Cell Outage Detection using Deep Convolutional Autoencoder in Mobile Communication Networks

Yeh-Hong Ping and Po-Chiang Lin
Department of Electrical Engineering, Yuan Ze University, Taoyuan, Taiwan, R.O.C.
Email: kenping1@gmail.com, pclin@saturn.yzu.edu.tw
Tel: +886-3-4638800 Ext. 7333

***Abstract*—The cell outage detection is an important issue of the self-organizing networks defined by the 3GPP. The objective of the cell outage detection is to determine whether these exists any cell outage in mobile communication networks. The cell outage detection problem is important in next generation mobile communication networks due to the increasing number of base stations. Using machine learning techniques to detect the cell outage would be promising. However, the data imbalance and the users' privacy issues make the machine learning based cell outage detection more challenging. In this paper, we propose a cell outage detection method using the deep convolutional autoencoder, which is an unsupervised learning approach. We formulate the cell outage detection problem as an anomaly detection problem. The proposed method could solve this anomaly detection problem by using the normal measurement data only. The proposed method does not rely on the cell outage data and the location information of users. Comprehensive system-level simulations validate the performance of the proposed method.**

***Index Terms*—Self-Organizing Network, Self-Healing, Cell Outage Detection, Autoencoder, Convolutional Neural Network.**

I. Introduction

With the evolution of mobile communication networks, the modulation frequency becomes higher and higher, and the total number of users, including both humans and machines, also dramatically increases [1]. In order to improve the network performance, the deployment of small cells has become an inevitable trend.

During the long-term operation of base stations, some degradation or failure may occur, which cause coverage holes or poor signal quality. The cell outage detection (COD), which is part of the self-healing in the self-organizing networks proposed by the 3GPP, aims to solve this issue [2] . Cell outage detection is the task of determining whether some cell is degraded or failed to provide mobile service to users. When the outage cell is detected, the coverage holes or the service degradation areas could be compensated by the cell outage compensation (COC) methods [3].

Due to the increasing number of base stations, the data imbalance, and the users' privacy issues, enabling cell outage detection is with critical challenges [4].

In order to solve these issues, we propose a cell outage detection method using the deep convolutional autoencoder. The cell outage detection problem is formulated as an anomaly detection problem. We develop a deep convolutional autoencoder to learn to identify cell outage from the dataset which is based on the measurement reports collected from user equipment (UE). Comprehensive system-level simulations validate the performance of the proposed method.

The major contributions of this paper are threefold:

1) We design a novel cell outage detection method called the Cell Outage Detection with Convolutional Autoencoder (CODCA) method. In order to deal with the data imbalance issue, the proposed method is based on the unsupervised learning. Even when the cell outage data is still not available, the proposed CODCA would be trained by using the normal data. The tedious data labeling work could be avoided.
2) In order to address the users' privacy concern, the proposed CODCA method does not rely on the location information of users. The CODCA method only uses the RSRP and RSRQ values of the serving cell and the neighboring cells, and the radio link failure (RLF) information in the measurement report from user equipment. The location information of users is not required in the proposed CODCA method.
3) The proposed CODCA method is based on the convolutional neural network technique. Thus, the number of parameters in the model could be reduced, and thus the overfitting problem could be avoided.

The rest of this paper is organized as follows. In Section II we describe the related work in the literature. The system model is presented in Section III. The proposed CODCA method is described in Section IV, followed by the simulation results and discussions in Section V. Finally, conclusions are presented in Section VI.

II. Related Work

Moysen and Giupponi provided a comprehensive introduction and literature survey for applying machine learning techniques in Self-Organizing Networks [5]. They showed that there exist some related work about COD. Most of them use the supervised learning techniques, such as fuzzy logic, support vector machine (SVM), and k-nearest neighbors (KNN).

This work was supported in part by by Ministry of Science and Technology (MOST), Taipei, Taiwan, R.O.C. under grant number MOST 108-2221-E-155-023-MY2.

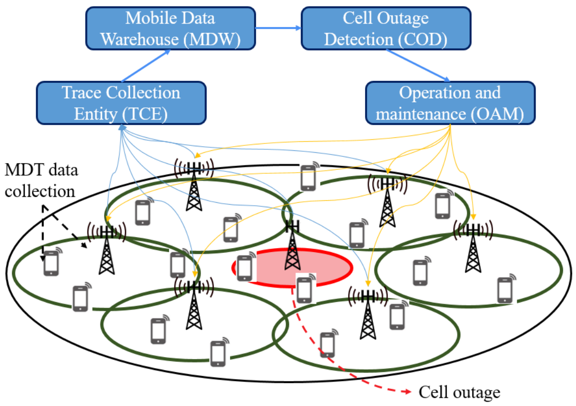

Fig. 1. The system model.

Khatib et.al. presented a root cause analysis system based on fuzzy logic [6]. They proposed a genetic algorithm to learn the rule base. They showed that the obtained results are comparable or even better than those obtained by human experts. Ciocarlie et.al. proposed an adaptive ensemble method framework for modeling cell behavior to deal with the cell anomaly detection problem [7]. They uses Key Performance Indicators (KPIs) to determine cell-performance status. By using real cellular network data, their proposed method could significantly improve the detection quality. Onireti et.al. proposed a cell outage management (COM) framework for heterogeneous networks [3]. In their work, they use the KNN to detect cell outage.

In [8], we already proposed a cell outage detection method, called CODA, based on the autoencoder neural network. However, we used the fully-connected layers to build the model. The number of parameters might be large and thus it would be possible to overfit. In this paper, we use the convolution layers in the model with the benefit to reduce the number of parameters and to avoid overfitting.

III. System Model

Fig. 1 shows the system model. The mobile communication network consists of multiple cells. One or more of these cells might be degraded or failed. Based on the Minimization of Drive Tests (MDT) [9], the user equipment in each cell would collect the measurement reports, including the Reference Signals Received Power (RSRP), Reference Signals Received Quality (RSRQ), and Radio Link Failure (RLF), and send the measurement reports to the Trace Collection Entity (TCE). The measurement reports in the TCE are processed to generate the ready-to-use dataset. The dataset is saved in the Mobile Data Warehouse (MDW). The Cell Outage Detection (COD) method would use the dataset to predict the cell outage, and send the prediction result to the Operation and Maintenance (OAM) to decide the followup actions, e.g., to compensate the service degradation of coverage hole.

TABLE I
Network Architecture of the Proposed CODCA Method.

Layer (Type)	Output Shape	Activation Function	Num. Parameter
Input	(None, 4, 4, 3)		0
Conv2D	(None, 4, 4, 9)	tanh	252
MaxPooling2D	(None, 2, 2, 9)		0
Conv2D	(None, 2, 2, 27)	selu	2214
MaxPooling2D	(None, 1, 1, 27)		0
Conv2D	(None, 1, 1, 27)	tanh	6588
UpSampling2D	(None, 2, 2, 27)		0
Conv2D	(None, 2, 2, 9)	selu	2196
UpSampling2D	(None, 4, 4, 9)		0
Conv2D	(None, 4, 4, 3)	selu	246

IV. Proposed CODCA Method

Consider a mobile communication network which consists of n cells. In the following explanation, we use $n = 4\times4 = 16$ cells. Suppose that an UE generates a measurement report $\mathbf{x}$, as (1) shows.

We use the deep convolutional autoencoder to detect whether the measurement report $\mathbf{x}$ is normal or not. Table I shows the network architecture of the proposed CODCA Method. There are two symmetrical parts in the model, including the encoder and the decoder. The higher half of Table I shows the encoder. The objective of the encoder is to find the compressed representation of the input features which are the RSRP, RSRQ and RLF values from surrounding cells, so that the most important features could be kept. The high-dimensional measurement report could be represented as the low-dimensional coding. The lower half of Table I shows the decoder. The objective of the decoder is to reconstruct the input data from the coding. The output of the decoder is the *reconstruction* $\bar{\mathbf{x}}$.

The proposed CODCA method tries to learn the identity function:

$$\bar{\mathbf{x}} = f(\mathbf{x}) \approx \mathbf{x} \tag{2}$$

During the training of this convolutional autoencoder neural network, the back propagation algorithm is adopted to minimize the reconstruction error L:

$$L(\bar{\mathbf{x}}, \mathbf{x}) = \|\bar{\mathbf{x}} - \mathbf{x}\|^2 \tag{3}$$

After the training process, the model is used to detect the anomaly of the new inputs. We would choose an appropriate decision threshold which depends on the precision-recall tradeoff. When the reconstruction error of the new input data is below the decision threshold, this new input data is predicted as normal; otherwise, a cell outage is predicted.

Fig. 2 shows the detailed illustration of convolution layer in the proposed CODCA method. In the proposed CODCA method, take $n = 4 \times 4 = 16$ as an example, there would be totally 11,496 trainable parameters .

V. Simulation Results and Discussions

We use ns-3 to build the simulation scenarios and to generate simulation results [10]. Fig. 3 shows the simulation scenario which consists of 16 cells There are 50 mobile stations randomly deployed in each cell in the scenario. There

$$\mathbf{x} = \{\mathrm{RSRP}_1, \mathrm{RSRP}_2, \ldots, \mathrm{RSRP}_n, \mathrm{RSRQ}_1, \mathrm{RSRQ}_2, \ldots, \mathrm{RSRQ}_n, \mathrm{RLF}_1, \mathrm{RLF}_2, \ldots, \mathrm{RLF}_n\}. \tag{1}$$

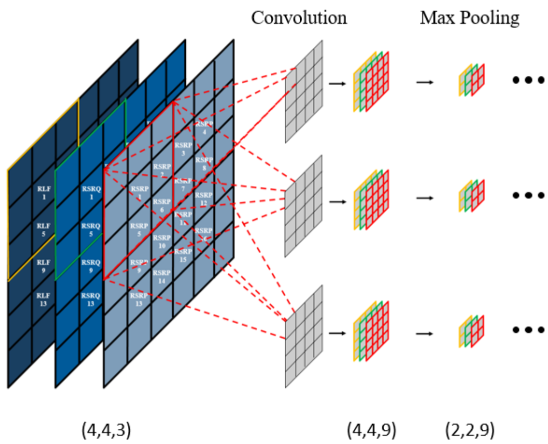

Fig. 2. Convolution.

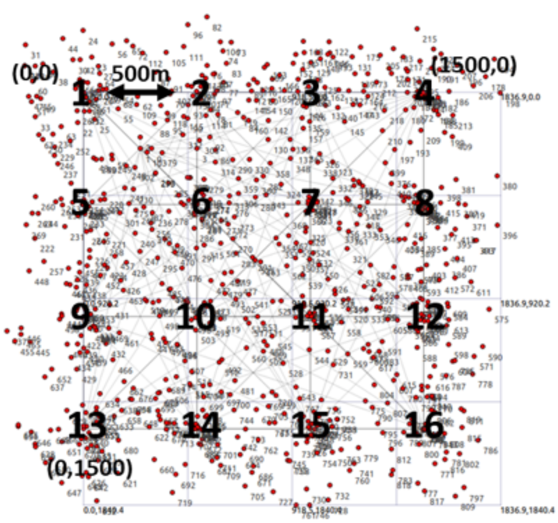

Fig. 3. Simulation scenario.

TABLE II
SIMULATION PARAMETERS.

Parameter	Value
Num. Base Stations	16
Num. Mobile Stations	800
Distance between Base Stations	500m
Frequency	Band 7
Transmission Power (Normal)	43 dBm
Transmission Power (Outage)	30 dBm
Path Loss Model	Log-Distance
Antenna	Omni Directional Antenna
Mobility Model	Random Waypoint
Handover	A2-A4-RSRQ
Epoch	200
Batch Size	128
Optimizer	adam
Loss	MSE
Padding	Same
Stride	1
Num. Filter	3
Kernel Size	3×3

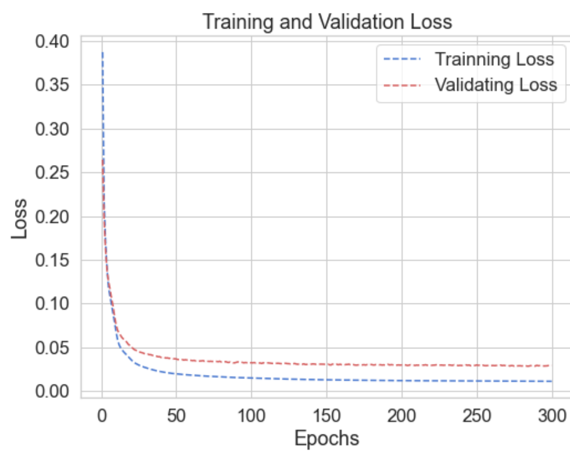

Fig. 4. Training and validation loss.

are totally 800 mobile stations. Table II shows the detailed simulation parameters. We prepare four datasets generated by the simulation. One dataset is the normal dataset, and the other three datasets are the cell outage datasets. For each cell outage dataset, we choose one of the cells in Fig. 3 to be the outage cell, and change the transmission power of this outage cell to 30 dBm. For the three cell outage datasets, we choose cell 4, cell 5, and cell 11 to be the outage cell, respectively.

Fig. 4 shows the training vs. validation loss. Both the training and validation losses decrease rapidly at the first few epochs. They keep almost consistent after 100 epochs. Fig. 5 shows the Receiver Operating Characteristics (ROC) curve. The area under the curve (AUC) is 0.9388. Fig. 6 shows the reconstruction error for normal and outage data. The figure show that the proposed CODCA method could effectively separate the normal data and the outage data. The decision threshold is set as 0.024, and is represented as the green line in Fig. 6. Fig. 7 shows the confusion matrix.

Table III shows the performance comparison between the proposed CODCA and our previous work CODA. The results show that the proposed CODCA method could outperform the previous CODA method by 1.5% to 2.8%.

VI. CONCLUSION

In this paper, we propose a cell outage detection method using the deep convolutional autoencoder. The cell outage detection problem is formulated as an anomaly detection problem. We develop a deep convolutional autoencoder to learn to identify cell outage from the dataset which is based on

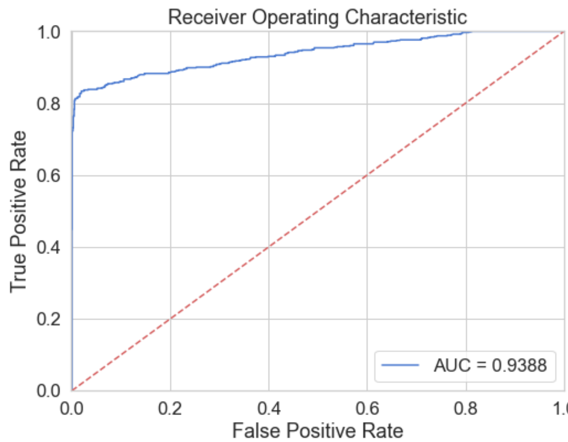

Fig. 5. ROC curve.

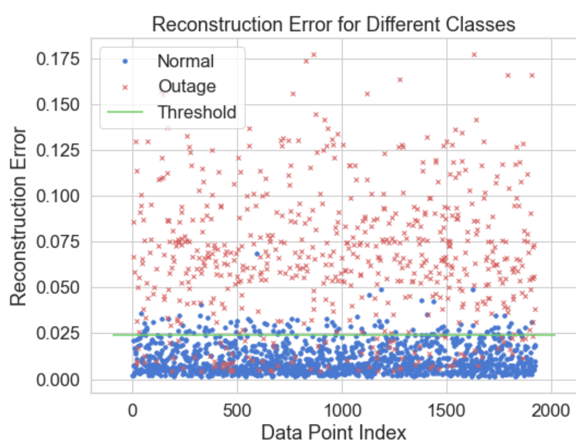

Fig. 6. Reconstruction error for normal and outage data.

the measurement reports collected from user equipment. Comprehensive system-level simulations validate the performance of the proposed method.

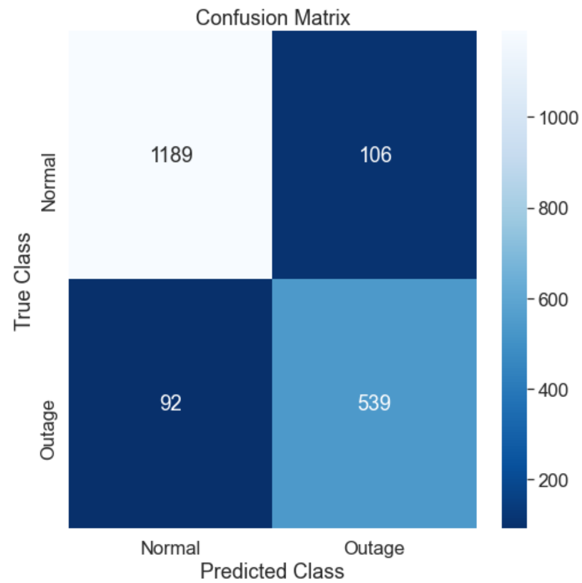

Fig. 7. Confusion matrix.

TABLE III
PERFORMANCE COMPARISON OF CODA AND CODCA METHODS.

Method	Dataset1	Dataset2	Dataset3	Average
CODA Accuracy	86.6%	84.8%	86.0%	85.8%
CODCA Accuracy	89.8%	86.3%	88.0%	87.9%
Improvement	2.8%	1.5%	2.0%	2.1%

REFERENCES

[1] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. K. Soong, and J. C. Zhang, "What Will 5G Be?" *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1065–1082, June 2014.

[2] 3GPP, "Self-Configuring and Self-Optimizing Network (SON) Use Cases and Solutions," TR 36.902, V9.3.1, 2011-03.

[3] O. Onireti, A. Zoha, J. Moysen, A. Imran, L. Giupponi, M. Ali Imran, and A. Abu-Dayya, "A Cell Outage Management Framework for Dense Heterogeneous Networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 2097–2113, 2016.

[4] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: How to Empower SON with Big Data for Enabling 5G," *IEEE Network*, vol. 28, no. 6, pp. 27–33, Nov 2014.

[5] J. Moysen and L. Giupponi, "From 4G to 5G: Self-Organized Network Management meets Machine learning," *Computer Communications*, vol. 129, pp. 248 – 268, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0140366418300380

[6] E. J. Khatib, R. Barco, A. Gómez-Andrades, and I. Serrano, "Diagnosis Based on Genetic Fuzzy Algorithms for LTE Self-Healing," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 3, pp. 1639–1651, 2016.

[7] G. F. Ciocarlie, U. Lindqvist, S. Nováczki, and H. Sanneck, "Detecting Anomalies in Cellular Networks using an Ensemble Method," in *Proceedings of the 9th International Conference on Network and Service Management (CNSM 2013)*, 2013, pp. 171–174.

[8] P.-C. Lin, "Large-Scale and High-Dimensional Cell Outage Detection in 5G Self-Organizing Networks," in *2019 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*. IEEE, 2019, pp. 8–12.

[9] J. Johansson, W. A. Hapsari, S. Kelley, and G. Bodog, "Minimization of Drive Tests in 3GPP Release 11," *IEEE Communications Magazine*, vol. 50, no. 11, pp. 36–43, November 2012.

[10] "The ns-3 Network Simulator." [Online]. Available: https://www.nsnam.org/