Probabilistic Faults Prediction in Cellular Networks

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Abstract – This paper summarises work in progress and reports on preliminary results on faults prediction modelling. Cellular networks are uncertain in their behaviours and therefore we use a Bayesian network to model them. We derive probabilistic models of the cellular network system in which the independence relations between the variables of interest are represented explicitly. We use a directed graph in which two nodes are connected by an edge if one is a direct cause of the other.

Index Terms: Fault Prediction, Bayesian network, Cellular networks, fault management and services.

I. INTRODUCTION

Every network service provider would want to have an edge over the others by offering high quality and reliable services to its customers as and when required. Though some of the cellular network operators have managed to have an edge over their competitors, this objective has become illusive with the complication of the services to be offered and more especially the technological development. The technological sophistication allows for the offering of, for example, traditional voice, ISDN data transfer, video on demand and video conferencing services. In trying to offer these services using the latest technology errors occur, which soon degenerate into faults that cannot be rectified in time. Synchronous Digital Hierarchy Multiplexers themselves and other Network Elements (NEs) have built in recovery methods and the behaviour of these NEs are highly specified by ITU (formerly CCITT), ANSI and ETSI and as such are deterministic.

II. FAULTS PREDICTION

The area has generated a lot of research. A dynamic Bayesian belief network for intelligent fault management systems is explored in [1]. While they explored ways of applying the Bayesian Belief Network in fault prediction, it falls short of explaining how services over the network are likely to be affected with the faults. An intelligent monitoring system using adaptive statistical techniques in [2] can detect faults before they actually occur but do not relate these faults to services.

The Bayesian Network provides the advantages of: mathematical support; robustness; facility for construction; capacity to identify, in polynomial time, all the conditional independence relationships, from the information propitiated by the Bayesian network structure; capacity for non-monotonic reasoning, through which previously obtained conclusions may be withdrawn as a result of new information.

The importance of fault prediction are: it is helpful in supporting project planning and steering; helps network managers in re-routing of network traffic in case of foreseen problems in a route; network managers can take corrective action before the faults occur, thereby ensuring services reliability and availability over the network; decision making; increases the effectiveness of quality assurance; system quality increases as more faults are found and operations cost will be minimized as faults are found earlier when they are cheaper to repair, etc.

The rigorous process of determining what will happen under specific conditions can be referred to as prediction. A telecommunications fault is an abnormal operation that significantly degrades performance of an active entity in the network or disrupts communication. All errors are not faults as protocols can mostly handle them. Generally faults may be indicated by an abnormally high error rate [3], [4]. Therefore fault prediction is the process of determining which telecommunication fault will occur under certain specific conditions. For example, we can predict that transmission failure will occur as a result of multiplexer failure.

The purpose of faults prediction is to enable timely and successful high-level service failures’ compromises or proactive failure correction, thereby increasing the chances for proactive error correction before failures set in. This leads to preventative maintenance, which consists of deciding whether or not to maintain a system according to its states, can decrease the cost of maintenance by avoiding overstocking of spare parts and over repairing.

We have used Bayesian network model to evaluate the probabilities associated with the occurrence of one or more faults, based on the information received from the system under diagnosis. This information is constituted by the alarms generated during the operation of the managed NE, or obtained as a result of previous correlation processes.

III. FAULTS PREDICTION MODEL

A Bayesian network is a directed acyclic graph in which each node represents a random variable (may be discrete or continuous) to which conditional probabilities are associated, given all the possible combinations of values of the variables represented by the directly preceding nodes. An edge in this graph indicates the existence of a direct causal influence between the variables corresponding to the interconnected nodes [Figure 1].

Figure 1: A fragment of Bayesian network
A subjective probability expresses the degree of belief of an expert related to the occurrence of a given event, based on the information this person has available up to the moment. We evaluate the conditional probabilities from empirical data obtained from a certain cellular network service provider. The data is about the study of the behaviour shown in the past by the system being studied.

Given a Bayesian network and a set of evidences it is possible to evaluate the network, that is, to calculate the conditional probability associated with each node, given the evidences observed up to the moment. Generally speaking, this is a NP-hard problem but with the use of appropriate heuristics and depending on the problem dealt with networks containing thousands of nodes may be evaluated in an acceptable time.

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![Figure 2: Example of a Bayesian network](image)

Figure 2 shows a Bayesian network of four nodes corresponding to discrete variables of two or three states each. The variables are Power (Po), Multiplexer (Mux), Cell (C) and Transmission (T) with Good, weak and blackout; Ok and faulty; normal, uncertain and abnormal; normal, uncertain and abnormal states respectively. Let the probability (P) of event X occurring be denoted by;

\[ P(X) \]  

Therefore we compute P(Po), P(C), P(T) and P(Mux) equals to 0.36%, 0.42%, 76.57% and 22.63% respectively. We derive local posterior probabilities, for each one of them is conditioned to the occurrence of a certain pattern of values of the direct predecessors of the node. For instance, assuming that multiplexer is ok, the only reason it may not discharge its functions is when power fails. This conditional probability is calculated using;

\[ P(Po, Mux, C, T) = P(Po) \cdot P(Mux) \cdot P(C \mid Po, Mux) \cdot P(T \mid Mux) \]  

Therefore if one knows a set of evidences \( e = \{ X_m = x_m, \ldots, X_p = x_p \} \), constituted by all the known values of the random variables of a Bayesian network, where \( \{ X_m, \ldots, X_p \} \subset X = \{ X_1, X_2, \ldots, X_n \} \), the calculation of the probability (or ‘belief’) that a variable \( X_k \notin \{ X_m, \ldots, X_p \} \) assumes the value \( x_k \) is given by

\[ P(X_k = x_k \mid e) = \frac{P(e \mid X_k = x_k) \cdot P(e)}{P(e)} \]  

To illustrate the above derivations, we use Bayesian network of figure 2. Supposing that \( e = \{ T= \text{abnormal} \} \) is the set of all the known evidences, the belief that the power is good is given by:

\[ P(Po = \text{Good} \mid T = \text{abnormal}) = \frac{P(Po = \text{Good}) \cdot P(T = \text{abnormal} \mid Po = \text{Good})}{P(T = \text{abnormal})} = 0.7629 \approx 99.6\% \]

IV. CONCLUSION

Probabilistic fault prediction models were presented. Further research will test the accuracy of the models and relate the eminent faults with services and how it impacts on cellular service providers.

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VI. REFERENCES


VII. BIOGRAPHY

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