Cell Degradation Detection based on an Inter-Cell Approach

*[1]Muhammad Zeeshan Asghar, [1]Paavo Nieminen, [2]Seppo Hämäläinen, [1]Tapani Ristaniemi,
[3]Muhammad Ali Imran, [1]Timo Hämäläinen
[1]*University of Jyväskylä Finland, Muhammad.z.asghar@jyu.fi*
[2]*Nokia Networks, seppo.hamalainen@nokia.com*
[3]*University of Glasgow UK, muhammad.imran@glasgow.ac.uk*

Abstract

Fault management is a crucial part of cellular network management systems. The status of the base stations is usually monitored by well-defined key performance indicators (KPIs). The approaches for cell degradation detection are based on either intra-cell or inter-cell analysis of the KPIs. In intra-cell analysis, KPI profiles are built based on their local history data whereas in inter-cell analysis, KPIs of one cell are compared with the corresponding KPIs of the other cells. In this work, we argue in favor of the inter-cell approach and apply a degradation detection method that is able to detect a sleeping cell that could be difficult to observe using traditional intra-cell methods. We demonstrate its use for detecting emulated degradations among performance data recorded from a live LTE network. The method can be integrated in current systems because it can operate using existing KPIs without any major modification to the network infrastructure.

Keywords*: Fault Management, Network Management Automation, Self-Organizing Networks (SON), Self-Healing, Long Term Evolution (LTE), Inter-cell analysis, Correlation based Cell Degradation Detection, Real LTE Network*

1. Introduction

The massive increase in the number of mobile subscribers and consequently a dramatic increase of mobile phone services have put operators under pressure for better quality of service and network reliability. The exponential growth of mobile broadband traffic is certainly caused by both the increasing demand for known and new data services, such as mobile internet access, online social networking and location-based services [1]. The usage of tablets, smart phones, application stores, social media and the data exchanges between end-users and clouds are all growing at a rapid pace. The use of these devices has also increased the demand for wireless video applications to a large extent and has put tremendous pressure on the wireless network infrastructure. In parallel to the exponential growth of mobile broadband traffic and high data rates, the small cells, e.g. pico and femto cells, on top of macro cells, have made network management more challenging. Furthermore, the competition between mobile operators is increasing and pushing them to provide better network performance in terms of network availability, robustness, coverage, capacity, and service quality. In order to tackle these challenges and eventually be able to attract and retain subscribers, the network operations need to be optimal all the time. Through a good performance of the network elements and low failure probability, the network can operate more efficiently reducing the necessity for equipment investments. It is not enough for operators to employ economic incentives to modify user behavior by adjusting tariff structures, but operators must also improve network capacity and network availability.

In addition to the coverage and capacity needs, the tasks of operation and maintenance of mobile cellular networks are vulnerable to errors as a huge amount of manual effort is needed to monitor and execute these tasks. In order to improve the fault management of cellular networks and to improve the efficiency and reliability of the networks, automation has to be introduced. These developments have triggered the concept of Self-Organizing Networks (SON) which is a built-in feature in Long-Term Evolution (LTE) and LTE-Advanced networks [2]. SON has been seen as an efficient solution for network management by the 3rd Generation Partnership Project (3GPP) [2], Next Generation Mobile Networks (NGMN) [3] and FP7 SOCRATE projects [4]. A detailed overview of the SON technology and the network management automation is given in [5] and [6]. The major domains of SON enabled networks are self-configuration, self-optimization and self-healing. Of these domains, the work presented in this paper focuses on self-healing which aims at automatic troubleshooting where detection and diagnosis of anomalies, temporary compensation of the effect of faults, and corrective actions are largely automated.

A fault in a cellular network refers to a defect at the hardware or/and the software level, which significantly degrades network performance and eventually leads to dissatisfaction of the users. Errors and problems almost always exist in networks due to the complexity and uncertainty of radio links. However, some errors may also be temporary and thus never develop into faults.

Although 3GPP use cases are focused on "cell outage", we adopt a more general concept of "cell degradation" which refers to the case where the performance of a cell in handling traffic is significantly lower than it is supposed to be. There are two types of cell degradations based on time duration: temporary and permanent. Temporary degradation refers to the situation when a cell performance is degraded for a short period of time and then recovers without external support. These degradations almost always exist in a cellular network. Permanent degradation refers to the situation when a cell remains degraded for a longer period of time. During the resulting period of degraded performance, users will not experience services with acceptable availability, reliability and quality of service (QoS) which may cause serious revenue loss for the operator. From the network management point of view, these fault situations should be handled quickly. SON's self-healing functionality can contribute to optimize the handling and resolving of faults in different situations. In principle, the degradations caused by faults should be detected, countermeasures should be taken to resolve the problem, and immediate compensation to the lost coverage should be triggered.

The fault management is performed at the operations support system (OSS) in which measurements are collected from network elements. The OSS usually stores all information of the network, e.g., network counters, configuration measurements, fault measurements etc. Several key performance indicators (KPIs) are computed from the network counters. Consecutive measurements of a KPI constitutes a time series that can be used for fault detection and triggering alarms. The performance of each cell can be characterized using KPIs and fault measurements, e.g., alarms.

Degradations might not be easy to detect, though, because they might not necessarily trigger alarms even when users are affected. Such a cell is called a "sleeping cell" in cellular network fault management research. It means the malfunctioning in the network is not visible to the operator until negative feedback from the customers is received in terms of complaints and loss of revenue at the coverage area. It is difficult to detect such a problem with traditional monitoring tools as in many cases the threshold is not violated and no alarms are generated.

This paper focuses on improving the detection part of self-healing, especially with respect to detecting sleeping cells. The rest of the paper is organized as follows. In Section 2, earlier work on the field is explored. In Section 3, the real-world LTE data used in our method evaluation is described. In Section 4, the method itself is outlined. In Section 5, computational experiments on the dataset are documented. Section 6 concludes the paper with some outlines for further research.

2. Related work

A method to detect coverage and dominance problems and to identify interferers in WCDMA networks was introduced in [7]. Signaling messages exchanged through the radio interface were used to calculate certain metrics for every cell during normal network operations reflecting real traffic distributions and geographical user locations. Competitive neural algorithms were used for fault detection and diagnosis in 3G cellular networks in [8]. Another cell outage detection algorithm based on the neighbor cell list reporting of mobile terminals was introduced by Mueller in [9]. An experimental system was developed for self-healing of 3GPP LTE networks in [10] where detection and compensation of cell outages were evaluated in a realistic environment. The impact of self-healing on KPIs such as the number of connected users and radio link failures was explored.

In [11][12][13] a series of cell degradation detection research was conducted. An ensemble method approach was proposed for modelling cell behavior and cell anomaly detection that computes a numerical measure, referred to as the KPI degradation level, to indicate the severity of degradation. The authors also claimed that their method was able to cope with concept drift as well. The papers dealt with the network's ability to automatically detect problems such as performance degradation or network instability stemming from configuration management changes.

In [14] a data mining approach for fuzzy diagnosis systems was proposed. In this paper a knowledge acquisition learning algorithm based on fuzzy logic was proposed for fault troubleshooting in LTE. Recently, in [15] indoor localization and user equipment data was employed for better sleeping cell detection and diagnosis for 5G ultra dense networks. In [17] a cell degradation detection method was proposed that uses correlation-based comparisons of observed KPI time evolution patterns against fictitiously degraded ones. The authors observed that comparison using longer trends is better than the traditional way of looking at single averages. A novel approach for cell degradation detection where the information of failed attempts in establishing a connection to a cell is communicated to the next connected cell is presented in [18]

The above approaches for cell degradation detection are based on intra-cell analysis of the operational base stations. In intra-cell analysis, profiles of different KPIs are built based on their history data. The current KPI levels are compared with their respective profiles and degradation is detected if the KPI exceeds a certain predefined threshold level. However, this threshold and profile approach has certain drawbacks. One of the disadvantages of the intra-cell approach is that large variations in KPIs lead to wide profiles, and, while complete outages are detected, degradations or sleeping cells are more difficult.

Initial work on inter-cell analysis can be found in [18][19][20]. The proposed methods characterize the normal behavior of the cell and build profiles for the faultless network behavior by either looking at its earlier behavior or comparing it to similar systems. Significant deviations from the profile are identified as abnormal behavior and an alarm is triggered if the deviant behavior persist for certain period of time. The correlation-based algorithm uses the correlations of cells within a geographical neighborhood. It is assumed that there exists an appreciable level of correlation between neighboring cells. The same operational fault detection (OFD) approach is followed by a statistical hypothesis test framework for determining faults.

In our proposed approach, the degradation detection is based on inter-cell analysis. It refers to the situation when KPIs from several cells are compared to corresponding KPIs of other cells instead of their own history based profiles. The main advantage of the inter-cell approach over the intra-cell approach is that it is less sensitive to the individual KPI variations. We exploit the idea that there are many cells in the network coverage area having similar behavior irrespective of their geographical locations. The idea was used in [21] in which it was suggested that the correlation coefficient between cell pairs can be used as a means for degradation detection in cells. In addition to the inter-cell analysis point of view, a main contribution of this work is the use of real-world KPI data collected from a live LTE network. Fictitious patterns resembling realistic sleeping cell scenarios are created to evaluate the method.

3. Sleeping cell detection using real-world data

In our computational experiments, we use one month (700 hours) of real-world data recorded from a live LTE network. The examined KPI time series consist of the downlink physical resource usage percentage (DL PRB) averaged over each of the 1 hour intervals in each of the cells in the network. In order to simplify the analysis somewhat, we selected only those 89 cells that had no missing values and no obvious periods of downtime. The cells are identified by their indices in the selected subset. We also applied two rounds of filtering consisting of a median filter (window size 3 hours) followed by convolution with a three-hour kernel of coefficients (0.25 0.5 0.25). Edge effects of the filtering were simply cut away as the original data set was slightly longer than the 700 hours selected for this study. Each of the time series was then scaled to the range of [0,1]. These simplifying preprocessing operations could easily be used also in a real usage scenario. Figure 1 shows the complete preprocessed time series of three arbitrarily selected cells. The problems involved in real-world data can be seen in this kind of figures: even though a natural 24-hour pattern emerges when averaging over all the cells, the peaks of any single cell are sporadic and long periods of inactivity occur amidst the peaks.

As the data is real, we cannot be sure whether actual degradations or faults exist in the recorded data. For the purposes here, we assume that the network was at least mostly healthy during the observation time. For method evaluation, we create artificial degradation patterns by gradually attenuating the time series with a linearly decreasing window function. A tiny amount of Gaussian noise is also added in order to maintain realism. Figure 2 illustrates the concept. The figure shows the original DL PRB of a cell (included also in Figure 1) and a simulated degradation that starts at time step 600 and reaches full depth (with no recovery) in 20 steps. We feel that the result is a valid approximation of a cell that quietly dies for some unknown, slowly accumulating, and possibly undetectable, causes lurking in the complexities real network hardware and software. For example, in Figure 2 we can see how a peak in the "dying-out" period is still present but with a lower magnitude than in the original, healthy, data.

For method evaluation, we compare the detection algorithm outcome of the original time series against the artificially degraded one for each of the cells. The number of detections for the degraded patterns yields the number of true positive identifications whereas the number of false positive ones is given by detections for the original patterns. Naturally, we would like the number of true detections to greatly overwhelm the number of false ones. An individual detector is trained for each cell using the part of the data that is not degraded for the testing phase.

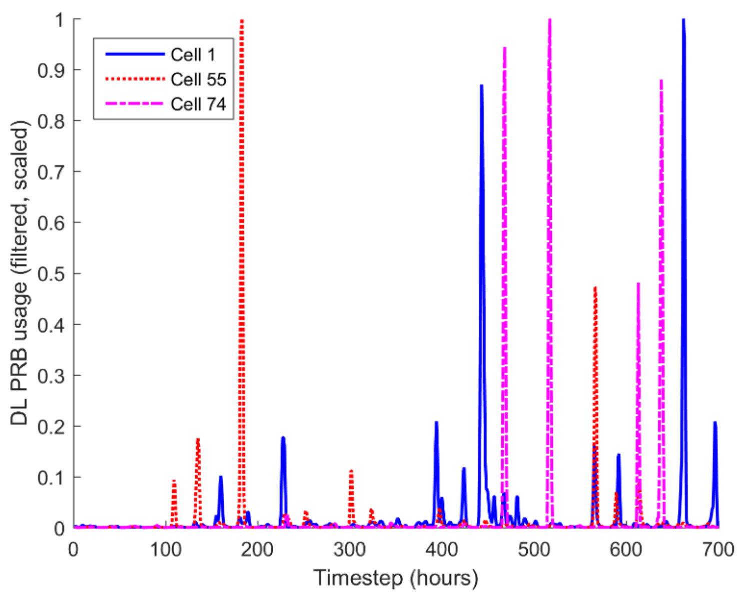

Figure 1. Examples of the KPI time series.

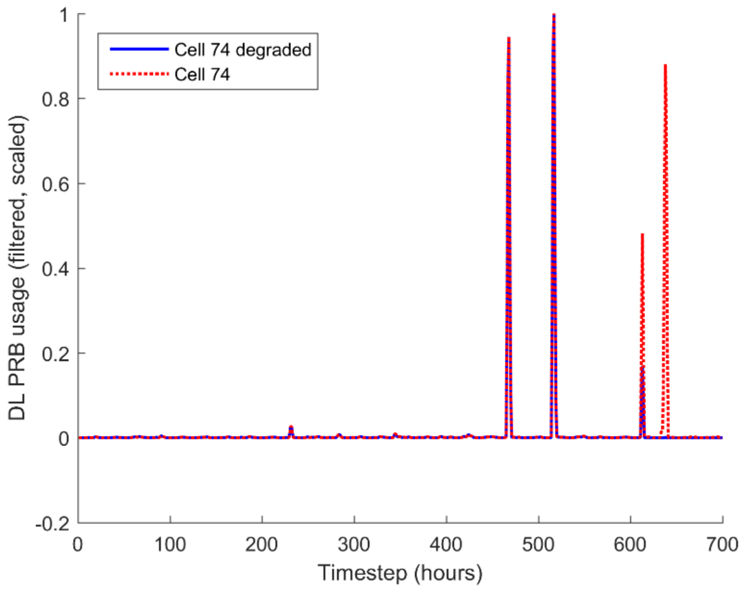

Figure 2. Example of the simulated degradation resembling the sleeping cell scenario.

4. Proposed Approach

This section presents our inter-cell analysis approach for cell degradation detection in cellular networks, consisting of the training phase of selecting comparing cells and the detection phase based on values derived from correlation values. We note that while we experiment now with the DL PRB, any other KPI, such as the number of active users, could be used.

4.1. Training phase and selection of comparing cells

In real networks, user behavior varies strongly depending on the time of day, the geographic location, and other factors. Although it might be that cells located near to each other would experience similar environmental conditions, this is not always true. It is possible that some cells exhibit behavior to each other independent of their geographic location. This might be caused due to a similar kind of user behavior depending mainly on the time of the day. It is vital to choose the right cells as comparing cells. This is done in an initial cell pair selection process.

The examined KPI of cell j is a time series $x_1^{(j)}, x_2^{(j)}, \ldots, x_n^{(j)}$. In both training and detection phases, we shall be looking at windows of L consecutive values leading up to time step t, i.e., $x_{t-(L-1)}^{(j)}, \ldots, x_{t-1}^{(j)}, \ldots, x_t^{(j)}$. Our method is based on the usual correlation coefficients $r_t^{(j,k)}$ between the time windows of two cells:

$$r_t^{(j,k)} = \frac{\sum_{i=0}^{L-1}\left(x_{t-i}^{(j)} - \bar{x}^{(j)}\right)\left(x_{t-i}^{(k)} - \bar{x}^{(k)}\right)}{\sqrt{\sum_{i=0}^{L-1}\left(x_{t-i}^{(j)} - \bar{x}^{(j)}\right)^2}\sqrt{\sum_{i=0}^{L-1}\left(x_{t-i}^{(k)} - \bar{x}^{(k)}\right)^2}},$$

where the mean values $\bar{x}^{(j)}$and $\bar{x}^{(k)}$are computed over the window. We aim to train a detector for each target cell under examination. The training phase encompasses the selection of a number of “comparing cells” that are highly correlated with the target cell. The number of comparing cells K is a parameter of the method, as is the window length L. No other parameters need to be selected by the user.

The coefficients are first computed for all the time stamps in a selected training set of windows and for all cells. Then the cells are scored by how many times they have appeared in the set of K most correlating ones within any of the time windows used for training. The K overall highest-scoring cells are selected as the set $C^{(j)}$ of comparing cells for the target cell. The minimum correlation coefficient values observed during training is selected as the correlation threshold $\tilde{r}^{(j)}$.

4.2. Detection value and time-since-detection

After the selection of the parameters, two further measures can be computed for any time window ending at step t: The "detection value" $d_t^{(j)}$ that we define as the number of comparing cells falling below the threshold, $d_t^{(j)} = \#\{k \in C^{(j)}: r_t^{(j,k)} < \tilde{r}^{(j)}\}$ and "time-since-detection" $s_t^{(j)}$ which is the number of time steps that $d_t^{(j)}$ has remained at its maximum possible value K. These measures are computed for the training time windows and the actual detection threshold $\tilde{s}^{(j)}$ is selected as $\tilde{s}^{(j)} = \max\{ s_t^{(j)}: t \in \text{training}\}$.

Once trained, the detector will continue working on unforeseen time windows, evaluating the two measures for each. An alarm is triggered at $x_t^{(j)}$ whenever $s_t^{(j)} > \tilde{s}^{(j)}$.

5. Experiments

For the experiments, we selected 24 as the time window size and 3 as the number of comparing cells. For training, we used the first 576 time windows, and the rest were used as the testing set for each cell. A degradation was always emulated starting from hour 600 in the way that was depicted in Figure 2 of Section 3. The detection value and time-since-detection were evaluated for both the healthy and the degraded time series versions. Figures 3 and 4 show the values for some selected cells. In Figure 3, the target cell was Cell 77 and the comparing cells automatically selected by our algorithm were Cells 78, 73, and 80, in the ranking order of the algorithm. From the indices we can tell that not all cells were located in the same site geographically (while Cells 77 and 78 may very well be, in fact). The figure shows the values of the detection measures both for the clean data used in training and the testing series with the emulated degradation in the end. The values are the same up to time step 576 which was the end of the training phase in our experiment. In the latter part, we can see that the detector has picked up the degradation and made a correct detection. A temporary rise in the time-since-detect value can also be seen, but the value never exceeds the threshold selected as the alarm trigger. Figure 4 shows the same values for a different case where an actual false alarm took place. Yet, the time-since-detect value never gets as high as it does for the degraded test pattern.

In total, the number of correctly detected degradations was 64 which amounts to 72 % of the cases available for testing. The number of false detections for the healthy time series was 12 which amounts to only 13 % of the cases. We conclude that, overall, the method is able to detect degradations while the level of false detections is considered acceptable.

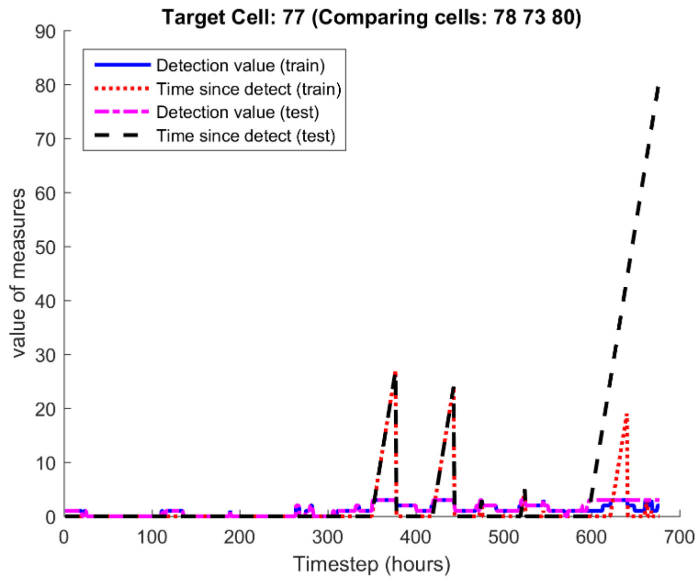

Figure 3. Detection values and time-since-detection indicators for selected cells.

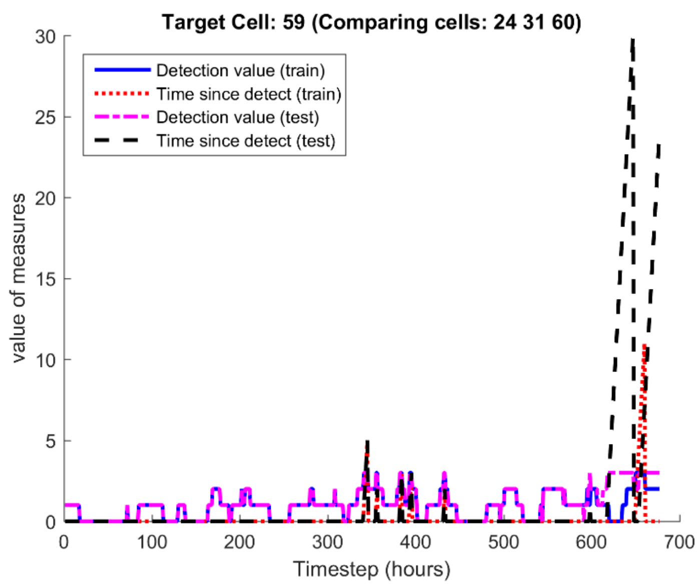

Figure 4. Detection values and time-since-detection indicators for selected cells.

6. Conclusion

In this paper we modified a correlation-based cell degradation detection method [21] and demonstrated its use on real-world KPI data recorded from a live LTE network. We find the results supportive of the argument that the inter-cell analysis approach is well-suited to cases difficult for traditional methods, such as sleeping cell detection.

This method can be easily integrated with traditional troubleshooting tools because all the measures are computed based on KPIs available in current infrastructures with no need for additional modifications. Indeed, future work is devoted to extending this method for more complex scenarios involving more KPIs. Future work also includes observing more data in a real network together with the operators' knowledge about a "ground truth" of any problems and faults that might have existed during the observation periods so that degradations would not have to be artificially emulated in order to perform method validation.

In theory, the training phase could be running all the time, thus allowing the comparing cell selection to adapt to changes in the operating environment. The identified cell pairs would then be better correlated all the time. If some, but not all, of the comparing cell correlations fall below the detection threshold, some additional cell performance monitoring would be needed in order to determine if it is in fact one of the comparing cells that is degrading instead of the target cell. Additional performance monitoring could include tracking other KPIs of the cells and checking if they pass certain thresholds that operators have set in the traditional way. Incorporating context to the self-healing research will help increase the detection accuracy. Some good examples of recent context-aware self-healing solutions can be found in [22][23][24].

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