DeCoNet: Density Clustering-Based Base Station Control for Energy-Efficient Cellular IoT Networks

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ABSTRACT Recently, there has been a rapid increase in the number of (small-cell) base stations (BSs) to support the massive amount of mobile data traffic and rapidly increasing number of mobile devices in beyond 5G (B5G) wireless communication systems or Internet of Things (IoT) networks. However, many of these BSs tend to waste a considerable amount of energy to support such data traffic and mobile devices. Therefore, the development of an efficient BS status control algorithm is important for realizing energy-efficient IoT networks. To reduce network energy consumption, we herein propose a density clustering-based BS control algorithm for energy-efficient IoT networks (DeCoNet). DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and OPTICS (Ordering Points To Identify the Clustering Structure) are utilized for partitioning high and low user-density regions. To find the effective number of BSs and their appropriate locations considering user-density differences, we utilize parameters obtained after applying density clustering algorithms to derive the thinning radius that is used to adjust the status of BSs in overall cellular IoT networks. Specifically, the average reachability-distance of each cluster in OPTICS and the distance between the outermost border users of each cluster in DBSCAN are used to obtain the radius of each cluster region. Through extensive computer simulations, we show that the proposed algorithms outperform the conventional algorithms in terms of average area throughput, energy efficiency, energy per information bit, and power consumption per unit area.

INDEX TERMS Density clustering, ultra-dense network, energy efficiency, thinning algorithm, cellular IoT networks, BS control.

I. INTRODUCTION

Future wireless networks such as the beyond fifth generation 5G (B5G) system or Internet of Things (IoT) system aim at supporting the rapidly increasing number of mobile devices and data traffic while reducing the network energy consumption compared to the fourth generation (4G) networks [1]. The B5G system will essentially help to establish the IoT as an indispensable part of our lives by setting up the foundation for unleashing its full potential [2], [3]. To achieve this goal, energy-efficient ultra-dense networks (UDNs) have been widely regarded as one of the most promising solutions for the future wireless networks [4]–[6]. In other words, base stations (BSs) may be deployed more densely to support the massive amount of data traffic generated by the various B5G convergence services such as smart factories, smart cities, smart homes, drone deliveries, and autonomous driving. Accordingly, the average distance between users and BSs is exponentially reducing, and therefore the link quality and network capacity could be enhanced significantly. However, this may result in severe interference among neighboring BSs, ushering in a vast amount of energy waste in the entire network [7]–[9]. Hence, reducing the network energy consumption is one of the most challenging issues for realizing UDNs in practice, particularly given that 80% of the energy in mobile networks is consumed in BSs [10], [11].

To minimize the network energy consumption in UDNs, a scheme to adjust the mode of BSs as (awake or sleep) was proposed in [12]. Furthermore, in [13], potential gains and limitations of the UDNs were studied,
which addressed the impact of idle-mode operation of BSs, transmission power of BSs, user density, and user distribution on the energy efficiency of UDNs. In [14], a centralized on/off optimization technique was proposed by using system-level simulations for heterogeneous networks. In [15], a Markov decision process (MDP)-based optimal wake-up mechanism for femto-cell BSs was proposed to minimize the energy consumption of heterogeneous networks, and in [16], energy-efficient user association and power allocation methods were proposed for mmWave-based UDNs with energy-harvesting BSs. Furthermore, Z. Jian et al. proposed a joint optimization framework for an energy-efficient switching on/off strategy and user association policy in dense cellular networks with partial conventional BSs in [17], and traffic load distribution-based on/off scheduling algorithms were proposed for energy-efficient delay-tolerant 5G networks in [18].

On the other hand, clustering techniques can be used for improving the network energy efficiency in UDNs by efficiently partitioning the BSs and users according to the density, position, etc. In [19], Liang et al. proposed a cluster-based energy-efficient resource allocation scheme for UDNs to reduce interference and boost energy efficiency. They utilized the k-means clustering algorithm to dynamically adjust the number of BS-clusters based on the density of the BSs. Moreover, [20] used a modularity-based user-centric clustering to decompose the UDNs into several sub-networks by exploiting the inherent group structure of users. However, they did not consider the user density for adjusting the modes of BSs in the UDNs. In this paper, to further improve network energy efficiency, we propose a novel density clustering-based BS control algorithm for energy-efficient (ultra-dense) cellular IoT networks (DeCoNet). DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and OPTICS (Ordering Points To Identify the Clustering Structure) are utilized for partitioning the users in the proposed DeCoNet algorithms. The main contribution of this paper is to partition high and low user-density regions to efficiently control the mode of BSs by using DBSCAN and OPTICS algorithms. After extracting the high user-density regions, a mobile network operator is able to determine the number and location of BSs to be awakened. The radii of the high user-density regions can be obtained by using the parameters found through the results of DBSCAN and OPTICS. We can find the thinning radius that is used to adjust the status of the BSs based on the distance between the outermost nodes in DBSCAN-based DeCoNet (D-DeCoNet) and the reachability-distance in OPTICS-based DeCoNet (O-DeCoNet). This paper also uses a thinning operation to apply area-based BS control algorithms for energy-efficient cellular IoT networks.

The rest of this paper is organized as follows. The Poisson point process (PPP) and thinning operation are described in Section II. Two density-based clustering algorithms are introduced in Section II: DBSCAN and OPTICS. In Section III, the proposed DeCoNet algorithms are explained. Section IV shows the simulation results in terms of the average area throughput, energy efficiency, energy per information bit, and power consumption per unit area. Finally, the conclusions are drawn in Section V.

II. PRELIMINARIES

A. POISSON POINT PROCESS (PPP) AND THINNING OPERATION

In PPP, the cumulative density function (CDF, \( F_r(R) \)) of the distance between the nearest serving BS and the user \((r)\) can be represented as [7], [21]

\[
F_r(R) = \mathbb{P}\{\text{Number of BSs closer than } R\} \\
= \mathbb{P}(r \leq R) \\
= 1 - e^{-\lambda_B \pi R^2}.
\]

(1)

Here, \( \lambda_B \) represents the BS intensity of the two-dimensional PPP defined in the specific space with a radius \( R \). From Eqn. (1), we can calculate the probability density function (PDF) of \( r \) in the homogeneous PPP \((f_r(r))\) as

\[
f_r(r) = 2\pi \lambda_B r \cdot e^{-\lambda_B \pi r^2}.
\]

(2)

In this paper, we denote the PDFs of \( r \) in the homogeneous PPP and Matérn hard core point process (HCPP) as \( f_{r,p}(r) \) and \( f_{r,t}(r) \), respectively. The thinning operation in the HCPP creates a group of new points by removing the points within the thinning radius \( (r_t) \) on the basis of reference points among all the original points generated by the homogeneous PPP. In this study, the thinning operation removes the points according to the following steps [7]:

- **Step 1:** Assign a random marked value (M) between 0 and 1 for all the points sampled by the PPP.
- **Step 2:** Find the points within \( r_t \) on the basis of the reference point, and remove the points with a smaller marked value than the reference point.
- **Step 3:** Repeat Step 1 and Step 2 for all the points in the entire network.

Accordingly, the intensity of the BS in the network is altered, and the PDF of the distance \( r \) between the BS and the user is also changed. In this case, the PDF of \( r \) after applying the thinning operation can be approximated as [7], [23], [24]

\[
f_{r,t}(r) \approx 2\pi r \lambda_B \cdot \frac{1 - e^{-\lambda_B \pi r_t^2}}{\lambda_B \pi r_t^2} e^{-\lambda r(r, r_t)}.
\]

(3)

where the intensity of the remaining BSs after the thinning operation can be expressed as \( \lambda_{B,t} = (1 - e^{-\lambda_B \pi r_t^2})/\pi r_t^2 \) [7], [25]–[27]. In Eqn. (3), \( \lambda^3 \) is a unique value that matches the sum of the PDF to 1. In addition, \( A(r, r_t) \) in Eqn. (3) can be described as follows [7], [23]:

\[
A(r, r_t) = \begin{cases} 
0 & 2r \leq r_t \\
\pi r^2 + r_t \sqrt{r^2 - \frac{r_t^2}{4}} & 2r > r_t \\
-(2 \cdot \arcsin \frac{r_t}{2r} + \arccos \frac{r_t}{2r}) \times r^2 & 2r > r_t 
\end{cases}
\]

(4)
$N(r_i)$ is the average number of users within the $i$th integration region. The entire space $S$ in the PPP can be quantized into bins with bounds $(r_i - \Delta r/2, r_i + \Delta r/2)$, where $r_i = r_0 + i \cdot \Delta r$ for $i \in \mathbb{Z}^+$ [8]. Here, we assume that $r_0$ is a clearance region, where no user is located. Therefore, $N(r_i)$ of the $i$th integration region, whose area is $2\pi r_i \Delta r$, can be expressed as [7–9]

$$N(r_i) = \sum_k \frac{(\lambda_u 2\pi r_i \Delta r)^k}{k!} e^{-\lambda_u 2\pi r_i \Delta r}, \quad k \in \mathbb{Z}^+. \quad (5)$$

Here, $\lambda_u$ denotes the user intensity in PPP. From Eqns. (2) and (5), we can calculate the total number of users within the BS coverage area. Therefore, the number of users in the BS coverage area ($N_{u, tot}$) is approximately calculated as [28], [29].

$$N_{u, tot} = \sum_i p_i(r_i) \cdot N(r_i), \quad (6)$$

where the probability mass function $p_i(r_i)$ can be calculated as $p_i(r_i) = \int_{r_i - \Delta r}^{r_i + \Delta r} f_x(r)dr$. In addition, in accordance with [7] and [22], the average number of users within the coverage area of each BS ($N_{u, tot}$) can be expressed as $\frac{\lambda_u}{\lambda_b}$.

### B. DENSITY-BASED CLUSTERING ALGORITHM

To achieve efficient control of a large number of BSs, network operators might partition the entire network area in accordance with active user density. Accordingly, user density-based clustering algorithms could be utilized for network partitioning. We herein introduce two of the representative clustering algorithms utilizing user density, namely, DBSCAN and OPTICS. In general, density-based clustering is used to extract regions having the desired user density or a higher distribution of objects (data or points). Several key terminologies used in the DBSCAN and OPTICS algorithms are summarized as follows [28], [29].

- **Directly density-reachable**: When an object $o$ has at least $\text{MinPts}$ of other objects ($p_1, p_2, p_3 \ldots$) within a radius ($\epsilon$), we assume that the objects $p_1, p_2$, and $p_3$ are directly density-reachable from the object $o$. Here, $\text{MinPts}$ denotes the minimum number of objects to form a dense region.

- **Density-reachable**: Assume that the objects $p_1, p_2$, and $p_3$ are directly density-reachable from $o_1$, and $q_1, q_2$, and $q_3$ are directly density-reachable from $o_2$. If the core objects $o_1$ and $o_2$ are directly density-reachable, we assume that $q_1, q_2$, and $q_3$ are density-reachable from $o_1$.

- **Density-connected**: If the objects $p$ and $q$ are density-reachable from object $o$, we assume that the objects $p$ and $q$ are density-connected.

1) **DBSCAN**

DBSCAN creates several clusters of indefinite shape according to the density of the neighboring objects. In DBSCAN, there exist three kinds of objects, namely, a core object, a border object, and an outlier object [28]. The descriptions for these nodes are as follows.

2) **OPTICS**

OPTICS defines the $\text{MinPts}$-distance of an object $p$, core-distance (CD) of an object $p$, and reachability-distance (RD) of an object $p$ with respect to an object $o$ [29].
Here, \( \text{MinPts} \)-distance represents the distance from \( p \) to its \( \text{MinPts} \)’ neighbors, and usually this \( \text{MinPts} \)-distance is the same as the CD when the \( \epsilon \)-neighborhood of \( p \) is greater than \( \text{MinPts} \). The CD of \( p \) can be defined as

\[
CD(p) = \begin{cases} 
\text{Undefined}, & \epsilon \text{-neighborhood}(p) < \text{MinPts} \\
\text{Minpts} - \text{distance}(p), & \text{otherwise}.
\end{cases}
\]

The reachability-distance of an object \( p \) with respect to another object \( o \) is the smallest distance such that \( p \) is directly density-reachable from the core object \( o \). That is, according to the definition, the reachability-distance cannot be smaller than the core-distance. The reachability-distance can be defined as

\[
RD(p, o) = \begin{cases} 
\text{Undefined}, & \epsilon \text{-neighborhood}(p) < \text{MinPts} \\
\max(\text{CD}(o), \text{dist}(o, p)), & \text{otherwise}.
\end{cases}
\]

Fig. 2 shows an example of the core-distance (\( CD(o) \)) and the reachability-distance (\( RD(p_1, o), RD(p_2, o) \)) when \( \text{MinPts} = 5 \). Accordingly, OPTICS can efficiently extract the boundaries of each cluster in the entire network area by using the reachability-distance plot [29].

### III. DeCoNet: PROPOSED DENSITY CLUSTERING-BASED BS CONTROL ALGORITHM

In the proposed DeCoNet algorithm, the entire network is divided into several subnetworks, and the status of each BS is determined according to the condition of each subnetwork. To partition the entire network, the users can be classified using the density-based clustering algorithms such as DBSCAN and OPTICS, described in Sec.II-B1 and Sec.II-B2, respectively. As a result, each cluster formed by the clustering algorithms is mapped to each subnetwork. Each subnetwork obtains the thinning radius (\( r_i \)) based on the clustering results (the number of users and a cluster radius (\( r_i \))) for determining the awake/sleep mode of the BS. The proposed DeCoNet algorithm for improving energy efficiency in ultra-dense IoT networks performs the following procedures.

As shown in Step 1 in Algorithm 1, BSs and users are generated within the entire network area with \( \lambda_B \) and \( \lambda_u^L \), where \( \lambda_B \) and \( \lambda_u^L \) denote the densities of the BSs and users in the low-density area, respectively. To model crowded network environments such as a stadium or a shopping mall, high user-density regions are randomly distributed within the entire network area, and the users in the high-density region are generated with \( \lambda_u^H \), as shown in Step 2. The density-based user clustering algorithm (DBSCAN or OPTICS) divides the entire network into multiple subnetworks. Network area partitioning is performed to determine the number of BSs that need to be awake in each subnetwork. In other words, OPTICS and DBSCAN extract the dense areas in the entire network area to control the BSs according to the number of active users for improving the network energy efficiency while minimizing the cell throughput degradation.

In Step 3, the users are partitioned using OPTICS in O-DeCoNet and DBSCAN in D-DeCoNet. That is, the subnetworks are extracted using density-based clustering algorithms. In Algorithm 1, Option 1 represents the steps to extract subnetworks in O-DeCoNet. In Step 3.1, each user calculates the \( \text{MinPts} \)-distance to find the core-distance (\( CD(i) \)) of itself. Then, O-DeCoNet randomly selects the first user \( i \) in \( S_u \) and defines new sets \( S_{SEED}^i = S_u \) and \( S_{ORDER} = \emptyset \). After comparing \( \text{Dist}(i, j) \in j \notin S_u \) with \( CD_i \), the larger value will be set to a temporary-value \( TV_k \) for all \( k \) in Step 3.3. Here, \( \text{Dist}(i, j) \in j \notin S_u \) denotes the distance between the \( i \)-th user and other users in \( S_u \). In Step 3.4, O-DeCoNet compares the current reachability-distance (\( RD_k \)) with the temporary-value (\( TV_k \)) and sets the smaller value as the final reachability-distance (\( RD_k \)) for all \( k \). Then, user \( i \) is removed from \( S_{SEED} \) and added to \( S_{ORDER} \) in Step 3.5. In Step 3.6, the user \( i \) with the smallest \( RD \) is determined as the next \( i \), and the steps from 3.3 to 3.6 are repeated until \( S_{SEED} \) becomes empty. The point \( j + 1 \) satisfying \( RD_j^{ORDER} \geq RD_{j+1}^{ORDER} \) becomes the start point of the cluster \( S_u^{i, \text{start}} \), and the point \( k \) satisfying \( RD_k^{ORDER} \leq RD_{k+1}^{ORDER} \) becomes the end point of the cluster \( S_u^{i, \text{end}} \). In Step 3.8, if \( k - j \geq \text{MinPts} \), all successive users between \( S_u^{i, \text{start}} \) and \( S_u^{i, \text{end}} \) form a new cluster. Particularly in OPTICS, the size of the extracted high user-density regions can be controlled by the parameter \( \xi \). For example, if we strictly set the value of \( \xi \), the area throughput of O-DeCoNet could be smaller but the energy efficiency of O-DeCoNet could be higher, and vice versa.

Option 2 represents how to extract subnetworks in D-DeCoNet. In Step 3.1, when user \( i \) has at least \( \text{MinPts} \) of other users within \( \epsilon \), the user \( i \) is set as ‘core user’ for all \( i \). If a certain core user \( i \) is located within \( \epsilon \) of another core user \( j \), then the users \( i \) and \( j \) are set as ‘density-connected’ users in Step 3.2. The D-DeCoNet extracts these density-connected users into a cluster. In Step 3.4, the users who do not satisfy the condition of a core user but are within \( \epsilon \) of another core user are set as border users. The border users (\( S_u^{b, \text{end}} \)) are also included in the same cluster (\( i \)) with these core users in Step 3.5. After applying density-based clustering algorithms, unique output parameters can be obtained. In OPTICS, \( RD \) and \( CD \) for each user are obtained. Furthermore, in DBSCAN, the type of user (core, border, outlier) is determined. Fig. 5 shows an example of an RD plot in O-DeCoNet.

After clustering the users with \( RD_i \) in OPTICS and the distance between the outermost border users in DBSCAN, the proposed DeCoNet algorithm can find the radius of each cluster (\( r_c \)). In O-DeCoNet, we can find that \( RD \) values of each cluster are similar. This finding means that the average \( RD \) value for each cluster could be the radius of the cluster region. Consequently, we can obtain \( r_c \) by averaging all the \( RD \) values in each cluster. In addition, \( r_c \) can be calculated
trolling the modes of BSs can be calculated as the number of users belonging to each cluster in the RD plot. In Eqn. (9), \( \text{Card} \left( S_i \right) \) indicates the number of users in cluster \( i \).

In Eqn. (10), the number of BSs that need to be awakened (\( N_i^{\text{awake}} \)) can be derived by dividing \( \text{Card} \left( S_i \right) \) by \( \mu_B \). Here, \( \text{Card} \left( S_i \right) \) is the number of users included in the cluster \( i \), and \( \mu_B \) is the capacity of the BS. The capacity of the BS is the number of users that can be supported through the BS. In Step 6 in Algorithm 1, with the \( r_i^k \) by Eqn. (10), the modes of neighboring BSs within a distance of \( r_i^k \) from the specific BS are changed from awake to sleep in the cluster \( i \). A different value of \( r_i \) could be applied for each subnetwork in accordance with the user density. A block diagram of the proposed DeCoNet algorithm is shown in Fig. 3.

In Fig. 4, there are three clustered areas and one non-clustered area. Therefore, we finally have four subnetworks that have different user densities. The thinning process of the proposed DeCoNet algorithm is shown in Fig. 4. Here, there are three kinds of users, namely, a core user, a border user, and an outlier user. The core and border users are those users included in each cluster, while the outlier users are the nonclustered users. One of the border users can be considered as the outermost user to determine the size of each cluster.
The total network size is 1 km² and the number of high-density areas is assumed as 3. The capacity of each BS is 100. Thus, each BS can support a maximum of 100 users. Depending on the type of the proposed DeCoNet algorithm (O-DeCoNet, D-DeCoNet), the sizes of the subnetworks could be different. For performance comparison, we consider two conventional algorithms, namely, the ACEnet algorithm [7] and the always-awake (AA) algorithm. In ACEnet, the BS mode control is performed according to the user density of the entire network. This algorithm does not consider the difference in user density for each unit area. Furthermore, in the AA algorithm, the status of every BS must always be awake regardless of the user density and status.

We consider fixed and random locations of the high user-density areas in the simulations. The user density of the high-density area and low-density area are \( \lambda_u^H = 4 \times 30 \times 10^3 \) and \( \lambda_u^L = 1 \times 10^3 \), respectively. If we assume the radius of a high-density area as 100 m, the connection density of this area becomes approximately 0.95 user/m². This value is almost the same as the target value of the connection density in IMT-2020, 1 user/m² [1]. The BS density (\( \lambda_B \)) is \( 0.1 \times 10^3 \), and the transmission power of the BS is 0.25 W. The details of the simulation parameters are shown in Table 1.

### TABLE 1. Simulation parameters.

| Parameter                     | Value          |
|-------------------------------|----------------|
| Network Size                  | 1 km × 1 km    |
| Total Bandwidth \((B)\)       | 10 MHz         |
| Number of High-Density Areas  | 3              |
| Deployment Strategy for High-Density Areas | Fixed & Random |
| User Density of High-Density Area \((\lambda_u^H)\) | \( 4 \times 30 \times 10^3 \) |
| User Density of Low-Density Area \((\lambda_u^L)\) | \( 1 \times 10^3 \) |
| BS Density \((\lambda_B)\)    | \( 0.1 \times 10^3 \) |
| Path-loss Exponent \((\chi)\) | 3.5            |
| BS Transmission Power \((P_{tx})\) | 0.25 W         |
| Power Consumption by Circuit \((P_c)\) | 5.4 W          |
| Power Consumption in Standby State \((P_o)\) | 0.7 W          |
| Amplification Efficiency \((\eta)\) | 0.23          |
| BS capacity \((\mu_B)\)       | 100            |

## B. PERFORMANCE METRICS

To evaluate the performance of the proposed (O-DeCoNet and D-DeCoNet) and conventional (ACEnet and AA) algorithms under various network conditions, we consider four performance metrics, namely, energy per information bit (\( \eta_i \)), power per area unit (\( \eta_A \)), area throughput (\( T_A \)), and energy efficiency (\( \eta_E \)). Here, \( \eta_i \) and \( \eta_A \) are utilized to evaluate the energy efficiency at the network level of the UDN environment where the BSs and the users are densely distributed [30], [31].

The unit of \( \eta_i \) is W/bps, and this metric is known to be suitable for the performance evaluation of urban environments. The unit of \( \eta_A \) is W/km², and this metric is widely utilized for the performance evaluation of suburban and rural environments. Moreover, \( \eta_A \) and \( \eta_i \) are represented as

\[
\eta_i = \frac{\sum_{i \in \text{awake}} P_B(i)}{\sum_{i \in \text{awake}} \sum_{j \in S_{ij}} \log(1 + \gamma_j^i)} \text{ [W/bps]},
\]

\[
\eta_A = \frac{\sum_{i \in \text{awake}} P_B(i) \chi_B(i)}{\sum_{i \in \text{awake}} \chi_B(i)} \text{ [W/km²].} \tag{11}
\]

Here, \( \gamma_j^i \) is the signal-to-interference-plus-noise ratio (SINR) of user \( j \) against BS \( i \), and \( P_B \) can be obtained by calculating the total amount of power consumed by the BS as follows: \( P_B = (1/\sigma) \cdot P_{tx} + P_c + P_o \). In this equation, \( \sigma \) is the amplification efficiency and \( P_{tx} \) is the transmission power of the BS. \( P_c \) and \( P_o \) denote the power consumed by the circuit and the power consumed in the standby state, respectively. Furthermore, \( \chi_B \) is the size of each BS area formed by Voronoi tessellation.

In addition, \( T_A \) and \( \eta_E \) can be calculated as

\[
T_A = \frac{\sum_{i \in \text{awake}} \sum_{j \in S_{ij}} \log(1 + \gamma_j^i)}{\sum_{i \in \text{awake}} \chi_B(i)} \text{ [bps/km²]},
\]

\[
\eta_E = \frac{\sum_{i \in \text{awake}} \sum_{j \in S_{ij}} \log(1 + \gamma_j^i)}{\sum_{i \in \text{awake}} P_B(i)} \text{ [bit/J].} \tag{12}
\]
FIGURE 4. Density-based user clustering for creating subnetworks (left); Thinning-based BS status adjustment (right).

FIGURE 5. Example of RD plot in O-DeCoNet.

C. SIMULATION RESULTS

Fig. 6 shows the results of the number of users included in each cluster after applying the clustering algorithms, OPTICS and DBSCAN. The results of D-DeCoNet are well matched with the user density of the high user-density area. On the other hand, O-DeCoNet obtains a relatively lower value than that of D-DeCoNet because the cluster points are excluded in the reachability-distance plot corresponding to the parameter of OPTICS ($\xi$). Here, $\xi$ is a steepness parameter to extract clusters as described in Step 3.7 in Algorithm 1. In a reachability-distance plot, the user $i+1$ satisfying $RD_i \times (1 - \xi) \geq RD_{i+1}$ becomes the start point of a cluster, and the user $j$ satisfying $RD_j \leq RD_{j+1} \times (1 - \xi)$ becomes the end point of the cluster. All successive points between the start point $i+1$ and the end point $j$ form a cluster. The number of users belonging to each cluster could vary by the steepness parameter $\xi$. That is, O-DeCoNet would create relatively small clusters compared to D-DeCoNet. This reduces the utilization of BSs in the high user-density areas. Accordingly, D-DeCoNet has the highest throughput among these algorithms.

Fig. 7 shows the simulation results with respect to the area throughput, energy efficiency, energy per information bit, and power per area unit of O-DeCoNet, D-DeCoNet, ACEnet, and AA in the case of fixed deployment of high user-density areas. Fig. 7(a) shows the area throughput according to the average number of users in high user-density areas. The proposed O-DeCoNet and D-DeCoNet algorithms perform thinning operations to put the neighboring BSs into sleep mode depending on the user density. Consequently, the total amount of interference generated by the neighboring BSs can be reduced because of these mode changes. These findings indicate the throughput improvement of the proposed O-DeCoNet and D-DeCoNet algorithms. In O-DeCoNet and D-DeCoNet, the BS mode control algorithm is adaptively utilized according to the active user density because the subnetworks are constructed using density-based clustering algorithms such as OPTICS and DBSCAN. Therefore, the proposed algorithms outperform the conventional AA and ACEnet algorithms with respect to the area throughput. Moreover, ACEnet has the smallest $T_A$ because this algorithm does not consider the difference in the user density in the entire network. Furthermore, the AA algorithm causes a severe interference problem because all the BSs in the entire

FIGURE 6. Average number of users in each cluster; random deployment (up) and fixed deployment (down).
network are always kept in the awake state. The reason for the slight performance difference between O-DeCoNet and D-DeCoNet is the difference in the shape of the clusters formed by each clustering algorithm.

Fig. 7(b) shows the energy efficiency according to the average number of users in high user-density areas. Because ACEnet does not consider the user distribution, this algorithm has an energy wastage problem in low-density areas. It causes performance degradation in terms of energy efficiency. Due to similar reasons, the AA algorithm has the lowest energy efficiency among these algorithms. On the other hand, because the proposed O-DeCoNet and D-DeCoNet algorithms control the BSs adaptively considering the user density by area, these algorithms achieve better performance than the conventional ACEnet and AA algorithms. The difference in cluster shape in the high user-density areas causes a slight difference in $\eta_E$, as shown in Fig. 7(b). Fig. 7(d) shows the power per area unit according to the average number of users in high user-density areas. From this figure, we can find the total power consumed by the BSs. In the AA algorithm, all the BSs are always kept in the awake mode because there is no thinning algorithm. In this algorithm, the total amount of power consumed in the BSs does not change regardless of the change in the user density. In addition, O-DeCoNet and D-DeCoNet have lower energy efficiency when the number of users in a high user-density area is $4K$ compared to the case of $2K$. This occurs because the relative increment ratio of the throughput in the case of $2K$ is larger than the decrement ratio of the amount of saved power due to the BS mode changes compared to the case of $4K$.

On the other hand, O-DeCoNet, D-DeCoNet, and ACEnet utilize the thinning operation to adjust the status of BSs in consideration of the user density. However, because the ACEnet algorithm does not partition the areas according to the user density, $\eta_A$ increases continuously until it reaches the $\eta_A$ of the AA algorithm. That is, the total number of users

![Figure 7](image-url)
is 90.5K, and the number of users in each high user-density area is 30K; the \(\eta_A\) of ACEnet is almost the same as the \(\eta_A\) of AA. In addition, when the number of users in the high user-density area becomes 4K, all the BSs in this area should become awake. Accordingly, from this point, \(\eta_A\) saturations occur in the O-DeCoNet and D-DeCoNet algorithms. We can observe a similar performance tendency in Fig.7(c). Figs. 7(c) and 7(d) show that the proposed DeCoNet algorithms have significant advantages in terms of power consumption.

Fig. 8 shows the simulation results with respect to the area throughput, energy efficiency, energy per information bit, and power per area unit of O-DeCoNet, D-DeCoNet, ACEnet, and AA when the high user-density areas are randomly deployed. The AA and ACEnet algorithms exhibit similar performance regardless of the placement of the high user-density areas. As shown in Fig. 8(a), the area throughput of the proposed DeCoNet algorithms in the case of fixed deployment of high user-density areas is smaller than that of the proposed DeCoNet algorithms in the case of fixed deployment of high user-density areas. This is the reason why the inter-distance between high user-density areas in the case of random deployment could be less than that in the case of fixed deployment. That is, relatively more severe interference can be generated from adjacent BSs in the case of random deployment.

From the reachability-distance plot of the proposed O-DeCoNet algorithm, it can be seen that when the inter-distance between the start point and end point of the cluster decreases, the size of the cluster also decreases. Accordingly, the number of BSs that need to be awake in this cluster could decrease. Consequently, the area throughput in Fig. 8(a) is relatively small compared to that in Fig. 7(a). That is, as the awake BSs become closer, the interference generated by the users included in these awake BSs could increase. Therefore, the gap of \(\eta_A\) between O-DeCoNet and D-DeCoNet in Fig. 8(d) is decreased compared to that in Fig. 7(d). On the other hand, the gap of \(\eta_E\) between \(\eta_E\) of
O-DeCoNet and D-DeCoNet increases from $\times 1.0345$ to $\times 1.0975$.

V. CONCLUSIONS

To improve the energy efficiency in ultra-dense cellular IoT networks, we proposed two novel DeCoNet algorithms: OPTICS-based DeCoNet and DBSCAN-based DeCoNet. To consider the difference in the user density per area, we partitioned the entire network into several subnetworks. After partitioning, we exploited thinning operations to determine the status of the BSs. The thinning radii that were required to adjust the status of the BSs were calculated from the distance between the outermost nodes in the case of D-DeCoNet and the reachability-distance in the case of O-DeCoNet. Through extensive computer simulations, we showed that the proposed O-DeCoNet and D-DeCoNet algorithms outperform the conventional ACEnet and AA algorithms in terms of average area throughput, energy efficiency, energy per information bit, and power consumption per unit area in the case of fixed and random placements of high user-density areas.

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