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System for automated diagnosis in cellular networks based on performance indicators

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SUMMARY

This paper presents a system for automated diagnosis of problems in a cellular network, which comprises a method and a model. The reasoning method, based on a naive Bayesian classifier, can be applied to the identification of the fault cause in GSM/GPRS, 3G or multi-systems networks. A diagnosis model for GSM/GPRS radio access networks is also described, whose elements are available in the network management systems (NMSs) of most networks. It is shown that the statistical relations among the elements, that is the quantitative part of the model, under certain assumptions, can be completely specified by means of the parameters of beta density functions. In order to support the theoretical concepts, a model has been built based on data from a real network and the automated diagnosis system has been used to classify problems in a cellular network, showing that the solution is easily implemented and that the diagnosis accuracy is very high, therefore leading to a reduction in the operational costs of running the network. Copyright © 2005 AEIT.

1. INTRODUCTION

The mobile telecommunication industry has and is still undergoing extraordinary changes brought about by the introduction of new technology and market forces. The operators and manufacturers of mobile equipment are undertaking huge efforts to adapt the cellular networks to the new technologies, while aiming to maintain the level of service of the current networks. Consequently, the operation of the radio network is becoming increasingly complex [1, 2]. In the past, operators managed to cope with rapid technological changes by increasing their workforce. However, due to the financial pressures this is not a viable strategy anymore and the only feasible option of reducing operational costs is to increase the level of automation.

Automation can be applied in very different areas of the radio network: frequency planning [3], parameter optimisation [4], troubleshooting [5] etc.

This paper is focused on troubleshooting of the radio access network, which consists of detecting problems (e.g. cells with a high number of dropped calls), identifying the cause (e.g. interference) and solving the problems (e.g. improving the frequency plan). If a cell is temporarily non-operational due to a fault, probably neighbouring cells will also be affected, leading to degradation in performance of a cluster of cells. Therefore, it is crucial to ensure that cells are rapidly brought back into operation. In most cellular networks, troubleshooting is currently a manual process, accomplished by experts in diagnosis. They are personnel dedicated to daily analyse the main performance indicators and the alarms of the cells, aiming to isolate the cause of the problems. Normally the experience on how to identify problems is kept ‘secret’, every expert follows his own rule of thumb and if he leaves the company, his experience is lost. Furthermore, the growing size of cellular networks, together with their increasing complexity, make it very difficult for a human to analyse such a large amount of information.

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If troubleshooting were automated, highly experienced staff could be released from the mundane aspects of daily troubleshooting tasks and could focus on the more complex cases. One additional benefit is that knowledge from different experts could be stored in the troubleshooting system, therefore making expert troubleshooting knowledge available to the business at all times.

The first step in troubleshooting is fault detection, which is the identification of poorly performing cells, based on performance indicators and alarms. The second step, the diagnosis, is the cause identification, that is the automatic reasoning mechanisms to find out the cause of the problems. Finally, problem solving is the execution of the actions to solve the problems.

Automated diagnosis has been extensively studied in other fields, such as diagnosis of diseases in medicine [6], of problems with printers [7], in communication networks [8], of faults in satellite ground stations [9] etc. However, up to our knowledge, no references can be found about automated diagnosis in the radio access network of cellular networks. The research in this area has been centred in fault detection and in alarm correlation. Thus, in References [10, 11] a method to detect anomalous performance of network elements of cellular systems is presented, which is based on comparing the current functioning of an element with its normal behaviour. On the other hand, numerous references on alarm correlation can be found [12, 13], which are the interpretation of multiple alarms so that a new meaning is assigned to these alarms. Although alarm correlation can be considered a first step in the diagnosis of faults, they do not provide conclusive information to identify the cause of problem, especially if the possible causes are not only faults in pieces of equipment. Other categories of faults, such as interference or lack of coverage are difficult to identify if performance indicators are also not considered.

This paper proposes a method (inference engine) and a model (knowledge base) for automated diagnosis of problems in the radio access networks of GSM/GPRS networks, which takes into account not only alarms but also network performance indicators. The method presented here is also valid for 3G if some performance indicators are changed in the model.

The method is based on a naive Bayesian classifier [14], which calculates the probabilities of all the possible causes using the Bayes’ rule. The knowledge base that the classifier requires will be named, the diagnosis model. It has two important parts: a qualitative part, comprising the elements of the model; and a quantitative part, formed by the relations among the components.

The naive Bayesian classifier can be studied using the theory of Bayesian Networks [15, 16], which allows efficient representation of a joint probability distribution over a set of random variables. Thus, in References [5, 17] an automated diagnosis tool based on Bayesian Networks was presented and tested in a cellular network, showing promising results. The main difficulties were found in building the model because there was not enough information available in order to learn it from data. Therefore, the model was built based on knowledge from troubleshooting experts. The continuous variables were discretised and the experts had to elicit a high number of probabilities and thresholds for the discretised intervals. A knowledge acquisition tool was also built in order to help the experts in building the model. The designed system achieved acceptable results after some iterative improvement phases, however it was very sensitive to the parameters and it had to be re-adjusted if it was going to be used in a different cellular network. The main difficulties came from the fact that most variables are continuous by nature, therefore investigating the behaviour of those variables was considered necessary to improve the accuracy of the diagnosis. Knowing the continuous probability density functions (pdfs) may be useful either to directly build the model, or help to find an optimum discretisation. Another added advantage of knowing the distributions is that they could be used for generating random cases that simulate the behaviour of the network in order to compare and evaluate different models. The method proposed in this paper, the naive Bayesian classifier, requires knowing some pdf, which can be continuous or discrete.

Thus, there are some important differences between the system in Reference [5] and the one proposed in this paper. First, in Reference [5] the performance indicators were discretised, whereas in this paper they are treated as continuous variables. Second, Reference [5] is completely based on human expertise, whereas this paper combines knowledge from experts with data from the network.

Furthermore, this paper describes the causes, symptoms and conditions of a model that could be used for diagnosis of a GSM/GPRS access network. The statistical behaviour of the elements of the model is investigated and it is demonstrated that they fit beta distributions.

This paper is organised as follows: in Section 2 some definitions used in diagnosis are introduced and the reasoning method for automated diagnosis is presented. The main elements of the diagnosis model for a GSM/GPRS network are shown in Section 3. Section 4 proposes the quantitative part of the model, for example the conditional pdfs of the performance indicators. In Section 5, the
method and the model are tested using data from a real network and the results are presented. Finally, Section 6 summarises the work and outlines some conclusions.

2. AUTOMATED DIAGNOSIS

2.1. Definitions

The first step in troubleshooting is the detection, that is the identification of the cells with problems. A problem is a situation occurring in a cell that has an influence in the service. Every operator uses a different method to identify the problematic cells, which can be based on different performance indicators, for example dropped calls, access failures, congestion etc. [10]. Once the cells with problems are isolated, a diagnosis of the cause of the problems should be done separately for each problematic cell. A cause or fault is the defective behaviour of some logical or physical component that can provoke failures and generate a problem, for example interference, hardware fault etc. A symptom is a performance indicator whose value can be a manifestation of a fault, for example the number of handovers due to interference. Finally, a failure is an anomalous value of a symptom, which can be caused by a fault, for example excessive number of interference handovers. Therefore, a problem is a type of failure that has an influence in the service.

The most severe problem for mobile network operators is the cells experiencing a high number of dropped calls because a dropped call may have a very negative impact on the service offered to the end user. The dropped call rate (DCR) is a good indicator about the quality of the network, being normally around 1 or 2% in mature networks. The model proposed in this paper is applied when the problem in the cell is a high number of dropped calls; slight modifications to the model should be made in case the problem was another one, for example call set-up problems.

The main elements of the model are:

- **Causes**: they are the possible faults that may be causing the high number of dropped calls.
- **Symptoms**: they are manifestations of the causes.
- **Conditions**: they are factors that may have an impact on the causes.
- **Links**: they are the relations among the previous elements.

The first three elements can be modelled as random variables, whereas the last one can be modelled by means of pdfs. The aim of the diagnosis is to identify the cause of a problem once the values of some symptoms and conditions are known.

2.2. Method for automated diagnosis

The diagnosis can be considered as a classification problem typical in machine learning applications [18], where the classes would be the causes and the attributes would be the symptoms. One of the most effective classifiers, in the sense that its predictive performance is competitive with state-of-the-art classifiers, while being very simple, is the naive Bayesian classifier. It has proven to be effective in many practical applications, including text classification, medical diagnosis and system performance management [19].

The classifier takes a case \( E \) (set of \( N \) attributes, \( A_j \)), it computes a set of discriminant functions of the case, \( f_i \), one for each class, and it assigns the case to the class whose function is maximum. For the naive Bayes classifier the discriminant functions are

\[
 f_i(E) = P(C_i) \prod_{j=1}^{N} P(A_j = a_k \mid C_i)
\]

where \( P(C_i) = P(C = c_i) \) is the prior probability of the class \( c_i \), and \( P(A_j = a_k \mid C_i) \) is the conditional probability of the attribute \( A_j \) given class \( c_i \).

In other words, the naive Bayes classifier finds the maximum a posteriori probability (MAP) hypothesis given the attributes. By Bayes’ theorem and assuming that the attributes are independent given the class

\[
P(C_i \mid E) = \frac{P(C_i) \prod_{j=1}^{N} P(A_j = a_k \mid C_i)}{P(E)}
\]

where \( P(E) \) can be ignored to calculate the maximum because it is the same for all classes.

The assumption that the attributes, that is symptoms when used for diagnosis, are independent given the class, that is the cause, is unrealistic. Nevertheless, it has been demonstrated that even if strong attribute dependencies exist, the Bayes classifier performs very well [19–21]. Furthermore, the Bayes classifier has many advantages, such as its simplicity, learning and classification speed.

Consequently, automated diagnosis can be performed by calculating the probability of each cause given a set of symptoms and conditions as follows

\[
P(C_i \mid E, D) = \frac{P(C_i \mid D) \prod_{j=1}^{N} f(A_j = a_k \mid C_i)}{f(E \mid D)}
\]

\[
= k \cdot P(C_i \mid D) \prod_{j=1}^{N} f(A_j = a_k \mid C_i)
\]

where \( E \) is a vector of evidences for \( N \) symptoms, \( D \) is a vector of \( M \) conditions, and some probabilities have been
substituted by pdfs because most symptoms are continuous. In Equation (3) it has also been assumed that the symptoms are independent of the conditions given the cause. The cause with the highest posterior probability is assumed to be the one that is causing the high number of dropped calls in a cell.

In order to apply Equation (3), the probability of the causes, given the conditions and the pdfs of the symptoms given the causes, are required. Therefore, defining the model for diagnosis means specifying the qualitative part (causes, symptoms and conditions) and the quantitative part (probabilities). The probabilities can be computed from a database of labelled examples. However, in most cases the amount of available data is very limited and calculating the conditional density functions is not possible, especially if nothing is previously known about them. This has been tackled in the bibliography by discretising the continuous attributes or assuming that the pdfs are Gaussian [22, 23].

In the following sections, the model for diagnosis will be presented and it will be shown that due to the characteristics of the symptoms, the definition of the conditional pdf consists of setting some parameters for a known distribution.

3. QUALITATIVE DIAGNOSIS MODEL

The model presented hereafter is for diagnosis in the radio access network of GSM/GPRS systems. The qualitative part of the model consists of three types of elements: causes, symptoms and conditions. All the components can be modelled using random variables: causes and conditions are discrete random variables, whereas in the case of symptoms, they are modelled either as continuous random variables (performance indicators) or as discrete variables (alarms).

3.1. Causes

Causes are modelled as discrete random variables with two states: present or absent. A more complex model could consider degrees of occurrences of the causes, for example absent/mild/severe. The causes of high dropped call rate that normally appear in the radio access networks can be grouped in:

(a) Interference: Most current networks are interference limited, due to the tight frequency reuse patterns used. The sources of interference can be very diverse: cochannel interference, adjacent channel interference, other operator transmitting in the same frequency, intermodulation, interference from other systems etc. In any case, the interference causes high bit error rate and frame losing, which finally leads to the release of the radio channel, that is to a dropped call.

(b) Coverage: If the received signal level is lower than the sensitivity of the receivers (of the base station or of the mobile phone), the call is dropped due to lack of coverage. This cause can be further divided in two groups: bad coverage in the borders of the cell or shadow regions. The former is usually present in rural areas with low density of population. The shadow regions are areas where the signal level is too low due to the presence of obstacles, and they are more common in regions with high density of population. If there is a coverage fault, the quality will also be degraded and the call will be dropped either because of the low level or the poor quality.

(c) Hardware: This cause groups the faults in the equipment of the base station. The base station modules are composed of elements that deteriorate over time, some failing gradually and others suddenly. The faulty component can be a TRX, the combiner, the antenna, a connector, a cable, a preselector, the power supply etc. The effects of a hardware fault can go from both reduced signal level and quality to only a quality decrease in one of the radio links. In most cases, when there is a hardware fault numerous alarms are triggered.

(d) Transmission: These are faults in the transmission links, either in the Abis interface between the BTS and the BSC or in the A interface between the BSC and the MSC.

(e) Transcoder: The transcoder functionally is part of the BTS, although normally it is physically situated in a remote location near the MSC. It provides rate adaptation to the 64 kbps required by the A interface.

(f) Others: This category groups all the possible causes of dropped calls not previously listed, which does not happen so often: wrong parameters setting, missing adjacencies, fading etc.

3.2. Symptoms

The performance of the network can be measured using multiple performance indicators. The most important ones are called key performance indicators (KPI) and they are collected daily by the network management system (NMS) with the help of counters situated in different points of the network. Besides, the NMS provides information about thousands of alarms from network elements, which may help to identify the cause. When one of the
faults described in Subsection 3.1 is causing problems in a cell, the value of some performance indicators change from their nominal values and some alarms may also be triggered. This is the reason why the experts in troubleshooting daily analyse the KPI and alarms of the cells with problems in order to diagnose the cause, and then solve the problems.

In the proposed model, the KPI are represented by continuous random variables (in most cases with values between 0 and 1), whereas the alarms are modelled as discrete variables with two possible states: on/off. An alternative model can discretise the KPI in order to work only with discrete random variables.

3.2.1. Key performance indicators. The most meaningful KPI used for diagnosis in the radio access network are the following:

(a) Dropped call cause: Most manufacturers of network equipment provide a rough estimation of the fault that is causing the high number of dropped calls. These statistics in most cases do not point to the final cause. For example, the counter for signalling failures in the Abis interface can increase if the BSC does not receive acknowledgement of the channel activation from the BTS, if measurement reports are not received from the BTS, etc. The final cause of the previous failures can range from a problem in the BTS to interference in one TRX.

These symptoms are normally measured as the percentage of dropped calls due to a given cause, the main causes are shown in Table 1.

(b) Quality and level: These performance indicators are based in measurements of the radio link done during a call by the mobiles and the base stations. These measurements were defined to be used by the handover and power control algorithms [24]. On the one hand, the average of the power signal level (in dBm) of the samples in one measurement period (one SACCH multiframe) is calculated and mapped in a value between 0 and 63, the RXLEV. On the other hand, the quality is measured as the BER before the channel decoding during the measurement period and mapped to a value between 0 and 7, the RXQUAL. The MS measures the level and quality in the downlink for the serving cell and the signal level received from the neighbouring cells, and sends Measurements Reports to the BSS in the SACCH channel. Likewise, the BTS measures the level and quality in the uplink.

The statistics in the NMS regarding these indicators are normally in the shape of number of samples (one sample being the value corresponding to one measurement) in each RXLEV or RXQUAL band (= value) during a given period, for example a day. The symptoms considered for diagnosis purposes are normally the percentage of samples in a given band. Some symptoms commonly used are shown in Table 2. For example, if there is no problem in a cell most measurements would have a BER of less than 0.2%, which is band 0, therefore a symptom of a fault causing quality problems would be the ‘Percentage of samples of RXQUAL in bands 1 to 7’.

(c) Handovers: When there are problems in a cell, the number of handovers normally increases. Furthermore, the type of handover helps to identify the cause of the problems. For example, if the number of handovers due to signal level is high, probably there is a lack of coverage. The main symptoms related to handovers used for diagnosis are shown in Table 3. They are measured as the percentage of handovers due to a certain reason.

(d) Others: There are other performance indicators that can support the diagnosis; the main ones are shown in Table 4. They are related to the value of the Timing Advance, the uplink interference measurements on the idle slots, the RACH load etc.

3.2.2. Alarms. The current NMSs provide thousands of alarms, which are triggered by certain call events. They may indicate a fault or not. For example, if the traffic increases an alarm may be triggered, which would not indicate a fault. On the other hand, a fault in a piece of equipment may affect another piece of equipment, making its alarms trigger. Due to these reasons, it is very difficult to identify the cause of problems based only on alarms.

Although alarm correlation, that is the interpretation of multiple alarms giving a new meaning to the original alarms, has been extensively studied in the bibliography [12, 13], no attention has been paid to diagnosis based on performance indicators. This is the reason why this paper is focused in the study of KPI for diagnosis. Nevertheless, if alarms were used together with KPI, the diagnosis would be more accurate.

Table 1. Main causes for dropped calls in network statistics.

<table>
<thead>
<tr>
<th>Radio failure</th>
<th>Abis interface failure</th>
<th>A interface failure</th>
<th>LAPD failure</th>
<th>Transcoder failure</th>
</tr>
</thead>
</table>

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3.3. Conditions

The conditions can be grouped in functionalities and configurations. Functionalities are techniques that the operators normally apply in order to improve the network quality, for example frequency hopping, power control, discontinuous transmission, reception diversity, etc. Configurations are special characteristics of certain cells that have an impact on the faults that normally occurs, for example the climate, the type of cell, etc.

If the influence of the conditions were taken into account, the diagnosis would be more accurate. For example, if frequency hopping were active it would be less probable that the cause of the excessive dropped calls was interference.

Conditions are modelled as discrete random variables, whose values are the possible states of the configuration or functionality.

4. QUANTITATIVE DIAGNOSIS MODEL

In order to statistically define the model completely, the joint density function of the random variables explained in Section 3 should be specified. This task could easily be achieved if large databases of previous cases were available, where the values of all random variables were known. Unfortunately, this is not normally the case: although there are historical databases containing the value of the performance indicators, the actual cause is missing. Therefore, in order to simplify the design of the model under these limitations, some reasonable assumptions will be made: (i) only one cause is present at a time; (ii) symptoms are independent of the conditions given the cause; (iii) symptoms are independent given the cause. The first two assumptions normally happen to be the case in a mobile network, whereas the last supposition is not correct for most symptoms. However, as it was explained in Subsection 2.2, the naive Bayes classifier has been shown to be very effective even if the last assumption does not hold.

Under these circumstances, the quantitative model is composed of the following probabilities:

1. Probability of each cause given that there is a problem (high DCR) and given the conditions. The probabilities of the causes are not required for all the possible combinations of conditions because normally only some of them are possible.
2. Pdfs of the symptoms given each cause.

The first probabilities can easily be elicited by experts in troubleshooting. The pdf for an alarm given the causes is reduced to the probability of the alarm being active given each cause, which, if the number of considered alarms in the model is low, can also be obtained from the experts’ knowledge. Nevertheless, defining the conditional pdf for the performance indicators is much more complex because these symptoms are continuous variables, and therefore, they should be first discretised in order to be elicited by experts.

However, there is an alternative solution: if the symptoms followed a known density function, finding the pdf would become a parameter estimation problem. Indeed, some advantage can be taken from the definition of the performance symptoms: all of them can be obtained from

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Table 2. Main quality and level symptoms used for diagnosis.

| Percentage of samples in UL with RXQUAL in bands 1 to 7 (BER > 0.2%) |
| Percentage of samples in DL with RXQUAL in bands 1 to 7 (BER > 0.2%) |
| Percentage of samples in UL with RXLEV < 10 (level < -100 dBm) |
| Percentage of samples in DL with RXLEV < 10 (level < -100 dBm) |
| Percentage of samples in UL with RXQUAL in bands 5 to 7 and RXLEV > 16 (BER > 3.2% and level > -95 dBm) |
| Percentage of samples in DL with RXQUAL in bands 5 to 7 and RXLEV > 16 (BER > 3.2% and level > -95 dBm) |

Table 3. Main handover symptoms used for diagnosis.

| Percentage of UL signal level handovers |
| Percentage of DL signal level handovers |
| Percentage of UL quality handovers |
| Percentage of DL quality handovers |
| Percentage of UL interference handovers |
| Percentage of DL interference handovers |
| Percentage of intracell handovers |

Table 4. Other symptoms used for diagnosis.

| Percentage of samples with TA > 10 (distance > 5.5 km) |
| Percentage of samples with TA < 4 (distance < 2.2 km) |
| Percentage of samples on idle channels out of band 1 |
| Percentage of RACH load |
the percentage of samples complying with a given condition $C$. In other words, they are the relative frequency of one of the two possible outcomes of an experiment (condition $C$ achieved or not), which can be described by a Bernoulli random variable $X$. For example, for the symptom ‘Percentage of samples in UL with RXLEV < 10’, the condition is ‘RXLEV < 10’, therefore a random variable $X$ with two values, 0 and 1, corresponding to $RXLEV < 10$ and $RXLEV \geq 10$ respectively, can be defined. Even in the presence of the same cause, the relative frequency for $X = 1$ is not always equal: it varies with the cell, the date etc. Then, let $Y$ be another random variable, having real values in the interval $[0,1]$, representing the expert’s belief concerning the relative frequency with which $X = 1$, if a cell and day is randomly chosen. The expert’s belief is such that

$$P(X = 1 | Y = y) = y$$  (4)

That means that if the expert knew that the relative frequency of $X = 1$ were $y$, his belief concerning the occurrence of 1 in the first execution of the experiment would be $y$.

The probability of a symptom is the expert’s belief concerning the relative frequency with which the condition $C$ is achieved, that is, it is the probability of $Y$. Therefore, calculating the pdf of a symptom is the same as computing the pdf of the random variable $Y$.

The beta density function has a long tradition in representing beliefs concerning a relative frequency [25]. It has been applied in modelling prior beliefs in medical diagnosis [26], land cover proportions in geological models [27], frequency distributions of solar radiation indexes [28], etc.

The equation for the beta density function is the following

$$f(x) = \frac{\Gamma(a + b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{b-1}, \quad 0 \leq x \leq 1$$  (5)

where $a$ and $b$ are positive real numbers and $\Gamma(x)$ is the Gamma function.

Different arguments to support the use of the beta pdf can be found in the bibliography. First, if a uniform density function is used to represent prior beliefs (or more generally, a beta pdf), then it can be demonstrated that the posterior density function, after some data is known, is beta [26]. The second argument was given by Zabell [29]: if certain assumptions about an individual’s belief are made, then that individual must use the beta density function to quantify any prior beliefs about a relative frequency. The demonstration was done for the Dirichlet distribution, which is a generalisation of the beta distribution to the case of more than two alternatives.

The conclusion is that the pdf of all symptoms given the causes in the diagnosis model can be approximated by beta density functions or combinations of them. Therefore, the only required information to completely define the conditional probabilities in the model are the parameters $a$ and $b$ of the beta distributions for each pair symptom/cause. Those parameters can either be elicited by experts [25] or they can be obtained from data by means of appropriate techniques [30].

5. RESULTS

5.1. Diagnosis model

A model covering the most common causes of dropped calls and the most meaningful performance indicators used for diagnosis was developed based on Section 3. The qualitative model contains 7 groups of causes and 24 symptoms. The quantitative model explained in Section 4 was built by combining the knowledge of GSM experts and data from a real network. The experts elicited the prior probabilities of the causes based on their experience, whereas the conditional probabilities of the symptoms given each cause were obtained using information collected by the NMS during a period of 4 weeks. The NMS keeps databases with the daily value of the performance indicators for all cells under its supervision. Nevertheless, the main difficulty to obtain the probability functions comes from the fact that the cause of the problems is not in the NMS. In order to overcome this limitation, some assumptions were considered:

- The spatial and temporal statistical characterisation of the network is the same. In other words, the cases used to build the model can be obtained not only from a given cell along different days, but also from different cells in the network. The reason for that supposition was the need to obtain as many cases as possible in a short time.
- Hundreds of cells presenting a high dropped call rate were analysed by engineers, giving as a result a set of classified cases, in which the symptoms and the causes were known. It is assumed that the diagnosis was correct, although it was not checked.

Furthermore, the information about the conditions and alarms was not available, therefore it has not been included in the model. The diagnosis accuracy could be improved if
at least the type of cell and a few hardware alarms were considered. The number of cases was about 300 for the most probable causes, whereas for the least probable causes the number of cases was only about 40. These cases were used to obtain a maximum likelihood estimates (MLE) [30] of the $a$ and $b$ parameters for the beta pdf of each symptom given each cause.

For example, Figure 1(a) shows the density function of the symptom ‘percentage of uplink samples with RXQUAL in bands 1–7’ given that there is a lack of coverage. The beta density function obtained using the MLE fits quite well with the normalised histogram of the network data. The figure also shows the value of $a$ and $b$ and the 95% confidence intervals. In order to estimate the goodness of fit, the probability–probability (P–P) plot [31] is presented in Figure 1(b). Its linearity indicates that the fitted beta agrees closely with the true underlying distribution. Figure 2 shows the same graphics for the symptom ‘percentage of dropped calls due to an Abis failure’ given that there is a transmission fault, and Figure 3 corresponds to the symptom ‘percentage of handovers due to uplink quality’ given that there is an interference problem in the uplink. From these graphics and the results of Chi-square tests [31] it is considered that the proposed diagnosis model fits very accurately with the real data from the GSM network.

![Figure 1. (a) Conditional probability density function (pdf) of the symptom ‘percentage of UL samples with RXQUAL in bands 1–7’ given lack of coverage, (b) P–P plot for beta distribution and data.](image1)

![Figure 2. (a) Conditional pdf of the symptom ‘percentage dropped calls due to Abis failure’ given that there is a transmission fault, (b) P–P plot for beta distribution and data.](image2)
Figure 4 presents the modelled beta density function for the symptom ‘percentage of samples in uplink with RXLEV < 10’ conditioned to the different possible causes. This type of graphic provides a lot of information about the performance indicators. For example, it can be observed from Figure 4 that the represented symptom can be used to identify a hardware or coverage problem in case its value is high. From Figure 4 it can also be concluded that even if there is a hardware or coverage problem, the value of this symptom may be low, which justifies the use of an automated diagnosis tool that takes into account the statistical behaviour. This figure also explains why finding a good discretisation of the continuous symptoms is so complex, due to the smooth shape of the density functions.

5.2. Diagnosis method

The method explained in Section 2 was applied together with the model presented in Subsection 5.1 in the design of an automated diagnosis system. The system was used to diagnose 643 cases from a real network and the results were compared with the manual analysis done by a GSM network expert, whose conclusion about the cause of the problems was considered to be correct (gold-standard).

The classification accuracy (percentage of cases in which the diagnosis of the automated system, i.e. the cause with the highest probability, coincided with that of the human expert) was 71%. The percentage of cases in which the real cause was the first or the second in the ranked probabilities given by the system was 91%. The level of confidence, that is the probability of the most probable cause, was 0.94 for the cases in which the automated diagnosis was correct and 0.85 for the cases with incorrect diagnosis. The probability that the system gave for the real cause was studied even when it was not the highest one: its average value was 0.7 and its standard deviation 0.4.

The diagnosis accuracy was studied separately for each cause, calculating the type I error (false negatives) and the type II error (false positives). From Figure 5 it can be observed that most errors are considerably low with some exceptions: type I error is very high (76%) for the cause ‘hardware’, this can be explained by the fact that this cause of problems normally triggers several alarms related to hardware, which are not considered in the analysis because they were not available. If they had been taken into account (which would be the normal situation), then the results would have been much better for this cause.
and the total diagnosis accuracy would have been higher. The accuracy could have also been improved if the alarms related to transmission had been considered, therefore reducing the type I error (28%) for the cause ‘transmission’. From Figure 5 it can be observed that most cases that are incorrectly classified are diagnosed as having a lack of coverage.

6. CONCLUSIONS

This paper has presented a system for automated diagnosis, composed of a model and a method, supporting the research with trials in real networks. The main objectives when designing the system were that it had to achieve high diagnosis accuracy and, very importantly, it had to be easily implemented in an operator network. It should be pointed out that although the proposed model is valid for diagnosing problems only in the radio access of GSM/GPRS networks, the method is also directly applicable in 3G or multi-systems networks if the appropriate models are used.

The proposed method is based on a naive Bayesian classifier, which is extensively used in other domains because of its good results and simplicity. Furthermore, the elements of the model have been presented, describing the main types of causes, symptoms and conditions for a GSM/GPRS network. The values of the selected symptoms have the characteristic that they are manifestations of the current cause of problems in the cell and, at the same time, they are normally available in the NMS of all operators. Beta density functions have been proposed to model the statistical behaviour of the performance indicators, proving that they fit data from a real network very accurately.

In order to support the theoretical contributions of this paper, a model has been built based on knowledge of GSM experts and databases from a real network and it has been used, together with the proposed method, to diagnose problems in cells from a real network. The obtained classification accuracy is comparable with the one obtained by a human expert, with the added advantage of the higher speed of the automated system. The results can be improved if the conditions and alarms are taken into account, having shown that the worst results are obtained for those causes that trigger several alarms, which were not considered.

Using an automated diagnosis system is essential to reduce operational costs in the current and future cellular networks, due to their increasing complexity. The proposed system is expected to significantly improve the operational efficiency, while being easily integrated into the management systems.

The proposed quantitative model has many other applications apart from being used together with the Bayesian classifier. First, the behaviour of a GSM network in the presence of problems can be simulated by means of generating random samples from the modelled beta distributions. In that way, the generated cases can be taken as a reference in order to compare different diagnosis systems. Furthermore, the estimated density functions can be considered the actual distributions in order to easily discretise the continuous variables for those diagnosis systems that require discrete variables.

Future research includes comparing the results obtained with the Bayesian classifier with the ones obtained by other diagnosis systems, for example Bayesian Networks with discretised symptoms. Besides, more trials of the current system should be done in a different operator’s network in order to reinforce the presented results.

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