

# UE Throughput Guaranteed Small Cell ON/OFF Algorithm with Machine Learning

Tae-Yoon Park, Jong-Won Han, and Een-Kee Hong

**Abstract:** Ultra-dense network (UDN) has been considered a promising solution to improve the signal quality of cell edge UEs and enhance the serving coverage. However, a large number of small cells causes severe inter-cell interference and high energy consumption, and efficient small cell management is an important issue. In this paper, a UE throughput guaranteed small cell on/off algorithm in UDN environment is proposed to solve the problem of UE throughput reduction due to small cell off process. The proposed small cell on/off algorithm with machine learning is executed by the following processes: First, the network attributes that affect UE throughput are analyzed. Second, the correlation between UE throughput and network attributes is evaluated through multiple linear regression analysis. Third, through understanding the correlation between UE throughput and network attributes, we determine the proper criteria for small cell on/off process. Simulation results show that the proposed small cell on/off algorithm can improve the total network energy efficiency as well as efficiently ensure sufficient UE throughput. Compare to the conventional algorithm, the proposed algorithm shows more than 75% improvements of average network energy efficiency. whole network.

**Index Terms:** Cell densification, energy efficiency, machine learning, small cell ON/OFF, throughput, UDN.

## I. INTRODUCTION

TO cope with the explosive growth of mobile devices and applications, network capacity problem is becoming a hot research topic. UDN where small cells (SCs) are densely deployed is one of the promising key solutions for the capacity problem. Since the frequency reuse factor is 1 in the conventional systems, more frequency reuse effect is exploited and more radio resources allocated to user equipment (UE) with cell densification [1]. But cell densification causes severe inter-cell interference, high network complexity, and frequent handover problem.

The SC on/off scheme, first proposed in 3GPP Release 12, plays a critical role in efficient network operation. The scheme enables the improvement of network energy efficiency (NEE) by turning off unnecessary cells [2]. As shown in Fig. 1, UEs of

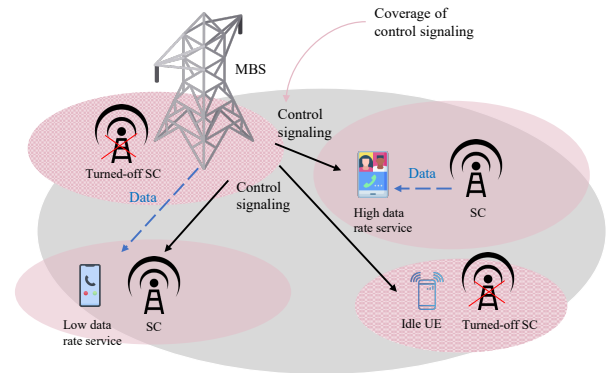


Fig. 1. Network setup of the proposed model.

low data rate service are connected to macro base station (MBS) and UEs of high data rate service are connected to SC. However, in terms of overall network energy efficiency, it is beneficial to turn off SCs that have small number of connections with UEs. In particular, the role of SC on/off is expected to become more important in UDN because the probability of occurring unnecessary cells is higher than the conventional network. However, turning off SCs can be a burden on other cells and the QoS can be degraded [3], [4]. Thus, enough consideration should be given about which cells to be turned off.

Many researches have been performed on SC on/off strategies. The most basic method is to turn off inactive SCs [3]. However, in the UDN environment, the degree of improvement in NEE by turning off only the SCs that have no connection with UE is not significant. Since the coverage of SC is often overlapped in the UDN environment, the network operates surplus SCs, and the efficient management of SCs should be developed.

It is an important task to determine which SCs are to be turned off because the traffic load should be handed over to the surrounding SCs. Many studies have addressed the issue of determining proper SCs to be turned off. In [6], the SCs that did not overload the neighboring cells due to handover load were turned off to ensure energy efficiency and QoS. In [7], with an aim to mitigate the co-frequency interference with less signaling overheads and measurement processes, a centralized SC on/off algorithm based on interference contribution ratio was proposed. In [8], since the gain of cell densification is saturated, the appropriate number of active SCs was founded, and excess SCs were turned off.

However, the previous researches performed SC on/off process based on the average network throughput and did not consider the effect of SC on/off on individual UE throughput. As the ensuring QoS of UE becomes important, SC on/off process should be carried out under the condition of ensuring sufficient

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UE throughput. However, since it is difficult to consider the individual UE throughputs at the same time, to find the proper SCs to be turned off it is a sophisticated challenge. Turning off cells changes network attributes such as inter-cell interference and NEE, each attribute has a different impact on UE throughput. In order to guarantee UE throughput, we should figure out the effect of each attribute on UE throughput. Since it is difficult to predict how the altered network attributes after SC on/off affect UE throughput, we use the multiple linear regression model in finding a correlation between UE throughput and network attributes. Multiple linear regression model is a typical analysis model to estimate the correlation between dependent variable and several independent variables. Through understanding the correlation between UE throughput and network attributes, we determine the criteria for SC on/off to improve NEE without significant UE throughput reduction. The contributions of this paper are summarized as follows.

- In consideration of UE throughput, we propose an algorithm that increases NEE through SC on/off process as well as solves UE throughput degradation problem. The network attributes that affect UE throughput after SC on/off are analyzed.
- Through the analysis on correlation between UE throughput and network attributes, we provide criteria for turning off cells that do not degrade UE throughput.
- We acquire reliability of algorithm and improve performance by using machine learning that can utilize a lot of data convincingly.

The remainder of this paper is organized as follows: In Section II, we present system model. The proposed algorithm for predicting UE throughput is described in Section III, and we show performance results in Section IV. Finally, concluding remarks are given in Section V.

## II. SYSTEM MODEL

This paper consider mainly downlink communication in UDN environment. All UEs and SCs are deployed according to the Poisson point process (PPP) [5]. SCs are denoted by  $S_n$ .  $UE_{n,k}$  ( $k = 0, 1, 2, \dots, K_n - 1$ ) represents the  $k$ th UE in the  $n$ th SC. The signal to interference plus noise ratio (SINR) of the  $k$ th UE associated with the  $n$ th SCs is

$$SINR_n^k = \frac{P_n^T h_{n,k}}{\sum_{i=1}^{i \neq n} P_i^T h_{i,k} + N_0 BW_{n,k}}, \quad (1)$$

where  $P_n^T$  is the transmission power of SC,  $S_n$  and  $h_{(n,k)}$  is the channel gain between SC  $S_n$  and  $UE_{(n,k)}$  including the path loss and shadowing effect.  $N_0$  is the noise power spectral density and  $BW_{(n,k)}$  is the bandwidth allocated to  $UE_{(n,k)}$ . UE is associated with a cell that provides the largest reference signal received power (RSRP) among the SCs.

When a SC is turned off with SC on/off process, the UEs in inactive cells are handed over to neighboring cells. At time  $t$ , the traffic arrival rate of UE is modeled as an independent Poisson distribution with mean arrival rate,  $\lambda(x, t)$  where  $x$  denotes the location of UE. Its requested data size is assumed to be an

exponentially distributed random variable with mean,  $1/\mu(x, t)$ . The average traffic load  $r(x, t)$  of UE is defined as

$$r(x, t) = \frac{\lambda(x, t)}{\mu(x, t)}. \quad (2)$$

The maximum data rate of the  $k$ th UE served by SC  $S_n$  is given by

$$R_{n,k} = BW_{n,k}(1 + SINR_{n,k}). \quad (3)$$

The power of SC is divided into transmission power,  $P^T$  and basic power,  $P^b$ . The basic power is the power consumption for baseband processor, cooling equipment, and so on. The power consumption of the  $n$ th SC can be expressed as

$$P_n = I_n(P^T + P^b) + (1 - I_n)P^b, \quad (4)$$

where  $I_n$  indicates the state of the  $n$ th SC,  $I_{n=1}$  means that SC is active and  $I_{n=0}$  means SC is turned off. NEE can be used to determine how efficiently energy is being used [2].

$$NEE = \frac{\sum_{n=0}^{N-1} \sum_{k=0}^{K_n-1} R_{n,k}}{\sum_{n=0}^{N-1} P_n}. \quad (5)$$

## III. ALGORITHM FOR PREDICTING USER DATA THROUGHPUT

SC on/off process has the various effects on the network because the traffics of turned off cells are handed over to neighboring cells. Although several SCs are turned off in order to improve NEE, the UEs in turned off cell may be connected to a SC that shows a lower RSRP than original cell and UEs in neighboring cell have to share the radio resource with handover UEs [9]. Therefore, the SC on/off process is carried out after sufficient consideration. In this section, we first analyse how each network attribute affects UE throughput. Among the network characteristics changed after the SC on/off, the characteristics affecting the throughput were investigated. Five of the most influential attributes were selected and defined as characteristics that affect throughput. Then, since the selected network attributes have different effects on UE throughput, we consider all network attributes together by analyzing the correlation between the combined effect of all considered network attributes and UE throughput. We use multiple linear regression analysis to figure out the correlation.

### A. Network Attributes Related to Small Cell ON/OFF

The SC on/off process changes the attributes of network and results in the UE throughput variation. We predict the variation due to SC on/off through the analysis on the correlation between network attributes and UE throughput. In this paper, five network attributes that have a significant effect on UE throughput are selected.

Table 1 is a result of preliminary task to find network attributes that have a significant correlation with UE throughput. Normalized value means that the amount of throughput variation due to small cell on/off process and normalized by the UE

Table 1. Normalized throughput variation result from small cell on/off process.

Network attributes	Normalized value
Throughput	1
Total power consumption	0.78231216218
Total traffic load	-0.68542154223
The high-loaded cell ratio	-0.45332123119
Total number of UEs in a cell	-0.14532152127
The inter-cell distance	0.23456195921
Total number of edge area UEs	-0.04234400663
Total center area UEs	0.00234520121
The delay-sensitive UE ratio	-0.08293145131

throughput Among 8 network attributes, five network attributes that have meaningful correlation with UE throughput were selected. Five attributes were selected as follows.

**Total power consumption (TPC):** Power consumption is proportional to the number of active SCs. As the number of active SCs increases, the number of UEs per cell decreases and wider bandwidths can be allocated to UEs. The higher power consumption is, the more the gain of UE throughput. When the power of SCs is 30 dBm, the total power consumption of the network is as follows

$$TPC = 1W \times \text{Number of Active Cells.} \quad (6)$$

**Total traffic load (TTL):** Total traffic load represents the sum of the traffic loads of UEs distributed in network. Increasing the amount of traffic to be processed leads lowering the throughput per UE.

$$TTL = \sum r(x, t). \quad (7)$$

**The high-loaded cell ratio (TCR):** The high-loaded cell ratio represents the percentage of SCs with a higher system load than 0.5 [6]. The system load is defined by the sum of the average traffic load in (2) divided by the maximum data rate in (3).

$$H_n = \sum_{k=0}^{K_{n-1}} \frac{r(x, t)}{R_{(n,k)}}. \quad (8)$$

Since the radio resource per UE is limited in high-loaded cell, the lower UE throughput is provided in the higher high-loaded cell ratio network.

$$TCR = \frac{\text{number of high loaded cell}}{\text{Total number of Cells}}. \quad (9)$$

**Total number of UEs in a cell (TU):** As the number of UEs in a SC increases, the radio resources per UE decreases. Even though each traffic load of UE is different, the number of UEs is one of import network attributes for SC on/off.

**The inter-cell distance (TD):** The shorter distance between active cells causes the higher inter-cell interference and results in reducing UE throughput. And it is advantageous because the distance between cell and UE is short when the turned off SC UE is handed over to the neighbour cell. By selecting a cell having shorter TD to be turned off, the longer TD is achieved and it gives a positive effect on throughput.

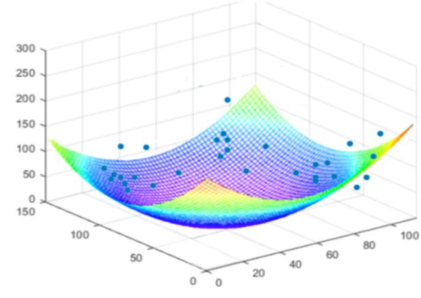


Fig. 2. Example of multiple linear regression model.

### B. Multiple linear Regression Analysis on Correlation between Network Attributes and UE Throughput

To analyse the correlation between the five network attributes and the UE data throughput, we use a multiple linear regression analysis. We can figure out the impact of each network attributes on UE throughput based on correlation analysis and determine the criteria for SC on/off. Multiple linear regression analysis can be used to estimate the correlation between various dependent and multiple independent variables. Fig. 2 is an example of the model obtained through the analysis.

The model of multiple linear regression analysis is follows

$$y_k(i) = y_0(i) + \bar{\beta} \cdot \bar{x}, \quad (10)$$

$$\bar{\beta} = (\beta_1 \beta_2 \beta_3 \beta_4 \beta_5)^T, \quad (11)$$

$$\bar{x} = (x_1 x_2 x_3 x_4 x_5). \quad (12)$$

$\bar{x}$  is the input variables of each network attribute, and is the slope coefficients for variables. In the  $i$ th simulation,  $y_0(i)$  and  $y_k(i)$  are the throughputs of the  $k$ th UEs before and after performing SC on/off, respectively. Since it is difficult to find out the exact values of  $\beta$ , we adjust the values iteratively to minimize the estimation errors on determining  $\beta$  values. The process of finding the minimum value described above is called the gradient descent method.

The weight is updated by using the gradient for each parameter calculated by differentiating the error function for all data by weight. At this time, the value that determines how much gradient to use is called the learning rate. The equations for error are as follows

$$L_i = \sum_{k=0}^{k_1+k_2+k_3+\dots+k_{n-1}} (y_k(i) - \hat{y}_k(i))^2 \quad (13)$$

$$= \sum_{k=0}^{k_1+k_2+k_3+\dots+k_{n-1}} (y_k(i) - \sum_{j=1}^r (\beta_j \times x_j))^2. \quad (14)$$

$L_i$  is the sum of squared errors of the UE throughput predictions of the  $i$ th simulation,  $\hat{y}_k(i)$  is the predicted throughput of the  $k$ th UE in the  $i$ th simulation.  $N_S$  is total number of simulations used for multiple linear regression analysis, and  $r(= 5)$  is

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**Algorithm 1. The Proposed Small Cell ON/OFF with Machine Learning.**


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- 1: **Input** :  $x_r(i)$  and  $u(i)$
  - 2: **for**  $i=1$  to  $N_S$  **do**
  - 3:   Save 5 attributes and throughputs :  $x_{1,2,3,4,5}(i), \overline{u(i)}$
  - 4:   **Find correlation** :
  - 5:   | minimize the sum of squared errors
  - 6:   | optimize with gradient descent optimizer
  - 7:   | update  $\hat{\beta}$
  - 8: **end for**
  - 9: Generate final multi- linear regression model
  - 10: **Small cell selection**
  - 11:   | Identify applicable adjustment combinations
  - 12:   | Combination selection: max NEE
  - 13:   | Turn off the small cells of combinations: max NEE
- 

the number of considered network attributes. We find the point  $m$  that shows the minimum prediction error.

$$m = \frac{\partial}{\partial \beta_i} \quad (15)$$

$$= -2 \sum_{k=0}^{k_1+k_2+k_3+\dots+k_{n-1}} (y_k(i) - \sum_{j=1}^r (\beta_j \times x_j)) x_j = 0. \quad (16)$$

$$\beta := \beta - \alpha \sum_{k=0}^{k_1+k_2+k_3+\dots+k_{n-1}} (y_k(i) - \sum_{j=1}^r (\beta_j \times x_j)) x_j, \quad (17)$$

where  $\alpha$  is the learning rate. If the slope is a positive value, the  $\beta$  value decreases as the value of  $\alpha$  increases. With a high learning rate, we can cover more ground each step, but we risk overshooting the lowest point since the slope of the hill is constantly changing. With a very low learning rate, we can confidently move in the direction of the negative gradient since we are recalculating it so frequently. A low learning rate is more precise, but calculating the gradient is time-consuming.

### C. The Proposed Small Cell ON/OFF Algorithm with Machine Learning

The proposed SC on/off process is performed by two stages. In the first stage, we gather the training data for multiple linear analysis through simulations. In the second stage, SC on/off processes are applied with the multiple linear analysis result, and its performances are evaluated.

**First stage:** We run the simulations repeatedly as many as possible to get the training data for multiple linear regression analysis. The simulation is processed as follows:

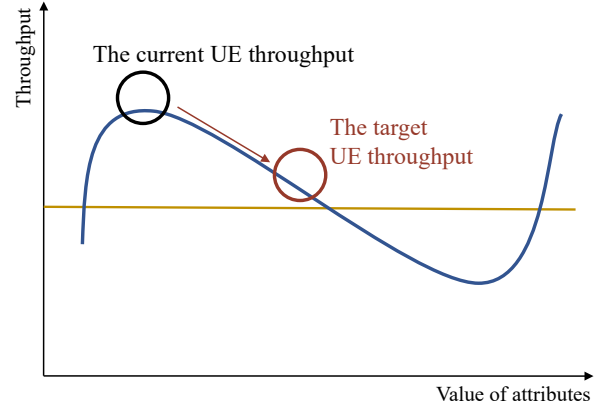


Fig. 3. Throughput prediction and adjustment.

UE throughput depends on the various attributes of the network. Through system-level simulation under the various network conditions, the throughputs of UEs are gathered to achieve training data. SCs and UEs are randomly deployed with PPP, cell association processes are carried out based on the largest RSRP, and the values of network attributes,  $xr(i)$  and all UEs throughput  $u(i) = (u_0(i), u_2(i), \dots, u_{K_n-1}(i))$  are stored. Based on these achieved simulation data, we find optimal values of  $\beta$  with multiple linear regression analysis.

**Second stage:** We choose the proper SCs to be turned off based on the optimal values of  $\beta$ , and the SC on/off process is carried out. The simulation is processed as follows.

Based on the training data acquired through the first stage, correlation between network attribute and UE throughput is evaluated. We examine how much each network attribute have an impact on UE throughputs. For example, when increasing the total power consumption by 1 W, the throughput increases by 0.5 bps/W. In this way, a model is created by considering the correlation between the network attributes and UE throughput. The initial weighting values in (10), are randomly designated, the values of  $\beta$  are adjusted to reduce the estimation errors in (11) with linear regression model. Based on the final model that shows the minimum prediction error, it is possible to select cells to be turned off. While the condition to support the minimum required UE throughput is satisfied, we can find several sets of SCs to be turned off. Among the candidate, we choose the set to provide the best NEE.

Fig. 3 illustrates an example of multiple linear regression analysis created by the algorithms mentioned above. The current UE throughput can be adjusted to the target UE throughput by predicting the change in throughput based on multiple linear regression analysis.

## IV. SIMULATION AND RESULT

In this section, we evaluate the correlation between network attributes and UE throughput that is derived by multiple linear regression analysis and the validity is confirmed by the reliability test. The SC off process is applied based on the confirmed



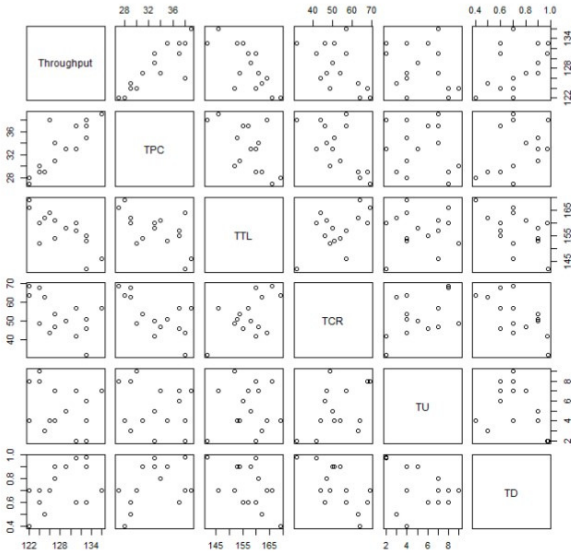


Fig. 4. Reliability test: Correlation tendency.

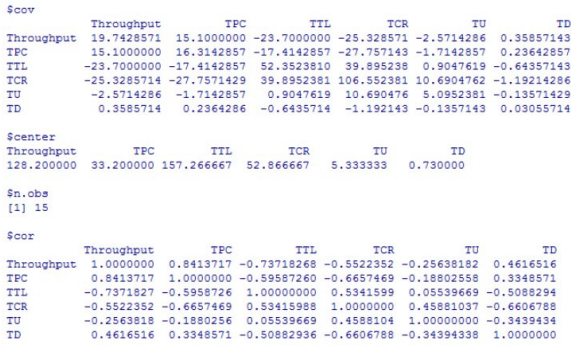


Fig. 5. Reliability test: Correlation coefficient.

multiple linear regression model and the performances of the proposed algorithm are analysed. Multiple regression analysis is the process to estimate the relationship between multiple independent variables and a dependent variable. The reliability of analysis is decreased when some of independent variables are highly correlated. Strong correlations between independent variables applied to the analysis may lead to unreliable prediction. This phenomena is known as multicollinearity. In order to solve this problem, we need to remove the strongly correlated independent variables and select proper independent variables. Fig. 4 shows the correlation tendency between network attributes and UE throughput. Total power consumption (TPC) and the inter-cell distance (TD) show a positive linear relationship. This means that the UE throughput tends to increase each network attribute increases. Total traffic load (TTL), the high-load cell ratio (TCR) and the number of UE in a cell (TU) show a negative linear relationship. This means that the UE throughput tends to decrease as network attributes (TTL, TCR, TU) increases.

Fig. 5 shows the result of finding the correlation coefficient between UE throughput and network attributes. As long as the

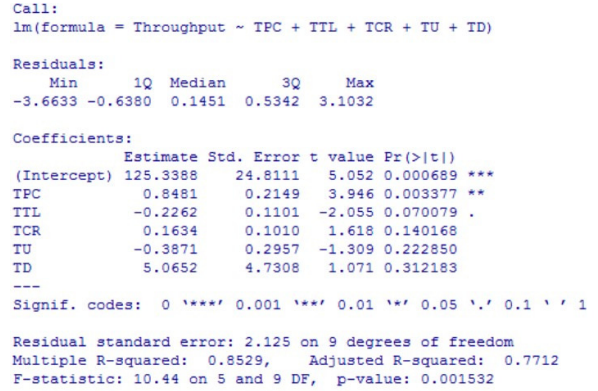


Fig. 6. Reliability test: Multicollinearity analysis.

Table 2. Simulation parameters.

Parameter	value
The number of deployed cells	400 cells
Maximum of UEs	100 UEs
Small cell transmit power	10 dBm
Small cell basic power	20 dBm
Required UE throughput	100 Mbps
Bandwidth	20 MHz
Thermal noise spectral density	-174 dBm/Hz

training data is accumulated, the process is repeated and the accurate correlation coefficient is founded. It can be seen that TPC, TTL, and TCR that have higher correlation coefficient than others are the key attributes and have large impact on the UE throughput. Thus, the three attributes are mainly adjusted to turn off cells to ensure throughput of UEs. Fig. 6 shows the result of multicollinearity analysis.  $P_r$  value is the indicator to confirm multicollinearity. Usually, if the value exceeds 0.5, it can be regarded that the corresponding independent variable has a strong correlation. This means that the variable is less reliable. The five network attributes used in the targeted multiple regression analysis have values less than 0.5, which means that these attributes considered are adequate in terms of correlation strength. This confirms that these network attributes have sufficient reliability for the analysis.

In the general UDN environment, the number of SCs is assumed to be larger than the number of active UEs. In our simulation, the maximum number of SCs is set to 400 and the number of UEs is randomly selected with the exponential distribution. The maximum number of UEs is limited by 100.

Fig. 7 shows the network throughput normalized by 1 Hz bandwidth and 1 km<sup>2</sup> area according to the number of SCs. As the number of SCs increases, the gain of network throughput increases but the gain of cell densification is saturated. Thus, in terms of NEE, it is necessary to find the optimal number of SCs subject to guarantee the minimum UE throughput. We compare the total network power consumption SC on/off algorithms in Fig. 8. The number of SCs is set to 400. In the conventional algorithm, the SCs that have connections with UEs are activated, and the remaining SCs are in sleep mode. The basic power,

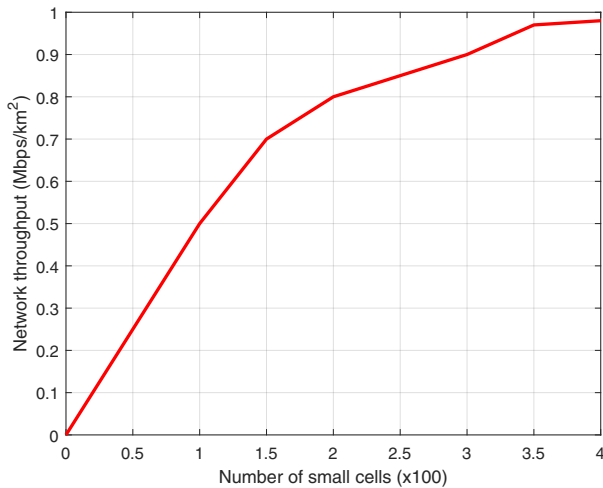


Fig. 7. Network throughput.

Pb represents the power consumption of sleep mode cell and is set to 20 dBm. The total power consumption of active cell is the sum of basic power and transition power,  $P_T$  of 10 dBm [3]. The Random ON/OFF algorithm randomly selects additional 20% or 30% of the active cells in the above conventional SC on/off scheme and turns off. The proposed SC on/off with learning denoted by Proposed ON/OFF is the algorithm that predicts UE throughput through correlation between UE throughput and network attributes and selects the SCs to be turned off.

As the number of UEs increases, the total power consumption to support UEs is shown in Fig. 8. It is confirmed that the power consumptions of random on/off algorithms are less than that of the conventional algorithm. Learning on/off operates sufficient number of cells to satisfy the required UE throughput.

Fig. 9 shows the cumulative distribution function (CDF) of UE throughputs. The UE throughputs of random on/off algorithms are less than that of conventional SC on/off algorithm due to less cell densification gain. The proposed on/off algorithm improves the UE throughput with less active cells and results in improving NEE.

Fig. 10 shows NEE that represents how the network is operating efficiently. When the number of UEs is small, NEE of Random ON/OFF is lower than that of the conventional algorithm since the number of SCs is insufficient. Otherwise, as the number of UEs increases the NEE of random on/off is improved since the coverage of SCs is overlapped. The proposed ON/OFF with machine learning selects the proper set of SCs to be turned off that can handover the traffic load to neighboring cells without significant throughput loss. Compare to the conventional algorithm, the proposed algorithm shows more than 75% improvements of average network energy efficiency.

## V. CONCLUSION

In this paper, we proposed a SC on/off algorithm that can provide sufficient UE throughputs with high network energy efficiency. The proposed SC on/off algorithms can predict the variation of UE throughputs with multiple linear regression analysis and determine which cells to be turned off. In addition, the

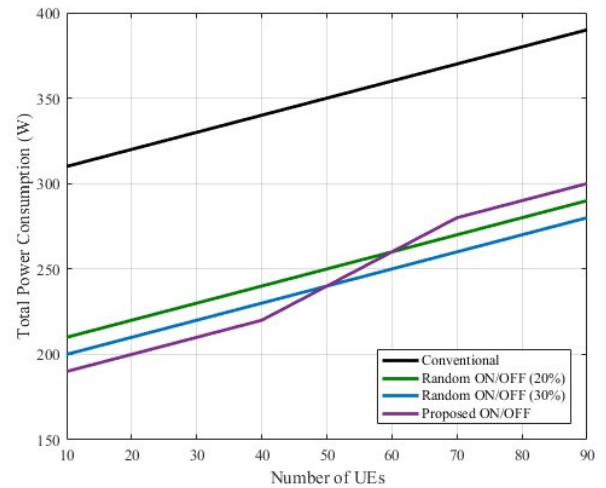


Fig. 8. Total power consumption.

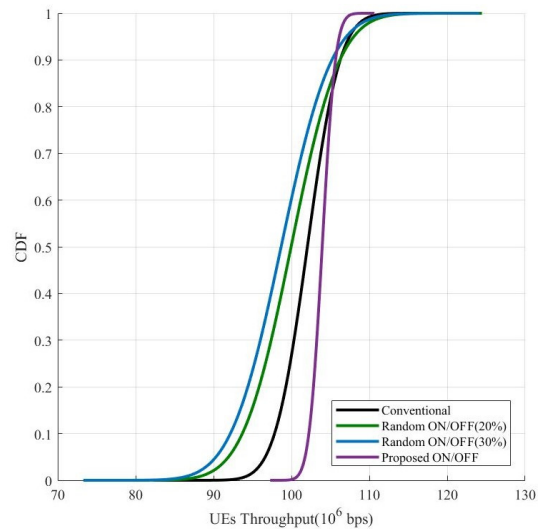


Fig. 9. UE throughput.

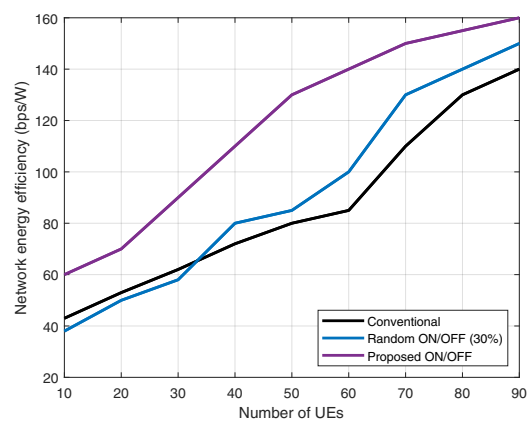


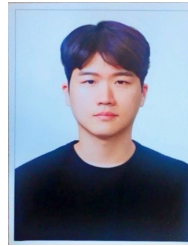
Fig. 10. Network energy efficiency.

accuracy of the algorithm was improved through the reliability test. Performances of the proposed algorithms were compared with those of the conventional and random SC on/off algorithms.

Conventional algorithms improve energy efficiency, but often fail to guarantee minimum UE throughput. The higher average UE throughput with a network energy efficient manner can be achieved with the proposed SC on/off algorithm since it takes individual UE throughput into consideration. The proposed algorithms provided more than 75% gain in network energy efficiency while guaranteeing UE throughput. This confirms that our algorithm ensures sufficient minimum UE throughput and improves reasonably energy efficiency.

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