Anomaly Detection in Multi Tiered Cellular Networks Using LSTM and 1D-CNN

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Research Article

Keywords: cell outage detection, self-organizing networks, LSTM, femtocells, 1D-CNN, deep learning

Posted Date: February 22nd, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-201604/v1>

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Abstract

Self Organizing Networks (SONs) are considered as one of the key features for automation of network management in new generation of mobile communications. The upcoming fifth generation (5G) mobile networks are likely to offer new advancements for SON solutions. In SON concept, self-healing is a prominent task which comes along with cell outage detection and cell outage compensation. 5G networks are supposed to have ultra-dense deployments which makes cell outage detection critical and harder for network maintenance. Therefore, by imitating the ultra-dense multi-tiered scenarios regarding 5G networks, this study investigates femtocell outage detection with the help of Long Short- Term Memory (LSTM) and one-dimensional Convolutional Neural Networks (1D-CNN) by means of time sequences of Key Performance Indicator (KPI) parameters generated in user equipments. In proposed scheme, probable anomalies in femto access points (FAP) are detected and classified within a predetermined time sequence intervals. On the average, in more than 80% of the cases the outage states of the femtocells are correctly predicted among healthy

and anomalous states.

Full Text

This preprint is available for [download as a PDF](#).

Figures

$$\begin{array}{l}
 \text{User 1} \quad \left[\begin{array}{c} cqi_0, cqi_1, \dots, cqi_{t-1}, cqi_t, cqi_{t+1}, \dots, cqi_T \\ sinr_0, sinr_1, \dots, sinr_{t-1}, sinr_t, sinr_{t+1}, \dots, sinr_T \end{array} \right] \\
 \\
 \text{User 2} \quad \left[\begin{array}{c} cqi_0, cqi_1, \dots, cqi_{t-1}, cqi_t, cqi_{t+1}, \dots, cqi_T \\ sinr_0, sinr_1, \dots, sinr_{t-1}, sinr_t, sinr_{t+1}, \dots, sinr_T \end{array} \right] \\
 \\
 \vdots \\
 \\
 \text{User n} \quad \left[\begin{array}{c} cqi_0, cqi_1, \dots, cqi_{t-1}, cqi_t, cqi_{t+1}, \dots, cqi_T \\ sinr_0, sinr_1, \dots, sinr_{t-1}, sinr_t, sinr_{t+1}, \dots, sinr_T \end{array} \right]
 \end{array}$$

Figure 1

Time sequence structure of UE data

Figure 2

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The repetitive architecture of LSTM units in time steps

Figure 3

Unit structure of LSTM

Figure 4

1D-CNN Convolution Structure of a 2-featured UE time sequenced data

Figure 5

Employed CNN layers with dimensions

Figure 6

LSTM Accuracies at 2 dB

Figure 7

1D-CNN Accuracies at 5 dB

Figure 8

Accuracies of LSTM and 1D-CNN for all shadowing conditions and ROI choices

Figure 9

Accuracies of LSTM at 2 dB shadowing

Figure 10

Accuracies of 1D-CNN at 5 dB shadowing

Figure 11

Recall rates of LSTM and 1D-CNN at 30 meters of ROI under ensemble averaging

Figure 12

TPRs of LSTM at 2 dB Shadowing in binarized view

Figure 13

TPRs of 1D-CNN at 5 dB Shadowing in binarized view

Figure 14

TPRs of 1D-CNN and LSTM at 8 dB Shadowing with Ensemble Averaging in binarized view