction network. In Proc. 18th Int. Joint Conf. Artifical Intelligence, 2003.

[3] D.Spiegelhater, A. Dawid, S. Lauritzen, and Cowell. Bayesian analysis inexpert systems. Statistical Science, 8(3):219-283, 1993.

[4] Yu D. C., Nguyen T. C., and Haddawy P.. Bayesian network model for reliability assessment of power systems. IEEE Trans on Power Systems, Vol.14 (2) (1999), 426-432.

[5] Mahadevan S., Zhang R. X., and Smith N.. Bayesian networks for system reliability reassessment [J]. Structural Safety, Vol.23(3) (2001), 231-251.

[6] N. Bashir, H. Ahmad. Ageing of Transmission Line Insulators The past,Present and Future [C]. Proceedings of 2nd IEEE International Conference on Power and Energy (PECon 08), 2008: 30-40.