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RESEARCH ARTICLE

Dynamic Channel Assignment for Downlink and Uplink Decoupling in Wireless Networks

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ABSTRACT The demand for wireless communication capacity continues to increase with the extensive usage of smartphones, tablets, and devices that are related to the Internet of Things (IoT). However, devices and base stations are diversified, and base stations of various sizes are mixed. In existing cellular networks, the transmission powers of the base stations are different. If the downlink received power from the base station that belongs to the device is maximum, the uplink received power from the device at the base station is not always the maximum. This study maximizes the power that is received from the device through downlink-uplink decoupling (DUDe). DUDe can improve the spectral efficiency by selecting the downlink base station and the uplink base station independently in a network with base stations with different transmission powers. This study focuses on two technologies, DUDe and the dynamic channel assignment (DCA). It proposes an association algorithm to solve the dynamic combinational optimization problem for uplink and downlink cellular networks separately using DUDe. When a user device arrives, it first connects to the base station that has the maximum capacity at that time. Subsequently, by using the base station assignment at that time as an individual, the proposed method performs a more optimal base station assignment with DCA by using a genetic algorithm. The computer simulations demonstrate that the proposed method can achieve up to a 140 % higher spectral efficiency than the existing DUDe in the fixed channel assignment (FCA).

INDEX TERMS Downlink-uplink decoupling (DUDe), dynamic channel assignment (DCA), wireless networks, device association, multi-channel.

I. INTRODUCTION

The demand for wireless communication is increasing with the increasing usage of smartphones, tablets, and the Internet of Things (IoT) devices. Massive multiple-input multiple-output (MIMO), millimeter-wave, optical free-space communication, and energy harvesting technologies have been studied in the context of 5G, B5G, and 6G to increase the wireless communication capacity [1], [2], [3], [4], [5].

This study focuses on the association between wireless network devices and base stations to cope with the increasing capacity. Fig. 1 shows the connection method that is used in current cellular networks. The macro cell base station transmits data with strong power. The small cell base station and the user device transmit data with a weak power at the

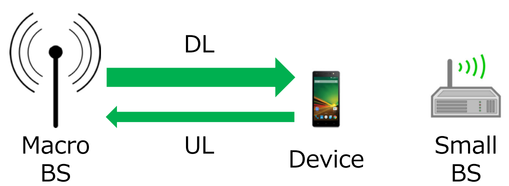

FIGURE 1. Current cellular networks: Case 1: the device connects both the downlink and uplink to the macro cell base station.

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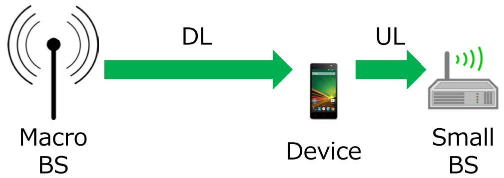

FIGURE 2. Downlink and uplink decoupling: Case 2: the device connects the downlink to the macro cell base station and the uplink to the small cell base station.

same frequency. In current cellular networks, the base station notifies the available channels, and then the device selects and connects to the channel so that it can be used from the available channels.

Currently, cellular phone networks use a fixed channel assignment (FCA) that does not change the channel once it is connected. More specifically, the device connects the uplink and downlink to the same base station that has the highest downlink received signal strength indication (RSSI) from the base station to the device. Fig. 1 depicts an example where the RSSI at the device is stronger for the signal from the macro cell base station. Thus, the device connects to the macro cell base station for both uplink and downlink.

This work adopts two technologies for the proposed method: downlink-uplink decoupling (DUDe) and a dynamic channel assignment (DCA). DUDe is a system that improves the spectral efficiency by selecting a downlink base station and an uplink base station independently in a network with multiple types of base stations. Several studies have revealed its effectiveness [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25]. Fig. 2 shows the basic concept of DUDe. By comparing Fig. 1 and Fig. 2, it is clear that DUDe can improve the spectral efficiency of the system. Fig. 1 and Fig. 2 assume that the distance between the small cell base station and the device is closer than the distance between the macro cell base station and the device. In DUDe, the device connects the uplink to the small cell base station that is nearer and achieves a higher RSSI than that of the macro cell base station. In our previous study [25], we proposed a Signal to interference and a noise ratio BaseD First-Come First-Association (SBD-FCFA) method, which uses DUDe with the FCA mechanism. However, SBD-FCFA has poor performance because FCA is used and devices, once connected, do not change connection.

In contrast, DCA is a method to improve spectral efficiency by connecting to an optimal base station by dynamically changing the channel [26]. DCA is more suitable than FCA for use with DUDe. When using DUDe, the uplink interference changes depending on the base station to which the new-arrival device connects. When using FCA, an originally connected device does not change base station or frequency when a new device joins. Thus, with FCA, the connection pattern cannot optimally adapt when a new device joins, and improved performance is achieved with DCA, for which the connected base station changes.

In current cellular networks, each operator occupies one frequency, such that the operator centralizes control by collecting all the information with a controller. On the other hand, when DUDe is not used, the uplink and downlink are connected to the same base station. When considering only the downlink, the device connects to the base station with the highest power that is received to maximize the performance. As a result, DCA changes the base station so it is connected by the device. DCA does not have many advantages in terms of the current cellular networks and it is not practically used.

When implementing DUDe and DCA on a mobile cell phone network, the computational complexity of determining the base station to which each terminal connects is a problem. Thus, Section II discusses the computational cost when using mobile cell phone networks with DUDe and DCA. The problem of determining which base station to form a connection with DUDe and DCA is classified as a dynamic combinational optimization problem [27], [28]. However, the main object of the existing dynamic combinational optimization problem is the graph problem. Therefore, we cannot use the algorithm that is proposed in the dynamic combinational optimization problem for the DUDe and DCA base station allocation. To the best of our knowledge, no other dynamic channel allocation schemes in the literature are comparable to the DUDe system. This is because they cannot be adapted to the uplink channel allocation that is considered in DUDe.

From this point of view, this study proposes an algorithm that considers the dynamic combinational optimization problem while separating the uplink and downlink of the cellular network by using DUDe. In this algorithm, first, the controller connects each device in the order of arrival to the base station with the maximum capacity at that time. Next, the controller uses the current base station assignment as a parent and it performs a more optimal base station assignment with the DCA by using a genetic algorithm. To solve the combination optimization with an approach such as machine learning, the same or a similar situation must arise repeatedly and the computer must learn the situation.

However, in wireless networks, the placement of the base stations varies from place to place, and the location of the devices changes from time to time. Under such circumstances, when using machine learning, it makes a decision that is based on past information. This is not practical in terms of not being able to secure the time that is necessary for learning. The genetic algorithm, on the other hand, does not require a large amount of past information. In an environment with two macro cells, 20 small cells, and 50 devices, the proposed method yields a performance improvement of approximately 40 % in comparison with SBD-FCFA by using FCA when analyzed through a computer simulation.

The rest of this paper is organized as follows. Section II presents the DUDe's system model in the heterogeneous wireless networks and discusses the computational problem. Section III describes the proposed method. Section IV presents and discusses the performance evaluation results that are obtained by the simulation, and it confirms the

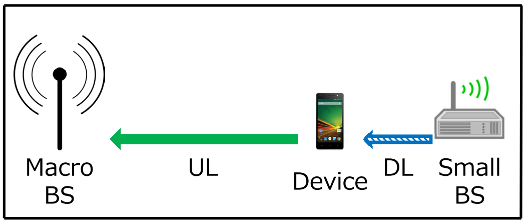

FIGURE 3. Case 3: device connects the uplink to the macro cell base station, and the downlink to the small cell base station.

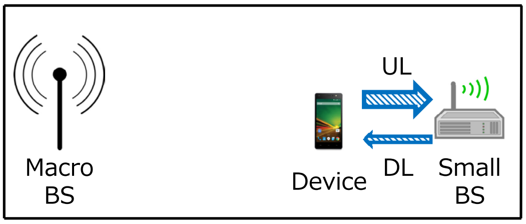

FIGURE 4. Case 4: device connects both downlink and uplink to the small cell base station.

effectiveness of the proposed methods. Finally, Section V concludes this paper.

II. SYSTEM MODEL

This study assumes that a device can use different frequency bands for uplink and downlink communication in the DUDe system. We can also assume that the transmission power of the macro cell base stations is larger than the small cell base stations. In addition, uplink and downlink communications are performed using time division multiplexing. In a Non-DUDe scenario, the uplink and downlink connection pairs are the same, and so there is no need to consider the uplink destination. However, in the case of DUDe, the uplink destination can be changed to a destination that maximizes the uplink capacity regardless of the downlink connection. During uplink connection, use of the same frequency as those of neighboring devices causes interference. Therefore, the interference in the uplink connection must be considered.

A. BASE STATION SELECTION METHOD

Fig. 1 to Fig. 4 show examples of connections in DUDe where the macro cells and small cells use different frequency channels, as assumed in this work. The green arrow represents the frequency band that is used by the macro cell base station. The blue striped arrow represents the frequency band that is used by the small cell base station. As DUDe uses multiple frequency channels, the following four types of communication methods to the base stations are conceivable.

- Case 1: The downlink and uplink to the macro cell base station (Fig. 1)
- Case 2: The downlink to the macro cell base station and the uplink to the small cell base station (Fig. 2)
- Case 3: The uplink to the macro cell base station and the downlink to the small cell base station (Fig. 3)
- Case 4: Both downlink and uplink to the small cell base station (Fig. 4)

B. COMPARISON OF INTERFERENCE MODEL

This work considers DUDe in which the macro cells and small cells use randomly allocated frequency bands from the same multiple frequency pool. Thus, the interference model becomes different from the existing research [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24]. Many existing studies assume that the macro cell base station and the small cell base station communicate with the same frequency band. For example, the following previous studies [8], [9], [10], [11] are pioneering studies in which stochastic geometry is used to clarify the outage and association probabilities when using DUDe in single-channel multi-tier heterogeneous networks. In contrast to [8], [9], [10], and [11], we propose a method for dynamic channel and connection assignment in a heterogeneous network using multiple channels; this approach is then evaluated through simulation. In this study, each base station is assumed to use one of several shared channels (resource blocks). Another difference is that the system model in the present study is not for analysis, but for concrete clarification of the simulation environment.

A few investigations [12], [13], [14], [15], [16], [17], [18], [19] have studied the base station selection problem based on the premise that the frequency channels are the same for the uplink and downlink when using DUDe. The other studies assume that the macro cells and small cells use completely different frequency bands [20], [21], [22], [23], [24]. These studies assume a different interference model for the macro cells and small cells.

In contrast, this study assumes an interference model in which a macro cell base station and a small cell base station use a common channels pool in which DUDe uses multiple channels. Specifically, the macro cell base station and the small cell base station each select one channel. Next, the device connects to the same channel as the base station. Furthermore, this study assumes a model in which each device randomly joins and leaves to represent a practical changing environment.

Note that, in this work, the channel is assumed to be a divided channel within the allocated frequency. In particular, we assume the resource blocks that are considered in cellular systems. A base station continues to use a randomly allocated frequency and the channel allocated to a base station does not change dynamically. In this work, we do not study channel allocation to the base stations, but rather propose a method to dynamically change the base station to which a device connects. It is common and realistic for existing cellular systems for base stations to continue to use the assigned channel and for devices to change the channel to which they connect depending on the base-station frequency channel.

Note also that the assumed sharing channel mechanism differs from orthogonal frequency division multiple access (OFDMA). OFDMA requires either subcarrier orthogonalization at one base station or very accurate synchronization among multiple base stations when attempting to orthogonalize OFDMA subcarriers among base stations. In this

TABLE 1. Main notation of interference model.

Notations	Definitions
Φ_{M}	Set of points representing the position of the macro cell base stations
Φ_{W}	Set of points representing the position of the small cell base stations
Φ_{d}	Set of points representing the positions of the devices
$\lvert\Phi_{\mathrm{M}}\rvert$	Number of elements in Φ_{M}
$\lvert\Phi_{\mathrm{W}}\rvert$	Number of elements in Φ_{W}
$\lvert\Phi_{\mathrm{d}}\rvert$	Number of elements in Φ_{d}
$d \times d$	Area size
x_{M_j} $(\in \Phi_{\mathrm{M}})$	Position of the jth macro cell base station (M_j)
x_{W_k} $(\in \Phi_{\mathrm{W}})$	Position of the kth small cell base station (W_k)
x_{d_l} $(\in \Phi_{\mathrm{d}})$	Position of the lth device (d_l)
P_{M}	Transmission power of the macro cell base station
P_{W}	Transmission power of the small cell base station
P_{d}	Transmission power of the device
$S^{\mathrm{D}}_{\mathrm{M}_j\mathrm{d}_l}$	Downlink received power from the jth macro cell base station (M_j) for the lth device
$S^{\mathrm{D}}_{\mathrm{W}_k\mathrm{d}_l}$	Downlink received power from the kth small cell base station (W_k) for the lth device
$S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{M}_j}$	Uplink received power from the lth device at the jth macro cell base station (M_j)
$S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{W}_k}$	Uplink received power from the lth device at the kth small cell base station (W_k)
$h_{*^1*^2}$	Rayleigh fading of the path between $*^1$ and $*^2$
α	Path loss exponent
Φ^n_{M} $(\in \Phi_{\mathrm{M}})$	Set of the device positions of the macro cell base stations that communicate by using channel n
Φ^n_{W} $(\in \Phi_{\mathrm{W}})$	Set of the device positions of the small cell base stations that communicate by using channel n
$\tilde{\Phi}^n_{\mathrm{d}}$ $(\in \Phi_{\mathrm{d}})$	Set of device positions that connect the uplink to the base station by using channel n
σ^2	Noise power

study, we assume a wider channel than OFDMA subcarriers for channel allocation in an environment holding multiple base stations and multiple devices. The only control signals required for the proposed method are the location information estimated from the received power provided by the device to each base station and the base station exchange performed by the device. The proposed method does not require precise time synchronization, unlike multiple-base-station OFDMA.

C. INTERFERENCE MODEL

This study defines the signal to interference and noise ratio (SINR) model of DUDe by using multiple frequency channels. This is an extended model of the SINR model that is adopted from [14]. The interference model incorporated in this study is not for analysis, but for concrete clarification of the simulation environment. Table 1 lists the major symbols that are used in this section. Φ_{M}, Φ_{W}, and Φ_{d} represent the set of points that depict the positions of the macro cell base stations, small cell base stations, and devices, respectively. The base stations and devices have a continuous uniform random distribution in an area of $d \times d$ km^2. The number of devices, macro cell base stations, and small cell base stations are set to $|\Phi_{\mathrm{M}}|$, $|\Phi_{\mathrm{W}}|$, and $|\Phi_{\mathrm{d}}|$, respectively.

x_{M_j} $(\in \Phi_{\mathrm{M}})$ represent the position of the jth macro cell base station (M_j). x_{W_k} $(\in \Phi_{\mathrm{W}})$ represent the position of the kth macro cell base station (W_k). x_{d_l} $(\in \Phi_{\mathrm{d}})$ represent the position of the lth macro cell base station (d_l). j, k, and l are the natural numbers that are assigned to each macro cell base station, small cell base station, and device, respectively. This study defined P_{M}, P_{W}, and P_{d} as the transmission powers of the macro cell base station, the small cell base station, and the device, respectively.

We can consider the downlink SINR of the lth device (d_l) from the base stations. The downlink received power ($S^{\mathrm{D}}_{\mathrm{M}_j\mathrm{d}_l}$) from the jth macro cell base station (M_j) for the lth device is $S^{\mathrm{D}}_{\mathrm{M}_j\mathrm{d}_l} = P_{\mathrm{M}} h_{\mathrm{M}_j\mathrm{d}_l} \|x_{\mathrm{M}_j} - x_{\mathrm{d}_l}\|^{-\alpha}$. $h_{\mathrm{M}_j\mathrm{d}_l}$ represents the Rayleigh fading path between the jth macro cell base station (M_j) and the lth device (d_l) which is an exponentially distributed random variable with a unit mean. $\|x_{\mathrm{M}_j} - x_{\mathrm{d}_l}\|$ is the distance between the point x_{M_j} and x_{d_l}, and α is the path loss exponent. The downlink received power ($S^{\mathrm{D}}_{\mathrm{W}_k\mathrm{d}_l}$) from the kth small cell base station (W_k) is $S^{\mathrm{D}}_{\mathrm{W}_k\mathrm{d}_l} = P_{\mathrm{W}} h_{\mathrm{W}_k\mathrm{d}_l} \|x_{\mathrm{W}_k} - x_{\mathrm{d}_l}\|^{-\alpha}$, where $h_{\mathrm{W}_k\mathrm{d}_l}$ is an exponentially distributed random variable with a unit mean representing the Rayleigh fading of the path between the kth small base station (W_k) and lth device (d_l). $\|x_{\mathrm{W}_k} - x_{\mathrm{d}_l}\|$ represents the distance between the point x_{W_k} and x_{d_l}.

In DUDe that uses multiple frequency channels, the interference in the downlink depends on the frequency channel that is used by each base station. Specifically, a device that is connected to the base station by the downlink has interference from communication on the same frequency channel. Therefore, we can define Φ^n_{M} $(\in \Phi_{\mathrm{M}})$ as a set of device positions of the macro cell base stations that communicate by using channel n, and Φ^n_{W} $(\in \Phi_{\mathrm{W}})$ as a set of device positions of small cell base stations that communicate by using channel n, where n is a natural number.

When the $\hat{l}$th device ($\mathrm{d}_{\hat{l}}$) connects to the $\hat{j}$th macro cell base station ($\mathrm{M}_{\hat{j}}$) by the downlink with channel n, the SINR for the device is obtained as follows.

$$\mathrm{SINR}^{\mathrm{D}n}_{\mathrm{M}_{\hat{j}}\mathrm{d}_{\hat{l}}} = \frac{S^{\mathrm{D}}_{\mathrm{M}_{\hat{j}}\mathrm{d}_{\hat{l}}}}{\sum_{x_{\mathrm{M}_j} \in \Phi^n_{\mathrm{M}} \setminus \{x_{\mathrm{M}_{\hat{j}}}\}} S^{\mathrm{D}}_{\mathrm{M}_j\mathrm{d}_{\hat{l}}} + \sum_{x_{\mathrm{W}_k} \in \Phi^n_{\mathrm{W}}} S^{\mathrm{D}}_{\mathrm{W}_k\mathrm{d}_{\hat{l}}} + \sigma^2}, \tag{1}$$

where σ^2 represents the noise power.

Similarly, when the $\hat{l}$th device ($\mathrm{d}_{\hat{l}}$) connects to the $\hat{k}$th small cell base station ($\mathrm{W}_{\hat{k}}$) by the downlink with channel n, the SINR for the device is obtained as follows.

$$\mathrm{SINR}^{\mathrm{D}n}_{\mathrm{W}_{\hat{k}}\mathrm{d}_{\hat{l}}} = \frac{S^{\mathrm{D}}_{\mathrm{W}_{\hat{k}}\mathrm{d}_{\hat{l}}}}{\sum_{x_{\mathrm{M}_j} \in \Phi^n_{\mathrm{M}}} S^{\mathrm{D}}_{\mathrm{M}_j\mathrm{d}_{\hat{l}}} + \sum_{x_{\mathrm{W}_k} \in \Phi^n_{\mathrm{W}} \setminus \{x_{\mathrm{W}_{\hat{k}}}\}} S^{\mathrm{D}}_{\mathrm{W}_k\mathrm{d}_{\hat{l}}} + \sigma^2}. \tag{2}$$

The interference in the uplink with DUDe that uses multiple frequency channels also depends on which frequency channel it is used by the base station that is connected to

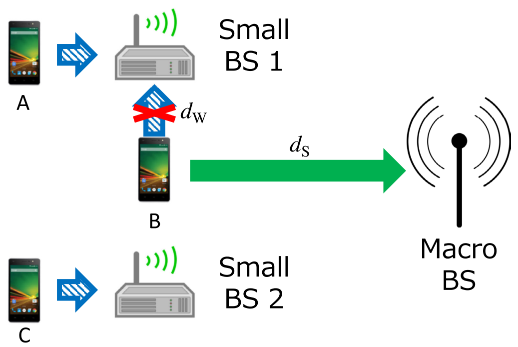

FIGURE 5. Uplink optimal connection: device B should not connect the uplink to the nearest base station (Small BS 1).

each device. Specifically, a device that is connected to a base station by the uplink is affected by the interference from the communication of the other devices by using the same frequency channel. This study defines $\tilde{\Phi}^n_{\mathrm{d}}\,(\in \Phi_{\mathrm{d}})$ as the set of device positions that connect the uplink to the base station by using channel n.

Similar to the downlink, the uplink received power ($S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{M}_j}$) from the lth device (d_l) in the jth macro cell base station (M_j) is $S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{M}_j} = P_{\mathrm{M}} h_{\mathrm{d}_l\mathrm{M}_j} \|x_{\mathrm{M}_j} - x_{\mathrm{d}_l}\|^{-\alpha}$. From this, $h_{\mathrm{d}_l\mathrm{M}_j}$ is the exponentially distributed random variable with a unit mean that represents the Rayleigh fading. In the lth small cell base station network, the uplink received power ($S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{W}_j}$) is $S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{W}_k} = P_{\mathrm{W}} h_{\mathrm{d}_l\mathrm{W}_k} \|x_{\mathrm{W}_k} - x_{\mathrm{d}_l}\|^{-\alpha}$, where $h_{\mathrm{d}_l\mathrm{W}_k}$ represents Rayleigh fading.

When the $\hat{l}$th device ($\mathrm{d}_{\hat{l}}$) connects to the $\hat{j}$th macro cell base station ($\mathrm{M}_{\hat{j}}$) by the uplink with channel n, the SINR at the macro cell base station is obtained as follows.

$$\mathrm{SINR}^{\mathrm{U}n}_{\mathrm{d}_{\hat{l}}\mathrm{M}_{\hat{j}}} = \frac{S^{\mathrm{U}}_{\mathrm{d}_{\hat{l}}\mathrm{M}_{\hat{j}}}}{\sum_{x_{\mathrm{d}_l}\in\tilde{\Phi}^n_{\mathrm{d}}\setminus\left\{x_{\mathrm{d}_{\hat{l}}}\right\}} S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{M}_{\hat{j}}} + \sigma^2}. \tag{3}$$

When the $\hat{l}$th device ($\mathrm{d}_{\hat{l}}$) connects to the $\hat{k}$th small cell base station ($\mathrm{W}_{\hat{k}}$) by the uplink with channel n, the SINR at the small cell base station is obtained as follows.

$$\mathrm{SINR}^{\mathrm{U}n}_{\mathrm{d}_{\hat{l}}\mathrm{W}_{\hat{k}}} = \frac{S^{\mathrm{U}}_{\mathrm{d}_{\hat{l}}\mathrm{W}_{\hat{k}}}}{\sum_{x_{\mathrm{d}_l}\in\tilde{\Phi}^n_{\mathrm{d}}\setminus\left\{x_{\mathrm{d}_{\hat{l}}}\right\}} S^{\mathrm{U}}_{\mathrm{d}_l\mathrm{W}_{\hat{k}}} + \sigma^2}. \tag{4}$$

D. COMPUTATIONAL PROBLEM TO SEARCH FOR THE OPTIMAL CONNECTION

The computational cost to search for the optimal connection in DUDe networks increases exponentially due to two problems. One problem is that the optimal uplink connection of each device is not always the closest base station when maximizing the spectral efficiency. Fig. 5 shows an example of the uplink optimal connection problem. In Fig. 5, when devices A–C connect to the nearest base station as shown by the blue striped lines, device A and device B can cause interference to each other. As a result, the uplink spectral efficiency decreases. To increase the spectral efficiency, device B should connect to a distant macro cell base station that is not the nearest neighbor base station.

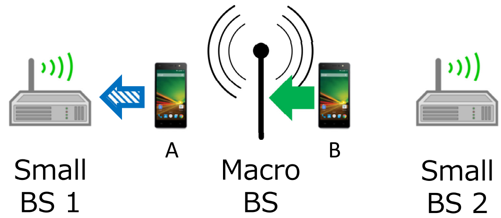

FIGURE 6. Optimal connection changes drastically before the new device arrives.

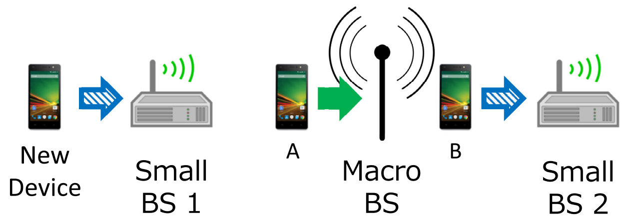

FIGURE 7. Optimal connection changes drastically after the new device arrives.

In detail, when device B uplinks to Micro-cell Base Station 1, the SINR of the device B uplink is

$$\mathrm{SINR}_{\mathrm{W}} = \frac{P_{\mathrm{d}}}{\sigma^2 + I_{\mathrm{A}}}\left(\frac{\lambda}{4\pi d_{\mathrm{W}}}\right)^2, \tag{5}$$

where the strength of the received power at Base Station 1 from device A is defined as I_{A}, the device B transmission power is P_{d}, λ is the wavelength, and the distance between device B and Base Station 1 is d_{W}. In contrast, when device B is connected to the macro-cell base station, the signal-to-noise ratio (SNR) of the uplink connection is

$$\mathrm{SNR}_{\mathrm{M}} = \frac{P_{\mathrm{d}}}{\sigma^2}\left(\frac{\lambda}{4\pi d_{\mathrm{M}}}\right)^2. \tag{6}$$

Therefore, it is optimal to connect to a more distant macro-cell base station rather than to the nearest small cell base station when the following condition is satisfied:

$$\begin{aligned} &\mathrm{SINR}_{\mathrm{W}} < \mathrm{SNR}_{\mathrm{M}} \\ &\leftrightarrow d_{\mathrm{M}} < d_{\mathrm{S}}\sqrt{\frac{\sigma^2 + I_{\mathrm{A}}}{\sigma^2}}, \end{aligned} \tag{7}$$

where the distance between device B and Base Station 2 is d_{M}. At this time, evaluating all the connection combinations to achieve the optimal uplink spectral efficiency causes a computational explosion. Therefore, a method that can find a suboptimal solution with a small number of calculations is necessary.

The other problem is that the optimum connection changes significantly when a new device joins the network. Fig. 6 and Fig. 7 show an example of a drastic optimal connection change after the new device arrives. In Fig. 6, device A connects the uplink to the small cell base station 1, and device B connects to the macro cell base station. We can suppose that a new device arrives in this situation as shown in Fig. 7. In the

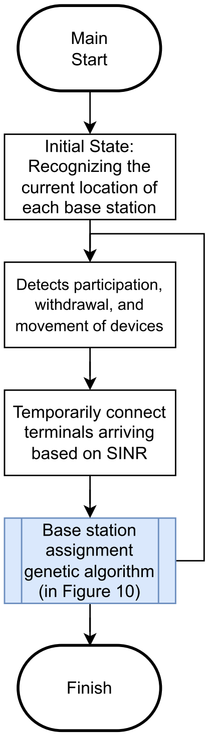

FIGURE 8. **Overall algorithm of the proposed method.**

situation where these three devices operate in the network, the optimal uplink connection is that the new device connects to the small cell base station 1, device A connects to the macro cell base station, and device B connects to the small cell base station 2. Similar to this situation, the participation of new devices changes the optimal connection base station for many devices. Every time a new device is joined, it is necessary to find a good combination of connections, which includes changing the existing connections. Since mobile devices move quickly, it is necessary to find a good connection adaptively with a small number of computations. Note that formulating the optimization problem is prohibitively difficult due to the dynamic switching of connections and channels among the devices. Even if the devices are placed randomly, their positions while using a particular channel will not be random due to the dynamic switching behavior. This makes it difficult to define coordinates that are not random and incorporate them into the optimization problem formulation.

III. PROPOSED METHOD: GA-BASED DCA

A. OVERVIEW

We proposed a genetic algorithm based DCA (GA-based DCA) for multi-channel DUDe networks to calculate a near-optimal connection combination in a short time. Fig. 8 shows the whole algorithm of the proposed method. **Algorithm 1** shows the overall algorithm of the proposed method. First, the proposed method recognizes the current location of each base station.

Algorithm 1 Overall Algorithm of the Proposed Method

Initial State: Recognizing the current location of each base station
while do
  Detects participation, withdrawal, and movement of the devices
  Temporarily connect arriving devices based on the SINR
  Base station assignment genetic algorithm
return

Second, the proposed method updates the device sounding reference signal (SRS) information [29], which is used in the long term evolution (LTE) when a device joins or leaves. The newly joined device connects to the base station with the highest SINR of the downlink at that time. The signal strength information, such as the received power from the device, is known by the base station that uses SRS [29]. We assumed that the signal strength information is obtained by using SRS in the proposed method along with the other comparable methods. We also assumed that all the information is aggregated in one server to achieve control. This was conducted since this study considers the operation in a specific divided area. This method of collecting local information and optimizing it is similar to the method that is used in enhancing the inter-cell interference coordination (eICIC) for cellular networks [29]. The backhaul networks for aggregating the information are assumed to be ideal and free of capacity and delay constraints. This is because the wired line is considered to have a larger capacity for the information aggregation.

The signal strength information, such as the received power from the devices, is updated periodically by using SRS. The SRS are sent at carrier-defined time intervals that range from 2 ms to 160 ms [29]. This study assumes that the addition and removal of devices are caused by human movement. Thus, the proposed method can obtain the SRS in a sufficiently short interval. In this investigation, we can assume that the SRS is acquired periodically, not only for the proposed method, but also for all the other methods.

Third, the proposed method calculates the uplink SINR that is based on (3) and (4). Finally, the proposed method updates the device association by using the base station assignment genetic algorithm that is described in Section III-B to maximize the sum of the spectral efficiency.

B. GENETIC ALGORITHM

A general genetic algorithm is a randomized parallel search strategy that can find the optimal solution for a particular problem. This is obtained by seeking the maximum/minimum of the appropriate fitness function [30], [31]. The strength of the genetic algorithm is that it can find the near-optimal solution quickly by restricting the search space in an intricate manner. In general, no reasonable assumption for the genetic

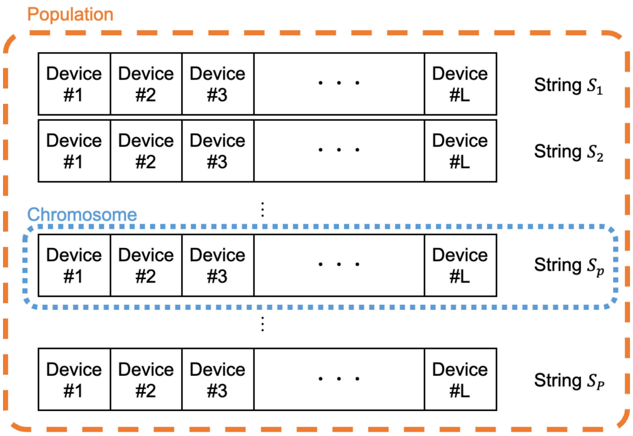

FIGURE 9. Structure of the population strings.

algorithms assures that a fast convergence to the global optima have been obtained [31]. However, by considering the suitable choices of all the genetic algorithm probabilities, this can prove that the asymptotic convergence results are similar [31]. The proposed method aims to find a suboptimal solution in the problem space of DCA in DUDe in a sufficiently short time while considering device participation and withdrawal. This is why the proposed method uses a genetic algorithm rather than other optimization techniques such as neural networks and simulated annealing.

The proposed base station assignment genetic algorithm proceeds iteratively to improve a set of solutions. This is referred to as the population $\mathrm{P}(t)$ for each iteration t. At each iteration t, the proposed algorithm creates a new population $\mathrm{P}(t)$ from the previous population $\mathrm{P}(t-1)$ by using a set of genetic operators. This study defines the population as an array of strings S_p $(1 \leq p \leq P$, P is population size) as shown in Fig. 9. Each row of the array represents the chromosome strings in a population, and each column represents the genes. The gene of the lth columns represents the base station in which the lth device connects to $(1 \leq l \leq L(= |\Phi_{\mathrm{d}}|))$. The fundamental genetic algorithm uses binary bits as the genotype; however, the proposed method uses natural numbers as the genotype to represent a base station that each device connects to.

Fig. 10 shows the details of the proposed base station assignment genetic algorithm. **Algorithm 2** shows the details of the proposed base station assignment genetic algorithm. The algorithm consists of the following operations: 1. Make the initial population (set the latest connection as an initial individual and make the other initial individuals random); 2. Crossover; 3. Evaluation with the fitness function; 4. Reproduction; and 5. Mutation. The proposed genetic algorithm repeats 2–4 operations times the number of generations.

1) INITIAL POPULATION

The proposed method generates the initial population for each chromosome string as follows.

- The proposed method sets each gene in S_1 as the number that represents the latest connection.
- Each gene in $S_2, S_3, \ldots, S_P$ is a randomly chosen natural number from 1 to I (I is the number of base stations).

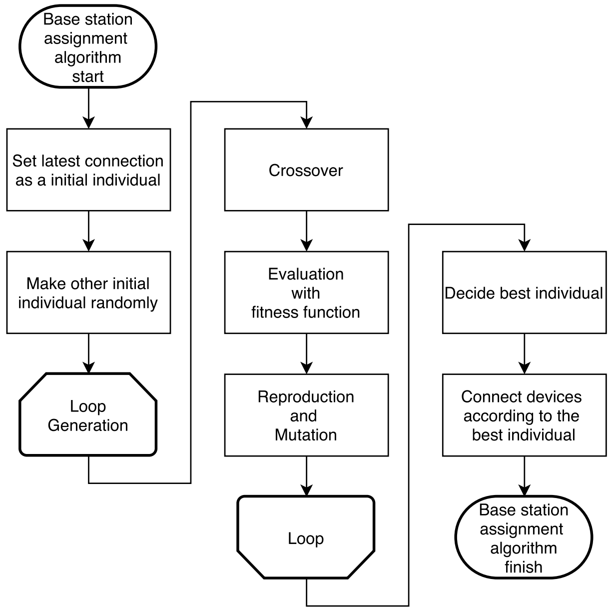

FIGURE 10. Base station assignment genetic algorithm.

2) CROSSOVER

The proposed method executes a uniform crossover to create $\lfloor P \times \{\gamma/(1-\gamma)\}\rfloor$ children, where γ represents the crossover rate. The parent chromosome strings S_u and S_v $(1 \leq u, v \leq P)$ are selected randomly. The random probability $\mathrm{Pr}_l^{\mathrm{f}}$ is generated for each lth gene in the chromosome string. If the random probability $\mathrm{Pr}_l^{\mathrm{f}}$ is greater than or equal to 0.5, the lth gene of the child chromosome string is set as lth gene of S_u. In contrast, if the random probability $\mathrm{Pr}_l^{\mathrm{f}}$ is less than 0.5, the lth gene of the child chromosome string is set as lth gene of S_v. This operation is repeated to create $\lfloor P \times \{\gamma/(1-\gamma)\}\rfloor$ children.

3) FITNESS FUNCTION

We can define the fitness function E_p for each string S_p from the SINRs of all the devices. The fitness function E_p is defined as follows.

$$E_p = \sum_{l=1}^{L} \log_2 \left(1 + \mathrm{SINR}_l^{\mathrm{U}}\right), \tag{8}$$

where $\mathrm{SINR}_l^{\mathrm{U}}$ represents the uplink SINR for the lth device.

4) REPRODUCTION

The proposed method preserves the chromosome string, which achieves the best fitness function (E_p) value and then it chooses $P-1$ strings with a simple biased roulette wheel.

5) MUTATION

A uniform mutation is proceeded in the proposed method to avoid converging the local optima. One chromosome string

Algorithm 2 Base Station Assignment Genetic Algorithm

Input: Information of the latest connection
Output: Base station assignment
// 1. Initial population
Initial chromosome individual S_1 based on the latest connection information
Initial individuals with the other chromosome $S_2, \ldots, S_P$, randomly
for $i = 1, \ldots, n_{\text{gen}}$ **do**
  // Repeat the number of generation operations n_{gen} times.
  for $j = 1, \ldots, \lfloor P \times \{\gamma/(1-\gamma)\}\rfloor$ **do**
    // 2. Crossover to create $\lfloor P \times \{\gamma/(1-\gamma)\}\rfloor$ children
    Randomly select the parent chromosome S_u, S_v
    for $l = 1, \ldots, L$ **do**
      if $\text{Pr}_l^{\text{f}} \geq 0.5$ **then**
        lth gene of $S_{\text{child},j}$ is set as the lth gene of S_u
      else
        lth gene of $S_{\text{child},j}$ is set as the lth gene of S_v
  // 3. Fitness function
  Evaluation with the fitness function (E_p)
  // 4. Reproduction
  Preserve the best chromosome
  Choose other $P - 1$ chromosome strings with a simple biased roulette wheel
  // 5. Mutation
  Select one chromosome string (S_p) randomly
  for $l = 1, \ldots, L$ **do**
    if $\text{Pr}_l > \text{Pr}_{\text{Mu}}/L$ **then**
      Set the lth gene of S_p as a randomly chosen natural number from 1 to I
Select the best chromosome individual from $S_1, \ldots, S_P$
Decide the base station assignment by interpreting the best chromosome
return

is selected for the mutation. The proposed method generates random probabilities Pr_l for each gene in the string S_p. If the generated random probability Pr_l is greater than the mutation probability that is divided by the number of devices Pr_{Mu}/L ($\text{Pr}_l > \text{Pr}_{\text{Mu}}/L$), the proposed method sets the lth gene as a randomly chosen natural number from 1 to I (I represents the number of base stations).

IV. EVALUATION

This section shows the performance of the proposed method by using a computer simulation. Specifically, we can verify the effectiveness of the proposed GA-based DCA method by evaluating the spectral efficiency and the computational cost in small-scale networks and large-scale networks.

TABLE 2. Simulation parameters.

Parameter	Assumption
$d \times d$	1×1 km^2
P_{M}	46 dBm
P_{W}	20 dBm
P_{d}	20 dBm
σ^2	-90 dBm
α	4
P	40
n_{gen}	100

Algorithm 3 Overall Algorithm of the RSSI Base Method

Initial State: Recognizing the current location of each base station
while do
  Detects participation, withdrawal, and movement of the devices
  A new device connects to the base station with the highest SNR
return

A. EVALUATION ENVIRONMENT

We evaluated the spectral efficiency and computational cost by performing computer simulations of the proposed method. The base stations and devices are randomly placed within the 1×1 km^2 area. We used the typical transmission power values of DUDe system in [6]. We set the transmission power of the macro cell base station (P_{M}) to 46 dBm, the transmission power of the small cell base station to 20 dBm (P_{W}), and the transmission power of the device (P_{d}) to 20 dBm. We set the noise floor σ^2 as -90 dBm and the path loss coefficient α as 4. In this study, we assume a Rayleigh fading wireless channel with a log-distance path loss model as shown in Section II-C. For simplicity, the simple isotropic antenna is used at both the transmitter and receiver. As for the mobility scenario, we considered a static environment where devices do not move. However, the performance is evaluated on the situation in which a device appears at a new location as the device moves, etc. Table 2 lists the simulation parameters. This work assumes full-buffered traffic. The spectral efficiency is the sum of the Shannon capacities between the devices and base stations. The simulation was performed 100 times, and this section shows an average of the 100 simulations that were performed. We evaluated the computational cost by measuring the computational time of the simulation by using the Xeon(R) CPU X7542 that has a speed of 2.67 GHz.

We used the RSSI base, the SINR-based decoupling with the first-come first-association (SBD-FCFA), and applying a brute-force search as the comparison methods.

Algorithm 4 Overall Algorithm of the SBD-FCFA Method

Initial State: Recognizing the current location of each base station
while do
  Detects participation, withdrawal, and movement of the devices
  New device connects the base station with the highest SINR
return

- Non-DUDe
  In the non-DUDe method, a device makes an uplink connection to the base station with the strongest RSSI in the downlink.
- RSSI Base (FCA)
  The RSSI Base is an FCA method that is used in [14]. **Algorithm 3** presents the details of the RSSI base scheme. Every new device connects to the base station where the uplink received power is the highest when the device arrives. The received power is estimated from the SRS information. The SRS is used in the cellular networks [29]. Once the uplink destination of a device is determined, the destination is not changed.
- SBD-FCFA (FCA)
  SBD-FCFA is an FCA method that we proposed in [25]. **Algorithm 4** shows the details of the SBD-FCFA scheme. In the SBD-FCFA scheme, as for the SINR base scheme, a new device determines its uplink destination when it is connected. The new device connects to the base station with the highest SINR, which is estimated based on the RSSI that is calculated from the SRS information. Once the uplink destination of a device is determined, the destination is not changed.
- Brute-force (DCA)
  Brute-force search is a method that can achieve the optimal spectral efficiency, but it requires a lot of computational costs. When a new device arrives in the networks, applying the brute-force method can solve the optimal connection pattern and it renews all the existing connections.

We performed comparisons with the above three methods, and the GA-based DCA. In this section, we set the parameters of the GA-based DCA as follows. The crossover rate is $\gamma = 0.75$, and the mutation probability is $\mathrm{Pr_{Mu}} = 0.01$.

B. ANALYTICAL EVALUATION ON COMPUTATIONAL COST

To show the computational costs of the proposed method and other methods, we evaluated this property analytically. The RSSI base method calculates the SNR for all devices; therefore, the RSSI base calculation complexity is $O(|\Phi_\mathrm{d}|)$. Second, SBD-FCFA calculates the SINR for all devices; thus, the computational complexity of SBD-FCFA is $O(|\Phi_\mathrm{d}|^2)$. The computation times of RSSI base and SBD-FCFA differ because RSSI base computes the SNR whereas SBD-FCFA computes the SINR; thus, the computational complexity of the latter is $|\Phi_\mathrm{d}|$ times higher because of the need to compute interference. In the Brute-force method, the computation complexity is $O((|\Phi_\mathrm{M}| + |\Phi_\mathrm{W}|)|\Phi_\mathrm{d}|^2)$ because this method computes all device and base station path combinations.

In contrast, for the GA-based DCA, the SINR is calculated for the number of genes for each device ($|\Phi_\mathrm{d}|$) in each generation. Therefore, the computational complexity of the GA-based DCA is $O(n_\mathrm{gen} \times P \times |\Phi_\mathrm{d}|^2)$. The GA-based DCA is $n_\mathrm{gen} \times P$ more computationally intensive than SBD-FCFA because the GA-based DCA performs the same calculations as SBD-FCFA for the number of genes multiplied by the number of generations. However, for the proposed GA-based DCA, the number of generations and the number of genes are fixed at n_gen and P, respectively. Thus, the computational complexity of the GA-based DCA is $O(n_\mathrm{gen} \times P \times |\Phi_\mathrm{d}|^2) = O(|\Phi_\mathrm{d}|^2)$.

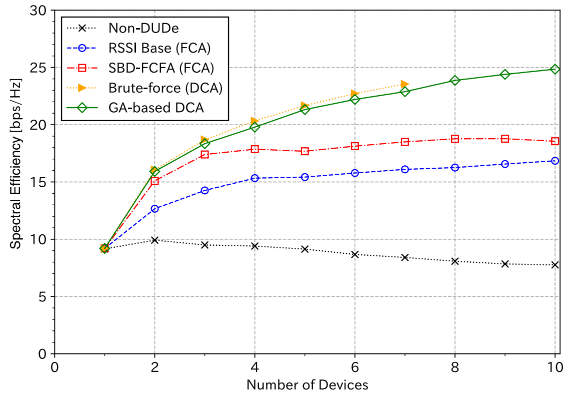

FIGURE 11. Sum of the spectral efficiency in the small networks.

C. EVALUATION IN SMALL NETWORKS

First, we evaluated the fundamental evaluation in the small size networks with one macro cell base station and four small base stations by using two common channels. This assumed that the network size is sufficiently small to avoid a calculation explosion when using the brute-force method. Fig. 11 shows the uplink spectral efficiency when the number of devices ($|\Phi_\mathrm{d}|$) was changed from 1 to 10. The spectral efficiency of the non-DUDe decreases as the number of devices increases. Because of the high transmission power of the macro cell base station, many devices in the non-DUDe system attempt to connect to the same macro cell base station. As a result, the amount of interference between the devices increases, and the total spectral efficiency decreases.

In contrast, the four methods that use the DUDe can achieve a higher total spectral efficiency than the non-DUDe method, even when the number of users increases. Even with DUDe methods, the total spectral efficiency hits a ceiling despite the increase in the number of devices. This is because the amount of inter-device interference increases as the number of devices increases. As a result, this suppresses the

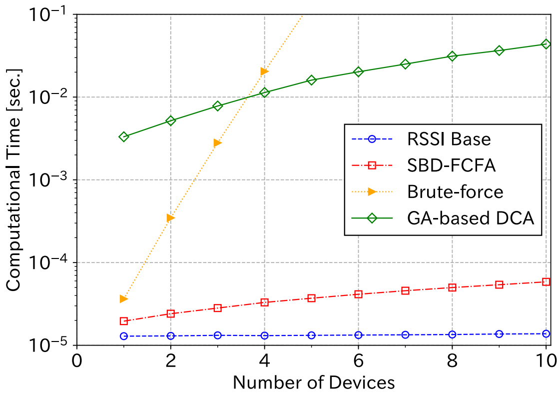

FIGURE 12. Computational time in small networks.

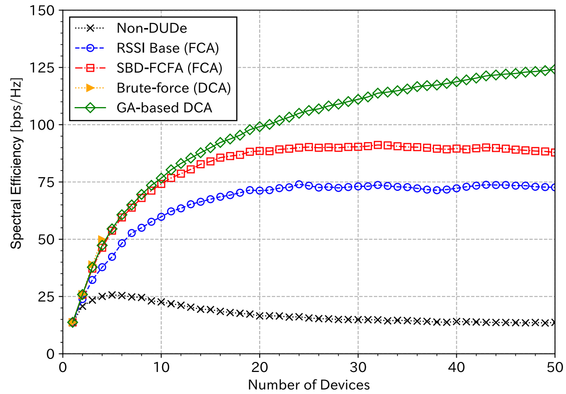

FIGURE 13. Sum of the spectral efficiency in large networks.

increase in the total spectral efficiency. The GA-based DCA achieved a 130 % spectral efficiency of the SBD-FCFA. This is an effect of the DCA mechanism in the proposed method.

In addition, the GA-based DCA achieved a 95 % spectral efficiency of the brute-force search. In the proposed GA-based DCA, when considering the number of generations in the GA, the number of generations (n_{gen}) was set to a certain value a priori. Therefore, the genetic algorithm will terminate regardless of whether it has converged to the optimal solution. In this simulation, we specifically set the number of generation (n_{gen}) to 100. From the simulation results that are shown in Fig. 11, we can see that the proposed method is almost equal to the brute-force method, which achieved the optimal solution. This indicates that the proposed method approaches the suboptimal solution. The simulation results show that the proposed method that is based on the GA can obtain the suboptimal solution in the problem space of DCA in DUDe even with a certain number of computations.

When using the connection selection algorithm in a practical environment, the computational cost of the connection selection algorithm should be low. Fig. 12 shows the computation time of each method in the simulation environment. We performed the evaluation on the computational time to measure the computational cost. The computational cost of the GA-based DCA is less than the brute-force search when the number of devices is larger than three. This is because the computational cost of the GA-based DCA is bounded to the maximum number of generations ($n_{\mathrm{gen}} = 100$). The simulation evaluation shows that the computation can be completed within a sufficiently short computation time for the actual user participation and withdrawal, even with the GA-based DCA. Note that the SBD-FCFA and GA-based DCA results exhibit curvilinear trends because the computation time is expressed on a log axis in Fig. 12.

D. EVALUATION IN LARGE-SCALE NETWORKS

In order to clarify the performance in more detail, we performed the evaluation under large-scale networks. Large-scale networks have two macro cell base stations and 20 small cell base stations, which use four common channels. We evaluated the sum of the spectral efficiency and computational cost by varying the number of devices ($|\Phi_{\mathrm{d}}|$) from one to 50.

Fig. 13 shows the sum of the uplink and spectral efficiency. The spectral efficiency of the brute-force method cannot be evaluated due to the large computational cost. In the non-DUDe method, when the number of devices exceeds five, the total spectral efficiency decreases as the number of devices increases. Similar to the simulation results for the small networks, this behavior is observed because many non-DUDe devices establish their uplinks with the macro cell base station. This increases the amount of interference in the device dynamics. In contrast, for the four DUDe methods, more devices establish the uplink to the small cell base station, and the total spectral efficiency increases as the number of devices increases.

Even with DUDe methods, the total spectral efficiency hits a ceiling despite the increase in the number of devices. This finding is similar to the results for the small networks. In addition, the amount of the inter-device interference increases as the number of devices increases; thus, suppressing the increase in the spectral efficiency. The GA-based DCA achieved a 140 % spectral efficiency of the SBD-FCFA and a 160 % spectral efficiency of the RSSI base when the number of devices is 50. These results suggest that the DCA mechanism increases the spectral efficiency under large-scale networks.

To clarify whether the proposed method can be used in large-scale networks, we evaluated the computational time. Fig. 14 shows the computational time for the different methods. The GA-based DCA was within 1 s even when the networks consist of 50 devices. Similar to the results for the small networks, the proposed method achieves a sufficiently short computation time for human motion. Therefore, the GA-based DCA can be applied to a practical large-scale network environment. Note that the SBD-FCFA and GA-based DCA results exhibit curvilinear trends because the computation time is expressed on a log axis in Fig. 14.

We performed the evaluation in an environment that repeats the device arrival and another device removal to clarify the effect of the DCA mechanism of the GA-based DCA.

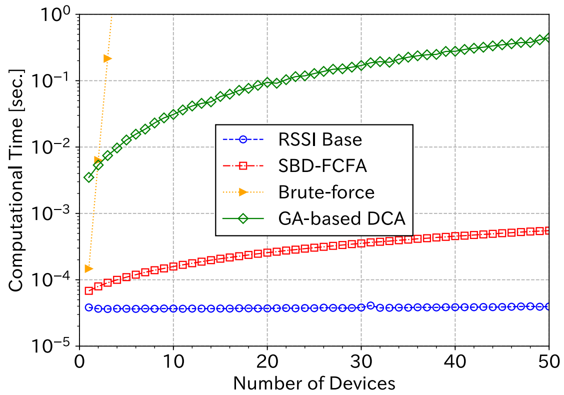

FIGURE 14. Computational time in large networks.

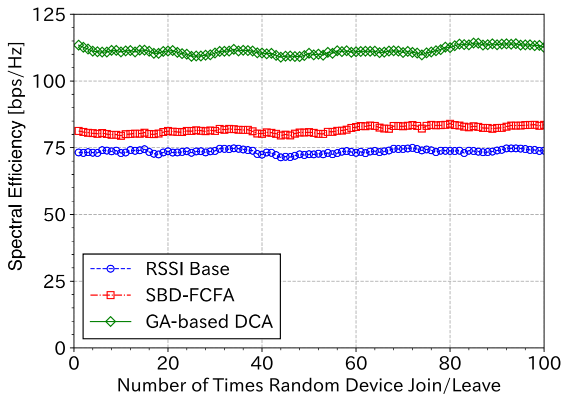

FIGURE 15. Sum of the spectral efficiency transition with the user arrival / left in the large networks.

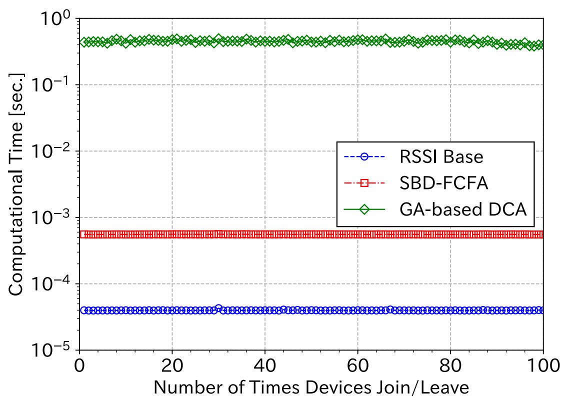

FIGURE 16. Computational time transition with the user arrival / left in the large networks.

In this simulation, a device arrives and another device leaves 100 times. Fig. 15 shows the sum of the uplink spectral efficiency transition when there were 50 devices. The GA-based DCA maintains a 140 % uplink spectral efficiency of the SBD-FCFA. The results of Fig. 15 suggest that the proposed method adapts the network change.

We performed a simulation of the computational time under the same environment, which repeats the device arrival and removal. Fig. 16 shows the computational time. The GA-based DCA keeps the computational time under 1 s. The result shows that the GA-based DCA computational cost is not significantly affected by the network environment.

V. CONCLUSION

This study focused on two technologies, DUDe and DCA, to enhance the capacity of the wireless networks. We proposed an association algorithm, the GA-based DCA, as a dynamic combination optimization problem under cellular networks with a separated uplink and downlink using DUDe. By using SINR as the base station selection index and using GA, the GA-based DCA selects the base station while considering the interference while using a small number of calculations. Finally, we evaluated the proposed method by performing a computer simulation. We confirmed that the SBD-GA can achieve a spectral efficiency that is up to 140 % more efficient than the existing DUDe in FCA. Moreover, the GA-based DCA is stable within 1 s. A study on the performance of DUDe system when incorporating massive MIMO at the macro-BS is future works.

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