Intelligent User Localization Application in Open-RAN Framework

Sanghui Lee* and Jaewook Lee†
*Department of Intelligent Robot Engineering, Pukyong National University, Busan, Korea
†Department of Information and Communication Engineering, Pukyong National University, Busan, Korea
E-mail: dltkdgml4730@pukyong.ac.kr, jlee0315@pknu.ac.kr

***Abstract*—In this paper, we propose an intelligent user localization application that adjusts based on the number of active base stations in the mobile network. To achieve this, we collect mobile network data using a simulator that supports the Open-RAN framework. Evaluation results demonstrate that the proposed application accurately predicts user locations when the number of active gNodeBs (gNBs) exceeds three.**

I. Introduction

The Open Radio Access Network (Open-RAN) framework is an emerging concept that aims to transform traditional mobile network architectures into open, interoperable, and intelligent systems. This openness facilitates flexibility, cost-efficiency, and innovation, enabling the seamless integration of AI applications for tasks such as UE positioning, energy management, and network optimization [1]. These compelling features have garnered significant attention from both academia and industry [2].

In the Open-RAN framework [3], various Open-RAN nodes (e.g., the Service Management and Orchestration (SMO) framework, Open-RAN Network Functions (NFs), the O-Cloud, and RAN Intelligent Controllers (RICs)) are interconnected via standardized interfaces (e.g., A1, O1, Open Fronthaul, O2, E2) as shown in Fig. 1. In the Open-RAN framework, a key component is the RIC node, which is divided into two types: the non-real-time RIC (non-RT RIC), responsible for long-term optimization and policy control, and the near-real-time RIC (near-RT RIC), which handles near real-time operations [4]. Specifically, the near-RT RIC enables near real-time control of services across E2 Nodes (i.e., O-CU-CP, O-CU-UP, and O-DU nodes). To achieve this, the near-RT RIC hosts various xApps, including AI models, and communicates with E2 nodes via the E2 interface. Additionally, xApps can interact with other NFs through the Y1 interface to receive AI-based mobile network services from NFs and/or to provide analytics information to them. Meanwhile, the near-RT RIC and the non-RT RIC are connected via the A1 interface, which facilitates policy definition and enrichment data exchange for the near-RT RIC and allows the non-RT RIC to gather mobile network data.

The modular design of the O-RAN architecture accelerates the rapid development and deployment of diverse AI applications (xApps) targeting specific objectives, such as intelligent user equipment (UE) positioning [5]. In [5], the AI application for UE positioning within the Open-RAN framework was developed. To mitigate the adverse effects caused by fluctuations in Signal-to-Noise Ratio (SNR) values, a moving average (MA) preprocessing technique was applied. Unfortunately, [5] only considered a scenario where a static and sufficient number of active base stations (i.e., the number of active gNodeBs in a 5G network) continuously provide mobile network data for inferring the target user's position. In contrast, by activating only the minimum number of base stations necessary to maintain sufficient location accuracy, the energy consumption of mobile network operations can be significantly reduced. [6] In this paper, we propose an AI application that performs UE positioning according to the number of active gNBs to analyze the relationship between the number of active gNBs and the accuracy of the user's location. To make the AI model, we propose an MA-based SNR data preprocessing technique. In addition, the AI model takes SNR values and location data from active gNBs as inputs, adjusted for the specific gNB combination. The evaluation results show that the proposed AI application accurately predicts UE (User Equipment) positions when the number of active gNBs (gNodeBs) exceeds 3.

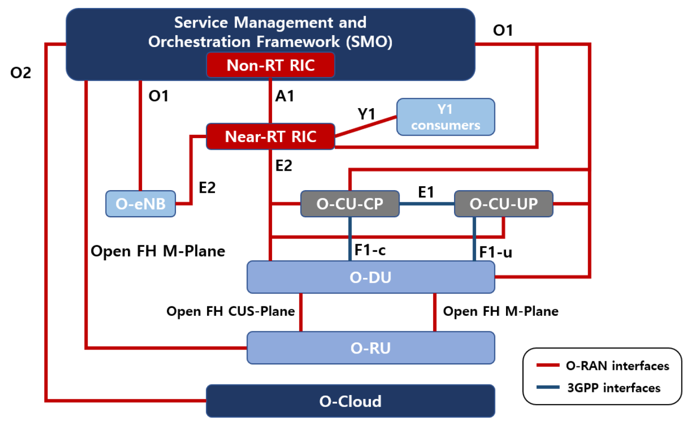

Fig. 1. Logical Architecture of Open-RAN [3]

The remainder of this paper is organized as follows: the AI model for UE positioning relative to gNB count is proposed in Section II. Experimental results are presented in Section III. Concluding remarks are provided in Section IV.

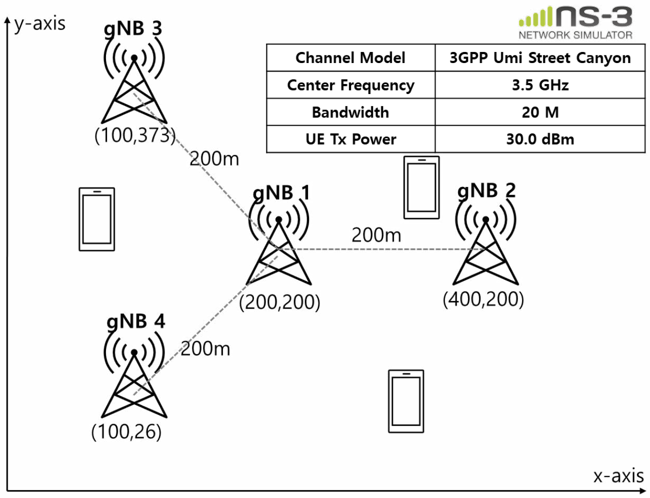

Fig. 2. Simulation Environment.

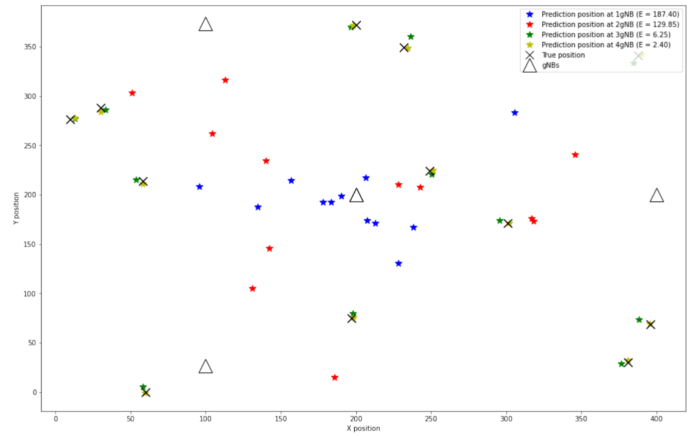

Fig. 3. The prediction positions.

II. Intelligent User Localization Application

In this section, we propose a UE positioning AI models according to the number of active base stations (gNBs). For our research, we set up a simulation environment using Network Simulator-3 (NS-3) with Open-RAN framework [7], as shown in Fig. 2. The simulation environment comprises four gNBs and twelve UEs with fixed locations. gNBs measure the SNR values of the UEs, which serve as input data for UE positioning. With the measured values, xApp conducts the preprocessing step to extract the necessary features (e.g., SNR values per UE and the location coordinates of each UE and gNB) required for UE positioning from each UE trace extracted through the simulator. Additionally, as in previous research [5], we apply the MA technique to alleviate the randomness of SNR values, selecting a time window size of 5 seconds which produced the best predictive performance. We design the AI models at different numbers of active gNBs, incorporating various gNB combinations. For instance, when three gNBs are active, we use trace files for combinations such as $(1110, 1101, 1011, 0111)$, where 1 indicates an active gNB, and 0 represents an inactive one. Each digit in the binary combination represents the on/off status of specific gNB, with the positions fixed to indicate specific gNBs. Given the variability in SNR values between gNBs, distinguishing SNR sources becomes challenging without additional information. Therefore, we include the gNB location coordinates as input data, enabling the model to identify SNR values by source. This setup results in a total of four AI models, each corresponding to scenarios with 1 to 4 active gNBs.

We employ a Multi-Layer Perceptron (MLP) architecture with 512 hidden neurons across 6 layers. Each model uses the SNR values and gNB locations as input features, with the XY coordinates of the UE as output values. The input dimension of each model varies according to the number of active gNBs. We train the AI model with 60000×15 (gNB combinations) training samples using the Adam optimizer, with a learning rate of 0.001, a dropout rate of 0.2, an MSE loss function, and ReLU activation function.

III. Simulation Results

To evaluate the performance of the proposed AI model, we utilize the RMSE (Root Mean Square Error) value E. The formula for calculating RMSE is provided in $E = \sqrt{\frac{1}{I}\sum_i^I ||y_i - \hat{y}_i||^2}$, where E is derived by computing the distance difference between the predicted position of UE and the actual UE position. I represents the number of test samples, y_i indicates the true UE position of the i-th sample, and $\hat{y}_i$ stands for the predicted UE position obtained from the trained AI model. In our experimental setup, the gNBs are fixed at predetermined locations, while the UE positions are randomly assigned for each simulation.

Fig. 3 visualizes the true positions of the UE and gNBs, as well as the predicted positions of the UE for each AI model in a specific simulation. In this figure, large triangles represent the four fixed gNB locations, and the X marker denotes the true positions of the UE. The predicted positions of the UE for models with 1 to 4 active gNBs are displayed as stars in blue, red, green, and yellow, respectively. Notably, the predictions of the models with 3 and 4 active gNBs exhibit higher accuracy.

Fig. 4 presents the effect of gNB count on UE positioning accuracy, comparing the RMSE values of each model. As shown in the graph, the RMSE values are lowest when the gNB count is 4, with a similarly low RMSE observed at a gNB count of 3. Specifically, the RMSE decreases sharply as the gNB count increases up to 3, beyond which it stabilizes, showing only a minor difference compared to the 4-gNB model. This result indicates that with at least 3 active gNBs, the model can achieve reasonably accurate UE positioning. Furthermore, it suggests that turning off the remaining gNB may allow for energy savings while maintaining satisfactory prediction performance.

IV. Conclusion

In this paper, we develop and evaluate an AI model for UE positioning in mobile networks based on the Open-RAN

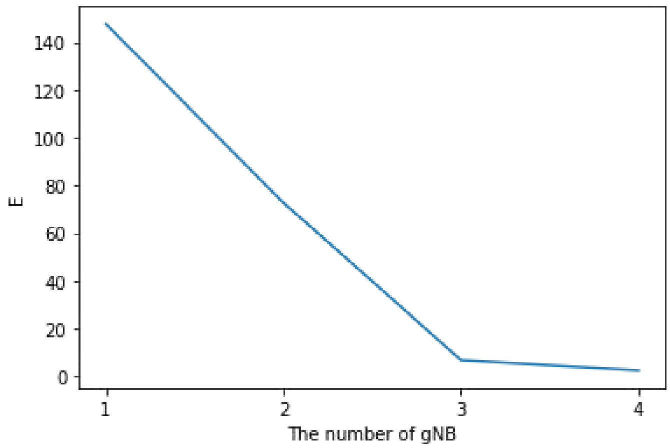

Fig. 4. The effect of the number of gNBs.

framework, comparing performance across varying numbers of active gNBs. Our results show that the model achieves higher accuracy in positioning when three or more gNBs are active. Thus, deactivating non-essential gNBs while retaining only those necessary for accurate UE positioning yields benefits in terms of energy efficiency. Future research will aim to extent this study to more complex environments with a larger number of gNBs and UEs, as well as to investigate optimal strategies for selecting which gNBs to deactivate to further enhance energy efficiency.

ACKNOWLEDGEMENT

This work was supported in part by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (No. RS-2023-00225468, Development of RAN Intelligent Controller for O-RAN intelligence) and in part by the National Research Foundation(NRF), South Korea, under project BK21 FOUR (Smart Robot Convergence and Application Education Research Center).

REFERENCES

[1] S. K. Singh, R. Singh, and B. Kumbhani, "The Evolution of Radio Access Network Towards Open-RAN: Challenges and Opportunities" in *Proc. IEEE Wireless Communications and Networking Conference Workshops(WCNCW)*, Seoul, Korea, Apr. 2020.

[2] D. Wypiór, M. Klinkowski and I. Michalski, "Open RAN—Radio Access Network Evolution, Benefits and Market Trends" *Appl. Sci.*, vol. 12, no. 1, pp. 408, Jan 2022.

[3] O-RAN Alliance "O-RAN Architecture Description 12.0," *O-RAN.WG1.OAD-R003-v12.00*, Jun. 2024.

[4] L. Bonati, S. D'Oro, M. Polese, S. Basagni, and T. Melodia, "Intelligence and Learning in O-RAN for Data-driven NextG Cellular Networks," *IEEE Communications Magazine*, Oct. 2021.

[5] Sanghui Lee, Seung-Eun Hong, Hoon Lee, and Jaewook Lee, "Intelligent Application for User Equipment Positioning in Open-RAN," in *Proc. International Conference on ICT Convergence (ICTC) 2024*, Jeju, Korea, Oct. 2024.

[6] O-RAN Alliance "O-RAN Use Cases Analysis Report 15.0," *O-RAN.WG1.TR.Use-Cases-Analysis-Report-R004-v15.00*, Oct. 2024.

[7] A. Lacava, *et. al.,* "ns-O-RAN: Simulating O-RAN 5G Systems in ns-3," *arXiv preprint arXiv:2305.06906*, Jun. 2023.