Diagnosis method for Analog Circuits fault using Bayesian network

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Abstract. Aiming at the uncertain problem in analog circuit fault diagnosis, a new method based on Bayesian network is proposed. Given a set of measurements from the circuit, and a set of possible faults, the task is to calculate the probability that the faults are present. This paper then discusses the methodology for diagnosis and the associated procedures for block-level diagnosis of analogue circuits in detail. Finally, the correctness and effectiveness of this method are validated by the fault diagnosis result of a voltage regulator used car radio.

Introduction

Traditional troubleshooting methods are based on rule-based reasoning, which are suitable for domains that are "black and white". But they are not well suited to domains that are fuzzy or have a significant percentage of uncertain cases. Analog circuits feature a huge complexity with multiple components that interact with each other in complicated ways. Therefore, the knowledge acquired for the diagnostics can be uncertain and incomplete. In this case, the diagnostics is not always well served by rule-based reasoning. A feasible approach to avoid the problems is to use Artificial Intelligence (AI) diagnosis methods. Recently, much research endeavors have been done for fault diagnosis of analog circuits by using several techniques, such as logic-based expert system[1], fuzzy relation[2] based expert system, artificial neural network, optimization techniques based approach, etc. They diagnose the fault from different ways. However, each approach has its limitations. This paper focuses on the construction and application of the Bayesian network model.

Fault diagnosis is a process of reasoning the cause-effect or fault-symptom relations and in almost all cases single symptom will be caused by several faults, while single fault will exhibit several symptoms [3]. In this situation, Bayesian network provides an alternative approach to tackle the diagnosis problem.   In Ref. [4], a discriminate analysis and a distance rejection in a Bayesian network were combined in order to detect new types of fault. Ref. [5] draws from Bayesian decision theory, reliability theory, and signal detection theory, to provide an end-to-end probabilistic treatment of the fault diagnosis and prognosis problem.

The paper is organized as follows. Section 2 presents the fundamental of Bayesian network. Then the proposed modeling procedure (structure and parameter) will be presented. In the next section, diagnosing a multiple voltage regulator faults will be presented as case study. Section 5 concludes this paper with discussion on the results obtained and future work.

Bayesian Networks

Bayesian network, also known as probability network or belief network [5], are well established as a representation of relations among a set of random variables that are connected by edges and given conditional probability distribution at each variable. As shown in Fig. 1, an edge from X_1 to X_2 indicates that X_1 causes X_2.

Conditional probability distribution (CPD) is specified at each node that has parents, where prior probability is specified at the node that has no parents , and we call this node as root node. As shown in Figure 1, the CPD of variables X_2 and X_3, are $P(X_2|X_1)$ and $P(X_3|X_1)$ respectively; and the prior probability of X_1 is $P(X_1)$.
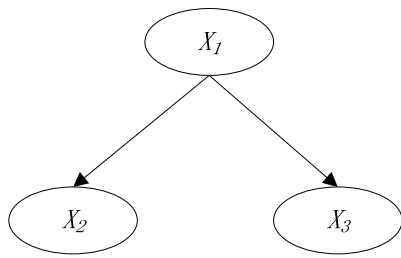
Fig. 1 A simple Bayesian network

Fig. 2 an example of analog circuit

The edges in the Bayesian network represent the joint probability distribution of the connected variables. The fundamental rule of probability calculus shown that:

$$P(X_2, X_1) = P(X_2 | X_1) \cdot P(X_1) \tag{1}$$

In general, the joint probability distribution for any Bayesian network, given nodes $X = X_1, ..., X_n$ is:

$$P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i | parents(X_i)) \tag{2}$$

Where parents (X_i) is the parent set of node X_i. Eq. 2 is known as the chain rule[6], which indicates the joint probability distribution of all variables in the Bayesian network as the product of the probabilities of each variable given its parents' values.

Inference in the Bayesian network means once some evidence about variables' states are asserted into the network, the effect of evidences will be propagated through the network and the probabilities of adjacent nodes are updated. The situation is mathematically formalized as the Bayes theorem,

$$P(X_1 | X_2) = \frac{P(X_2 | X_1) \cdot P(X_1)}{P(X_2)} \tag{3}$$

which represents the probability of node X_1 given evidence X_2. The term $P(X_1|X_2)$ denotes the posterior probability of node X_2 and can be computed when $P(X_1|X_2)$ and prior probability $P(X_1)$ are known; and $P(X_2)$ denotes a normalizing factor, which is determined as follow.

$$P(X_2) = P(X_2 | X_1) \cdot P(X) + P(X2 | \neg X_1) \cdot P(\neg X_1) \tag{4}$$

Where $\neg X_1$ denotes the complement of variable X_1. In fault diagnosis application, variable X_1 may be interpreted as the hypotheses of fault and evidence X_2 is the observed symptoms.

Modeling Circuit Using Bayesian Network

Modeling an analog circuit comprises two parts, the structure modeling and parameter modeling.
Modeling Assumptions
When we build separate models for each fault, we make an assumption that the faults remain independent given the observations. This is primarily made for technical reasons, in order to be able to build separate models for each fault and the dependencies that are irrelevant will not be learned.
Structural Modeling
The first step of building a Bayesian Network structure of an analog circuit is to identify the model variables. The next step is to define all the possible states for each of the variables. A state is a predefined parameter of the model variable by a limited value. The final step is to construct the dependency graphs among these variables representing the cause effect relationship, which are depicted by directed acyclic graph. All these steps together constitute the Bayesian Network structure modeling of an analogue circuit.
Parameter Modeling
Once the structure modeling is completed, the conditional probabilities among the model variables are determined. A conditional probability table specifies the probability of a dependent model variable being in a certain state assuming its parent model variable to be in a one of its
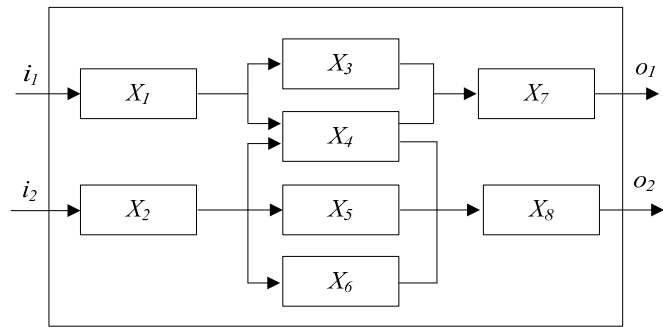
certain state. This table are either built automatically or constructed from the knowledge of a domain expert. A learning algorithm, e.g. Expectation Maximization or Conjugate Gradient [7], uses case information to determine the conditional probabilities among the dependency parameters.

Case Study

In this case, we use a multiple output voltage regulator with a power switch as example, which is intended for use in car radios. Because of the low voltage operation of the car radio, low voltage drop regulators are used. When both regulator 2 and the supply voltages (V_{P1} and $V_{P2} > 4.5V$) are available, regulators 1 and 3 can be operated by means of one enable input. In a normal situation, the voltage on the reset delay capacitor is approximately 3.5V. The power switch output is approximately VP-0.4V. At operating temperature, the power switch can deliver at least 3A. At high temperature, the switch can deliver approximately 2A. The second supply voltage VP2 is used for the switchable regulators 3 and 4. This input can be connected to a lower supply voltage of $\geq 6V$ to reduce the power dissipation of the regulator. Therefore, regulator 1 is the most critical regulator with respect to an out of regulation condition caused by a low battery voltage.

With the knowledge of probability values for all blocks, in combination with relationships among the model variables, a common parent block can be iteratively deduced to finally result in a fewer number of possible failing functional block candidates that have the highest likelihood in explaining the observed failure in the circuit. The failing functional candidate(s) are correlated to the ones selected by the diagnostic expert.
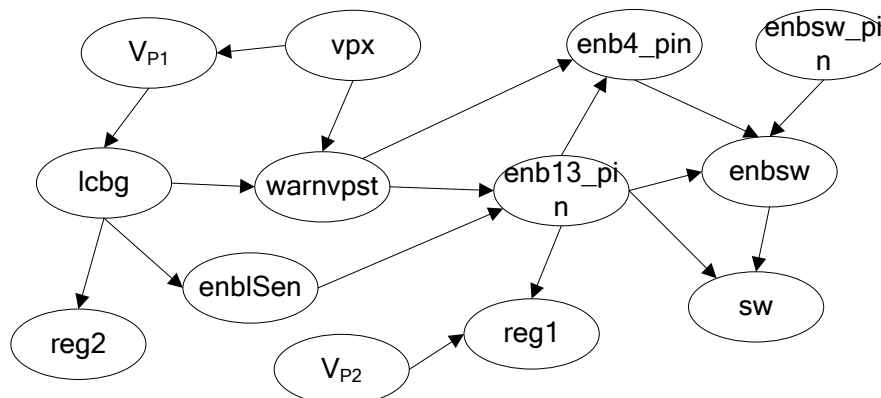

Fig. 3 Bayesian Network Model of the Voltage Regulator

Table 1 State and Probabilities of the Variables

No.	Variable	State	Prob.	No.	Variable	State	Prob.
1	V_{P1}	low	20.0	7	sw	short circuit	16.3
		intermediate	59.9			normal mode	71.6
		nominal	20.0			clamp level	10.5
		loaddump	0.01			others	1.6
2	V_{P2}	low	20.0	8	reg1	switch off/defect	16.8
		intermediate	59.9			in regulation	80.2
		nominal	20.0			out of regulation	3.0
		loaddump	0.01	9	reg2	switch off/defect	16.8
3	vp1x	bad state	18.5			in regulation	80.2
		off state	18.5			out of regulation	3.0
		on state	44.5	10	lcbg	non operational	13.4
		off-up	18.5			nominal operating	86.6
4	enb13 pin	bad state	2.0	11	enbsw	non-active	86.2
		good state	98.0			active	13.8
5	enb4 pin	bad state	2.0	12	warnvpst	off	66.4
		good state	98.0			on	33.6

6	enbsw pin	bad state	2.0	13	enblSen	non-active	79.6
		good state	98.0			active	20.4

The updated probability table shows all the enable model variables, enb4, enb13 and enbsw are nonfunctional, as they indicate higher probability values for nonactive state. The suspicion then falls back to their parent model variable, warnvpst. Further backward iteration indicates a parent model variables, lcbg. The probability values indicate a functioning lcbg (98.2%). Hence it can be concluded from the given test conditions and observed failure that out of eight model variables two, warnvpst and hcbg belong to the suspect list.

Conclusions

This paper describes a systematic procedure to construct a Bayesian Network for diagnosing an analog circuit. Design and test specification such as ATE logs, together with actual fail information are used to construct the model. A voltage regulator circuit was modeled following the procedure and diagnostic case studies validated the Bayesian diagnosis method and the procedure successfully. The future work includes some related theoretical problems, such as cross correlation between monitor outputs, and temporal dependency of historical data samples. Also, some practical implementation issues will be investigated.

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