Data-Driven Intelligent Outage Management for High Shadowing Environments in 5G&B Networks

Waseem Raza*, Muhammad Umar Bin Farooq*, Aneeqa Ijaz* and Ali Imran*‡
*AI4Networks Research Center, School of Electrical & Computer Engineering, University of Oklahoma, OK, USA
‡James Watt School of Engineering, University of Glasgow, United Kingdom.
Email: {waseem, umar.farooq, aneeqa, ali.imran}@ou.edu

***Abstract*—In the evolving landscape of 5G and forthcoming 6G networks, managing outages becomes increasingly complex due to higher Base Station (BS) densities and the consequent rise in outage instances. Addressing this, we introduce a sophisticated, two-tiered outage management framework that leverages artificial intelligence for enhanced efficiency and automation. Our approach features an innovative AI-based cell outage detection strategy, named Impv-XGBoost, which excels in high-shadowing conditions and with sparse training data, outperforming traditional methods. The framework's second tier employs an actor-critic reinforcement learning scheme for cell outage compensation, finely tuning compensating BS's tilt and transmit power. This method uniquely integrates outage and compensating base station's user equipment coverage, ensuring equitable service quality. By incorporating Jain's fairness index and the geometric mean in its reward mechanism, our approach achieves fair and efficient outage management, demonstrating notable improvements in user coverage during BS outages.**

***Index Terms*—Actor-critic, Reinforcement Learning, Self-Healing, Outage Detection and Compensation, Jain's Fairness Index, Geometric Mean.**

I. Introduction

The data-driven applications and 5G and Beyond (5G&B) wireless technologies have significantly increased the complexity of cellular networks, evolving from 2G to 5G. This complexity arises from the integration of advanced technologies, a surge in adjustable network parameters, and an increase in heterogeneous Base Station (BS) deployments [1]. Consequently, there is a pressing need for more automated and intelligent network management strategies. Self-Organizing Networks, as defined by 3GPP [2], provide a solution by promoting autonomous network management throughout the network's life cycle, including deployment, optimization, and maintenance. Notably, self-healing functions, such as Cell Outage Detection (COD) and Cell Outage Compensation (COC), play a critical role in addressing operational issues [3].

The advent of 5G and subsequent generations introduces a paradigm where traditional self-healing approaches, such as software updates, network monitoring, and hardware expansions, are insufficient. The complexity of these networks, characterized by their architectural heterogeneity and the vast array of connected devices and applications, challenges the efficacy of existing SON-based self-healing strategies. For instance, identifying 'sleeping cells'—outages caused by hardware or software failures—becomes particularly challenging without the aid of operational and maintenance alarms. Ensuring prompt detection of such outages and implementing effective compensation measures, without impairing the functionality of operational network components, is crucial for maintaining network integrity in the 5G era and beyond [4], [5].

To tackle the challenges in outage management, Artificial Intelligence (AI) is increasingly utilized to improve detection and compensation mechanisms. AI methods, leveraging Minimization of Drive Test (MDT) data, effectively identify anomalies in MDT reports from User Equipment (UE) within an affected base station's coverage, aiding in swift outage localization and repair. Furthermore, AI-driven compensation techniques, especially those using Reinforcement Learning (RL), adjust neighboring base stations' parameters to lessen outage impacts on users. These strategies focus on enhancing service quality for impacted UEs, using key performance indicators like Reference Signal Received Power (RSRP) or Signal-to-Interference-plus-Noise ratio, focusing AI's role in bolstering self-healing network capabilities [6], [7].

A. Related Work

The literature on cell outage management plays a crucial role in bolstering the robustness and reliability of 5G&B networks, traditionally segmented into three main areas: COD, COC, and integrated strategies addressing both COD and COC. COD research bifurcates into non-AI methodologies, which, despite their abundance, are hindered by a reliance on extensive manual analysis, rendering them less feasible for the dynamic and intricate 5G&B environments. The transition towards AI-based COD techniques, such as the dynamic affinity propagation clustering algorithm [8] and K Nearest Neighbor (KNN) based anomaly detection [9], represents a significant advancement towards automating outage detection. However, these AI-based solutions encounter challenges in high shadowing or limited training data scenarios, emphasizing the need for enhanced research efforts in this domain.

For COC the evolution from traditional to AI-infused strategies, especially leveraging deep reinforcement learning for dynamic parameter adjustment, marks a pivotal shift. Notable is the introduction of a deep RL framework for COC in ultra-dense networks utilizing Q-learning [10]. Despite these advancements, AI-driven COC methodologies have yet to fully tackle the challenge of ensuring user fairness, often sidelining the equitable allocation of network resources among users affected by outages. Efforts to amalgamate COD and COC under a unified framework are in their infancy but are deemed essential for the development of all-encompassing outage management solutions. Preliminary studies [7] and [11], apply machine learning for both detection and compensation and provide a foundation. Nevertheless, these integrated approaches frequently overlook the collective performance impact on users during an outage or the scalability challenges associated with compensating multiple base station failures, underlining the necessity for scalable and adaptable integrated solutions.

Current research highlights significant gaps, notably in crafting AI-based COD solutions adept at navigating issues of shadowing and sparse datasets. Moreover, the development of COC schemes that prioritize user fairness and the amalgamation of COD and COC into a comprehensive framework remains paramount. These insights drive the motivation for our proposed work, aiming to establish a nuanced, effective, and equitable outage management strategy that addresses the limitations outlined in existing literature, thus advancing outage management capabilities within 5G&B networks.

B. Proposed Approach and Contributions

This study presents a streamlined, dual-layer framework targeting the critical aspects of COD and COC within high-shadowing and data-sparse environments. Illustrated in Fig. 1, the framework enhances detection accuracy and employs reinforcement learning for COC, optimizing compensating BS (cBS) settings for optimal UE service restoration. It introduces an innovative reward system, utilizing Geometric Mean (GM) and Jain's fairness Index (JFI), to guarantee fair UE treatment.

- **Enhanced COD with Impv-XGBoost:** We introduce an improved XGBoost algorithm, termed Impv-XGBoost, optimized with a specific *scale-pos-weight* hyper-parameter for distinguishing between normal and outage conditions. This method significantly outperforms existing models in high-shadowing scenarios and with sparse MDT data, showcasing superior detection capabilities under challenging conditions.
- **Novel COC Strategy Using SARL-AC:** A novel Single-Agent Reinforcement Learning with Actor-Critic (SARL-AC) method is proposed for outage compensation. This approach aims to restore the RSRP for UEs affected by an outage (oUEs) by optimally adjusting the antenna tilt and transmit power of the compensating BS. It uniquely considers the RSRP distribution of both oUEs and the cBS's originally served UEs (sUEs) in the feedback and reward mechanisms, ensuring the compensation process does not negatively impact the sUEs' service quality.
- **Advanced Reward Calculation for Fairness:** The reward function is refined by integrating Jain's fairness index and the geometric mean of RSRP values, enhancing the fairness of UE compensation. The incorporation of this index improves convergence time, while GM minimizes fluctuations in the learning process without significantly affecting convergence speed.

These contributions collectively address the existing gaps in outage management by providing a robust solution that ensures high detection accuracy, effective compensation, and fair treatment of UEs in 5G and beyond cellular networks.

Rest of the paper is organized as following. In Section II, we discuss the network model and proposed outage management framework, whereas the outage detection and compensation mechanisms are discussed in Section III. First subsection of Section IV, discusses the proposed outage detection schemes using ML based anomaly detection methods, while the second subsection is focused on employing RL based outage compensation. Section V, discusses the simulation setup, outage detection performance, and outage compensation results in three different subsection, and Conclusion and Future Works are discussed in Section VI.

II. Network Model and Proposed Framework

This section outlines the network model under consideration and introduces a novel two-tier outage management framework aimed at addressing outage detection and compensation within a 3GPP-compliant wireless network environment.

A. Network Model

Our study is based on a 3GPP-compliant wireless network model, comprising macro-cells divided into three sectors, each equipped with one directional antenna. The model adheres to the LTE standard for scheduling and physical resource block allocation in each transmission time interval. Users are randomly deployed and associated with the base station offering the highest RSRP, following a predefined trajectory. The model utilizes a free-space path loss model augmented with Gaussian-distributed shadowing for RSRP calculation. The network area is segmented into bins of size $10m \times 10m$, with an assumption of constant shadowing standard deviation within each bin. Outage scenarios are simulated by selectively disabling BSs, thereby affecting the RSRP values for associated UEs, which necessitates compensation measures to restore service quality. This model underpins the data generation, COD, and RL-based cell COC solution implementations.

B. Proposed Outage Management Framework

The proposed framework is structured around two main modules: outage detection and localization, and outage compensation, as depicted in Fig. 1.

1) MDT Data Collection: In line with 3GPP standards [12], UEs are configured to report radio measurements, including RSRP and Reference Signal Received Quality (RSRQ) values, from serving and neighboring cells. These measurements, alongside user location and *channel quality indicator* values, are compiled in the trace collection entity for subsequent analysis. The collected MDT data facilitates various big data-enabled self organizing functions such as mobility robustness optimization and load balancing, particularly focusing on machine learning-based outage detection mechanisms [13]. The MDT data, forming a concatenated feature vector $\mathbb{V} = \{R_s, R_{n_1}, R_{n_2}, R_{n_3}, Q_s, Q_{n_1}, Q_{n_2}, Q_{n_3}, c\}$,: where R_s and Q_s denote the RSRP and RSRQ from the serving base station, R_{n_i} and Q_{n_i} represent these values from the top three

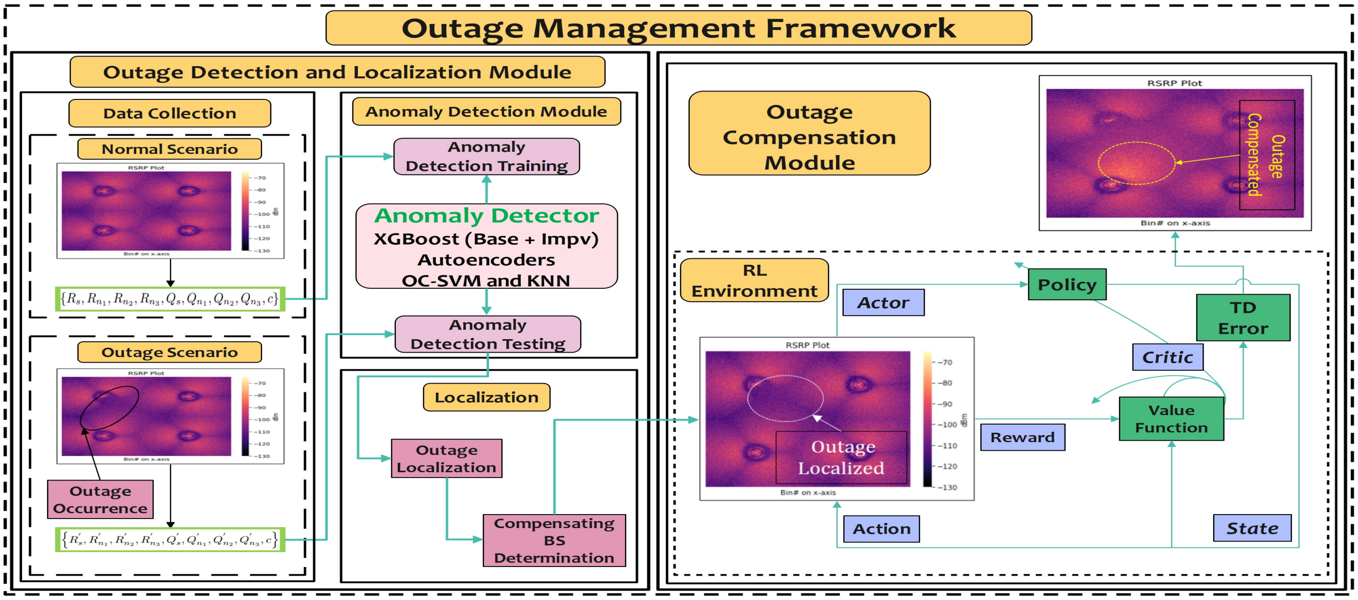

Fig. 1: The outage management framework illustrating machine learning-based outage detection using minimization of drive test data and actor-critic reinforcement learning for outage compensation. It includes modules for **Data Collection**, an **Anomaly Detection**, where machine learning models are trained on normal scenario data, and tested on outage data. It also includes a **Localization** module, where outage area is figured out and compensating base station is determined. The **Outage Compensation** module employs deep neural network, and actor critic based reinforcement learning mechanisms to adjust compensating base stations' parameters, enhancing service for affected users.

neighboring base stations, and c denotes the channel quality. The generation and utilization of MDT data in both normal and outage scenarios underpin the training of anomaly detection models and the operational efficacy of the outage detection and compensation modules within the framework.

2) Outage Detection and Compensation Modules: This module is crucial for detecting outages through the analysis of deviations in MDT data generated under outage conditions. The anomaly detection models, discussed in detail in subsection III-A1, trained on normal scenario data, identify significant variations that indicate outages, enabling precise localization and effective response strategies. Following outage detection, the framework's focus shifts to compensation, leveraging an actor-critic RL technique to adjust compensating BS parameters, such as power and antenna tilt, without compromising service quality for UEs initially served by the compensating BS as shown in Fig. 1. This module embodies a comprehensive approach to outage management, integrating deep learning techniques in both detection and compensation processes to ensure network resilience and service continuity.

III. Outage Detection and Compensation

This section delves into the details of COD and COC components of our framework, which involve the traditional unsupervised methods with advanced techniques for efficient outage identification and RL based outage compensation.

A. Outage Detection Mechanism

1) ML based Anomaly Detection Schemes: We explore conventional unsupervised methods like One-Class Support Vector Machine (OC-SVM) and Autoencoder (AE), alongside supervised approaches such as KNN and an enhanced version of Extreme Gradient Boosting (XGBoost), termed Improved XGBoost (Impv-XGBoost), which excels in scenarios with limited training data and reduces training time.

- **One-Class Support Vector Machine (OC-SVM):** OC-SVM, a prevalent method in anomaly detection, trains solely on normal class data and tests against mixed data to identify anomalies [14]. It leverages a non-linear function to map input data to a higher dimension, establishing a non-linear boundary for improved data separability.
- **Autoencoder (AE):** AEs are neural networks designed to compress input data into a lower-dimensional space and then reconstruct it. They are evaluated based on the reconstruction error between the original and reconstructed data. For outage detection, AEs are trained with normal data and tested with mixed data, where high reconstruction errors indicate potential outages.
- **K-Nearest Neighbor (KNN):** KNN, a straightforward classification algorithm, is ideal when data distribution is unknown. It calculates the distance between a test instance and training samples, often using Euclidean distance, and classifies the test instance based on the majority vote from its K nearest neighbors. For skewed distributions, a weighted classification method prioritizes closer neighbors in the decision-making process.
- **Extreme Gradient Boosting (XGBoost, Impv-XGBoost):** XGBoost is known for its computational efficiency and high performance in binary classification tasks, thanks to its resistance to overfitting and

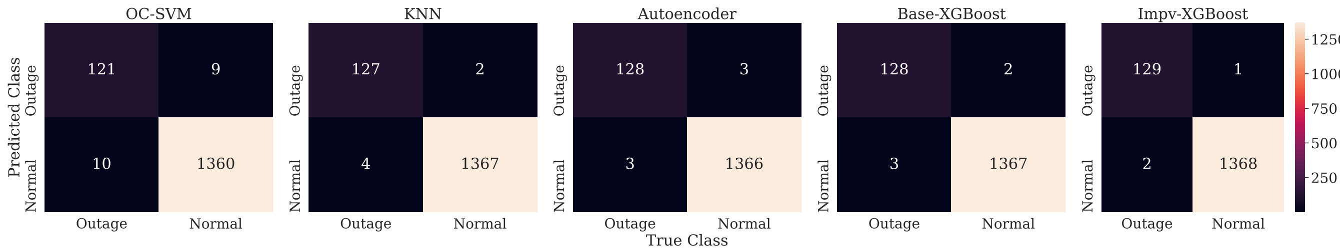

Fig. 2: Confusion matrices for the comparing schemes with 4dB of shadowing and 300 users per sq. km.

parallelization capabilities [15]. The Impv-XGBoost adaptation for detection employs hyperparameter optimization, using the AE output to fine-tune the *scale-pos-weight* parameter to get the idea of class distribution in training data.

2) Cell Outage Detection: Utilizing minimization of drive test data, our approach models a fault-free network scenario for outage detection, paralleling anomaly detection techniques like credit card fraud detection [16]. Machine learning models trained on this baseline data identify outages by detecting anomalies, characterized by unusually high prediction errors. Feature vectors are adjusted using a *robust scaler* to enhance model resilience against outliers. The evaluation focuses on three baseline methods and enhanced XGBoost models, examining their performance in diverse conditions. The effectiveness of our proposed method, particularly in handling shadowing and data sparsity, will be detailed in Section IV-B.

B. Outage Compensation Approaches

Addressing cell outages effectively requires not only precise detection and localization but also a robust compensation mechanism. This subsection presents our proposed RL-based compensation solution, focusing on utilizing a compensating base station to restore service for affected UEs.

1) Reinforcement Learning Background: RL underpins our approach, involving concepts such as agents, environments, states, actions, rewards, policy, and value functions, as outlined in Fig.1. RL's goal is to train agents to optimize actions in an environment to maximize cumulative rewards, based on the Markov decision process framework, defined by a tuple $D = [\mathcal{S},\ \mathcal{A},\ P(s|s,a), r, \gamma]$. Here, $\mathcal{S}$ and $\mathcal{A}$ represent the sets of states and actions, respectively, $P(s^{t+1}j|s_i^t, al)$ denotes the probability of transitioning from state s_i to s_j upon action a_l, $r(s,\ a)$ is the immediate reward and γ is the discount factor emphasizing the value of future rewards. RL involves training an agent, in this context, a cBS, through interactions within its environment aimed at sequential decision-making. Formally, an RL problem is articulated through the Markov decision framework, emphasizing the importance of learning optimal policies for action selection to maximize long-term rewards. This is captured by the state value function $\mathcal{V}^{\pi}(s) = \mathbb{E}\left\{\sum_{t=0}^{\infty} \gamma^t r(s_t, \pi(s)) | s_t = s\right\}$, where $\mathcal{V}^{\pi}(s)$ represents the expected future rewards from state s under policy π, and π is the optimal policy maximizing these rewards.

The actor-critic method merges policy-based and value-based RL strategies, facilitating direct learning from experience via temporal difference methods. It consists of an actor-network, learning the policy, and a critic network, evaluating the actions based on the learned policy. This method ensures a balanced exploration of the action space and exploitation of the gained experience, guiding toward optimal reward accumulation.

The use of MDT reports is crucial not only for detecting outages but also for selecting a suitable cBS and categorizing UEs for effective compensation. MDT data, enriched with UE location information, aids in localizing the outage and identifying potential cBS based on coverage potential. UEs affected by the outage UEs and those served by the compensating BS i.e., sUEs are distinguished for tailored compensation strategies, ensuring service restoration for oUEs while maintaining quality for sUEs. This nuanced approach underscores the complexity of outage compensation, necessitating sophisticated RL models to balance service restoration with network stability.

2) SARL-AC: Single Agent RL with Actor-Critic: Now we discuss on employing single-agent reinforcement Learning with actor-critic method for outage compensation, focusing on formulating and solving the compensation problem.

The SARL-AC environment consists of key components defined as follows:

a) ***State****:* It is defined by a tuple $[P_{tx}, \theta_{tilt}, \bar{R}^{\mathcal{X}}u, \bar{R}^{\mathcal{S}}u]$, representing downlink transmission power, antenna tilt, and mean RSRPs of xUEs and sUEs.

b) ***Action****:* The action includes four possible actions: increasing or decreasing antenna tilt and transmission power.

c) ***Reward****:* It is computed by employing arithmetic mean, geometric mean, and Jain's fairness index of user RSRP values. The total reward combines these components and adjusts the actor-critic learning based on temporal difference error, indicating whether the probability of selecting a current action should increase or decrease.

The SARL-AC approach integrates actor and critic networks within a neural network framework featuring shared layers and distinct output layers for action probabilities and value estimates. Training involves episodes where actions are evaluated and rewarded, with the actor-network learning to optimize total rewards and the critic network assisting in action selection. The training process, including loss calculations for actor and critic components, aims to enhance overall compensation ef-

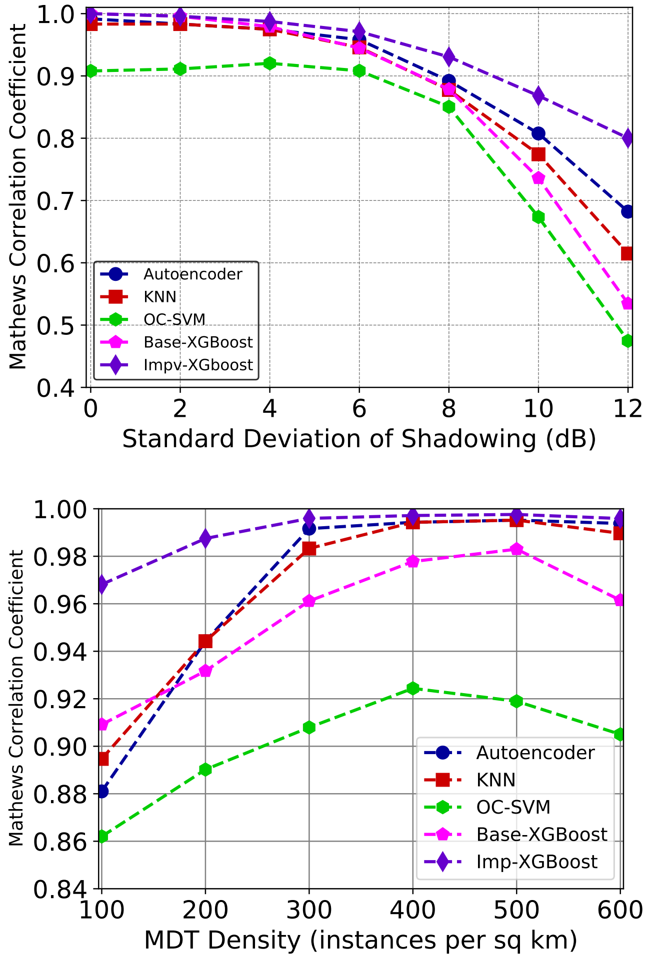

Fig. 3: Comparing the progress of cell outage detection schemes with varying (1) standard deviation of shadowing and (b) MDT density (users population) in terms of Matthews correlation coefficient.

fectiveness. The efficacy of SARL-AC in improving RSRP for affected UEs while maintaining network stability is discussed in Section IV-C.

Table I: Parameter values for simulations

System Parameters	Value
Number of macro Base Stations	9
Number of micro Base Stations	15
Number of sectors per macro Base Stations	3
Number of Users	$2500 - 15000$
Operating frequency of macro Base Stations	2100 MHz
Operating frequency of micro Base Stations	2500 MHz
Bandwidth of macro Base Stations	15 MHz
Bandwidth of micro Base Stations	20 MHz
Transmit power of macro Base Station	43 dBm
Transmit power of micro Base Station	20 dBm
Standard deviation of shadowing	$0 - 12$ dB
Base stations height	30 m
Small Base stations height	10 m

IV. Performance Evaluation

This section evaluates our proposed outage detection and compensation approaches, detailing simulation parameters and analyzing performance under different network conditions, including shadowing and user density variations. We examine compensation strategies through the SARL framework and a multi-agent actor-critic RL approach for multiple base station outages, assessing their effects on RSRP for affected users (oUEs) and coverage for served users (sUEs). Simulation setups are elaborated.

A. Simulation Setup

Utilizing a 3GPP-compliant LTE simulator, we generated MDT data across a $5Km \times 5Km$ area served by 9 macrocells and 16 micro-cells to simulate both normal and outage scenarios, with outage simulated by setting transmit power to 0dBm. Key simulation parameters are detailed in Table I. We evaluated COD schemes through confusion matrices, and Matthews correlation coefficient, focusing on their performance under varying shadowing and MDT densities.

B. Outage Detection Results

The evaluation under a shadowing of 4 dB and user density of 300 users per $sqkm$ revealed that Impv-XGBoost outperformed other models, misclassifying minimal instances. While OC-SVM showed acceptable performance, its misclassification rate was significantly reduced by Impv-XGBoost, even in higher shadowing conditions as shown in Fig. 3a. The performance of all models decreased with increased shadowing, highlighting the superior robustness of Impv-XGBoost. Additionally, increasing MDT density generally improved detection accuracy across all models, particularly for AE due to its reliance on extensive training data. However, Impv-XGBoost demonstrated superior performance across different shadowing levels and MDT densities, indicating its efficacy as a COD solution even in challenging environments as depicted in Fig. 3b and Fig. 3c for various conditions. These results underscore the potential of Impv-XGBoost in providing a reliable COD solution that excels in high shadowing conditions with efficient training time, setting the stage for the discussion on outage compensation solutions in the following section.

C. Outage Compensation Results

In this sub-section, we discuss the progress of the outage compensation solution based on the SARL-AC algorithm 4. The labels in each figure show the values of the combination of rewards in terms of AM (r_A^R), JFI (r_J^R), and GM (r_G^R), respectively. For instance, the combination “210” describes the case of $r_A^R = 2$, $r_J^R = 1$, and $r_G^R = 0$, which means JFI-assisted training is carried out. Along with the arithmetic mean of RSRP, the rewarding process should include the fairness mechanism to ensure that the overall mean values stick to the respective target after convergence. If fairness is included in terms of GM of RSRP only, it is depicted with the Rewards-201. Results show a faster convergence and less fluctuation from the target RSRP compared to the

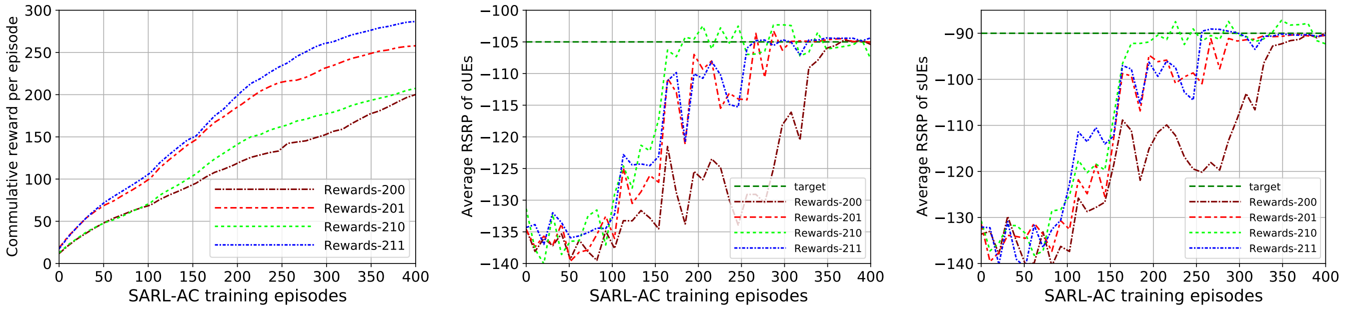

Fig. 4: The outage compensation with SARL training considering cUEs (oUEs + sUEs): (a) commutative rewards pattern for different combinations for training episodes, (b) average RSRP variations to training episodes for different rewards combinations for outage UEs, (c) average RSRP variations to training episodes for different rewards combinations for served UEs.

200 combination. The outage compensation with JFI-based rewarding is shown with Rewards-210. This case accelerates the convergence process and reaches the target values in the shortest episodes, however, it cannot reduce the random fluctuations. Finally in the last comparison, both the JFI and GM based rewarding are used in Rewards-211. This result strikes a balance in terms of the convergence time and post-convergence fluctuations minimization.

V. Conclusion

This research introduces an AI-based framework for efficiently detecting and compensating network outages in 5G&B networks. Utilizing the Improved XGBoost (Impv-XGBoost) model, our approach achieves high detection accuracy under conditions of significant shadowing with minimal training data, addressing key limitations of existing algorithms. For outage compensation, we apply an actor-critic-aided SARL method, optimizing the network's response base station failures. This method carefully balances service restoration for affected users and coverage maintenance for unaffected users, employing a reward mechanism that combines the GM and JFI to ensure equitable treatment across users. Our results demonstrate the effectiveness of this combined reward strategy in improving the learning process's stability and speed. Future directions include advancing proactive self-healing of multiple base station failures and root cause analysis capabilities within emerging network configurations, such as unmanned air vehicles assisted base stations for critical scenarios.

VI. Acknowledgment

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