# A Handover Statistics based Approach for Cell Outage Detection in Self-organized Heterogeneous Networks

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**Abstract—Recently, densified small cell deployment with overlay coverage through Heterogeneous Networks (HetNets) has emerged as a viable solution for 5G mobile networks. Cell Outage Detection (COD) which is the essential functionality in Self-Organizing Network (SON) is designed to autonomously deal with unexpected faults. Typical methods for detecting cell outage are usually based on Manual Drive Tests (MDT). However, it is difficult to detect small cell outage by MDT measurements in HetNets, because the User Equipment (UE) served by these small cells can switch to the macro cell and keep the Reference Signal Received Power (RSRP) and Signal to Interference plus Noise Ratio (SINR) values normal. To resolve this issue, we propose a COD architecture based on the handover statistics. Our model concentrates on cell outage detection in a two-tier heterogeneous network. We process sequential handover statistics spatially and temporally in conjunction with data mining methods. Also, an improved LOF algorithm (M-LOF) is proposed to enhance the detection performance based on handover statistics. To evaluate the system performance, a set of tests has been carried out using some reasonable assumptions and network simulator we designed. The results of simulation show that our system is more effective to detect cell outage in comparison to the architecture using MDT measurements.**

***Keywords—Cell Outage, Handover Statistics, Heterogeneous Networks, Self-Organizing Networks, Local Outlier Detection***

## I. INTRODUCTION

The ever increasing demand for wireless Internet and introduction of new multimedia services are driving the need for ultra-dense and multi-tiered 5G heterogeneous wireless networks [1]. Naturally, maintaining such dense networks is extensively complicated and costly for mobile operators. Due to the high cost of network extension via macro base stations (MBSs), small cells are envisioned as a key solution to accommodate the rapidly growing user population and the associated traffic load. The self-organizing network (SON) paradigm aims to replace the classic manual configuration, post deployment optimization, and maintenance in cellular networks with self-configuration, self-optimization, and self-healing functionalities [2]. An elementary use case in Self-Healing, referred to Cell Outage Detection (COD) [3] in which the collected network measurements are used to detect and locate the potential outage.

Typical methods for detecting outage cells are usually based on Manual Drive Tests (MDT) or via subscriber complaints. These solutions not only need time and resource consuming, but also need expert knowledge or prior experience. Recently, there has been many research work in terms of the aspect of self-healing, especially in cell outage detection. Researchers have applied methods from machine learning domain such as unsupervised algorithms which don't need any prior experience, as well as Hidden Markov Model [4] to estimate a cell outage in Heterogeneous Networks (HetNets). Also, Bayesian Network used to automate diagnose for Universal Mobile Telecommunications System networks [5]. In [6], a classification-based approach is achieved for cell outage detection. The paper [7] proposes a cooperative femtocell outage detection architecture which consists of a trigger stage and a detection stage. The paper [8] detects cell outages in an autonomous fashion by first pre-processing the MDT measurements using multi-dimensional scaling method and further employing it together with machine learning algorithms to detect and localize anomalous network behavior.

As described above, the classification model usually collects the MDT reported measurements such as Reference Signal Received Power (RSRP) and Signal to Interference plus Noise Ratio (SINR) in which the handovers of UEs between small cell and macro cell are not considered. As shown in figure 2, the UEs served by outage small cells can switch to the macro cells. So it is not applicable to detect cell outage by means of the MDT measurements in HetNets. Consequently, no abnormous MDT measurements of these transferred UEs can be used to detect outage. In paper [9], the proposed algorithm monitors situations where the number of Incoming Handover (inHO) becomes zero as a potential symptom of cell outage. In some cases, performance counter is not available in the Operations Support System (OSS) of outage cells, we could not get data from the sleeping cell, so it is unpractical to detect outage cell directly.

In this paper, we suppose the cell may switch to sleeping mode and reduce power consumption when failures occur. Outage cell does not have the capacity to carry any traffic. Normally at this point, all users served by this cell have to be offloaded to its neighboring cells. This often results in a huge number of handovers in HetNets. Notes that the rising handovers of neighboring cells could be easily detected by

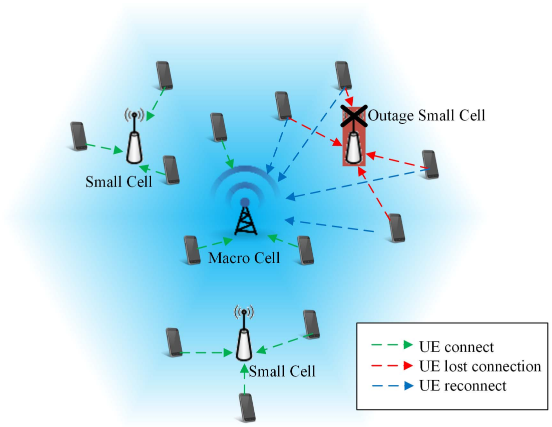


Fig. 1. Handovers of UEs in HetNets

methods of data mining. We discuss our algorithm by using the temporal data of inHO statistics. Considering the situations above, a local outlier factor based detector is adopted in two-tier cellular heterogeneous network. The rest of paper is structured as follows: In section II, we propose a cell outage detection framework, which includes the detail procedures and gives a brief description of LOF based detector that used to detect the anomalous behavior of temporal inHO data. Section III provides a simulation scenario, and shows the result of our proposed method. Finally, Section IV concludes the paper.

## II. SYSTEM MODEL

The proposed COD framework adopts a four step approach including data collection, pre-processing, data mining and localization block as shown in Fig 1. In this model, the measurements collected from sites are fed into the analysis block which can process these data automatically. In this way, the anomalous behavior can be detected timely and minimize the performance degradation of network.

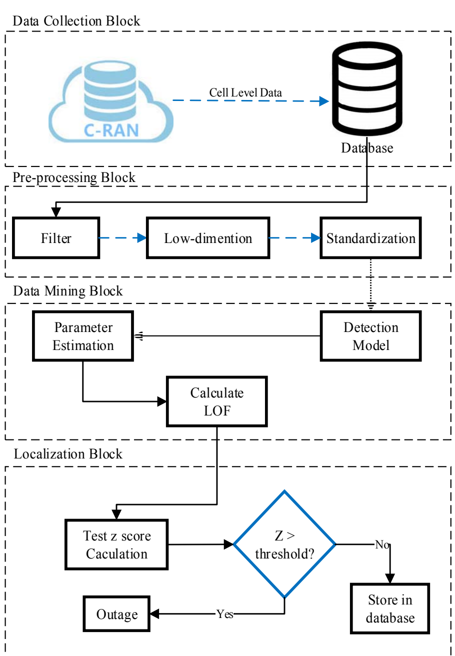


Fig. 2. Local Outage Detection Framework

### A. Data Collection Block

For the purpose of developing automated fault detection and localization solutions for cell outage, the cell-level data are collected. We suppose the cell outage as the site outage. Typically methods for COD are usually based on MDT measurements as show in Table II. These radio measurements are generated from sub-scribers while the cell inHO measurements are reported by a base station. The inHO data streams in Table I are categorized within big data as cell level information that our system uses to analyze.

TABLE I
CELL-LEVEL DATA

| Measurements | Description |
|---|---|
| Time | Transmission Time Interval |
| Cell Info | Cell Global Identity (CGI) |
| Cell Localization | Longitude and Latitude Information |
| Cell inHO | Cell Incoming Handover |

TABLE II
USER-LEVEL DATA

| Measurements | Description |
|---|---|
| Time | Transmission Time Interval |
| RSRP | Reference Signal Received Power in dBm |
| RSRQ | Reference Signal Received Quality in Db |

### B. Pre-processing Block

After finishing the work of data collection, the system is processed to extract feature vector Z corresponding to each temporal data. Since the inHO data is collected from different BS at different time, the data vector is designed as two forms which conforms to time-and-space analyses. In order to do length-wise normalization and carry out standardization processing to the data, we slice the time sequences to sub-sequences.

*1)* For the temporal analysis, 5 TTIs data are augmented into one feature vector $T_i$ as shown in Equation 1 where i represents the order of sub-sequence.The 5-dimensional feature are focusing on exactly one cell's inHO data, which is used to find out the time that outage happened.

*2)* For the spatial analysis, the feature vector $S_j$ is combined with 10 TTIs data where j represents the identity of the cell. At every slot of 10 TTIs, we collect vector from all of the cells in the scenario to detect the anomalous cell's location.

### C. Data Mining Block

Local outlier factor (LOF) detection is an unsupervised anomaly detection algorithm. The more difference between the sample and its neighbors, the higher outage factor score will be assigned. The algorithm starts by first computing the k-distance of cell $p$ denoted as $d_k(p)$ ,represents the distance between cell $p$ and its $k^{th}$ nearest neighbor. $N_{d_k(p)}(p)$ is the set includes every cell which distance to cell $p$ is smaller than k-distance.

The reachability distance of cell $p$ with respect to cell $o$ denoted as $reach\_dist_k(p,o)$.

$$reach\_dist_k(p,o) = \max\{d_k(o), d(o,p)\} \tag{1}$$

The local outlier factor (LOF) of cell $p$ is defined as

$$LOF_k(p) = \frac{\sum_{o\in N_{d_k(p)}(p)} \frac{lrd_k(o)}{lrd_k(p)}}{\left|N_{d_k(p)}(p)\right|} \tag{2}$$

Description above is the definition of LOF. In our experiments, an improvement has been made in LOF algorithm called M-LOF since the effect of cell outage is partial. The mean distance of cell $p$ denoted as m-distance which is used to widen the gap between normal cells and outage cells.

The m-distance of cell $p$: Given the positive integer $k$, the m_distance of cell $p$ is defined as:

$$m\_d_k(p) = \varepsilon + \left[\frac{\sum_{o\in N_{d_k(p)}(p)} d(p,o)}{\left|N_{d_k(p)}(p)\right|}\right] \tag{3}$$

Here ε is a constant value to enhance the accuracy.

The m_distance neighborhood of cell $p$ denoted as $N_{m\_d_k(p)}(p)$, $N_{m\_d_k(p)}(p)$ is the set includes every cell which distance to cell $p$ is smaller than m-distance.

The local outlier factor of cell $p$:

$$LOF_m(p) = \frac{\sum_{o\in N_{m\_d_k(p)}(p)} \frac{lrd_m(o)}{lrd_m(p)}}{\left|N_{m\_d_k(p)}(p)\right|} \tag{4}$$

### D. *Localization Block*

The last step of the framework is localization block, the neighbor cell list is used to search the relation between the outage cell and its' neighboring cells by geographic information.

## III. Simulation Result

### A. *Simulation Setup*

In this section, we design a simulation platform so that our scenario parameters can be easily deployed and generate temporal data of cell inHO. As show in Fig 1, the database system collects and stores the data generated from the simulator. To simulate the HetNets network based on 3GPP specifications, we deploy a full dynamic network. In this experiment, the simulation environment is composed of 19 regular hexagonal macro cells with a cell load of 25 users. The UEs are randomly distributed in cells to generate handover statistics and MDT measurements. In order to simplify the experiment, we make some assumptions here. The rapid decrease of cell's transmit power indicates the cell outage.

The detailed simulation parameters are listed in Table III. At some time point in simulation, transmit power of macro cell 18 and small cell 61 are set to drop 40dBm to simulate cell outage. In this experiment, the simulation is configured to process for 150 TTI.

TABLE III
Simulation Parameters

| **Simulation Parameters** | **Value (unit)** |
|---|---|
| Macro Cell | 19 cells |
| Small Cell | 1 small cell per sector |
| User number | 25 per cell |
| User Distribution | Uniform Random |
| Link direction | Downlink |
| BS Tx Power | 46dBm |
| Path Loss Model | Cost231-Hata |
| UE velocity | 15 km/h |
| User distribution | Uniform |
| Cell Selection Criteria | Strongest RSRP |
| Simulation length | 150 TTI |
| Simulation resolution | 1 time step = 4 s/TTI |

### B. *Detection Results*

The cell inHO data which pre-processed in Section II is fed into the data mining procedure. Afterwards, M-LOF algorithm is supposed to detect anomalous behaviors of handover.

*1)* Spatial Analyses

For spatial analyze, we focus on the temporal data in one time period but from different cell. The local outlier factor of each cell at 95-105 TTI as show in Fig 3 is given after the data mining block processed. It can be observed that at 95-105 TTI, inHO data's factor values of cell 60, 62, 13, 74, 75, 76 are far larger than the normal reference value which is less than 1. As discussed earlier in Section II-C, M-LOF tries to maximize the factor values of anomalous cells. Consequently, outage cells can be distinguished from the normal cells. As a comparison, the result using the MDT measurements as data source is also given in Fig 3. The M-LOF values of cells using MDT data are smoother than inHO data so that the outage cell cannot be detected.

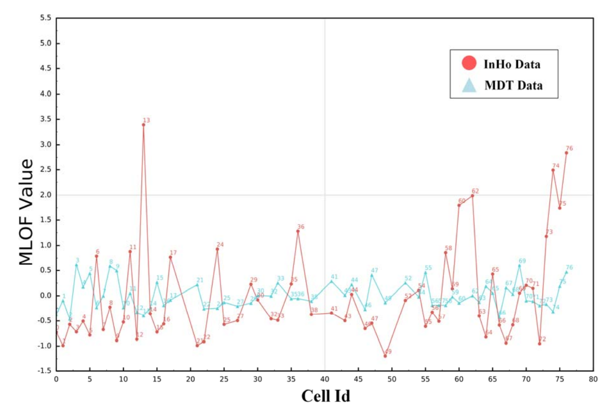


Fig. 3. Spatial Analyze of MDT/InHO data

In order to find out the localized correlation of these anomalous cells, Fig 4 mark the local outlier factor on the map. The M-LOF values are indicated by the size of point and depth of color. As discussed earlier, the cell outage could led to the anomalous behavior of neighbor cell. The outage cells are manually signed on Fig 4 marked by red point. It can be observed that the outage cells do not have the capacity to carry any traffic. At this point, all users served by these cells have to be offloaded to its neighboring cells. This brings a sudden UE handover increase. As we can see, the anomalous behavior cells are exactly the neighbors of outage cells marked by deep blue points. Therefore, these points can be used for localization.

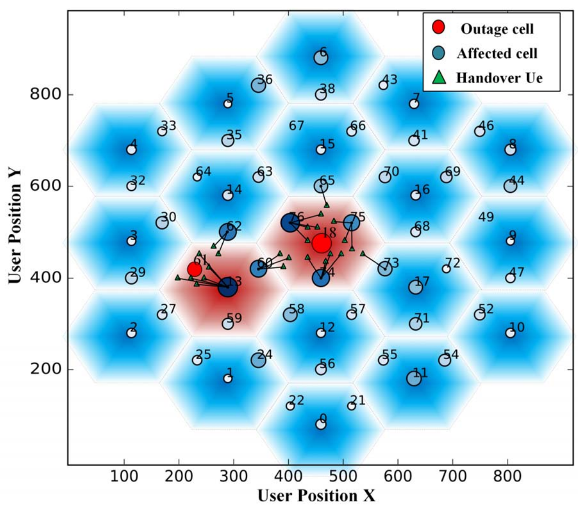


Fig. 4. Spatial Distribution Map of M-LOF.

*2) Temporal Analyses*

Fig 5 shows the value of local outlier factor in time domain of cell 13 which is found to be abnormal. As it shows, the factor value in 90-100 TTI is much larger than other normal value which is corresponding to the result of special analyze. The peak in 0-5 TTI is not in our consideration since the initial accession of UEs influence the result.

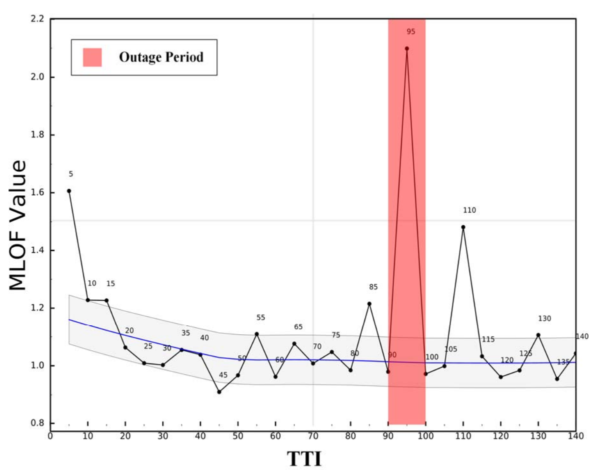


Fig. 5. M-LOF of Temporal Analyze

## C. Performance Evaluation

The discussion above is only one instance of simulation. Several outage situations have been generated in our simulation which is used to evaluate our system performance: some are outages that only affect one cell; and others are outages that occur in multi-cell. We analyzed the M-LOF detection performance under varying traffic conditions. Table IV presents the results in terms of the false positive rate and the false negative rate for each simulation.

TABLE IV
Performance Evaluation

| Result | LOF Value | M-LOF Value |
|---|---|---|
| False Negative Rate | 3% | 3% |
| False Positive Rate | 12% | 6% |

As show in Table IV, the LOF based detector obtains a 12% or 6% of false positive rate but a 3% of false negative rate. It means the outage cell can be almost wholly detected. The main cause of the 3% false negative rate is that the cell outages that affect cells with very low traffic cannot be detected. However, these outage situations have a low influence on the user experience and in the overall network performance. For this reason, it can be stated that, on the basic of LOF based detector approach, the cell outage can be detected successfully. As for M-LOF algorithm, we noticed that the false positive rate is 6% which is smaller than LOF's FP rate. Although the FN value of LOF and M-LOF is the same, the FP rate of M-LOF has a significant improvement which can enhance the accuracy of LOF algorithm. Compared to LOF algorithm, M-LOF pays more attention to local density which makes this improvement.

# IV. Conclusion

In this paper, we assume a cell outage detection framework based on inHO data in HetNets. Previous method based on MDT measurements can't detect the small cell outage due to the densified small cell deployment. In this case, the proposed system collects the inHO statistics to detect the anomalous behavior. The M-LOF algorithm is designed to handle temporal incoming handovers statistics. A series of simulated scenarios have been carried out to evaluate the M-LOF based detector system model which were analyzed spatially and temporally. Finally, the cell neighbor list is adopted to localize the position of outage cell. Simulation results have shown that our framework has a good performance of detection with high accuracy. In the near future, this framework will be applied in SON on a large scale.

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