

# Optimizing Spectrum-Energy Efficiency in Downlink Cellular Networks

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**Abstract**—The popularity of smart mobile devices has brought significant growth of data services for mobile service providers. Mobile users of data services are charged based on the amount of data used. Raising served data amount seemingly increases the profit; energy consumption rises correspondingly. Besides, spectral resources are licensed and limited for mobile operators to allocate. Increasing data services over the spectrum for the profit does not count the cost of energy. To assess the profitability, considered is the revenue-to-cost ratio. Optimizing the ratio is an economic incentive for mobile operators. Revenue is regarded as efficiency in spectrum use, the cost as energy consumption; therefore we interpret the revenue-to-cost ratio as spectrum-energy efficiency. In this paper, we study the spectrum-energy efficiency optimization problem where BSs are with the ability to perform cell zooming, sleep mode, and user migration. We formulate the problem into an integer linear program which is solvable by CPLEX to maximize spectrum-energy efficiency; meanwhile traffic demands by associated users in multicell/multiuser networks are met. To avoid high computation time, a heuristic algorithm is proposed to efficiently solve the formulated problem. Numerical analysis through case studies demonstrates energy consumption and efficiency improvements, and comparisons between near-optimal solutions against optimality.

**Index Terms**—Network optimization, energy saving, spectrum efficiency, revenue-cost ratio



## 1 INTRODUCTION

WITH the popularity of smart mobile devices, mobile service providers have experienced the recent phenomenal growth of data services [1]. While data services bring significant revenue, service providers are facing increasing operation costs due to the high energy level consumed in full operation. It has been reported that energy costs can account for as much as half of a mobile service provider's annual operating expenses [2], [3]. Moreover, global concern over climate change appeals for the further reduction in energy consumption. It is the best interest of network operators to find the most economical way to run wireless networks.

At the stage of network planning, cell size and capacity are fixed based on estimation of peak of traffic load [4], [5]. Each base station (BS) in a cellular network consumes roughly up to 2.7 kWh of electrical power [5], [6]. These BSs tend to be deployed densely to achieve wide area coverage. Switching off BS (or going into sleep mode) provides a great opportunity to reduce the total energy consumption

and operation cost. Past research efforts use profiled traffic patterns to determine statically when and where to switch off BSs [7]–[9].

On the other hand, users of data services are charged based on the amount of data accessed, and data transmission occurs over restricted spectrum bands. The operation revenue for a wireless operator is able to be raised, if the operator has the capability to increase the efficiency in its limited spectrum resource use. Spectrum efficiency of the wireless network has become a major research area in the past decade. It is worth noting, however, that focusing only on optimizing energy consumption may lead to unfavorable spectrum efficiency, and vice versa [10], [11].

To evaluate the profitability for mobile operators, we consider the revenue-to-cost ratio, similar to the price-to-earnings ratio on the stock market. Economically by pursuing a higher revenue-cost ratio, operators can appear confident that the network operation is able to yield competitive revenue per cost; with a lower revenue/cost ratio, the network proves expensive or even barely profitable for operation. As improving spectrum efficiency benefits increasing revenue, and reducing energy consumption helps in bringing down the cost, we translate the revenue-to-cost ratio into spectrum-energy efficiency. Since the data transmission takes place on data subcarriers, spectrum-energy efficiency is defined as the satisfied rate requirements per allocated data subcarrier per consumed energy ( $(\text{bits/s})/\text{data subcarrier}/\text{Joule}$ ). The spectrum-energy efficiency is able to serve as a profitability indicator in terms of the data rate succeeded (revenue) by the equal resources allocation (cost). A system achieving greater efficiency has the ability to, for the given subcarrier number and energy

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consumption, transmit more data amount (or transmit data faster), effectively contributing to generating more revenue. Optimizing spectrum-energy efficiency, accordingly, runs the most profitable network for operators with respect to incurring the equivalent cost.

In this paper we are aimed at maximizing spectrum-energy efficiency in the multicell/multiuser wireless networks. The ideas of BS cell zooming, sleep mode and user migration are considered to configure the association with mobile users for a given network, as they have been mentioned as effective methods for the reduction on energy consumption [12]. Considering all the possible developed network topologies, a challenging task is to search economical operation and association between BSs and users so that the overall energy is minimized.

The task becomes more challenging if spectrum efficiency is taken into account also, considering a trade-off between energy consumption and spectrum efficiency. Optimizing spectrum-energy efficiency is involved with improvements in spectrum efficiency and energy consumption, which are two of the most important issues for green wireless networks. The quality of BS operation has a predominant influence on spectrum-energy efficiency and therefore the operator's profitability and competitiveness, as low efficiency leads to a waste of the capital expenditures.

To obtain the optimal operation employing spectrum and energy efficiently, the mathematic formulation is developed. We transform the developed formulation into an Integer Linear Programming (ILP) problem which can be solved by CPLEX. In the modeled problem, resource constraints such as the finite number of data subcarriers per time slot and the maximum BS transmission power are considered in the wireless access system. Association assignments and operation modes are the decision variables, which reveal information about BSs' optimal operation modes and served users.

The contributions of this paper are summarized as follows. (i) To the best of our knowledge, this is the first work which examines the optimization model of the spectrum-energy efficiency maximization problem in the downlink transmission of cellular networks. Different from previous studies, this work improves the ratio of spectrum efficiency to energy consumption as increasing that of revenue to expenditure for service providers. We consider the interplay between the data subcarrier utilization over spectrum and transmit power in the wireless environment. (ii) The first designed model as holding a fractional objective function is translated into an ILP model so that the most efficient network operation with respect to the maximum spectrum-energy efficiency can be revealed by running the solver to mobile service providers. To avoid the exponential computation time on solving the ILP problem, a heuristic approach is devised for the purposes of finding a near-optimal solution and having a computationally trackable feature. A series of case studies are conducted to verify performance of the optimization framework as well as to demonstrate computational benefit of the heuristic algorithm.

The remainder of this paper is organized as follows. We review the related work in Section 2. In Section 3, the

system model is presented and the ILP model is proposed. A heuristic approach is proposed which enhances the computation efficiency in Section 4, followed by the numerical experiments in Section 5. Section 6 concludes this paper.

## 2 RELATED WORK

Some studies look for reducing energy consumption or enhancing energy efficiency from the contribution in a network accommodating macro BS and micro BS. The papers of [13], [14] show that under the full traffic load and power consumption models, the growth of the density of micro/picocells could contribute to the network energy efficiency. By shrinking the cell radius, the study of [15] demonstrates improvement on the energy efficiency of the radio access network. With the variation of the cell size it studies the energy consumption ratio and gain without degrading the quality of service. The work of [12] proposes centralized and distributed algorithms to verify the reduction of power consumption of a cellular network with cell zooming. The authors of [16] tackle the problem from the angle of BS components, stating that advanced power amplifiers can save energy.

There have been efforts adopting the switching on/off scheme by both academia and industry [7]–[9]. During off-peak periods the cellular network system appears highly likely to be consuming surplus energy. BSs might have no users to serve, for instance. In such circumstance, if the BSs can switch into sleep mode, the energy consumption is able to be reduced consequently. Additionally, the traffic load fluctuation implies that BSs do not necessarily transmit at the full power level when the traffic load is light, so that energy saving can be achieved [17], [18]. Whereas other green cellular network studies derive the tradeoff between energy efficiency and spectrum efficiency [10], [11] or investigate the relation between energy and throughput [19], [20], the principal objective of this paper is to optimize spectrum-energy efficiency.

Optimizing spectrum efficiency is different from optimizing network throughput. The latter purely looks at enhancing the overall data rate; the former pursues the manner in which data subcarriers are employed most efficiently. The same throughput can be delivered over various data subcarrier number, achieving different spectrum efficiency. In other words, enhancing throughput cannot ensure spectrum efficiency progresses accordingly. From the perspective of a network operator, since the operating licence of a frequency band is part of the cost base, and this resource is limited and valuable, it is beneficial to utilize data subcarriers efficiently. Economically, the revenue is derived from the data access granted to users. However, as digital transmission consumes different energy, the energy expenditure varies as well. Hence, there is a correlation between revenue and operation cost. We define and maximize spectrum-energy efficiency as a ratio to examine the correlation.

This paper investigates the optimization problem of spectrum-energy efficiency in wireless networks where cell sizes can vary, BSs can operate in sleep mode and the network blocking ratio is characterized. To switch BSs into sleep mode without the violation of the network blocking

TABLE 1  
DL CPE and Base Station Parameters

	User device		BS with 2x2 MIMO
Rx noise figure	6 dB	Tx power	35 dBm
Rx antenna gain	2 dBi	Tx antenna gain	16 dBi
Other Rx gain	0 dB	Other Tx gain	9 dB

ratio, two aspects are taken into account. First, the active cells that stay on must provide necessary radio coverage. Secondly within any cell, traffic demands from served users have to be satisfied. The problem is formulated as an ILP model which aims at maximizing spectrum-energy efficiency with adaptability to the traffic fluctuation such as special events, emergency response, or newly emerging hot spots that generate large traffic demands. Different from previous works, instead of settling a certain time during hours for turning on and switching off BSs, we realize that BSs operate according to solutions in a dynamic and real time way.

### 3 SYSTEM MODEL

In our work, the broadband wireless communication system which manages multiple users and BSs is considered with a blocking ratio. The important factors related to energy and data subcarrier are evaluated as well. Spectrum-energy efficiency is defined as the served traffic over allocated data subcarrier number per energy consumed. The goals are to (i) maximize spectrum-energy efficiency of the system, (ii) obtain the corresponding BS operation modes, and (iii) assign the serving BS to each user, such that the rate requirement of each associated user is satisfied.

Within a BS's coverage, a number of users appear, submitting its traffic service requirement. Without loss of generality, we assume that user traffic demand follows the random distribution. In the studied cases, we consider BSs located over different types of areas, each of which covers users distributed with different percentages. The assumed profiles of user devices and BS are given for the calculation of required transmission power in Table 1 [21]. The notations taken in the paper are listed in Table 2.

#### 3.1 Green Wireless Network Operation Strategy

Within cell coverage, BSs transmit clear signals so that quality signals can be received by users. The coverage is determined by the distance between BSs and served users. Generally, planners assume BSs operate fixed coverage. Actually, BS coverage is changeable via adjusting transmit power [12], [22]. Cells can zoom out (in) with increased (decreased) transmit power. BS can go to sleep mode to switch off energy consuming equipments; the neighboring cells is able to reconfigure the power level to guarantee the coverage [18].

With cell zooming and sleep mode operations as shown in Fig. 1, there is the capability for enhancing spectrum-energy efficiency. Fig. 1(a) shows a wireless access network with five BSs, where the central BS is surrounded by four BSs. BSs are located at the respective center of the cells,

TABLE 2  
Definitions of Important Symbols

Symbol	Definition
$d_{mn}$	The distance between BS $m$ and SS $n$ .
$N$	The number of SSs to be associated with the cells.
$M$	Total number of BSs.
$P_a$	The basic active mode energy consumption of BSs.
$P_s$	The sleep mode energy consumption of BSs.
$R_b$	The network blocking ratio.
$P_{max}$	The maximum transmission power for BSs.
$DS_t$	The maximum number of data subcarriers.
$\theta$	The minimum necessary SS number, $\theta = N \cdot (1 - R_b)$ .
$\mathbb{N}_{SS}$	The set of SSs, $ \mathbb{N}_{SS}  = N$ .
$\mathbb{N}_{BS}$	The set of BSs, $ \mathbb{N}_{BS}  = M$ .
$\mathbb{P}$	The set of traffic demand for SSs, $\mathbb{P} = \{\rho_n, \forall n \in \mathbb{N}_{SS}\}$ .
$\mathbb{D}$	The set of data subcarrier number for SSs, $\mathbb{D} = \{D_n, \forall n \in \mathbb{N}_{SS}\}$ .
$\mathbb{R}$	The set of spectrum efficiency, $\mathbb{R} = \{r_n, \forall n \in \mathbb{N}_{SS}\}$ , where $r_n = \frac{\rho_n}{D_n}$ .
$\mathbb{T}$	The set of transmission power between BS $_m$ and SS $_n$ , $\mathbb{T} = \{T_{mn}, \forall m \in \mathbb{N}_{BS}, n \in \mathbb{N}_{SS}\}$ .
$\mathcal{E}$	The total system energy consumed.
$\mathcal{C}$	The objective value of the problem.
$\mathcal{A}$	The BS-SS association matrix (decision variable), $\mathcal{A} = (a_{mn})_{M \times N}$ .
$\mathcal{O}$	The BS operation mode vector (decision variable), $\mathcal{O} = (o_m)_{1 \times M}$ .
$\mathbf{U}$	$\mathbf{U} = \{\mu_{mn}\} = a_{mn} \cdot \tau$ in the transformed model.
$\mathbf{V}$	$\mathbf{V} = \{\nu_m\} = o_m \cdot \tau$ in the transformed model.

designated by numbers; users are distributed among BSs, denoted by plus signs. As the users are relatively close to the centers of BS1 and BS3, the BSs can zoom in to release smaller cell sizes with reduced energy consumption (Fig. 1(b)). When BSs are in sleep mode, the energy consumption level is noticeably low; hence sleeping BSs can contribute to a major reduction in energy. Fig. 1(c) illustrates the neighboring BS4 can zoom out by associating the migrated users from BS3 so that BS3 can operate in sleep mode, and more data subcarriers are able to be allocated to carry out more data transmission. If neighboring BSs cannot adjust the cell sizes to cover more users due to the finite resource of subcarriers or restricted transmission power, considering the network blocking ratio, BS1 can still choose to sleep through disconnecting with the tolerable number of users as in Fig. 1(d). A sleeping BS has no service coverage, and the adjacent BSs can take over swept users to serve. With the ability to adjust cell size, switch to sleep mode and migrate users, the system is able to improve spectrum-energy efficiency.

#### 3.2 Spectrum-Energy Efficiency Optimization Model of Problem

The following sections present the optimization model for the BS spectrum-energy efficiency problem. Let  $\mathbb{N}_{BS} = \{BS_0, \dots, BS_{M-1}\}$  be the set of base stations with cardinality  $|\mathbb{N}_{BS}| = M$ . Similarly, let  $\mathbb{N}_{SS} = \{SS_0, \dots, SS_{N-1}\}$  be the set of users with cardinality  $|\mathbb{N}_{SS}| = N$ . The problem is defined as follows:



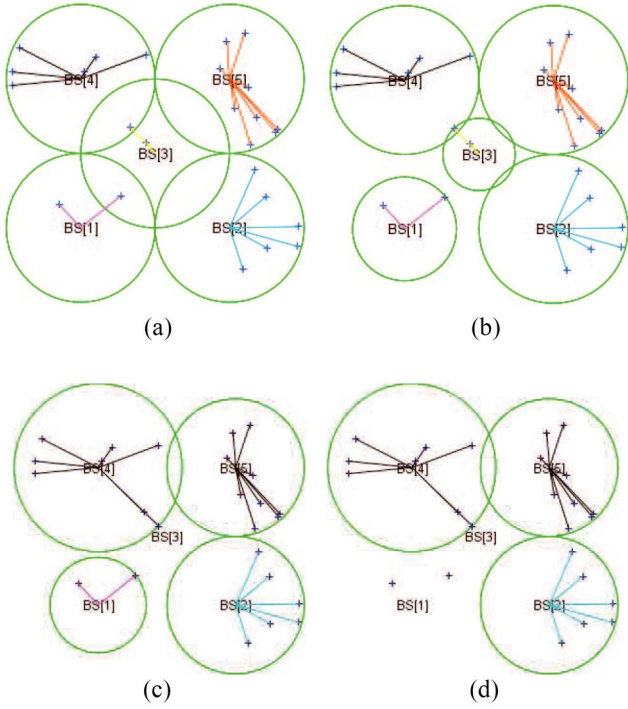


Fig. 1. Ideas of cell zooming in/out, sleeping operation and user migration. (a) Cells running regularly. (b) Cells with reduced transmission power. (c) Cells with increased transmission power. (d) Cells in sleep mode and reassociating users.

Given (i) the transmission power requirements of  $N$  users from the finite number of  $M$  BSs,  $T_{mn}$ , (ii) the rate requirement of each user,  $\rho_n$ , number of data subcarriers,  $D_n$ , (iii) the blocking ratio,  $R_b$ , and (iv) the maximum power,  $P_{max}$ , data subcarriers,  $DS_t$ , the basic active and sleep mode energy use of the BS,  $P_a$  and  $P_s$ , the problem is to maximize the system spectrum-energy efficiency, denoted as  $C$ , by associating users and BSs, deploying BSs in active mode. The expected output includes the network topology where association assignments and operation mode of BSs are specified,  $a_{mn}$  and  $o_m$ .

### 3.3 Decision Variables

The decision variables of the spectrum-energy efficiency problem are  $\mathcal{A}$  and  $\mathcal{O}$ .  $\mathcal{A} = (a_{mn})_{M \times N}$  is a BS-SS incidence matrix, or the *association matrix*.  $\mathcal{O} = (o_m)_{1 \times M}$  is a BS activation incidence vector, or the *operation mode vector*. The value of a decision variable is decided as follows.

$$a_{mn} = \begin{cases} 1, & SS_n \text{ assigned to } BS_m, \forall m \in \mathbb{N}_{BS}, n \in \mathbb{N}_{SS}; \\ 0, & \text{otherwise.} \end{cases}$$

$$o_m = \begin{cases} 1, & BS_m \text{ in active mode, } \forall m \in \mathbb{N}_{BS}; \\ 0, & \text{otherwise.} \end{cases}$$

When  $a_{mn}$  is asserted, the traffic served to  $SS_n$  is equal to the rate requirement,  $\rho_n$ , and  $o_m$  has to set a value of one correspondingly.

The BS cell size is the equivalent of the service area within which BSs are able to serve users by tuning up transmission power ( $T_{mn}$ ) over geographical distances. Cell zooming can be told by drawing a comparison of the service areas of two statues at different operation times. In other words, as the service area varies with the adjusted

TABLE 3  
Parameters per Modulation Scheme

Modulation	Sensitivity (dBm)	Data bit per symbol	SNR (dB)	Data rate (Mbps)
BPSK1/2	-89.6	0.5	6.4	0.86
QPSK1/2	-86.6	1	9.4	1.72
QPSK3/4	-84.8	1.5	11.2	2.58
16QAM1/2	-79.6	2	16.4	3.44
16QAM3/4	-77.8	3	18.2	5.16
64QAM2/3	-73.3	4	22.7	6.88
64QAM3/4	-71.6	4.5	24.4	>6.88

transmit power level, the BS is undertaking cell zooming. Cell zooming is realized as follows. For each active BS  $m$ , its cell size for an operation time  $t$ ,  $C_t^m$ , is measured by the transmission distance developed with the associated users as  $a_{mn} = 1, \forall n \in \mathbb{N}_{SS}$ . Based on the distances between BSs and users ( $d_{mn}$ ), the farthest user  $n'$  is recognized from  $n' = \arg \max_{n \in \mathbb{N}_{SS}} d_{mn'}$ , and the cell size is radiated with the distance by  $C_t^m = d_{mn'}$ . Compared to the cell size in the previous operation time of  $t_1$ ,  $C_{t_1}^m$ , if the BS size adjusts to a service area for a latter operation time of  $t_2$ ,  $C_{t_2}^m$ , the idea of zooming is realized. The cell carries out zooming in if  $C_{t_2}^m < C_{t_1}^m$ , zooming out if  $C_{t_2}^m > C_{t_1}^m$ .

### 3.4 Topology Constraint

The next constraint realizes the traffic request from an associated user is satisfied through a direct link with a BS. Each user can be served by up to one BS.

$$\sum_{m \in \mathbb{N}_{BS}} a_{mn} \leq 1, \forall n \in \mathbb{N}_{SS}, \quad (1)$$

For an individual BS  $m$ , if the result of  $\sum_{n \in \mathbb{N}_{SS}} a_{mn} = 0$ , it means the BS  $m$  operates in sleep mode. And the idea of user migration is put into action if an user is associated with a BS  $m$  different from the one  $m'$  it formerly connected. Namely, for an associated user  $n$ ,  $a_{mn} = 0$  and  $a_{m'n} = 1$  in the solution.

### 3.5 Constraints on BSs

This section defines the constraints in the BS domain. First, they ensure when links are offered in the solution, the total deployed data subcarriers of a BS cannot exceed the available data subcarriers in specified symbol time. In addition, based on rate requirements, the number of data subcarriers for mobile users varies.  $D_n$  indicates the number of data subcarriers for user  $n$ . We use decimal values for individual rate requirements,  $\rho_n$ , randomly chosen from the set of supported rates by the physical (PHY) layer (Table. 3).

For every BS providing associations, we limit the maximum transmission power level to a specific value. For various distances, links can be built with diverse transmission power levels from transmitters. We employ the notation of  $T_{mn}$  to demonstrate the minimum required transmission power from a BS  $m$  to a user  $n$ . We also enlist the constraints on the decision variables of BS operation modes,  $o_m$ . A BS operates in either sleep mode, taking a relatively low energy level, or in active mode, consuming a basic running energy plus the energy for transmission.

### 3.5.1 Transmission Power Constraint

The maximum power level,  $P_{max}$ , which a BS can transmit on in total is deliberately restricted at the power level of 20 Watts throughout our study [23]. The constraint is as follows:

$$\sum_{n \in \mathbb{N}_{SS}} (a_{mn} \cdot T_{mn}) \leq P_{max}, \forall m \in \mathbb{N}_{BS}, \quad (2)$$

The necessary transmission power levels,  $T_{mn}$ , from BSs can be learned fundamentally from a link budget equation [23]. The received signal at the user needs to be higher than the threshold over which the desired data rate can be guaranteed. Signal strength from BSs to users, however, is influenced with the propagation gains and the attenuation by miscellaneous losses. To reach the user who may suffer from comprehensive losses along the transmission, a BS has to send out the signal which is strong enough by the necessary power level,  $T_{mn}$ . Considering the desired Bit Error Rate (BER), receiver sensitivity is regarded as the minimum received power at the receiver side for the guaranteed signal strength [24].

Receiver sensitivity is listed in Table 3 [21], [25], [26]. As BS antennas are assumed to transmit ideally, feeder losses, connector losses and jumper losses are not considered. We consider fast fading margin and building penetration loss, whose values are assumed in simulation [21]. The COST-231 Hata and COST-Walfisch-Ikegami models are considered for path loss [27], [28]. We assumed the BS antenna height is 30(m) and the users' antenna height is 1(m) [29].

### 3.5.2 Data Subcarrier Constraint

The total number of data subcarriers a BS serves should not be greater than the available number of data subcarriers ( $DS_t$ ) on the channel bandwidth in the specified symbol time. This constraint is ensured by the following equation. For example, within one second, there are 14,000 symbols including DL and UL subframes, where each symbol carries 720 data subcarriers on a 10 MHz channel bandwidth.

$$\sum_{n \in \mathbb{N}_{SS}} (a_{mn} \cdot D_n) \leq DS_t, \forall m \in \mathbb{N}_{BS}, \quad (3)$$

As the available spectrum span is finite, the number of subcarriers to transmit data over the span is also limited. To obtain the number of data subcarriers for individual traffic demands, the equation bearing the relation of the data subcarriers number,  $D_n$ , to the rate requirement,  $\rho_n$ , is considered [30]. BPSK-1/2 requires less receiver-side power but achieves a smaller data rate; 64QAM-3/4 processes a higher power level and gives a higher traffic rate. This situation effects the spectrum-energy efficiency in wireless networks.

In the advanced broadband wireless technology such as WiMAX, the new coming or blocked users are able to follow the ranging processes to synchronize with BSs before a communication link is established. For example, the Round Trip Delay between users and BSs must be known to users. Those users are required to carry out successful an initial ranging process with BSs, and the responses to different ranging codes message from users to BSs are required, in which information regarding the adjustment is estimated for the power level of each user. The information about the

number of data subcarriers to meet each user requirement can be collected during the resource allocation procedure. Accordingly, when users are able to synchronize with BSs, the information about transmit power can be acquired and then used as input to our model without knowing the exact locations of all users. The values of  $T_{mn}$  and  $D_n$  are parts of the parameters passed during communication establishment and maintenance, which manifests the practicality of the proposed model. Once users have been associated, they will periodically send period ranging information to maintain communication between users and BSs. If the period ranging response message contains parameters that must be adjusted such as the change of the necessary transmit power level or rate requirement, the model needs to be executed to obtain the real-time optimal solution. In our work,  $T_{mn}$  and  $D_m$  are calculated in order to carry out our simulation model.

### 3.5.3 Operation Mode Constraints

The constraints in this part define in which mode a BS should run. If it is an BS operating at active mode,  $o_m$  is equal to one for BS  $m$ .

$$o_m \leq \sum_{n \in \mathbb{N}_{SS}} a_{mn}, \forall m \in \mathbb{N}_{BS}, \quad (4)$$

$$a_{mn} \leq o_m, \forall m \in \mathbb{N}_{BS}, n \in \mathbb{N}_{SS}, \quad (5)$$

Eq. (4) and (5) together satisfy that a BS switches into active mode as long as in charge of any communication; otherwise the BS is able to change to sleep mode without serving users.

### 3.6 Constraint on Blocking Ratio

For the entire model, the total number of the connected users must be higher than the required number of active users, realized by  $\theta = N(1 - R_b)$ , where  $N$  represents the total number of users, and  $R_b$  the value of the blocking ratio.

$$\sum_{m \in \mathbb{N}_{BS}, n \in \mathbb{N}_{SS}} a_{mn} \geq \theta, \quad (6)$$

$R_b$  denotes the blocking ratio, that the number of users cannot get access to the service divided by the total users demanding services. We have

$$R_b = \frac{\text{total number of users not associated}}{\text{total number of users requesting services}}.$$

There will be no blocked out users if the blocking rate is set to zero.

### 3.7 Objective Function

To identify the economical objective, we consider the revenue-to-cost ratio, serving as an indicator of the operator's profitability, analogous to the price-earnings ratio on the stock market. Since the way to work out the actual monetary values of the revenue and cost varies from case to case, the objective is transformed into a generalized objective function that maximizes the ratio of spectrum efficiency over energy consumed during the service operation. The goal is to attain a network design which is cost-effective, meaning the highest rate is conveyed per

resources allocated. As the most efficient network is capable of processing more data by comparison, with the given cost in terms of energy consumption, the revenue is on increase coming from data services offered. The relationship between the two objectives, although can be offered by taking a multi-criteria optimization approach, the approach is not able to measure the efficiency. With the optimal service rate per resources, the most profitable network design can be realized.

### 3.7.1 Spectrum Efficiency

We define the spectrum efficiency as a summation of the individual served traffic divided by the allocated data sub-carrier number for associated users, as the resources are distributed separately. The next expression presents the efficiency achieved as a whole.

$$\sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} \left( \frac{\rho_n}{D_n} \cdot a_{mn} \right) = \sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} (r_n \cdot a_{mn}). \quad (7)$$

### 3.7.2 Energy Consumption

Supposedly, the energy a sleeping BS will consume is  $P_s$ , 8 (Joules) [12]; on the other hand, the energy consumed by an active BS  $m$  comes from the summation of the basic active mode energy  $P_a$ , 20 (Joules) [23], plus the energy exploited to serve all its users,  $P_a + \sum_{n \in \mathbb{N}_{\text{SS}}} (T_{mn} \cdot a_{mn})$ ,  $\forall m \in \mathbb{N}_{\text{BS}}$ . The overall energy consumption is expressed as:

$$\begin{aligned} \mathcal{E} = & \sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} (T_{mn} \cdot a_{mn}) + \sum_{m \in \mathbb{N}_{\text{BS}}} (P_a \cdot o_m) \\ & + \sum_{m \in \mathbb{N}_{\text{BS}}} [P_s \cdot (1 - o_m)]. \end{aligned} \quad (8)$$

The complete formula of the objective function combines the Eq. (7) and (8).

$$\max \frac{\text{Spectrum Efficiency}}{\text{Energy Consum.}} = \max \frac{\sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} (r_n \cdot a_{mn})}{\mathcal{E}}. \quad (9)$$

Eq. (9) is the objective function to maximize the spectrum-energy efficiency in the model. As a result of the energy required for sleep mode,  $\mathcal{E}$  has a lower bound ( $P_s \times M$ ) even though no associations is formed by BSs with users. The case, therefore, will not arise that total energy consumption is very small (e.g., goes to zero). However, the problem involves a fractional objective function which cannot be considered as a linear programming model. We reformulate the problem into an ILP problem, so that a software package, such as CPLEX, is able to obtain the optimal solution.

## 3.8 Solving Optimization Problem with a Linear Fractional Objective Function

Eq. (9) has decision variables in both numerator and denominator, which is not the equation in the first degree. To eliminate the nonlinearity of the objective function, the model must be transformed to a model that is pure linear. Besides when the solution is found to this transformed model, the results can be recalculated back to the original model. In our problem the objective function is a ratio of two linear terms, and the constraints of Eq. (1)–(6) are linear.

Since the value of the denominator is positive, the discussed method in [31] is applicable to our model. Eq. (9) can be transformed to a linear function, developing an integer linear programming model.

Considering the original problem, the denominator is positive over the entire feasible sets of  $a_{mn}$  and  $o_m$ . In order to realize the model transformation and eliminate the non-linearity in the original model, variables  $\mu_{mn}$ ,  $v_m$  and  $\tau$  are introduced and satisfy:  $\mu_{mn} = \tau \cdot a_{mn}$  and  $v_m = \tau \cdot o_m$ , where  $\tau = \frac{1}{\mathcal{E}} > 0$ . The objective function is now given by

$$\max \mathcal{C} = \sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} (r_n \cdot \mu_{mn}), \quad (10)$$

subject to

$$\begin{aligned} \sum_{m \in \mathbb{N}_{\text{BS}}} [(P_a - P_s) \cdot v_m] + \tau \cdot M \cdot P_s + \\ \sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} (T_{mn} \cdot \mu_{mn}) = 1, \end{aligned} \quad (11)$$

$$\sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} \mu_{mn} \geq \tau \cdot \theta, \quad (12)$$

$$\sum_{n \in \mathbb{N}_{\text{SS}}} (T_{mn} \cdot \mu_{mn}) \leq \tau \cdot P_{\text{max}}, \quad (13)$$

$$\sum_{n \in \mathbb{N}_{\text{SS}}} (D_n \cdot \mu_{mn}) \leq \tau \cdot DS_t, \quad (14)$$

$$\sum_{n \in \mathbb{N}_{\text{SS}}} \mu_{mn} \geq v_m, \quad (15)$$

$$\sum_{m \in \mathbb{N}_{\text{BS}}} \mu_{mn} \leq \tau, \quad (16)$$

$$\mu_{mn} \leq v_m, \quad (17)$$

$$\mu_{mn}, v_m, \tau \geq 0, \quad (18)$$

Provided  $\tau > 0$  at the optimal solution, this linear programming model is equivalent to the fractional objective problem stated previously except the binary condition of decision variables. The values of the variables  $a_{mn}$  and  $o_m$  in the optimal solution to the fractional objective problem are obtained from dividing the optimal  $\mu_{mn}$  and  $v_m$  by the optimal  $\tau$ .

As all decision variables in the fractional objective model are binary, it is necessary to impose on the transformed model the constraints which reflect the binary essence. We know that  $\mu_{mn} = a_{mn} \cdot \tau$  and  $v_m = o_m \cdot \tau$ , in which case if  $a_{mn}$  is zero, then  $\mu_{mn}$  must be zero; otherwise,  $\mu_{mn} = \tau$  if  $a_{mn} = 1$ . For this purpose, with the following constraints, introduced are the binary variables,  $\alpha_{mn}$  and  $\beta_m$ , and a constant value  $Q$  holding a value greater than  $\mu_{mn}$ ,  $v_m$  and  $\tau$ .

$$\mu_{mn} - \tau - Q \cdot \alpha_{mn} \geq -Q, \quad (19)$$

$$v_m - \tau - Q \cdot \beta_m \geq -Q, \quad (20)$$

$$\mu_{mn} - \tau + Q \cdot \alpha_{mn} \leq Q, \quad (21)$$

$$v_m - \tau + Q \cdot \beta_m \leq Q, \quad (22)$$

$$\mu_{mn} \leq Q \cdot \alpha_{mn}, \quad (23)$$

$$v_m \leq Q \cdot \beta_m, \quad (24)$$

$$\alpha_{mn}, \beta_m \in \{0, 1\}, \forall m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}. \quad (25)$$



It is recognized in [31] that the problem of Eq. (1)–(6) and (9) are equivalent to that of Eq. (10)–(25). In other words, for example, if  $\mathbf{U}$  is a solution to the problem of Eq. (10)–(25), then we can obtain a solution  $\mathcal{A}$  to the problem of Eq. (1)–(6) and (9) from  $a_{mn} = \frac{\mu_{mn}}{\tau}$ ,  $\forall m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}$  that follows from  $\tau = \frac{1}{\mathcal{E}}$ . Although  $\mathcal{E}$  has become part of the new constraints, the transformed model still considers the transmission power requests from users while solving the problem. For instance, among a bunch of users with different spectrum efficiency values, the model has to look at the required transmit power in Eq. (3.8) from each user. A transmission, if demanding lower power also, with a small spectrum efficiency value can still hold a higher spectrum-energy efficiency value, resulting in a higher  $\tau$ . Since the value of  $\tau$  has the impact on that of both  $\mu_{mn}$  and  $v_m$ , not only  $r_n$  but also  $T_{mn}$  puts weight to the objective function.

## 4 HEURISTIC ALGORITHM

We develop heuristic approaches solving spectrum-energy efficiency problem to avoid the exponential increase in the computation time taken by CPLEX. In the wireless communication environment the number of users changes and the requirements fluctuate frequently; hence, heuristic algorithms are favored to solve the proposed optimization model in real time. The pseudocode is shown in Algorithm 1, taking the same inputs with CPLEX and is implemented using C programming language. The output includes the association between BSs and users,  $a_{mn}$ , and the operation mode of BSs,  $o_m$ . A heuristic algorithm is also devised to solve the minimizing energy consumption problem in a similar way.

### 4.1 Algorithm Design Principle

Initially, a preliminary solution is put forward under the definitions of the best and second best BS choices for users. Thanks to the substantial difference between the operation energy usages of active and sleep modes of a BS, it is beneficial to operating as many as BSs in the sleep mode. Moving the current users to other BSs could produce a better solution as well. The attempt is to seek a new solution bringing out an improved efficiency value by migrating users to the other BSs so that originally active BSs are able to switch into sleep mode. In addition, since in downlink transmission, BSs are the resources transmitting signals, the likelihood of interference generated between adjacent BSs is along with the transmission. Turning BSs into sleep mode possibly reduces the impact of this phenomena, alleviating the effect of interference.

### 4.2 Algorithm Description

After initialization (Line 2), the spectrum-energy efficiency values for associations between BSs and users are worked out by  $\frac{r_n}{T_{mn}}$  and stored in  $\mathbb{S}^E$ . The users are sorted in a decreasing order in terms of spectrum-energy efficiency and indexed in  $\mathbb{N}_{\text{SS}}$  (Line 3). By the function **BestBS4SS**, all users are assigned to the BSs that can provide the optimal spectrum-energy efficiency values for the users (denoted as  $I_n^1$ ).  $I_1^1 = \arg \max_{m \in \mathbb{N}_{\text{BS}}} S_{m1}^E$  then is mapped to the BS-SS association and BS operation mode decision variables

### Algorithm 1 Heuristic Spectrum-Energy Efficiency Maximization

**Input:**  $M, N, \mathbb{N}_{\text{BS}}, \mathbb{N}_{\text{SS}}, T, \mathbb{D}, \mathbb{P}, P_a, P_s, \theta, P_{\max}, DS_t$ ;

**Output:**  $\mathcal{C}, \mathcal{A}, \mathcal{O}$ ;

```

1:  $\mathcal{A} = \text{zeros}([M, N])$ ;  $\mathcal{O} = \text{zeros}([1, M])$ ;  $\mathbb{B}_m = \Phi$ ;
2: Calculate  $S_{mn}^E$  for associations between  $SS_n$  and  $BS_m$ ;
3:  $\text{Sort}(\mathbb{S}^E, 'desc')$ ;  $\text{Reorder}(\mathbb{N}_{\text{SS}})$ ;
4: for  $n = 1$  to  $N$  do
5:   BestBS4SS( $S_{mn}^E, \mathcal{A}, \mathcal{O}$ );
6: end for
7: for  $m = 1$  to  $M$  do
8:   BSConstraintChecker( $S_{mn}^E, \mathcal{A}, \mathcal{O}, DS_t, P_{\max}$ );
9: end for
10: if  $\sum_{m \in \mathbb{N}_{\text{BS}}, n \in \mathbb{N}_{\text{SS}}} a_{mn} < \theta$  then
11:   for  $n = 1$  to  $N$  do
12:     if  $\sum_{m \in \mathbb{N}_{\text{BS}}} a_{mn} = 0, \forall n \in \mathbb{N}_{\text{SS}}$  then
13:       SecondBestBS4SS( $S_{mn}^E, \mathcal{A}, \mathcal{O}$ );
14:     end if
15:   end for
16: end if
17: for  $m = 1$  to  $M$  do
18:   BSConstraintChecker( $S_{mn}^E, \mathcal{A}, \mathcal{O}, DS_t, P_{\max}$ );
19: end for
20: Calculate  $\mathcal{E}, C_m^D, C_m^E$  and  $C_m^S, \forall m \in \mathbb{N}_{\text{BS}}$ ;
21:  $\mathbb{F} \leftarrow \text{Sort}(\mathbb{C}^S, 'asce')$ ;  $\text{Reorder}(\mathbb{N}_{\text{BS}})$ ;
22: for  $m = 1$  to  $M$  do
23:   for  $m' = M$  to  $1$  do
24:     OptimizeEnergy( $\mathcal{E}, \mathbb{F}, \mathcal{A}, P_a, P_s$ );
25:   end for
26:   if  $\exists k, C_m^D + C_k^D \leq DS_t, C_m^E + C_k^E \leq P_{\max}$  then
27:     Migration( $k, \mathcal{A}, \mathcal{O}, P_a, P_s$ );
28:     Re-calculate  $\mathcal{E}, C_m^D, C_m^E$  and  $C_m^S, \forall m \in \mathbb{N}_{\text{BS}}$ ;
29:      $\mathbb{F} \leftarrow \text{Sort}(\mathbb{C}^S, 'asce')$ ;  $\text{Reorder}(\mathbb{N}_{\text{BS}})$ ;
30:      $m = 1$ ;
31:   end if
32: end for
33: Calculate  $\mathcal{C}$ ;
34: for  $m = 1$  to  $M$  do
35:   for  $m' = M$  to  $1$  do
36:     OptimizeEfficiency( $\mathcal{C}, \mathbb{F}, \mathcal{A}, P_a, P_s$ );
37:   end for
38:   if  $\exists k, C_m^D + C_k^D \leq DS_t, C_m^E + C_k^E \leq P_{\max}$  then
39:     Migration( $k, \mathcal{A}, \mathcal{O}, P_a, P_s$ );
40:     Re-calculate  $\mathcal{C}, C_m^D, C_m^E$  and  $C_m^S, \forall m \in \mathbb{N}_{\text{BS}}$ ;
41:      $\mathbb{F} \leftarrow \text{Sort}(\mathbb{C}^S, 'asce')$ ;  $\text{Reorder}(\mathbb{N}_{\text{BS}})$ ;
42:      $m = 1$ ;
43:   end if
44: end for
45: return  $\mathcal{C}, \mathcal{A} = (a_{mn})_{M \times N}, \mathcal{O} = (o_m)_{1 \times M}$ 

```

such that  $a_{I_1^1, 1} = 1$  and  $o_{I_1^1} = 1$ . The same operation repeats for the next user. The iteration stops when all the users are assigned. Then, a preliminary solution is established by this method. All of the users are served by the BSs with the maximum individual spectrum-energy efficiency values.

The function **BSConstraintChecker** verifies the preliminary solution is in conformity with the constraints of (2) and (3). If any of them is not achieved, the solution is not

valid and needs further improvements. While these two constraints are violated, the function finds and removes the users with lower spectrum-energy efficiency values,  $n = \arg \min_{n \in \mathbb{N}_{\text{SS}}} S_{mn}^E$ , within the BSs violating the constraints among all the initial active associations. The values of  $a_{mn}$  and  $o_m$  are updated accordingly. Since maximizing the total spectrum-energy efficiency, we keep the users causing higher spectrum-energy efficiency values associated in the solution.

In Lines 10–16, if the constraint of (6) is not met, for the remaining users without associations, we select the second best BSs that offer the second maximized spectrum-energy efficiency. Similar to the function **BestBS4SS**, the function **SecondBest4SS** assigns unassociated users by looking into  $I_n^L$ . The selected BS is mapped to  $a_{I_n^L, n}$  and  $o_{I_n^L}$ . Subsequently, the validity of the two fundamental constraints on BSs is checked again, by the function **BSConstraintChecker**.

In Lines 20–21, the system energy consumption ( $\mathcal{E}$ ), the number of subcarriers ( $C_m^D$ ) and the amount of energy ( $C_m^E$ ), spectrum-energy efficiency ( $C_m^S$ ) each BS performs are calculated, then BSs are sorted by the values of spectrum-energy efficiency in  $\mathbb{F}$ . Starting from the BS with the least efficiency value,  $BS_{F_1}$ , the function **OptimizeEnergy** first computes a new total energy consumption,  $\mathcal{E}'$ , by tentatively reassigning users originally connecting with that BS,  $n \in BS_{F_m}$ , to the other BSs,  $BS_{F_m}$ . If there exists a  $k = \arg \min_{k \in \mathbb{N}_{\text{BS}}} \mathcal{E}'$  such that the new solution consumes less energy,  $\mathcal{E}' < \mathcal{E}$ , and the constraints on BSs are still not violated, the function **Migration** sweeps all  $n \in BS_{F_m}$  to the new  $BS_{F_k}$  by updating  $a_{kn}$ ,  $a_{mn}$ ,  $o_k$ ,  $o_m$  and  $\mathcal{E}$ . The corresponding values are updated and  $\mathbb{C}^S$  is sorted again to reorder  $\mathbb{N}_{\text{BS}}$ . The procedure continues until there is no better solutions in terms of energy consumption,  $m = M$ . Lines 34–44 fulfill a similar function for finding a better solution by investigating spectrum-energy efficiency. **OptimizeEfficiency** looks for the existence of a better spectrum-energy efficiency value compared with the current solution by migrating users. After the last step, the final solution is found where the output values of  $a_{mn}$  and  $o_m$  is presented. The overall computation complexity of the algorithm is  $O(M^3N)$ .

## 5 NUMERICAL RESULTS

This section presents case studies where the WMAN OFDMA interface is assumed such as IEEE 802.16. The case studies are conducted to evaluate the solutions to the problem, the proposed heuristic algorithms in terms of optimality, and the computational efficiency. We compare the performance of minimizing energy consumption and maximizing spectrum-energy efficiency against the base cases, aiming to show the impact of the significance of optimizing BS-SS association and BS operation mode in multi-cell-multi-users scenarios. The computation time and solutions of CPLEX and the heuristic algorithms are investigated from the aspects of minimized energy, maximized efficiency as well.

The main system parameters taken into account in the simulations are tabulated in Table 4; Table 5 characterizes the building penetration loss correction values for users in different types of areas [21], including the user and area

TABLE 4  
System Parameters

Parameter	Value
Channel bandwidth	10 MHz
BS antenna height	$h_b = 30m$
MS antenna height	$h_m = 1m$
Path loss model	COST-WI and COST-Hata
Number of subchannels	30
Target BER	$10^{-6}$
Maximum transmission power	20 (Watts)
Fading	Fast fading margin
FFT size	1024
Thermal noise	-104 dBm
User distribution	Table 5
DL subframe duration	0.5 ms
Number of DL subframe	2000
Required data rate	Random
Modulation	BPSK, QPSK, 16QAM, 64QAM
Conventional BS cell radius	5 km
Implementation loss	2 dB
Guard time	1/8
Overhead	20%
TDD down/up ratio	3
Data subcarrier number	720

TABLE 5  
BPL Corrections and Percentages for Various Area Types

Type	Correction	Area Percent.	User Percent.
Rural	12 dB	65%	10%
Suburban	15 dB	20%	20%
Urban	18 dB	15%	70%

percentages. Users and BSs can be placed at three different types of areas, urban, suburban and rural areas.

Fig. 2(a) shows the illustrative network layout, in which the coordinates of each user and BS are illustrated, and the amount of traffic demand is proportional to the radius of the circle representing the user. Fig. 2(b) and (c) also show the resulting configurations of BS operation modes and the BS-SS associations, which are represented with the solid circles. The sizes of circles depict the corresponding energy consumption and spectrum-energy efficiency performance gains. These figures provide insights regarding the impact of the distance between BSs and users on the energy required and spectrum-energy efficiency of the destination.

### 5.1 Solving the Model

Fig. 3 displays the comparisons of the cases carrying the user number from 2100, where 11 BSs are in the system with a blocking ratio of 0.05 percent. In the base cases, all the BSs are in active mode, resulting in extremely high energy consumption. Nevertheless, since in our models the number of active BSs is minimized to save superfluous energy, it is clearly shown in Fig. 3(a) that for various numbers of users, the optimization model which mainly considers minimizing energy consumes the lowest overall energy to sustain



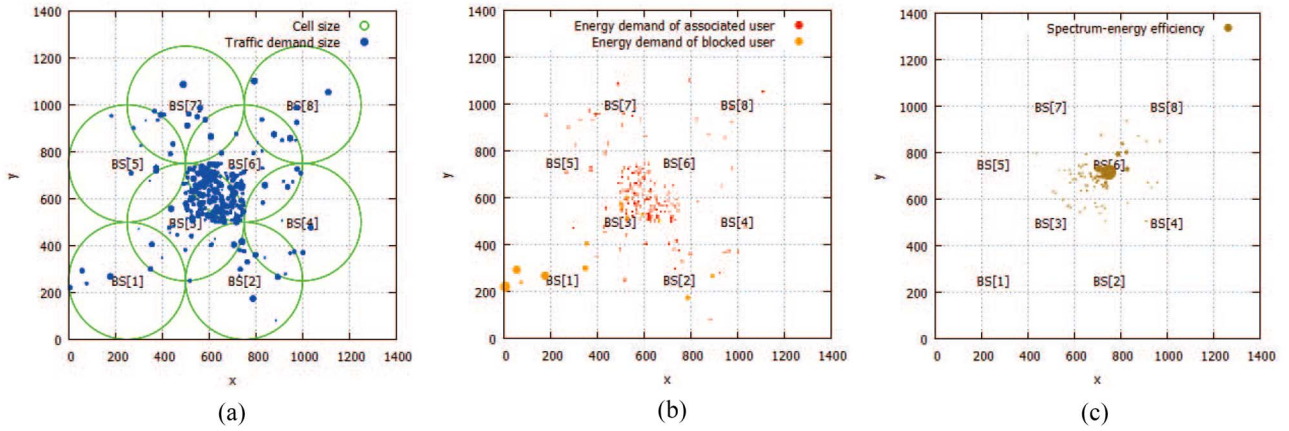


Fig. 2. Illustration of cell layout, geographical distribution of traffic demands, energy consumption and spectrum-energy efficiency for BSs in same scenario. (a) Network topology and traffic demands. (b) Optimal energy consumption. (c) Optimal spectrum-energy efficiency.

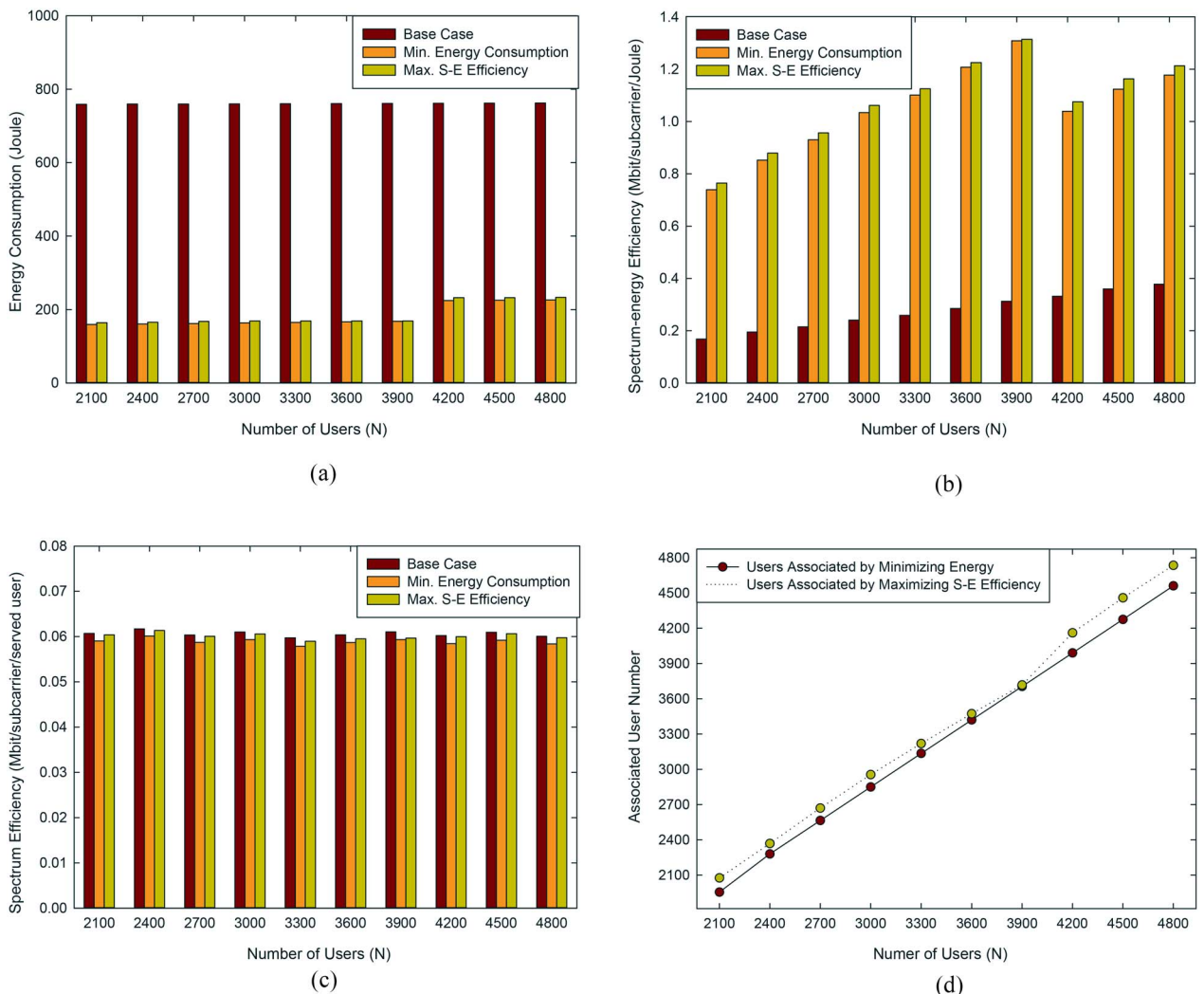


Fig. 3. Energy consumption, spectrum efficiency, spectrum-energy efficiency and associated user number versus number of users. (a) Energy consumption versus number of users. (b) Spectrum-energy efficiency versus number of users. (c) Spectrum efficiency versus number of users. (d) Associated user versus number of users.

the system, saving energy substantially from the base cases without energy optimization scheme.

As the number of users increases, the energy consumption difference descends between the scheme with conventional BSs and the scheme where the BSs

having the ability of saving energy consumption. The reason for this is since BSs have to cover more users, more transmission energy is devoted to the communication. Even more, the number of BSs which can operate in sleep mode decreases as a result of the rising number of

TABLE 6  
Energy Consumption, Spectrum Efficiency, Associated User Number Comparison Related to Base Cases

		Number of users	2100	2400	2700	3000	3300	3600	3900	4200	4500	4800
Energy Consumption	Min. Energy Consumption		21%	21%	21%	21%	22%	22%	22%	29%	29%	30%
	Max. S-E Efficiency		22%	22%	22%	22%	22%	22%	22%	30%	30%	31%
Spectrum Efficiency	Min. Energy Consumption		-2.8%	-2.5%	-2.7%	-2.7%	-3.1%	-2.8%	-2.8%	-3.0%	-2.9%	-2.8%
	Max. S-E Efficiency		-0.5%	-0.6%	-0.5%	-0.7%	-1.3%	-1.4%	-2.3%	-0.4%	-0.5%	-0.5%
Associated Users	Min. Energy Consumption		95%	95%	95%	95%	95%	95%	95%	95%	95%	95%
	Max. S-E Efficiency		99%	99%	99%	99%	98%	96%	95%	99%	99%	99%

requests for establishing associations. For example, while 4200 users are considered, one more BS has to operate in active mode compared with the case with 3900 users. The total energy consumption level goes down significantly from the scheme with conventional BSs as well when the objective is optimizing spectrum-energy efficiency. The BSs differ in service range based on the distribution of users and their traffic service requirements through adjusting the transmission power supply, putting the idea of cell zooming in/out into effect. The BSs with no users to serve are able to sleep, applying the idea of BS sleep mode. The users might connect with new BSs, putting the idea of migration into action. As the user number increases and the number of BSs to switch into sleep mode decreases, the amount of energy to save reduces. The signal strength for associated users are ensured to be solid since receiver sensitivity considers the SNR, guaranteeing a BER of  $10^{-6}$ .

The frequency reuse 1 scheme causes interference for the users at cell boundaries [32]. In cellular networks, however, the groups of frequencies can be reused, provided the same frequencies are not reused in neighboring cells. As the frequency reuse three technique is supported in the WMAN [33], [34], the reuse factor of 3 is considered in our study to manage interference from other cells, that is, three bandwidth parts are reused among cells. Moreover the restriction on power can help in reducing interference.

Fig. 3(b) depicts that the performance improvements on spectrum-energy efficiency. The base cases are not able to put in satisfactory performance; although bringing increased efficiency due to the significant amount of saved energy, minimizing energy leaves a room for optimizing spectrum-energy efficiency. The reason is that associations with low transmitting power could carry medium bandwidth, without weighting the efficiency in data subcarrier use while minimizing energy consumption. It doesn't take account of delivering information efficiently. However, the optimization of spectrum-energy efficiency takes into account both energy consumption and spectrum efficiency. By the maximization, both metrics can be ameliorated. It is worthy to mention that to achieve maximum spectrum-energy efficiency, a few conserved energy is contributed for the sake of improved performance, making a trade-off between minimizing energy consumption and maximizing spectrum-energy efficiency.

Table 6 compares the objective values (i.e., energy consumption ratio of optimum to base cases). It is observed that the energy to be consumed can be substantially reduced (70%) while minimizing energy, compared to the

network with conventional BSs operating regularly with a fixed cell size. The economic benefit in terms of achievable energy cost reduction is salient. Maximizing spectrum-energy efficiency and minimizing energy consumption decide the same number of BSs to operate in active mode but associate with different users and BSs.

Fig. 3(c) illustrates the comparison of spectrum efficiency per served user with optimization. Although having higher efficiency, the base cases consume a substantial amount of energy, manifesting the trade-off between energy consumption and spectrum efficiency. And minimizing energy consumption curtails spectrum efficiency. The percentage of lost spectrum efficiency by minimization is shown in Table 6. By maximizing spectrum-energy efficiency, the degradation of spectrum efficiency is able to be shortened.

Fig. 3(d) compares base cases with minimizing energy consumption and maximizing spectrum-energy efficiency in terms of associated user number. Minimizing energy consumption associates a minimum number of users, hence consuming the least energy, whereas maximizing spectrum-energy efficiency leads to more associated users, which proves advantageous for operators to collect payment from service users. In Table 6, presented is the number of associated user by two optimization models compared to the base cases. As the total user number reaches to the situation where more BSs are in active mode, the difference in the associated user number is on decrease. On average, maximizing spectrum-energy efficiency associates more users by 3.27%.

In the formulated problem, we are looking for the users which are able to contribute better spectrum-energy efficiency to the overall system. As the objective function is concerned about how efficiently data subcarriers are utilized and energy is consumed, it is essential to take into account both of spectrum efficiency and energy consumption. Approaching the problem from the spectrum-efficiency point of view only may produce the results which cannot benefit from optimizing energy consumption, and vice versa. Furthermore for the BS, over a single downlink transmission, small spectrum-efficiency can occur by a low transmit power level, achieving a higher spectrum-energy efficiency value comparatively. For example, two users with the same value of spectrum-efficiency can turn out having dissimilar spectrum-energy efficiency values, because of requiring different transmit power levels. For mobile users served by the same BS generating two levels of spectrum efficiency, there can exist the difference in spectrum-energy efficiency. The optimization model considers weight of each

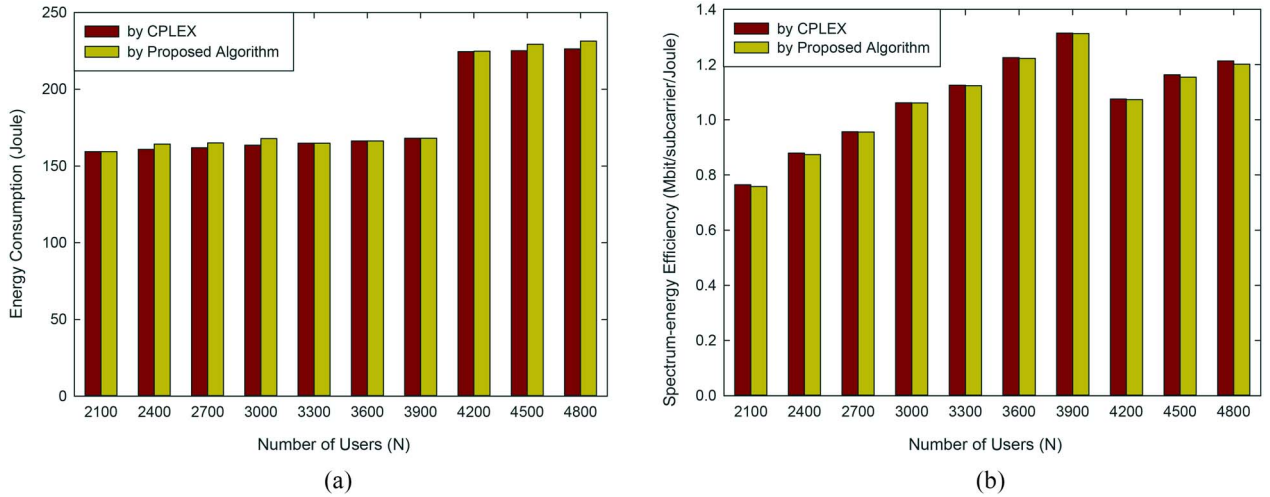


Fig. 4. Comparison of objective value of proposed algorithm against CPLEX. (a) Energy consumption comparison. (b) Spectrum-energy efficiency comparison.

user in terms of not only spectrum efficiency but also energy consumption while seeking the optimal solution. In the solution, therefore, the users without a service are intended to be those who are not able to help the system maximize spectrum-energy efficiency. Nevertheless, it is likely the blocked users are offered for data services in the next reached solution as the network traffic and topology vary frequently.

## 5.2 Performance Comparison of CPLEX and Heuristic Algorithm results

The optimization ILP formulation is solved by CPLEX 12.5, whose results are taken as benchmarks to evaluate the gap between optimal solutions and proposed heuristic counterparts. The comparisons are measured on the identical platform, a Linux machine equipped with 24 cores as well as 47 GB memory. To show the validity of the optimality of our proposed algorithm, we compare the results with the optimal one (obtained by CPLEX). We find that the final objective values of our proposed algorithm are fairly close to the optimum for all the cases under consideration.

Fig. 4 shows the performance differences between CPLEX and the algorithms with different number of users within 11 BSs in term of energy consumption and spectrum-energy efficiency under a network blocking ratio on 0.05 percent. The heuristic algorithm minimizing energy is compared in Fig. 4(a) with optimal energy consumption, where the optimality gap is less than 3%. And the heuristic algorithm maximizing spectrum-energy efficiency is compared in Fig. 4(b) with optimal spectrum-energy efficiency where the gap is less than 1%. The proposed heuristic algorithms can provide solutions with only slight degradation on energy and efficiency, but are much more computationally efficient.

The proposed algorithms demonstrate high computation efficiency as shown in Fig. 5. The computation time of the proposed algorithm increases linearly with the problem size (i.e., the total number of users and BSs), whereas the computation time shows an exponential growth with CPLEX. Even though taking less time to minimize energy, CPLEX spends more than 163 times the computation time with the heuristic.

More cases are considered as the problem size, the computation time and optimality gap are shown in Table 7. A difference of 1.26% on average is made between CPLEX

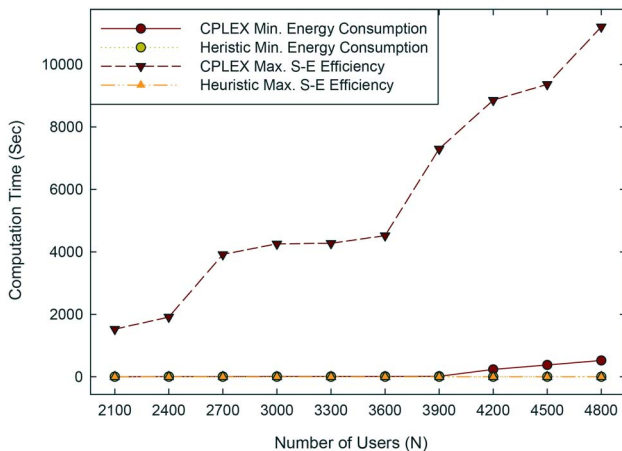


Fig. 5. Computation time comparison between proposed algorithm and CPLEX.

TABLE 7  
Problem Size, Computation Time for Proposed Heuristic and CPLEX Solving the Formulation

Num. of Nodes		Ave. Opt. Gap	Ave. Comput. Time (Sec.)	
BS	User		CPLEX	Prop. Heuristic
11	5100	1.21%	12767.30	0.09
11	5400	1.43%	13660.23	0.11
11	5700	1.57%	14801.97	0.11
11	6000	1.13%	24523.55	0.11
11	6300	1.38%	35286.79	0.10
11	6600	3.18%	43680.36	0.12
25	6600	0.36%	182643.99	0.21
25	6900	0.31%	385260.37	0.24



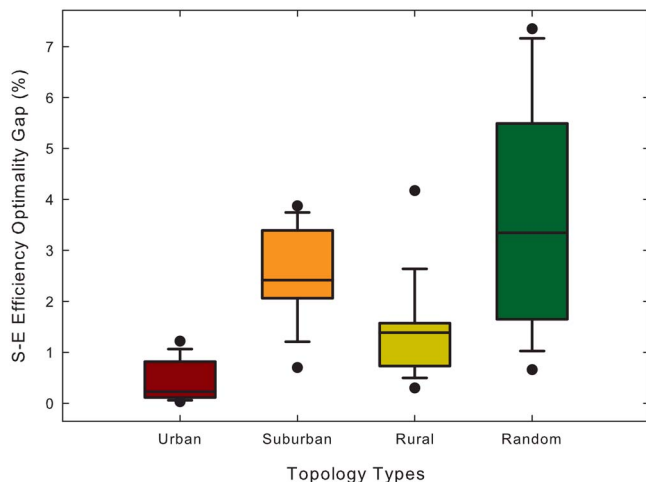


Fig. 6. Average gap for different topology types.

and the heuristic algorithm maximizing spectrum-energy efficiency in the studied cases. Nevertheless, it can be seen that the complexity of solving the problem grows dramatically as the network size increases. In contrast, our proposed heuristic algorithms can solve the problem at a very fast speed, saving 99% computation time. Moreover, a variety of topologies are considered with different percentage rates of users in each area type. In Fig. 6, for each topology type, more than 70% users are located within the areas on the x-axis, and the rest of users are randomly distributed in other area types. The considered number of users is from 2100 to 5700 with 11 BSs. From the box plot, the proposed algorithm is able to produce spectrum-energy efficiency different from optimality by less than 8%, and the mean of gap is less than 4%. This illustrates that the heuristic algorithm can find effective solutions for given topologies.

The solutions from CPLEX and algorithms are close, however, CPLEX solves the problems costly. As the numbers of users goes up, in contrast with the significantly rising computation time for CPLEX, the proposed algorithms solve the problem efficiently. The ratios of the solving time of CPLEX to that of the algorithms are considerable, which demonstrates its computation efficiency and scalability especially in practical large-scale networks.

## 6 CONCLUSION

From service providers' perspectives, saving energy is able to reduce electrical expenditure, and enhancing spectrum efficiency can increase revenue. To boost the profit, a network following spectral and energy efficient design is desired in wireless environments. In this paper, we conducted a study on the issue of spectrum-energy efficiency in broadband wireless networks under multiple BSs. Higher spectrum-energy efficiency means on the same amount of data subcarriers, less energy is consumed to achieve the higher data rate. The problem of association for each user and BS operation mode determination has been formulated into a unified optimization framework, aiming at enhancing the overall spectrum-energy efficiency. Maximizing spectrum-energy efficiency is able

to gain the energy saving and spectrum-energy efficiency, compared to the base cases consisting of conventional BSs in the presented scenarios. To suggest the solution to the optimization problem computationally tractable, heuristic algorithms have been developed. The framework should lay an economic foundation for the advanced green broadband wireless access network design by providing a guideline for the service providers in the effort of efficiency improvements.

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