Energy-Efficient Placement and Sleep Control of Relay Nodes in Heterogeneous Small Cell Networks

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Abstract Small cell (SC) provides low-power radio access with a relatively smaller coverage range than a macrocell. It has been regarded as a key solution for offloading traffic in the future 5G system. Previous works on energy-efficient placement of base stations (BSs) in cellular networks introduced placement and sleep control of low-power relay stations (RSs) to reduce the total power consumption for downlink transmission from BSs to users. As compared with legacy RSs, SC can serve as an RS with a larger coverage range though consuming a bit more circuit power. Hence, this work additionally considers to deploy small cells (SCs) in a one-dimensional highway cellular network with BSs and legacy RSs, and further models the power consumption minimization problem for placement and sleep control of legacy RSs and SCs in this network. Since the problem is hard to be solved analytically, a genetic algorithm with dynamic operator-selection mechanism is further proposed to resolve this problem. Performance of the proposed algorithm is evaluated via simulation with a practical experimental parameter setting.

Keywords Small cell network · relay node placement · sleep control · optimization

1. Introduction

As 4G technologies have become matured in recent years, increasing organizations have started focusing on future 5G technologies. It was estimated that number of communications devices will achieve 5 billion by year 2020 [1], but the current networking infrastructure and technologies could not afford such

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enormous future network flow. Hence, future 5G framework has lots of challenges to integrate a variety of heterogeneous communications systems such that they can communicate with each other [2], [3]. Cellular networks play an important role among those challenges for future 5G networks. Since the power price tends to increase over time, it is of key importance to investigate how to save power in cellular networks.

Previous works focused on reducing power consumption based on different placement strategies of base stations (BSs) in cellular networks [4]. Later, some works considered sleep control of multiple BSs, i.e., some BSs can be switched off to save power [5]. However, considering only BSs is not enough to achieve energy efficiency, because BSs are the main source of power consumption in cellular networks [5]. Therefore, some works started to introduce relay stations (RSs) to relay the transmission from users to BSs to avoid long-distance transmission power consumption [6].

Although RSs provide a good solution for reducing transmission power, it may cost too much circuit power of RS devices in the scenario when number of users is few but RSs still continue being active (consuming circuit power). Hence, some works considered that RSs can be switch off (or say, switched to the sleep mode) to save power [7]. That is, power consumption minimization for cellular networks with BSs and RSs is achieved by placement and sleep control of RSs. Recently, a key technique for offloading traffic in future 5G systems is to develop small cells (SCs), . As compared with legacy RSs, SCs can serve as RSs with a larger coverage range though consuming a bit more circuit power. Hence, it is of interest to investigate power consumption minimization in heterogeneous cellular networks with BSs, SCs, and legacy RSs.

This work considers a one-dimensional small cell network consisting of BSs, SCs, and legacy RSs along a highway, in which users in vehicles can access the Internet service via direct transmission with BSs; or SCs and legacy RSs can help serve as relay nodes for indirect transmission from BSs to users. For simplicity of the problem, this work considers only two BSs to be deployed at the two end of the highway segment to provide transmission services to users on the segment (Fig. 1). Once the optimal network deployment in this simplified case can be found, it can be extended to the deployment for any highway length with multiple BSs. Under such a framework, this work is concerned with deploying multiple SCs and legacy RSs and controlling their sleep modes, such that the total power consumption (consisting of transmission power between users and BSs, and circuit power of CSs and RSs) is minimized.

The problem of concern in this work extends the problem in [7] designed for cellular networks with

only BSs and RSs. The major difference of this work from [7] is to additionally consider SCs, such that the concerned problem is much interesting because SCs serving as relay nodes provide larger transmission coverage than legacy RSs though consuming a bit more power. Additionally, the concerned problem considers one more device type (i.e., SC) than [7], and hence, the problem model is more complicated. Since the problem in [7] has been shown to be hard to be solved analytically, the problem with extension of SCs in this work is also hard to be solved analytically. As a result, this work proposes a genetic algorithm (GA) with dynamic operator-selection mechanism to find energy-efficient placement and sleep control of SCs and legacy RSs along the highway. The proposed GA has some improved designs: two associated crossover operators, two local search operators, and a dynamic operator-selection mechanism for dynamically selecting the crossover and local search operators to be applied at each iteration of the main loop of the GA. Performance of the proposed GA is verified via simulation using parameters in real networks.

2. Related Work

2.1 Vehicular networks and future 5G networks

Lots of 5G technologies and standards have been launched, e.g., METIS [1]. 5G will be allocated with a much greater spectrum at untapped frequency bands, and will be installed with lower infrastructure costs. 5G will integrate Wi-Fi and cellular networks, and its backbone network will change from copper and fiber to mmWave [8] wireless connections, making it possible to achieve fast deployment and mesh-like connectivity with coordination between BSs. The work in [9] proposed a full duplex design for 5G networks to decrease interference and delay. The work in [10] investigated large-scale MIMO based wireless backhaul in 5G networks to increase the network efficiency. Based on the METIS project proposal [1], it was estimated that 5G products will appear after year 2020; and increasing wireless communications devices will be installed on vehicles to provide the function of network access point and communications with other vehicles. Hence, a lot of related vehicular network standards will be generated, allowing vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications of the devices from various vendors. For instance, the work in [11] investigated directional routing and scheduling for vehicular delay tolerant networks for better performance and energy efficiency. This work focuses on the future 5G technology for V2I communications.

2.2 Power consumption and sleep control in cellular networks

As the power price increases enormously, more and more telecom operators started focusing on how to reduce power consumption due to the network infrastructure (e.g., BSs), to reduce the operating costs while keeping the same service level [12]. In the past, the information and communications technology (ICT) products account for 2% of the global carbon emission [13]. Among these ICTs, cellular networks account for a high ratio. Hence, it has been interesting to investigate how to reduce power consumption in cellular networks, e.g., optimizing placement and sleep control of BSs, reducing power consumption via RS relaying, optimizing sleep control of RSs.

In cellular networks, power consumption of BSs accounts for almost 80% of power consumption of the whole network [5]. Hence, some previous works considered to optimize placement of BSs to reduce power consumption of BSs. The work in [4], [14] compared centralized and distributed frameworks [15] of BSs in cellular networks, analyzed local traffic conditions, and conducted simulation on a map to realize which framework can produce minimal transmission cost. By analyzing the relation between number of BSs and power consumption, the distributed framework performs better. The work in [1] considered to switch off multiple BSs in cellular networks during off-peak time for network flow while keeping the same service level of the whole system. They proposed three schemes of switching off BSs, allowing active BSs to cooperate with each other to extend to cover the range of the BSs that have been switched off. Their simulation results showed a 50% reduction of power consumption. The work in [5] proposed a management scheme for coordination among BSs to optimize power consumption and throughput while ensuring coverage of all users. The work in [16] proposed a femtocell downlink cell-breathing control framework for balance the coverage range and transmission rate. The work in [17], [18] proposed a distributed learning scheme, and applied it to wireless networks for achieving a better fault recovery ability.

On the other hand, some works investigated the problems of introducing relay stations (RSs) to reduce power consumption of BSs. The work in [6] considered a two-layer cellular wireless sensor network. Since sensors have limitation for power battery, the authors introduced RSs to reduce the network loading, and proposed a heuristic algorithm to optimize deployment of RSs to extend the total network life.

Some works considered sleep control of RSs. The work in [7] proposed to deploy BSs and RSs along a one-dimensional highway, and proposed a mathematical model for jointly optimize placement and sleep

control of RSs. Then, they applied numerical analysis to find the minimal power consumption of the whole network in different scenarios. Some works considered that both BSs and RSs can switch to the sleep mode.

2.3 Small cell and Wi-Fi technologies

Recently, increasing works investigated the network with small cells (SCs) [19]. The work in [20] proposed to apply SCs in the backhaul network in which if a user intends to transmit a message to another user, the user must transmit it to the core network. Take the system framework in this work for an example. The so-called backhaul network is the process where each vehicle transmits messages back to BSs. Since backhaul networks were deployed with fiber networks previously, the deployment cost is much high. Hence, the authors applied SCs to conduct deployment of densification, to satisfy the required high rates of fiber networks. They considered a mix-integer programming problem for this network environment, and developed an algorithm to solve an instance of wireless backhaul network in the Manhattan downtown. The work in [21] introduced SCs in the network with BSs, and optimized the downlink transmission via SC relaying. They also controlled the sleep of BSs. In their experimental macrocell network environment, numbers of BSs and SCs are given, and users are distributed uniformly. They then applied exhaustive search to solve the cost minimization problem. The work in [22], [23] investigated time division duplexing (TDD) transmission techniques in heterogeneous small cell networks with small cells and macrocells, to increase performance of heterogeneous networks. The work in [24] conducted a theoretical analysis on signal-to-interference plus-noise ratio of dynamic TDD transmission in small cell networks, and used interference cancellation (IC) schemes to decrease noise of upload and download. The work in [25] considered joint scheduling of access and backhaul for mmWave small cells, and proposed a centralized MAC scheduling scheme to promote performance of access and backhaul networks.

On the network with SCs, the work in [26] proposed the concept of sharing spectrum, in which SC devices can support protocols of Wi-Fi and SC. The advantage of doing so is that the SC devices can receive signals of both Wi-Fi and SC, in which SC utilizes an unauthorized spectrum of Wi-Fi for transmission. The almost blank subframes (ABS) is utilized to reduce interference in small areas, such that the ability of SC is raised while performance of Wi-Fi is not impacted. The work in [27] proposed an integrated approach with different network techniques for the problem of service configuration and distribution in a composite radio

environment (SCD-CRE), e.g., WLAN and cellular networks, to promote operating performance. The work in [28] developed a 2-tier cloud architecture in wireless networks, and then proposed a simulated annealing approach to reduce 40% of the user's price.

From the applications of integrating SC and Wi-Fi, the work in [2] considered that incorporation of the two devices provides a complementary effect in wireless networks, because Wi-Fi can usually offer services to more mobile users, e.g., laptops, tablets, cellular phones, and so on. However, it also leads to that number of the devices which can be supported by Wi-Fi is too large, such that the network is congested or cannot be used. In this situation, if the user can access 4G or 5G, the user can change to use the services provided by SCs, such that network congestion can be alleviated [29]. However, SCs still have some limitations, especially from cross-tier and co-tier interference [30]. On the other hand, Wi-Fi can help transmission during SC interference. Hence, the hybrid network of SC and Wi-Fi is a feasible solution in future 5G development.

2.4 Deployment problem

Lots of previous works on deployment of BSs existed. Some works focused on designing metaheuristic algorithms for deployment of BSs. The work in [31] considered the problem of optimizing deployment of BSs based on user distribution. They compared two deployments on a two-dimensional map: deployment of only macro BSs; and deployment of the heterogeneous network consisting of macro BSs and small-cell BSs. Users are distributed on the area of interest according to a Gauss distribution. Finally, the authors applied a simulated annealing algorithm to adjust locations of BSs. Their experimental results showed that deployment of heterogeneous networks performs better than that using only macro BSs. The work in [32] applied a particle swarm optimization (PSO) algorithm to deploy locations of BSs. Their simulation environment is based on real-world data. They used GPS to analyze locations of streets and information of users, and based on open-source data of real operators to determine locations of BSs. They then used the PSO algorithm to deploy instances with different numbers of BSs. The work in [33] considered a special deployment problem of BSs, in which deployment of BSs is concerned with locations of mobile nodes. Since it is difficult to achieve precise localization via GPS, the authors considered to use BSs to conduct localization.

2.5 Comparison of this work with related schemes

Comparison of this work with three main related schemes [5], [6], [7] in cellular networks under different factors is given in Table 1. From Table 1, all the previous schemes aims to find positions of devices to minimize power consumption, but did not consider real road conditions. By simulation of multiple BSs, the work in [5] to evaluate power consumption and throughput, which additionally consider sleep control of BSs, but no sleep control of RSs and SCs. In addition to BSs, the work in [6] additionally considered RSs to reduce transmission distance, but did not consider sleep control of RSs. The work in [7] considered the problem of sleep control of BSs and RSs on a one-dimensional road, but did not consider real road conditions. This work considers conditions of a real highway in Taiwan, and deploy RSs and SCs between two BSs in which sleep control of RSs and SCs are also considered.

3. Joint Problem of Placement and Sleep Control of Relay Nodes in Heterogeneous Small Cell Networks

3.1 System framework

For convenience of use, all the notations used in the concerned system and the proposed model are given in Table 2. Consider a highway as illustrated in Fig. 1, in which users in vehicles attempt to access downlink transmission services, which are supported by a one-dimensional small cell network, consisting of three devices: base station (BS), small cell (SC), and relay station (RS). Since SC also serves as an RS in this network, the last device is called *legacy RS* throughout the rest of this paper, to differentiate the two devices. Note that each device has a different function and a different coverage range. Hence, this network is heterogeneous. A user can transmit via a device only when falling within the coverage of the device. For simplicity, consider the highway segment between two BSs, and SCs and legacy RSs are deployed along the highway between the two BSs.

Each user in a vehicle can choose one of the following three transmission ways: direct transmission with a BS; indirect transmission via SC relaying; and indirect transmission via legacy RS relaying. As for indirect transmission, this work continues using the setting of the work in [7]: only allowing two-hop half-duplex DF relaying, i.e., indirect transmission allows only two hops from a BS to a relay node and then

to the user, because allowing multiple hops could consume too much circuit power of relay nodes [7].

The three device types in this system framework are detailed as follows. The main function of BS is to provide connectivity to the outside network. This work assumes that only two BSs are placed at the two end sides of the highway; and the user at any location along the highway can communicate with each of the two BSs. The function of SCs and legacy RSs is to serve as the relay node between users and BSs. Since long-distance transmission from a user to a BS may consume much power, transmission via delaying of SCs and RSs may reduce the transmission distance from the user to a BS and further reduce the total power consumption. Hence, it is of interest to decide deployment of SCs and RSs between the two BSs along the highway, so that the total power consumption is minimized. Additionally, each of SCs and RSs has two modes: active mode and sleep mode. Only active devices provide relaying, and hence consume circuit power constantly and transmission power when relaying. A device of SC or RS can switch to the sleep mode to save its circuit power. Hence, aside from deployment locations of SCs and RSs, their sleep control also affects the total power consumption. The main assumptions used in this work are as follows: 1) Numbers of SCs and RSs are predefined, respectively; 2) each device type has a different coverage range, based on specification of the vendors; 3) the user at any location along the highway can communicate directly with each of the two BSs; 4) this work aims to minimize the total power consumption of transmission and device circuits, and hence, interference among devices is assumed to be neglected, for simplicity; 5) this work focuses on power consumption of downlink transmission from devices to users, and the uplink transmission is not concerned; 6) each of SCs and RCs (excluding BSs) can switch to the sleep mode to save power.

3.2 Problem model

Based on the above system framework, consider a one-dimensional small cell network along a highway between two BSs. The problem of concern in this work is to determine deployment and sleep control of SCs and legacy RSs along the highway, so that the total power consumption is minimized.

The problem model in this work extends the model with BSs and RSs in [7] with SCs. Let D denote length of a highway between two BSs. Consider an x-axis along the highway. Hence, locations of the two BSs are 0 and D, respectively. The deployment problem in this work is to deploy n SCs (denoted by $s_1, s_2, \ldots, s_n$) and m RSs (denoted by $r_1, r_2, \ldots, r_n$) along the highway between the two BSs, i.e., to determine two vectors

$a = (a_1, a_2, \ldots, a_n)$ and $b = (b_1, b_2, \ldots, b_m)$ where a_i is the location of SC s_i along the x-axis for each $i \in \{1, 2, \ldots, n\}$; and b_j is the location of the RS r_j for each $j \in \{1, 2, \ldots, m\}$; $0 \le a_i, b_j \le D$.

For simplicity, each mobile user drives a vehicle along the highway with a constant speed v m/s. Each user has a request to communicate with a BS with a constant data rate r bits/s. Each user has the following three possible transmission ways: 1) The user communicates with a BS directly; 2) The user falls within the coverage range of some SC, so the BS closer to the SC transmits to the SC, and then the SC relays the transmission to the user; 3) The user falls within the coverage range of some legacy RS, so the BS closer to the legacy RS transmits to the legacy RS, and then the legacy RS relays the transmission to the user.

From the above, if the user does not fall within the coverage range of any SC or legacy RS, this work supposes that the user can always communicate with a BS. Let u denote location of the user along the highway, i.e., $0 \le u \le D$. The user rate γ in direct data transmission can be calculated as follows [7]:

$$\gamma = W \log_2(1 + \frac{\eta_B P_{Bu}}{d_{Bu}^{\alpha}}) \tag{1}$$

where W is the cannel bandwidth; η_B is the ratio of the antenna gain from the BS to the user and thermal noise; P_{Bu} is the transmission power from the BS to the user; d_{Bu} is the distance between the user and the BS that is closer to the user, i.e., $d_{Bu} = \min\{u, D - u\}$; α is the path-loss exponent, and is commonly 2, 3, or 4.

Rearrange the above equation. When direct transmission is applied, the transmission power P_{Bu} from the BS to the user can be calculated as follows:

$$P_{Bu} = \frac{(2^{\gamma/W} - 1) d_{Bu}^{\alpha}}{\eta_B} \tag{2}$$

Consider the second data transmission way. When some SC s_i serves as the relay node between the user and a BS, two transmission powers are generated as follows. The first is the transmission power P_{Bs_i} from the BS closer to SC s_i to the SC, which is calculated as follows:

$$P_{Bs_i} = \frac{(2^{2\gamma/W} - 1) d_{Bs_i}^{\alpha}}{\eta_{Bs}} \tag{3}$$

where d_{Bs_i} is the distance between SC s_i and the BS closer to SC s_i, i.e., $d_{Bs_i} = \min\{a_i, D - a_i\}$; η_{Bs} is defined similarly to η_B corresponding to the link from a BS to an SC. Note that half-duplex relaying of an SC or a legacy RS requires two time slots, such that the user rate for each hop requires 2γ.

The second is the transmission power $P_{s_i u}$ from SC s_i to the user, which is calculated as follows:

$$P_{s_i u} = \frac{(2^{2\gamma/W} - 1) d_{s_i u}^{\alpha}}{\eta_s} \tag{4}$$

where $d_{s_i u}$ is the distance between SC s_i and the user, i.e., $d_{s_i u} = | u - a_i |$; η_s is defined similarly to η_B corresponding to the link from an SC to a user.

Consider the third data transmission way. When some legacy RS r_j serves as the relay node between the user and a BS, two transmission powers are generated similarly to the above as follows. The transmission power P_{Br_j} from the BS closer to legacy RS r_j to the legacy RS is calculated as follows:

$$P_{Br_j} = \frac{(2^{2\gamma/W} - 1) d_{Br_j}^{\alpha}}{\eta_{Br}} \tag{5}$$

where d_{Br_j} is the distance between legacy RS r_j and the BS closer to legacy RS r_j, i.e., $d_{Br_j} = \min\{b_j, D - b_j\}$; η_{Br} is defined similarly to η_B corresponding to the transmission from a BS to a legacy RS. And the transmission power $P_{r_j u}$ from RC r_j to the user is calculated as follows:

$$P_{r_j u} = \frac{(2^{2\gamma/W} - 1) d_{r_j u}^{\alpha}}{\eta_r} \tag{6}$$

where $d_{r_j u}$ is the distance between legacy RS r_j and the user, i.e., $d_{r_j u} = | u - b_j |$; η_r is defined similarly to η_B corresponding to the transmission from a legacy RS to a user u.

Let $c(a_i)$ and $c(b_j)$ denote the coverage ranges of SC s_i at location a_i and legacy RS r_j at location b_j, respectively. Each user with location u chooses one of the above three data transmission ways, and hence, the total transmission power is calculated as follows:

$$\min\left\{ P_{Bu}, \bigcup_{\substack{i \in \{1,2,\ldots,n\}, \\ u \in c(a_i)}} \left\{ P_{Bs_i} + P_{s_i u} \right\}, \bigcup_{\substack{j \in \{1,2,\ldots,m\}, \\ u \in c(b_j)}} \left\{ P_{Br_j} + P_{r_j u} \right\} \right\} \tag{7}$$

In the above formula, if the first transmission way is chosen, the transmission power is P_{Bu}; if the second transmission way is chosen, the user must fall within the coverage range of some SC s_i (i.e., $u \in c(s_i)$), and the transmission power is the sum of the powers from the BS to SC s_i and from SC s_i to the user (i.e., $P_{Bs_i} + P_{s_i u}$); if the third transmission way is chosen, the user must fall within the coverage range of some legacy RS r_j (i.e.,

$u \in c(r_j)$), and the transmission power is the sum of the powers from the BS to legacy RS r_j and from legacy RS r_j to the user (i.e., $P_{Br_j} + P_{r_j u}$).

Aside from deployment of SCs and legacy RSs, their sleep controls also affect the total power consumption. Let P_{on}^{s} and P_{on}^{r} denote the circuit powers when an SC and a legacy RS are active, respectively. No matter whether an SC or legacy RS transmits to a user, the SC or legacy RS consumes circuit power, if it is active. As the vehicle arrival cannot be forecasted, the actual vehicle flow may be small, such that the power consumptions P_{on}^{s} and P_{on}^{r} of active SCs and legacy RSs may exceed the transmission power saving via SC relaying and legacy RS relaying.

As a result, this work considers that SCs and legacy RSs can independently switch to the sleep mode to save their circuit power. Let the active probability of the n SCs and m legacy RSs in the proposed model be denoted by $\beta = (\beta_1, \beta_2, \ldots, \beta_n)$ and $\rho = (\rho_1, \rho_2, \ldots, \rho_m)$, respectively, where $0 \le \beta_i, \rho_i \le 1$ for any i. Suppose that no coordination of sleep controls among SCs and legacy RSs exists. Since three data transmission ways (i.e., direct transmission, SC relaying, and legacy RS relaying) are considered by a user, the expected transmission power $P(u, a, b, \beta, \rho)$ for a user at location u is calculated as follows:

$$\mathbb{E}\left\{\min\left\{P_{Bu}, \bigcup_{\substack{i\in\{1,2,\ldots,n\},\\ u\in c(s_i)}} \left\{P_{Bs_i} + P_{s_i u}\right\}, \bigcup_{\substack{j\in\{1,2,\ldots,m\},\\ u\in c(r_j)}} \left\{P_{Br_j} + P_{r_j u}\right\}\right\}\right\} \tag{8}$$

Note that the work in [7] did not provide detailed calculation of the above equation. As one of the main contributions, this work provides it as follows:

$$\begin{aligned} &P(u,a,b,\beta,\rho) \\ &= \sum_{\substack{i\in\{1,2,\ldots,n\},\\ u\in c(s_i)}} \left(\min\left\{P_{Bu}, P_{Bs_i} + P_{s_i u}\right\}\cdot \beta_i + P_{Bu}\cdot(1-\beta_i)\right) + \sum_{\substack{i\in\{1,2,\ldots,n\},\\ u\notin c(s_i)}} P_{Bu} \\ &\quad + \sum_{\substack{j\in\{1,2,\ldots,m\},\\ u\in c(b_j)}} \left(\min\left\{P_{Bu}, P_{Br_j} + P_{r_j u}\right\}\cdot \rho_j + P_{Bu}\cdot(1-\rho_j)\right) + \sum_{\substack{j\in\{1,2,\ldots,m\},\\ u\notin c(b_j)}} P_{Bu} \end{aligned} \tag{9}$$

In the above equation, since all probability cases can be divided into the β cases and the ρ cases, the expected value is computed in the two case types.

This work supposes orthogonal channels in each cell to serve users. Hence, the total transmission power is the sum of transmission power for all users along the highway. Hence, the average total power

consumption P_{total} is calculated as follows:

$$P_{\text{total}} = \frac{\lambda}{v}\int_0^D P(u,a,b,\beta,\rho)\,\mathrm{d}u + P_{on}^{s}\beta^T e_n + P_{on}^{r}\rho^T e_m \tag{10}$$

where λ is the vehicle arrival rate (i.e., number of the vehicles that enter the concerned highway per second); e_n (resp., e_m) is an n-length (resp., m-length) vector where each element is 1.

With the above setting, the problem of concern in this work is modelled as follows:

$$\text{Minimize } P_{\text{total}} \tag{11}$$

$$\text{s.t.} \quad 0 \le a_i \le D, \quad \forall i = 1,\ldots,n \tag{12}$$

$$0 \le b_j \le D, \quad \forall j = 1,\ldots,m \tag{13}$$

$$0 \le \beta_i \le 1, \quad \forall i = 1,\ldots,n \tag{14}$$

$$0 \le \rho_j \le 1, \quad \forall j = 1,\ldots,m. \tag{15}$$

The problem is explained as follows. Objective (11) is to find placements, a and b, of SCs and legacy RSs and their active probabilities β and ρ, such that the average total power consumption P_{total} is minimized. Constraints (12) and (13) enforce the range of locations a_i and b_j to be [0, D]. Constraints (14) and (15) enforce the range of active probabilities β_i and δ_j to be [0, 1].

Since Equation (10) is a complex piecewise function, and it is impossible to precisely forecast the vehicle arrival rate, it is hard to solve the concerned problem analytically. Additionally, the problem considers one more device type (i.e., SCs), and hence, it is harder than the previous problem in [7]. As a consequence, this work focuses on developing a genetic algorithm for the problem of concern.

4. The Proposed Approach

This section proposes a GA [34] for the concerned problem. GA is inspired from natural selection in biology, and has been applied in vehicular technology. The idea of the GA is to encode a number of candidate solutions for the concerned problem as the so-called chromosomes, which constitute a population. Each chromosome is associated with a fitness value, which is used to evaluate goodness of the chromosome (i.e., performance of the corresponding candidate solution). Then, chromosomes are evolved with some operators (e.g., selection, crossover, mutation, and replacement) after a number of generations. The fittest chromosome

in the final generation is decoded as the final output solution. In the proposed GA, two associated crossover operators and two local search operators are designed to improve the solution searching process. Additionally, a dynamic operator-selection mechanism is developed to dynamically select the crossover and local search operators to be applied at each iteration of the main loop of the GA. By doing so, more diversity of the algorithm can be increased, such that possibility of finding the optimal solution is increased.

This section first describes how to encode a candidate solution for the concerned problem to ~~as~~ a chromosome, then describes how to decode a chromosome and evaluate its cost, and finally gives details of the proposed GA.

4.1 Solution encoding

Based on the problem setting, this work considers to deploy m SCs and n legacy RSs and control their active probabilities β and ρ along a highway between two BSs, such that the average total power consumption is minimized. When designing GA to solve the problem, the first step is to propose a solution encoding for the problem. The encoded instance is called a *chromosome*, which is a string of numbers (called *genes*). In this work, each chromosome consists of values of all decision variables of the concerned problem, i.e., all locations of SCs and legacy RSs along the highway and their active probabilities. Note that locations of BSs are not encoded in the chromosome, because their locations are fixed at 0 and D and they are not allowed be switched off.

The chromosome is represented as a $(2n + 2m)$-length string: $x = \langle a_1, a_2, \ldots, a_n \mid b_1, b_2, \ldots, b_m \mid \beta_1, \beta_2, \ldots, \beta_n \mid \rho_1, \rho_2, \ldots, \rho_m \rangle$ (Fig. 2), which consists of four parts. The first two parts are locations of n SCs and m legacy RSs, and each gene in the two parts is a real number from $[0, D]$. The last two parts are active probabilities of n SCs and m legacy RSs, and each gene in the two parts is a real number from $[0, 1]$.

4.2 Solution decoding and cost evaluation

Given a chromosome, it is important to design a scheme to evaluate performance of the chromosome. As the concerned problem is a minimization problem, the performance measure of a chromosome is called its *cost* in the proposed GA, instead of fitness. Remind that the objective (10) of the concerned problem includes an integral of users along the highway over $[0, D]$. However, it is impossible to know the real number of users and their possible locations along the highway. Hence, the work in [7] proposed a projected Newton method

in which each iteration re-generates new random locations of users and then optimizes a measure according those new user locations until the measure converges to a value.

This work does not follow the method in [7], because new random user locations at each iteration change the objective value a lot (such that the value is undeterministic) and it is not guaranteed that those new random user locations can represent their real locations. Instead, from the probability viewpoint, this work supposes that a reasonable fixed number of users are distributed evenly along the highway, and then calculates the average total power consumption (which is a deterministic objective value) according to the user locations. Note that distribution of users in this design can be adjusted according to the real application. Let η denote the number of users. Then, given a chromosome x consisting of a, b, β, and ρ, cost $\varphi_1(x)$ of chromosome x is calculated as follows:

$$\varphi_1(x) = \frac{\sum_{u=D/(\eta+1)}^{\eta \cdot D/(\eta+1)} P(u,a,b,\alpha,\beta)}{n+m} + \sum_{i=1}^{n} P_{on}^{s}\beta_i + \sum_{j=1}^{m} P_{on}^{r}\rho_j \tag{16}$$

The above equation is explained as follows. Since η users are distributed evenly along the highway [0, D], the gap between every two users is $D / (\eta + 1)$. Hence, their locations are $D / (\eta + 1)$, $2 D / (\eta + 1)$, …, and $\eta \cdot D / (\eta + 1)$. Hence, numerator of the first term in the above equation is the expected total power consumption of all users due to n SCs and m legacy RSs. To average it, the denominator is number of SCs and legacy RSs, i.e., $n + m$. As for the second and third terms in this equation, their matrix forms in (10) are modified as the summation form here.

The maximal value of cost $\varphi_1(x)$ (i.e., the worst total power consumption) occurs when no SCs and legacy RSs are applied to save power. That is, each user at location u adopts direct transmission and consumes power P_{Bu}. Hence, the maximal average power consumption $\varphi_{\max}$ is calculated as follows:

$$\varphi_{\max} = \sum_{u=D/(\eta+1)}^{\eta \cdot D/(\eta+1)} P_{Bu} \tag{17}$$

To use a normalized cost to evaluate chromosome x, the GA applies the following normalized cost $\varphi(x)$ of chromosome x:

$$\varphi(x) = \frac{\varphi_1(x)}{\varphi_{\max}} \tag{18}$$

The time complexity of computing the normalized cost is analyzed as follows.

Theorem 1. *The normalized cost can be computed in* $O(\eta \cdot (n + m))$ *time.*

Proof. The expected transmission power $P(u, a, b, \beta, \rho)$ in (9) can be computed in $O(n + m)$, as the first two terms are done in $O(n)$ and the last two terms are done in $O(m)$. Hence, the cost $\varphi_1(x)$ in (16) can be computed in $O(\eta \cdot (n + m))$, because the first term includes η times of calculating the expected value in (9), the second term can be done in $O(n)$, and the last term can be done in $O(m)$. Since the maximal average power consumption $\varphi_{\max}$ in (17) is done in $O(\eta)$, the normalized cost $\varphi(x)$ in (18) can be computed in $O(\eta \cdot (n + m))$ time.

Note that since η is a parameter in this problem, the normalized cost can be computed in leaner time.

4.3 The proposed genetic algorithm

The proposed GA is given in Algorithm 1.

Algorithm 1 PROPOSED_GA

```
Initialize the initial population in which each chromosome is generated randomly
while the maximal iteration number is not achieved do
  Evaluate the normalized cost of each chromosome in the current population
  Let Cp denote the set of parent chromosomes from the current population selected by roulette wheel
    selection
  for each pair of parent chromosomes in Cp do
    if rand(0, 1) < Q[1] then
      Conduct the one-point crossover operator on the two parents to generate two offspring
        chromosomes
    else
      Conduct the two-point crossover operator on the two parents to generate two offspring
        chromosomes
    end if
    Dynamically adjust Q[1] and Q[2]
  end for
  Replace worse chromosomes in the current population by better offspring chromosomes
  Conduct the mutation operator on the current population
  Select a part of chromosomes Cs from the current population
  for each chromosome in Cs do
    if rand(0, 1) < S[1] then
      Conduct the standard local search operator on the concerned chromosome
    else
      Conduct the random local search crossover operator on the concerned chromosome
    end if
    Dynamically adjust probabilities S[1] and S[2]
  end for
  Increase the current iteration number
end while
Decode the chromosome with the smallest cost as the final output solution
```

The main designs (including selection, crossover, mutation, local search operator, and dynamic operator-selection mechanism) in the proposed GA are detailed as follows.

1) Selection operator

At each iteration of the main loop of the GA, a part of the chromosomes in the current population are selected as the parent chromosomes for later crossover operators. This work applies the roulette wheel selection, which is explained as follows. First, create a roulette wheel in which the arc length of each slide is inversely proportional to the normalized cost of a chromosome, i.e., a smaller normalized cost accounts for a larger ratio of the pie chart. Then, select the parent chromosomes according to the slice arcs in the roulette wheel.

2) Associated crossover operator

After parent chromosomes are selected, each pair of the parent chromosomes reproduces offspring chromosomes via a crossover operator. This work considers two types of crossover operators: one-point and two-point associated crossovers. Consider two parent chromosomes $x_1 = \langle a_{11}, a_{12}, \ldots, a_{1n} \mid b_{11}, b_{12}, \ldots, b_{1m} \mid \beta_{11}, \beta_{12}, \ldots, \beta_{1n} \mid \rho_{11}, \rho_{12}, \ldots, \rho_{1m}\rangle$ and $x_2 = \langle a_{21}, a_{22}, \ldots, a_{2n} \mid b_{21}, b_{22}, \ldots, b_{2m} \mid \beta_{21}, \beta_{22}, \ldots, \beta_{2n} \mid \rho_{21}, \rho_{22}, \ldots, \rho_{2m}\rangle$.

The one-point associated crossover operator first finds a random number δ from $\{1, 2, \ldots, n + m - 1\}$, which is called the *cut point*. Let x_{11} be the substring of the first δ genes of x_1; x_{12} denote the substring from the $(\delta + 1)$-th to $(m + n)$-th genes of x_1; x_{13} denote the substring from the $(m + n + 1)$-th to $(m + n + 1 + \delta)$-th genes of x_1; x_{14} denote the substring of the remaining genes of x_1. Similarly, x_{21}, x_{22}, x_{23}, and x_{24} can be defined. Then, two offspring chromosomes are $x_{11}x_{22}x_{13}x_{24}$ and $x_{21}x_{12}x_{23}x_{14}$. That is, in the proposed crossover operator, locations and their corresponding active probabilities are swapped at the same time, because they are associated with each other. Similar to the above idea, the two-point associated crossover first finds two random cut points δ_1 and δ_2 from $\{1, 2, \ldots, n + m - 1\}$ so that $\delta_1 < \delta_2$. Then, the first offspring chromosome is almost the same with x_1 except the substring from δ_1-th to δ_2-th genes and the substring from $(n + m + \delta_1)$-th to $(n + m + \delta_2)$-th genes are from the genes in x_2 at the same locations; and the second offspring chromosome can be generated symmetrically.

3) Mutation operator

After crossover operator, there is a very small probability p_m to conduct the mutation operator, which is

explained as follows. If a chromosome is required to be mutated, one of the genes in the chromosome is chosen randomly. If the gene is in the first two parts of the chromosome, i.e., it represents the location of an SC or legacy RS, the gene is assigned with a random real number in [0, D]. If the gene is in the last two parts of the chromosome, i.e., it represents the active probability of an SC or legacy RS, the gen is assigned with a random real number in [0, 1].

4) Local search operator

Generally, the classical GA includes only selection, crossover, and mutation operators. Conducting a local search operator on the updated chromosomes is one of the most popular operators to improve the performance of GA. The GA with local search is also called a memetic algorithm. The idea of the local search operator is to search a possible better solution from the local neighborhood of the solution that is obtained currently. This work proposes two local search operators. First, the *standard local search operator* (e.g., Fig. 3(a)) randomly selects an SC or legacy RS, and then perturbs its location in a small range of its original location. Second, the *random local search operator* (e.g., Fig. 3(b)) perturbs the original solution violently. In this operator, locations of all SCs and legacy RSs are perturbed in a small range of their corresponding original locations. If the solution in which the local search operator is implemented performs better than the current solution, it replaces the current solution; otherwise, the current solution is kept.

5) Dynamic operator-selection mechanism

Since two associated crossover operators (i.e., one-point and two-point) and two local search operators (i.e., standard and random) are proposed in this work, no conclusion is made in this work for which combination of the four operators performs the best. Hence, by analogy from [35], this work proposes a dynamic operator-selection mechanism to dynamically select a crossover operator and a local search operator to be applied at each iteration in the main loop of the GA. By doing so, the operator with better performance has a higher probability to be selected; while the worse operator increases diversify of GA.

This mechanism respectively copes with crossover operators and local search operators. First, consider the mechanism for dynamically selecting crossover operators. Let one-point and two-point crossover operators be called operators 1 and 2, respectively. For $i \in \{1, 2\}$, operator i is associated with a probability $Q[i]$, and $Q[1] + Q[2] = 1$. Based upon $Q[i]$, each iteration of the GA selects operator i to be applied.

Initially, $Q[1] = Q[2] = 0.5$. As the number of iterations to be executed increases, the crossover operator is selected according to $Q[1]$ and $Q[2]$, and then the two probabilities are adjusted dynamically as follows. Let φ_{old} and φ_{new} denote the average normalized costs of the two parent chromosomes and the two offspring chromosomes, respectively, when executing the selected crossover operator i. If $\varphi_{new} < \varphi_{old}$,

$$Q[i] = Q[i] + \varepsilon \text{, for the selected operator } i; \tag{19}$$

$$Q[j] = Q[j] - \varepsilon \text{, for the other operator } j \tag{20}$$

where ε is calculated as follows:

$$\varepsilon = \left| \frac{\varphi_{new} - \varphi_{old}}{\varphi_{new} + \varphi_{old}} \right|. \tag{21}$$

If $\varphi_{new} > \varphi_{old}$,

$$Q[i] = Q[i] - \varepsilon \cdot \frac{t}{T} \text{, for the selected operator } i; \tag{22}$$

$$Q[i] = Q[i] + \varepsilon \cdot \frac{t}{T} \text{, for the other operator } j \tag{23}$$

where t is the current iteration number; T is the maximal iteration number. Note that when t approaches T, since the normalized cost tends to converge, ε becomes smaller, while t/T becomes larger. Hence, $\varepsilon \cdot t/T$ still has influence on the probability adjustment.

Next, consider the mechanism for dynamically selecting local search operators. Let standard and random local search operators be called the operators 1 and 2, respectively. For $i \in \{1, 2\}$, operator i is associated with a probability $S[i]$, and $S[1] + S[2] = 1$. Based upon $S[i]$, each iteration of the GA selects operator i to be applied. The rest of the mechanism is similar to that for the crossover operators except that φ_{old} and φ_{new} denote the normalized costs of the chromosome before and after executing the selected operator, respectively. Additionally, to avoid that the probability associated with some operator is too high so that the other operator has a too low probability to be selected, the threshold for the maximal selection probability is set to 0.9. By doing so, the operator with worse performance has a probability of at least 0.1 to be selected, to increase the diversity of the GA. Oppositely, the threshold for the minimal selection probability is set to 0.1.

5. Implementation and Experimental Results

5.1 Experimental setting

The experiments run on a PC with Intel i7-3770 CPU and 16G memory. The GA is implemented using C++ language. The parameters used in the experiments are given in Table 3, which is explained as follows. From the coverage range (16 km) of an antenna in [36], length of the highway D between two 5G BSs in this work is assumed to 10000 m. From the work in [37], this work considers bandwidth W = 28 GHz in 5G and downlink data rate γ= 1 GHz. To estimate the vehicle arrival rate, we refer the real data of annual average daily traffic (AADT) in Taiwan [38], and consider that SCs and legacy RSs are installed at the meddle island of the highway so that they can serve vehicles on the two lanes of the highway. The experiments consider three scenarios: congested, ordinary, and sparse traffics; and their corresponding vehicle arrival rates are set to λ = 0.5, 1.0, and 1.5 vehicles per second, respectively; and their corresponding vehicle speeds are 50, 70, and 90 km/hr (i.e., 13.89, 19.44, and 25 m/s), respectively. Hence, number of vehicles is calculated as $D / v \cdot \lambda$ = 10000 / 13.89 · 1.5 = 1079.91 vehicles in congested traffic; 10000 / 19.44 · 1 = 514.40 vehicles in ordinary traffic; and 10000 / 25 · 0.5 = 200 vehicles in sparse traffic. Hence, the experiments apply 1080, 510 and 200 vehicles in the three scenarios on the highway by default. Additionally, after a lot of experimental trials, number of iterations in the experiments is set to 2000.

As for BSs, SCs, and legacy RSs, coverage of a BS is the whole highway length; coverages of an SC and a legacy RS are 350 m and 250 m, respectively, from IEEE 802.11n protocol. The power consumption of an active SC or an active legacy RS is 50 mW. For parameters of η's, $\eta_{Bs} = 3.5\eta_B$, $\eta_{Br} = 4\eta_B$, and $\eta_s = \eta_r = \eta_B$ from [7], in which an SC consumes more power than a legacy RS (from $\eta_{Bs} < \eta_{Br}$, and Equations (3) and (5)) because it has larger transmission coverage. The parameter η_B is set such that the transmission power with direct transmission to satisfy the rate of the user at D/2 is 1 W [7].

5.2 Sensitivity analysis on different problem settings

Parameters of the proposed GA are set via experiments under various parameter settings. First, we analyze number of iterations. Consider three different parameter setting on numbers of SCs, legacy RSs, and vehicles. Then, one of the three numbers is modified to see its sensitivity analysis (see Figs. 4, 5, and 6).

From Fig. 4, the normalized cost in the case of 7 SCs is the lowest at the last iteration. Although the final normalized costs in the cases for 7 and 8 SCs are very close, a less number of SCs costs less. Hence, 7 SCs are applied. From Fig. 5, the cost in the case of 6 RSs is the lowest. Fig. 6 compares the results under different numbers of vehicles. From Fig. 6, the cost in the sparse traffic scenario (200 vehicles) is the lowest and has an obvious gap from those in the ordinary traffic scenario (510 vehicles) and the congested traffic scenario (1080 vehicles). Although it is reasonable from Fig. 6 that the cost in the congested traffic scenario is greater than that in the ordinary traffic scenario, the two costs do not differ too much. Hence, in practice it would be appropriate to deploy the small-cell network according to the ordinary traffic scenario.

5.3 Sensitivity analysis on parameter settings of GA

This subsection analyzes parameter settings of GA. Based on the above subsections, our experiments consider 7 SCs, 6 RSs, and three possible traffic scenarios. Unless stated otherwise, the ordinary traffic scenario is applied. First, number of chromosomes is analyzed. Fig. 7 gives the plots of normalized costs versus numbers of chromosomes in three traffic scenarios. From Fig. 7, as more chromosomes are used in the GA, the normalized cost decreases, but has less improvement after applying 80 chromosomes. Hence, 80 chromosomes are applied in the later experiments. Since roulette wheel selection and binary tournament selection are the most popular chromosome selection schemes, it is of interest to compare which scheme performs better. Fig. 8 gives the plots of normalized costs versus number of iterations under the two chromosome selection schemes in three traffic scenarios. From Fig. 8, the plots using roulette wheel selection improves faster than the other. Hence, the proposed GA applies the roulette wheel selection scheme.

For the crossover rate, based on the above parameter setting, many times of experimental trials of the proposed GA are executed to find an appropriate crossover rate. Fig. 9 considers the results under crossover rates 0.5-0.8. From Fig. 9, basically, the results do not differ a lot under different crossover rates, and almost has no difference when the rate is no less than 0.6. And, a larger crossover rate takes more computing time. Hence, the crossover rate is set to 0.6. As for the mutation rate, similarly, the mutation rate is set to 2% from Fig. 10.

Consider the local search operator. Fig. 11 gives the results of using the GAs with and without the local search operator. From Fig. 10, the GA with the local search operator converges faster than that without the

local search operator, and obtains a lower cost. Hence, the local search operator is useful in the proposed GA.

5.4 Experimental analysis under different numbers of stations

Based on the parameter setting detailed above, we conduct experimental analysis under different pairs of numbers of SCs and RSs as shown in Fig. 12, in which the experimental results for 9 combinations of numbers of SCs and legacy RSs are conducted. From Fig. 12, the best combination is 7 SCs and 6 RSs, because the total sum of the normalized costs of three scenarios for this combination is the smallest.

Since no previous works considered both SCs and RSs, we cannot compare performance of the proposed method with previous works. To manifest performance of the proposed method, comparison of the proposed method with and without SC considerations is further analyzed (Fig. 13), in which the number of RSs in the case without SCs is the same with the total number of SCs and RSs in the case with SCs, for fairness. From Fig. 13, the case with SC consideration always performs better than the case without SC consideration. When number of devices become large, SCs cover a larger range than RSs but consume more power, so that the performance gap between two cases becomes smaller (Fig. 13).

6. Conclusion

In future 5G framework, small cell (SC) is a key solution of offloading traffic. This work has considered a one-dimensional small cell network consisting of BSs, SCs, and legacy RSs along a highway, and investigated the joint problem of placement and sleep control of SCs and legacy RSs between two BSs such that the average total power consumption is minimized. This problem model is more complex than the previous works because it additionally includes SCs as the relay nodes such that users have one more option to transmit. The work further proposes a genetic algorithm (GA) with two crossover operators and two local search operators, and a dynamic operator-selection mechanism to solve this problem. By applying a real-world parameter setting, simulation has verified performance of the proposed GA. In the future, the concerned problem can be extended with QoS/QoE, and more hops of SC relaying and legacy RS relaying.

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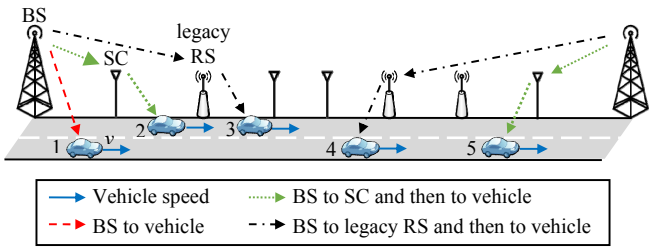

Fig. 1. Illustration of a heterogeneous small cell network along a highway, which consists of 2 BSs, 4 SCs, and 3 legacy RSs, to provide a downlink transmission service to 5 vehicles. Note that each device type has a different coverage range; hence, a vehicle can communicate with the device only when falling within the coverage range of the device. Users in vehicles can communicate with a BS directly (e.g., vehicle 1) or indirectly via SC relaying (e.g., vehicles 2 and 5) or RS relaying (e.g., vehicles 3 and 4).

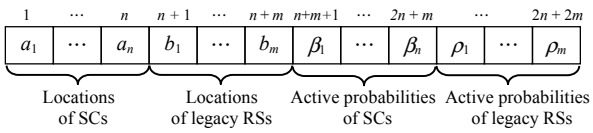

Fig. 2. Illustration of solution encoding.

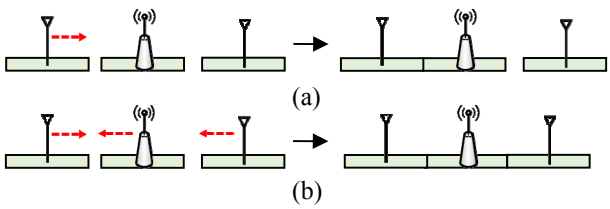

Fig. 3. Illustration of two local search operators. (a) Standard local search operator. (b) Random local search operator.

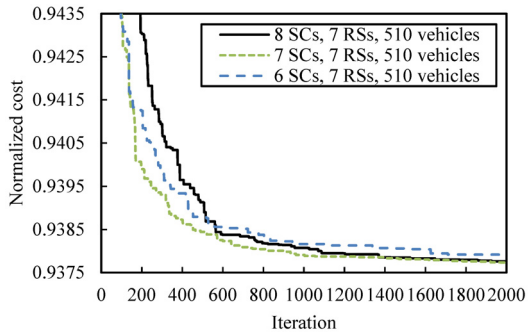

Fig. 4. Comparison under different numbers of SCs.

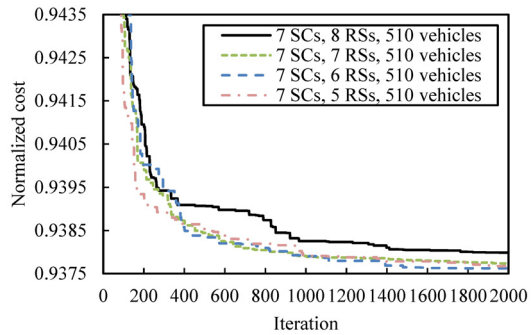

Fig. 5. Comparison under different numbers of legacy RSs.

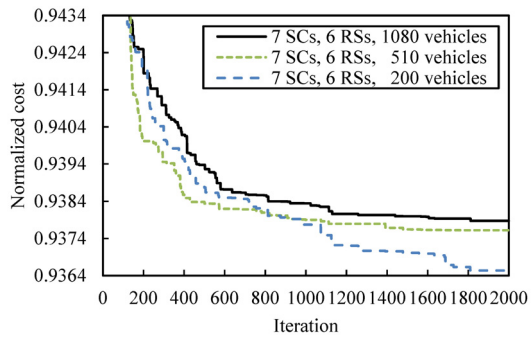

Fig. 6. Comparison under different numbers of vehicles.

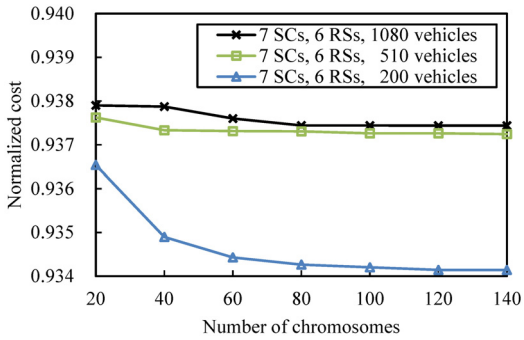

Fig. 7. Comparison under different numbers of chromosomes.

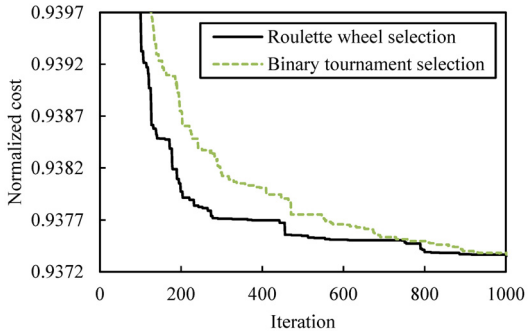

Fig. 8. Comparison under two chromosome selection schemes.

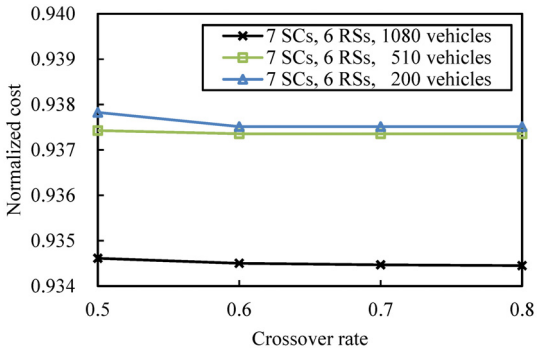

Fig. 9. Comparison under different crossover rates.

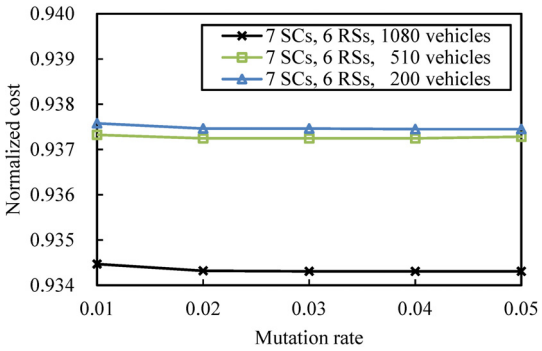

Fig. 10. Comparison under different mutation rates.

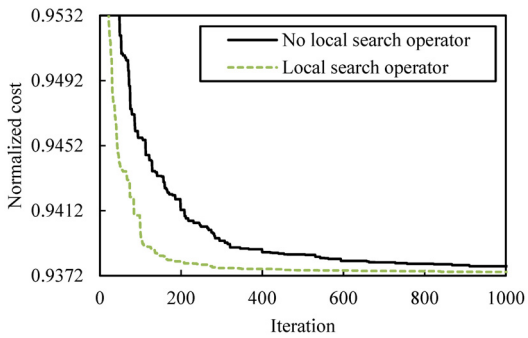

Fig. 11. Comparison of using the GAs with and without the local search operator.

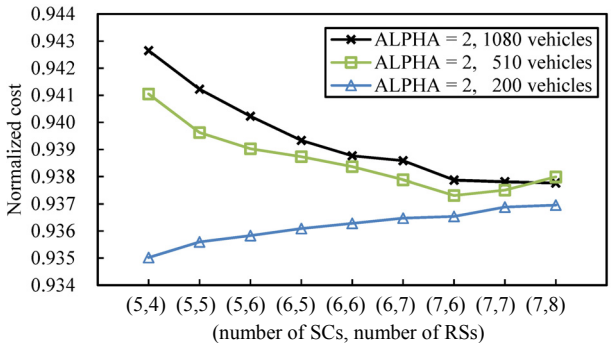

Fig. 12. Comparison under different pairs of numbers of SCs and RSs.

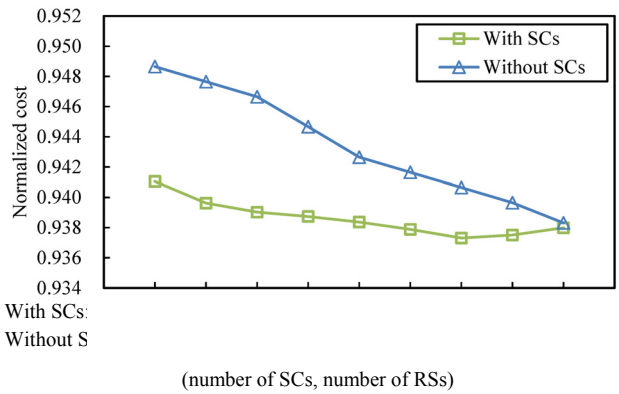

Fig. 13. Comparison of the proposed method with and without SC considerations, when $\alpha = 2$ and there are 510 vehicles.

Table 1. Comparison of this work with previous related schemes under different factors.

Factor	[5]	[6]	[7]	This work
Including BSs	Yes	Yes	Yes	Yes
Including RSs	No	Yes	Yes	Yes
Including SCs	No	No	No	Yes
Considering BS sleep control	Yes	No	No	No
Considering RS sleep control	No	No	Yes	Yes
Considering SC sleep control	No	No	No	Yes
Efficient placement	Yes	Yes	Yes	Yes
Minimized power consumption	Yes	Yes	Yes	Yes
Considering real road conditions	No	No	No	Yes

Table 2. Notations used in the concerned system and the proposed model.

Notation	Meaning
D	Length of a highway
γ	Data rate
W	Channel bandwidth
λ	Vehicle arrival rate
v	The vehicle speed
α	Path-loss exponent
s	Set of SCs, $s = \{s_1, s_2, \ldots, s_n\}$, where each s_i denotes a SC for $i \in \{1, 2, \ldots, n\}$
r	Set of RSs, $r = \{r_1, r_2, \ldots, r_m\}$, where each r_j denotes a SC for $j \in \{1, 2, \ldots, m\}$
a	Set of SC locations, $a = \{a_1, a_2, \ldots, a_n\}$, where a_i is the location of SC s_i along the x-axis for each $i \in \{1, 2, \ldots, n\}$
b	Set of RS locations, $b = \{b_1, b_2, \ldots, b_m\}$, where b_i is the location of RS r_j along the x-axis for each $j \in \{1, 2, \ldots, m\}$
P_{Bu}	Transmission power from the BS to the user
P_{Bs_i}	Transmission power from the BS closer to SC s_i to the SC
P_{s_iu}	Transmission power from SC s_i to the user
P_{Br_j}	Transmission power from the BS closer to legacy RS r_j to the legacy RS
P_{r_ju}	Transmission power from RC r_j to the user
d_{Bu}	Distance between the user and the BS that is closer to the user transmission power from the BS to the user
d_{Bs_i}	Distance between SC s_i and the BS closer to SC s_i
d_{s_iu}	Distance between SC s_i and the user
d_{Br_j}	Distance between legacy RS r_j and the BS closer to legacy RS r_j
d_{r_ju}	Distance between legacy RS r_j and the user
η_B	Ratio of the antenna gain from the BS to the user and thermal noise
η_{Bs}	Defined similarly to η_B corresponding to the link from a BS to an SC
η_s	Defined similarly to η_B corresponding to the link from an SC to a user
η_{Br}	Defined similarly to η_B corresponding to the transmission from a BS to a legacy RS
η_r	Defined similarly to η_B corresponding to the transmission from a legacy RS to a user u
P_{on}^s and P_{on}^r	Circuit powers when an SC and a legacy RS are active, respectively
β	Active probability of the n SCs, $\beta = (\beta_1, \beta_2, \ldots, \beta_n)$
ρ	Active probability of the m legacy RSs, $\rho = (\rho_1, \rho_2, \ldots, \rho_m)$
P_{total}	Average total power consumption

Table 3. Parameter setting

Parameter	Value
Highway length D	10000 m
Bandwidth W	28 GHz
User rate γ	1 GHz
Vehicle arrival rate λ	0.5, 1, 1.5 /s
Vehicle speed	90, 70, 50 km/hr
Coverage of a BS	Highway length D
Number of SCs	4-8
Coverage of SCs	350 m
Number of legacy RSs	4-8
Coverage of legacy RSs	250 m
Power consumption of active SCs	50 mW
Power consumption of active legacy RSs	50 mW
Parameters of η's	$\eta_{Bs} = 3.5\eta_B$, $\eta_{Br} = 4\eta_B$, $\eta_B = \eta_s = \eta_r$
Path-loss exponent α	2, 3, 4
Number of iterations	2000
Number of chromosomes	80
Selection of chromosomes	Roulette wheel selection
Crossover rate	0.6
Mutation rate	2 %