# An Energy-Efficient Ultra-Dense Network Cell Coverage Adjustment Algorithm


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***Abstract*— Ultra-dense network (UDN) plays a key role in 5G networks to provide ultra-high speed, ultra-low latency data services by densely deploying multiple small cells in specific areas. Numerous small cells can increase network capacity and improve quality of service (QoS), while the network structure has become more complex. Due to the large number of mobile users and frequent handover in these areas, the traffic demand varies rapidly over time. It induces a severe imbalance of mobile traffic load among small cells. The users suffering from load imbalance require frequent handover, which implies a significant increment in energy consumption. In this paper, we propose the cell range adjustment by biasing reference signal received power (RSRP) to achieve load balancing and higher energy efficiency. The values of bias are determined by considering the amount of cell traffic and cell range inversely proportional to the amount of cell traffic. To estimate the amount of cell traffic, the traffic prediction is performed based on long short-term memory (LSTM) algorithm. Simulation results show that our proposed cell range adjustment algorithm increases the throughput of edge users at the cost of a slight decrease in average signal-to-noise ratio (SNR).



***Keywords—Ultra-Dense Network(UDN), Cell Range Adjustment, User Association, Load Balancing, Traffic Prediction***


## I. Introduction

With the advancement of mobile communication technology, new services such as VR, OTT services, and autonomous driving have emerged. As the number of mobile users using these services increases, the average data usage per user is also growing exponentially and network failures occur frequently. To manage high-loaded data traffic, LTE Release 10 introduced a heterogeneous network (HetNets) structure that increases cell capacity per area by deploying small cells inside the macro cell [1]. Small cells reduce the physical distance to mobile users, allowing for low-power communication. And they can serve better quality of service (QoS) and improve energy efficiency in areas that require a large amount of power (e.g., cell boundary). The importance of small cells has increased, and the 5G network consists of densely deployed small cells, which is called to the ultra-dense network (UDN).

Although UDN increases network capacity, it causes some problems and challenges to network. The spatio-temporal traffic demands tend to change rapidly because of the deployment of dense cells at a large floating population. This can cause load imbalance and lower spectral efficiency among small cells [2]. Moreover, as the number of small cells increased, mobile network operators have become large energy consumers [3], [4]. In terms of terminal, it frequently attempts handover in UDN because of the characteristic of performing handover to enhance QoS, improve throughput, and reduce monetary cost [5]. As a result, power used for unnecessary handover accounts for about 20% of the total cellular network power consumption, and the terminal's battery performance is degraded [6], [7]. If base stations can adjust their coverages according to the traffic, load imbalance can be reduced by efficient utilization of frequency resources, and energy-efficient communication can be achieved by preventing unnecessary handovers.

As the cell coverage adjustment algorithm for small cells, cell range expansion (CRE) has been utilized [8]. However, in UDN, CRE cannot solve the load imbalance among small cells because of interference of adjacent small cells and rapid changes in spatio-temporal traffic demand [9]. Therefore, we propose an algorithm using traffic prediction to achieve load balancing among small cells in UDN. As shown in Fig.1, we first predict the mobile traffic load for each small cell during a certain amount of time, and calculate the bias values of CRE with predicted value. Small cells adjust their coverage by applying the computed bias.

This paper is organized as follows. First, in Section II, we overview the related works. Section III presents the simulation system model of UDN. In Section IV, a traffic prediction-based load balancing algorithm is proposed. Section V shows the simulation results, and conclusions are presented in Section VI.

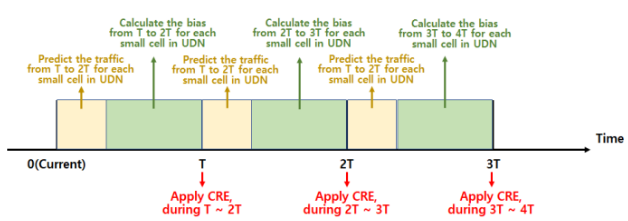


Fig. 1. Load balancing algorithm using traffic prediction

## II. RELATED WORKS

### A. Time Series Data & Analysis

Time series data is measured at regular time intervals, and it is chronological order data. The mobile traffic load is also time series data. It can be the amount of the UE's data or the base station's processed load. Time series analysis is the process of understanding data by analyzing relationships between multiple variables. The time series data is decomposed into three components: trend, seasonal, and residual using Seasonal and Trend decomposition using Loess (STL). STL has many advantages than classical, SEATS and X11 decomposition [10]. The STL allows users to adjust the rate of seasonality change, so it facilitates to decompose even if the seasonality changes over time. And abnormal values are decomposed into residual components to avoid affecting trend, seasonal components. Therefore, trend data shows the general change in traffic's rising or dropping pattern, and seasonal data shows the repeated pattern. Data in fig. 2. is a time series dataset that records mobile traffic load processed by a specific base station for one month from 00:00 09/17/2022 to 23:00 10/16/2022, provided by a mobile network operator in South Korea. Fig. 3. to fig. 5. show trend, seasonal and residual graphs, respectively. To formularize the time series decomposition,

$$y_t = S_t + T_t + R_t \, , \qquad (1)$$

$y_t$, $S_t$, $T_t$, $R_t$ are time series data, seasonal, trend and residual, respectively.

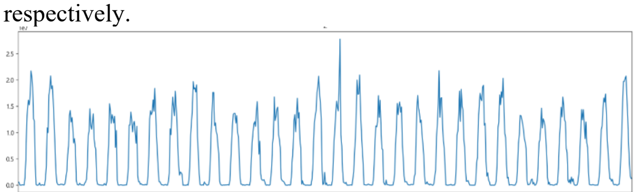

Fig. 2. The original data graph

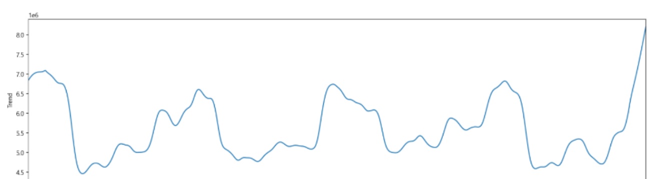

Fig. 3. The trend component

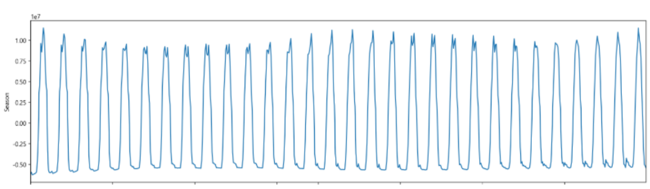

Fig. 4. The seasonal component

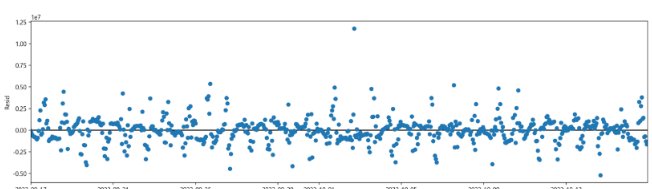

Fig. 5. The residual component

### B. Traffic Prediction

As mentioned earlier, the amount of mobile traffic varies significantly across time in densely populated places. It is necessary to proactively react for radical changes, such as securing system capacity to prevent network congestion. Therefore, prediction techniques are crucial in radio resource management (RRM). We can use time series data to predict future traffic patterns. We conducted traffic prediction using the data presented in fig. 2. We separated the data from 00:00 09/17/2022 to 23:00 10/13/2022 data for model training and the test is performed for the rest data. As proposed in [11], we use long short-term memory (LSTM) as the model for prediction of the original, un-pre-processed data. The predicted result is figured in fig. 6.

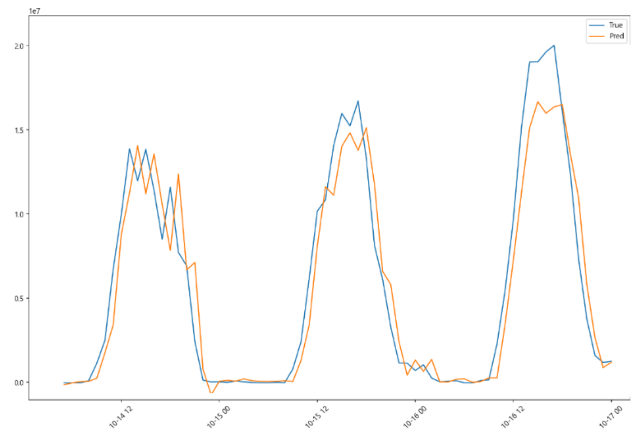


Fig. 6. Original data & predicted data

The orange line for predicted data is well follow the original data represented by blue line. This indicates a successful prediction and demonstrates the potential to cell rage adjust proactively by using prediction. The prediction model is being actively studied for performing faster and more accurately.

### C. Cell breathing and User Association

In CDMA-based cellular network generation, cell breathing, a mechanism for load balancing, was first introduced [12]. Heavily loaded cells decrease the coverage while not-heavy neighboring cells increase their coverage to compensate. This allows partial UEs located at the cell boundaries with low channel capacity to move to the new cell having a capacity margin and helps lighten base station traffic congestion. To adjust the coverage, the base station's transmission power was controlled [13].

In 4G and 5G, there are many researches and algorithms of user association to use environmentally and efficient base stations [14], [15]. One of them is the biasing technique, setting bias values for the received power of low-power BSs, such as small cells can offload UEs to lightly loaded BSs. But setting bias values is hard to determine optimally and takes a lot of time. A lot of approaches to solve these optimization problems have been studied: projected gradient descent (PGD), decision-making processes like game theory and Markov chain and reinforcement learning, etc. [15]. One of their challenges is that they require complex mathematical derivations and significant computational processing. Although using high-performance equipments, there is still time cost involved. Another issue in optimization problems is that the Jain's fairness index is commonly used as the objective function or evaluation metric [9], [16], [17]. However, it cannot consider the data rate or data needs of each user, even though each UE requires a different QoS. Therefore, we should consider the alternative metrics or objective functions in the user association's aspect. So, we proposed a simple and comfortable user association algorithm.

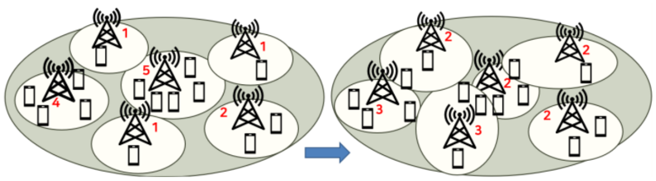

Fig. 7. The example of user association

## III. System Model

In this paper, we assumed that small cells can predict the data usage of mobile users and the cell traffic is predicted by aggregating the user traffics. Table 1 summarizes the average amount of data for specific services per hour. Each mobile user randomly selects one of these services and changes their applications over time. Table 2 summarizes the parameters used in the simulation. The locations of the small cells and mobile users are distributed according to a homogeneous Poisson point process. The parameters of eq. (2) are based on the general model presented in 4.1.1 of ITU-R P.1411-10, which can be found in Table 3. The model is applied in an urban high-rise building environment, with a frequency range of 0.8 to 38 GHz and a distance range of 30 to 715 m.

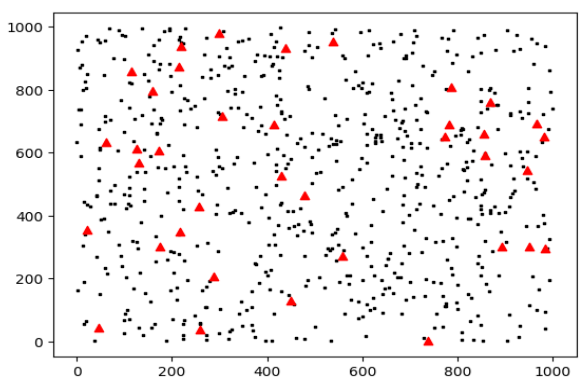


Fig. 8. Base stations (red triangle) and UEs distribution

TABLE I. Estimate of Application Data Usage Per Hour

| Application | Value |
|---|---|
| Internet | 0.53 GB |
| SNS | 1.49 GB |
| Video | 2.5 GB |
| Music | 0.86 GB |
| Video Chat | 1 GB |
| Game | 0.79 GB |

TABLE II. Simulation Parameter

| Parameter | Value |
|---|---|
| UE PPP ($\Phi u$)'s density ($\lambda u$) | 700 / km$^2$ |
| SBS PPP ($\Phi s$)'s density ($\lambda s$) | 40 / km$^2$ |
| Covered Area | 1000*1000 m$^2$ |
| Total simulation time | 10 hours |
| Predict period | 1 hour |
| Carrier frequency | 28 GHz |
| Transmit power | 30 dBm |
| Antenna gain | 18 dBi |
| Bandwidth | 800 MHz |
| Noise spectral density | -174 dBm / Hz |
| Path loss model | ITU-R P,1411-10 |

TABLE III. TU-R P.1411-10 α, β, γ, Shadowing Factor

| | α | β | γ | σ |
|---|---|---|---|---|
| NLOS | 4.00 | 10.2 | 2.36 | 7.60 |

$$Pathloss(d_s, f_c) = 10\alpha \log_{10} d_s + \beta + 10\gamma \log_{10} f_c + X_\sigma \qquad (2)$$

## IV. Proposed Algorithm

$$K_i = \frac{\frac{1}{Traffic_i}}{\sum_{j=1}^{N_{SBS}} \frac{1}{Traffic_j}} \times N_{SBS}\,,\ Bias_i = \begin{cases} K_i, & if\ K \geq 1 \\ 1, & if\ K \leq 1 \end{cases} \qquad (3)$$

$$\begin{aligned} RP_i &= Bias_i \times Received\_Power_i,\ for\ i = 1,2,\ldots,N_{SBS} \\ Connected\_BS_j &= \underset{i}{argmax}\, RP_i,\ for\ j = 1,2,\ldots,N_{UE} \end{aligned} \qquad (4)$$

Equation (3) is the formula for bias calculation. Algorithm 1 describes how eq. (3) is used in detail and how it is applied to each base station. For a predetermined period $T$, based on the connection between mobile users and small cells, the total mobile traffic load that each small cell should serve for the next interval is calculated. When determining the total mobile traffic load for each small cell, it can be expected that the larger the number, the more overloaded it will be. By using the fact that the inverse number of large one becomes smaller, we proposed cell range adjustment algorithm. In algorithm, mobile users measure the received signal power served by adjacent small cells and calculate the bias value based on the predicted mobile traffic load of these small cells, as shown in eq. (4). The bias values of small cells with low mobile traffic load are larger than small cells with high mobile traffic load. Therefore, users are more likely to associate with lightly loaded small cells by adopting the proposed algorithm. In addition, the proposed algorithm can prevent unnecessary handover by associating users with lightly loaded cells. Even though the practical received power from lightly loaded small cell is smaller than high loaded small cell, cell edge users are associated with lightly loaded cell resulted from considering bias value.

**Algorithm 1.** Proposed Cell Range Adjustment Algorithm

```
Initialize number of UEs with N_UE
Initialize number of SBSs with N_SBS
Initialize number of Predict Period with T

let current = xT, x ≥ 0
// Suppose the current time is xT

for a ∈ { 1, ..., N_SBS } do
    for b ∈ { current + T, ..., current + 2T } do
        Traffic_a = Traffic_a + Traffic_a_b
        // Calculate SBS traffic Traffic_a during
        // (current + T) to (current + 2T)
    end for
    Total = Total + 1/Traffic_a
end for

for a ∈ { 1, ..., N_SBS } do
    Bias_a = N_SBS * (1/Traffic_a) * 1/Total
    If Bias_a ≥ 1 then
        Bias_a = Bias_a
    else
        Bias_a = 1
    endif
end for
// Apply biases each SBS during (current + T) to (current + 2T)
```

The bias value ranges from 0 to the average cell traffic divided by each cell traffic that reflects each cell load condition compared to average network capacity. For the positive real values, the arithmetic average always greater than or equal to harmonic average. We induce the algorithm from arithmetic-harmonic mean inequality,

$$\frac{x_1 + x_2 + \cdots + x_n}{n} \geq \frac{n}{\frac{1}{x_1} + \frac{1}{x_2} + \cdots + \frac{1}{x_n}} \geq 0 \,. \quad (5)$$

$(x_1, x_2, \ldots, x_n)$ is the vector of the amount of predicted traffic of each cell. The upper bound of bias value is calculated by multiplying $\frac{1}{x_i}$ $(i = 1, 2, \ldots, n)$ to the average traffic value. Then

$$\frac{x_1 + x_2 + \cdots + x_n}{n} \times \frac{1}{x_i} \geq \frac{n}{\frac{1}{x_1} + \frac{1}{x_2} + \cdots + \frac{1}{x_n}} \times \frac{1}{x_i} \geq 0 \,. \quad (6)$$

The middle term of eq. (6) corresponds to the bias value, $K_i$ in eq. (3).

$$\frac{x_1 + x_2 + \cdots + x_n}{n} \times \frac{1}{x_i} \geq K_i \geq 0 \,. \quad (7)$$

The upper bound of the bias value is the mobile traffic load of a specific cell compared to the average network capacity. If the mobile traffic load of a specific cell is larger than the average network capacity, reduce the bias value to reduce the cell range. That is, if the predicted load of a small cell is larger than the average network capacity, the cell coverage is reduced by setting a smaller bias value. Similarly, the mobile traffic load to be covered by a small cell is smaller than the average network capacity, and the coverage is increased to approach to average network capacity.

## V. Simulation

Fig. 9. shows a graph comparing SNR depending on the introduction of the proposed algorithm. And fig. 10. shows capacity comparison. When looking at two graphs for the lower 20% of mobile users, proposed algorithm increases the throughput of edge users at the cost of a slight decrease in signal -to-noise ratio (SNR). Due to the influence of bias, there are cases that some mobile users connect to the base station at a longer distance, so the SNR is reduced slightly. In term of total network capacity, the proposed algorithm achieves capacity improvement. By pre-setting coverage by each base station in the UDN, unnecessary handover attempts of the terminal may be reduced. Therefore, it can reduce the network burden and save power consumption enabling energy-efficient communication with a long battery life.

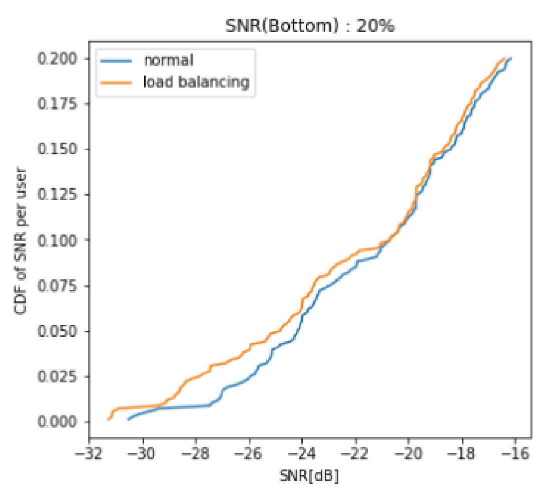


Fig. 9. Comparison graph of SNR according to the introduction of algorithms

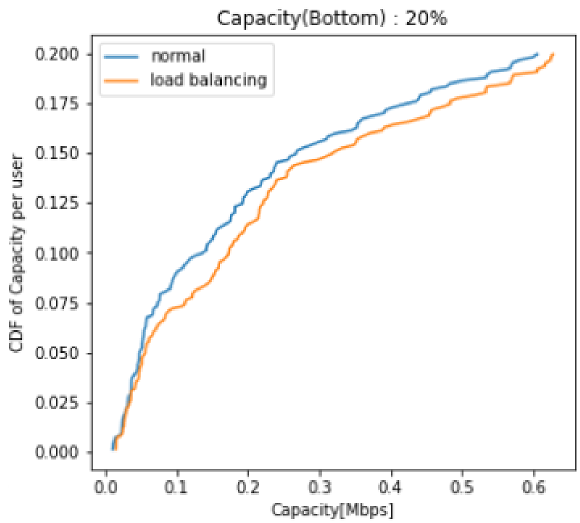


Fig. 10. Comparison graph of capacity according to the introduction of algorithms

## VI. CONCLUSION

The proposed algorithm is used for coverage adjustment of small cells in the UDN. By applying our algorithm, mobile users at heavily-loaded base stations are connected to other less-loaded cells in adjacent areas to distribute the traffic. The simulation result shows that the throughput of edge users is increased. In future research, we need to formulate this problem as an optimization problem and mitigate it with more sophisticated algorithms using reinforcement learning, which is expected to increase the network capacity and improve energy efficiency compared to the proposed algorithm.

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