Using Neural Networks for Alarm Correlation in Cellular Phone Networks

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Abstract

Alarm handling and especially alarm correlation tools are necessary to manage large telecommunication networks. In this paper we describe our neural network based alarm correlation system, which uses a Cascade Correlation neural network to correlate alarms in a GSM network. The results of our approach called Cascade Correlation Alarm Correlator (CCAC) are shown. The behaviour in the case of noisy data is discussed and compared in detail to a codebook approach. Furthermore we contrast the neural network approach to another solution developed by our group which uses model-based diagnosis.

1 Introduction

The main topic of this paper is fault management, especially alarm handling and alarm correlation in a GSM/DCS-mobile telephone network. Special attention is paid to the access network. The main problems addressed are alarm bursts, the task of alarm correlation and the development of tools to handle those bursts.

1.1 Structure of the GSM-Access-Network

Mobile networks based on GSM-standards [1] can be divided into three parts (see Figure 1). First the Mobile Station (MS) with the radio interface, second the access network with the Base Stations (BS) consisting of antennas, radio transceivers, cross connect systems and Microwave Links (ML) or Cable Links (CL) back to the Base Station Controller (BSC). Finally the BSC is connected to the third part, the switched network. The switched network consists of Mobile Switching Centers (MSC) and transmission equipment. Connections to the public ISDN are provided at least by one MSC

Due to the fast and cost-efficient installation of links in base station subsystems, new operating companies implement most of their connections with microwave links. Other links are established with leased lines. The resulting network topology is logically a star (LC1, LC2) and physically a tree, where the traffic to several base stations is distributed over a chain of microwaves and leased lines. There is only one transmission path from a BS to the related BSC. The access network is formed by up to 2000 network elements which need centralised control.

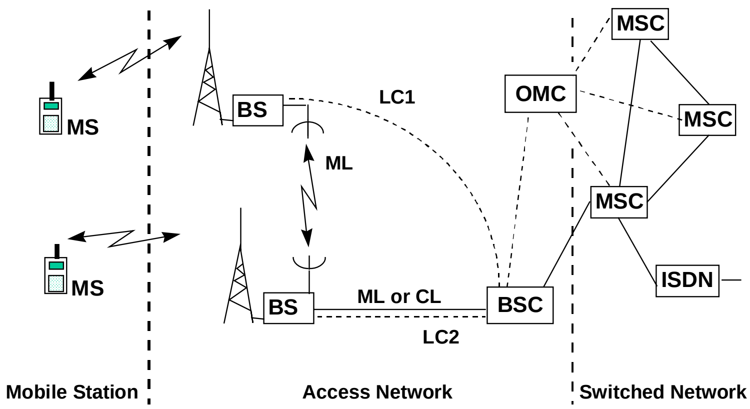

Figure 1: GSM-Access-Network

1.2 Necessity of alarm correlation

When a link fails, up to 100 and more alarms are generated and passed to the Operation and Maintenance Center (OMC). An example is shown in Figure 2. Each network element generates several alarms due to a link failure. The alarms are transmitted to the OMC. We define the produced alarm pattern as alarm vector.

To avoid overloading the operators, alarm correlation systems are required to filter and condense the incoming alarms and diagnose the initial cause of the alarm burst (e.g. the breakdown of a microwave link). It is essential that the system minimise the number of incorrect decisions.

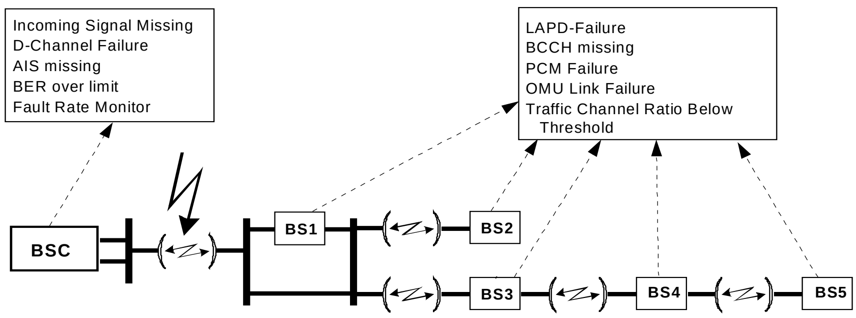

Figure 2: Alarms caused by a link failure

Taking into account the dynamic nature of growing cellular phone networks, such an alarm correlation system needs to be efficiently adapted to different topologies and extensions of network structure as well as to new and additional network elements.

Moreover, missing and additional alarms have to be tolerated without affecting the operation of the system. Missing and additional alarms are defined as noise. The noise is added to the original alarm vector.

2 Neural networks for alarm correlation

2.1 Benefits of neural networks

The neural network approach was chosen because of the expected benefits listed below:

- no expert knowledge is needed to train the neural network, neither for the initial configuration of the access network nor for its adaptation.
- if the alarm vector belonging to an initial cause is known, the neural network can be trained to transform the original alarm vector into the initial cause.
- if the configuration of the network is modified, the input and output layer of the neural network simply need to be adjusted and the new alarms with the initial cause pattern just have to be trained again.
- neural network are resistant to noise because of the generalising capabilities of the neural networks.

2.2 The alarm correlator based on neural networks

Due to the classifying problem only feedforward neural networks have been studied. Figure 3 shows the principle of mapping the alarms from the different network elements to the neural network. An alarm is represented by one neuron at the input layer. Each initial cause is represented by a neuron in the output layer. During training, the weights of the connections are trained and adapted.

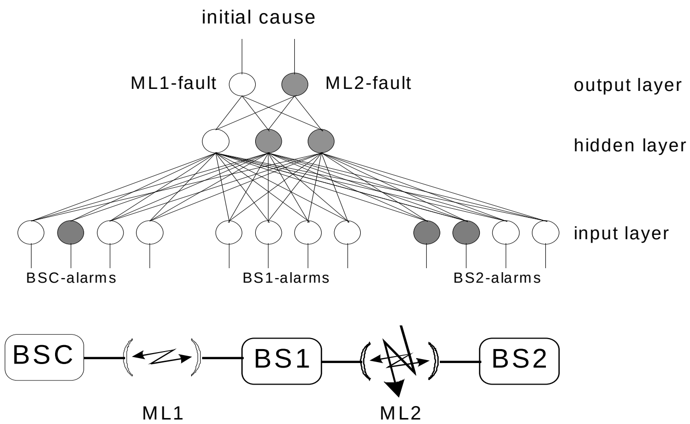

Figure 3: Mapping of alarms to the neural network

First, a learning algorithm was chosen. Backpropagation, modified Backpropagation, Quickprop and Cascade Correlation algorithms are compared in [2]. The Cascade Correlation algorithm minimises the count of operations during the training and is proposed as a learning algorithm for a neural network based alarm correlator. Compared with the other training methods, Cascade Correlation has another major advantage: no topology of the hidden layer has to be proposed. The necessary hidden neurons and their weights are generated during the training. This results in a minimum of training time, calculation time during runtime and memory requirements.

To model and train the Cascade Correlation Alarm Correlator (CCAC), the Stuttgart Neural Network Simulation (SNNS)-tool is used [3]. At the input layer, binary activation is applied. An active alarm is presented as “+1“ value at the corresponding input neuron. To achieve faster weight adaptation during training, the state “no alarm“ is noted as “-1“ instead of the usually used value “0“. As the related activation function the sigmoid hyperbolic tangent function was chosen. We assume that only one link is down at a time, so a winner-takes-all decision is used in the output layer.

3 Results from CCAC

To investigate the power of the Cascade Correlation Alarm Correlator (CCAC), the configuration shown in Figure 2 is used as reference network. A subset of 94 alarms from the real network was chosen to generate training and test patterns.

As first experiences showed, with respect to the minimisation of wrong decisions of the CCAC, training with noisy alarm vectors is not suitable. Thus training of our CCAC is only performed using the five non disturbed original alarm pattern (one for each link). To test the quality of our correlator, we have generated several test patterns, each consisting of 1250 noisy alarm vectors. To show the dependencies between correlation and noise, the noise is increased in steps of 5% of the generated alarms in original alarm vector. The results of the correlation process are divided into three classes: right, wrong or no decision. No decision is made if no neuron reaches the threshold of the winner-takes-all function.

Figure 4 shows how achieving the right decision depends on the noise in the alarm vector. The dotted line shows the correct classification of the CCAC trained only with the original alarms. With noise up to 20% all the patterns are classified correctly. If noise increases above 45% wrong diagnoses appear (solid line). The amount of cases where the CCAC makes no decision are represented by the dashed line.

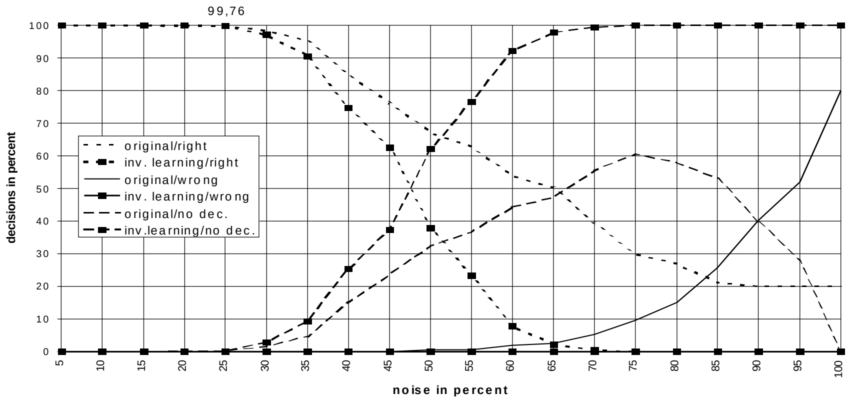

Figure 4: Noise dependent accuracy of the CCAC

To reduce the number of wrong decision, we have implemented a feature we call inverse learning: training patterns are presented to the neural network that must not activate any output neuron. In our reference network, adding one pattern for inverse learning (all inputs set to “-1“) eliminates any wrong decision. Figure 4 shows the results from the CCAC trained with inverse learning (marked with dots). Correct classification is done up to 20 %, in return the number of correct classified patterns decreases faster if noise increases.

4 Results from other approaches

4.1 Codebook approach

The codebook approach [4] reduces alarm correlation to a vector comparison during runtime. Because of the great number of possible alarm patterns, a subset is selected forming the codebook. In our example network (see Figure 2) the related codebook contains five original alarm vectors. The smallest Hamming distance of the vectors in the codebook is called code distance. The code distance in our example is 10. Therefore in the worst case noise up to 5 alarms is treated well. During runtime, the Hamming distances between the actual alarm vector provided and the known initial causes are calculated. The cause represented by the codebook vector with the smallest Hamming distance is proposed to be the initial cause. Figure 5 shows the correct classifications of a minimal distance decoder. The results of the minimal distance decoder represents the upper limit of a codebook approach, because in view of calculation time, codebooks are often minimised to a suitable code distance.

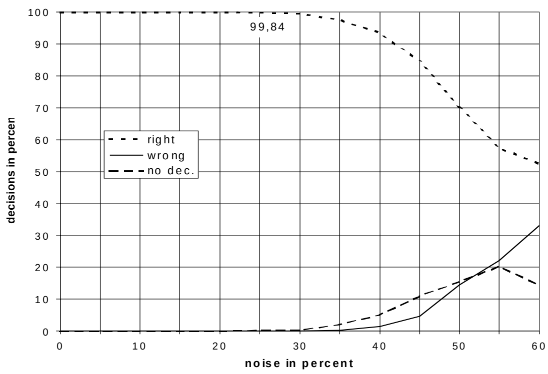

Figure 5: Results of the codebook approach

4.2 Model-based diagnosis

An alternative approach to alarm correlation is based on model-based diagnosis [5]. This approach uses a model of the device, called the system description (SD), often formalised as a set of formulas expressed in first-order logic. The system description consists of two parts:

1. A set of axioms characterising the behaviour of system components of certain types.
2. A set of facts modelling the topology of the system.

The simulation model SD is used to predict expected behaviour, given the observed input parameters. Diagnoses are computed by comparison of predicted vs. actual behaviour. In model-based systems changes of topology can be carried out easily without affecting the consistency of the system description. Furthermore, since diagnoses are computed using only a model of the correct system behaviour, unforeseen error situations can be diagnosed correctly.

A static model of the alarm behaviour, without using time windows to relate the alarm messages to the corresponding fault scenarios, is sufficient to handle the essential alarm cases. A deterministic model was developed describing the alarm propagation behaviour inside the network. It takes into consideration assumptions about the state (OK, abnormal) of microwave links. Using this model a set of faulty microwave links is determined such that the simulation of alarm propagation yields the observed alarm pattern.

Due to noisy alarm patterns in the case of an alarm burst the deterministic model was extended by a probability model for the loss of relevant alarm messages. The resulting statistical model was applied to a database of 32 representative test cases. In all these test cases except one the system identifies the correct diagnosis, either as the single plausible diagnosis, or as the most probable diagnosis. The model was implemented using the model-based diagnosis system DRUM-II, which is currently one of the most efficient diagnosis machines. The system and the results of alarm correlation using model-based diagnosis are described in detail in [6].

5 Comparison and outlook

The results show that the cascade correlation alarm correlator CCAC is well suited for alarm correlation tasks. To diagnose single faults with a winner-takes-all decision, training time is short and the resulting topologies are simple. The system is able to treat noise up to 25 percent of missing alarms while still achieving the right decision (99.76%). With inverse learning the CCAC makes no wrong decisions and operators will not be confused. As discussed in section two,_the CCAC can easily be adapted to changes in GSM access network topology.

Compared to the codebook approach, the CCAC shows similar results in classifying the correct initial cause. Whereas the codebook generates wrong outputs with respect to increasing noise (see Figure 5), the CCAC with inverse learning does not.

Our implemented model-based diagnosis system has not yet been tested with the large set of test vectors used in this paper, so the comparison can only be partial. Lost alarms are handled without difficulty using probabilities. Additional alarms have to be modelled explicitly by including the causes of these alarms. On the other hand, diagnosis performance seems similar to the CCAC, and the model-based system easily adapts to changes in topology and alarm behaviour.

The undertaxing of the neural network for recognising single alarms encourages us to do further work to handle multiple faults with the CCAC. The suitability of using knowledge based neural networks (as proposed in [7]) for this task will also be investigated.

Acknowledgements

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References

[1] European Standardisation Institute, “GSM-Specifications“; Sophia Antipolis 1994

[2] S. E. Fahlman, Chr. Lebiere, "The Cascade-Correlation Learning Architecture", in *Advances in Neural Information Processing Systems 2,* Morgan Kaufmann Publishers 1990, Los Altos CA, pp. 524-532.

[3] A. Zell e.a.: SNNS user manual, Version 4.0, Report No. 6/95, University of Stuttgart, 1995

[4] S. Klinger, S. Yemini, Y. Yemini, D. Ohsie, S. Stolfo; “A Coding approach to event correlation“ in *Integrated Network Management IV,* Chapman&Hall 1995, pp. 266- 277,

[5] Raymond Reiter. “A theory of diagnosis from first principles“ *Artificial Intelligence*, vol. 32, pp. 57-95, 1987

[6] P. Fröhlich, K. Jobmann, W. Nejdl, H. Wietgrefe; “Model based alarm correlation in cellular phone networks“ in *Proceedings of the International Symposium on Modelling Analysis and Simulation of Computers and Telecommunications Systems (MASCOTS’97),* pp. 197-204, 1997

[7] G.G. Towell, J.W. Shavlik, “Knowledge based artificial neural networks“ *Artificial Intelligence*, Vol. 70, Issue 1-2, pp. 119-166, 1994

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