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optimizing spectrum-energy efficiency in wireless networks

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Optimizing spectrum-energy efficiency in wireless networks

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DEDICATION

I would like to dedicate this thesis to my girlfriend Linda and to my colleagues without whose support I would not have been able to complete this work. I would also like to thank my friends and family for their loving guidance and financial assistance during the writing of this work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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ABSTRACT

The popularity of smart mobile devices has brought significant growth of data service for mobile service providers. Very often, mobile users of data service are charged based on the amount of data used. With the increasing revenue, mobile operators are also facing the increasing operation cost due to the high energy consumption. Meanwhile, as the access to spectral resource is limited, increasing spectrum efficiency is an economic incentive for operators alike. However, we are faced with the dilemma that focusing only on reducing energy consumption might incur the cost of decreasing spectrum efficiency. In this paper, we study the spectrum-energy efficiency enhancement problem by way of jointly considering the mechanisms of cell zooming, sleep mode and user migration. To gain the benefits economically, we formulate an optimization framework into an integer linear program which is solvable by CPLEX to maximize spectrum and energy efficiencies jointly as well as to meet the minimal traffic demand by associated users in multicell/multi-user networks. To avoid high computation time, a heuristic algorithm is proposed to efficiently solve the formulated problem. Numerical analysis through case studies demonstrates the energy saved and efficiency improvements and the comparison between the proposed heuristic algorithm against the optimal solutions.

CHAPTER 1. OVERVIEW

With the popularity of smart mobile devices, mobile service providers have experienced the recent phenomenal growth of data service [Fehske et al. (2011)]. While these data services bring significant revenues, operators are facing the increasing operation cost due to the high energy consumption. Recently, it has been reported that energy costs can account for as much as half of a mobile service provider's annual operating expenses [Zhang et al. (2010); Edler and Lundberg (2004)]. Moreover, global concern for climate change demands further reduction in energy consumption. It is the best interest of the wireless operators to find the most economical way to run a wireless network as both of the cost and the environment are considered.

In green cellular networks, the network design objective is to reduce the amount of energy consumption while maintaining satisfactory service for mobile users. At the stage of network planning, cell size and capacity are fixed based on estimation of peak of traffic load [Willkomm et al. (2009); Louhi (2007)]. Each base station (BS) in a cellular network consumes roughly up to 2.7 kWh of electrical power [Claussen et al. (2009); Louhi (2007)]. 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 [Marsan et al. (2009); Chiaraviglio and Torino (2008); Zhou et al. (2009); R3-100162 (2010)]. For our work, we propose to optimize energy consumption by considering the transmission energy used by BSs dynamically.

On the other hand, spectrum efficiency in wireless networks has been a major research area in the past decade. As users of data service are charged based on the amount of data used, the operation revenue for wireless operators is able to be raised, if the operator can increase the bandwidth capacity on its restricted spectrum resource. It is worth noting that focusing only on reducing energy consumption might lead to a poor spectrum efficiency. We propose a framework of optimal network design that optimizes spectrum-energy efficiency for next generation wireless networks.

In this paper, a number of mechanisms are incorporated which are recognized as effective design for improving energy consumption [Hasan et al. (2011); Niu et al. (2010)] as well as enhancing spectrum-energy efficiency in Wireless Metropolitan Area Networks (WMAN). These mechanisms include: 1) *Zooming out*: the coverage of a BS can be enlarged to take care of more cell-edge users. 2) *Zooming in*: the coverage can be reduced to serve high density users in the center, shortening the consumption of power. 3) *Sleep mode*: if a BS have switched to sleep mode, active BSs may try to take over the service supplement of the sleeping BS. 4) *User migration*: users disconnected from the former BSs due to the operation of sleep mode are reassigned to new BSs.

Given a multicell/multi-user wireless network along with a blocking probability, from the integration with these mechanisms, the overall energy consumption could be minimized. For example, the system energy of Fig. 1.1(b) is less than that of Fig. 1.1(a) because BS1 and BS3 transmit with lower energy, releasing smaller sizes. In Fig. 1.1(c), since the users originally connecting with BS3 can be taken over by neighboring BS4, BS3 is able to switch into sleep mode, saving the noticeable energy difference between active and sleep mode. Fig. 1.1(d) shows that BS1 turns into sleep mode as well, leading to much less system energy cost. Considering all the possible network topologies developed with aforementioned mechanisms, a challenging task is forming advantageous association between BSs and users so that the overall energy is minimized.

The task becomes more challenging if the spectrum efficiency improvement is considered jointly. We define spectrum efficiency as the satisfied bandwidth requirement over the allocated data subcarrier number, namely, $((bits/s)/data\ subcarrier)$. Based on user requests for bandwidth, data subcarriers are granted from BSs, resulting in different level of spectrum efficiency regardless of energy needs for users. The new optimal topology evolves if spectrum efficiency is accommodated into the energy consumption improvement. To measure spectrum-energy efficiency, a metric is defined in terms of spectrum efficiency divided by energy consumption in the unit of (*bits/data subcarrier/Joule*). Spectrum-energy efficiency is one of the most important issues for a wireless network. The quality of BS operation mode has a predominant influence on the operator's profitability and competitiveness. Low efficiency leads to a waste of the capital expenditures.

To obtain the optimal solution employing spectrum and energy efficiently, we model this problem as an ILP problem first. Within the formulated problem, resource constraints such as the infinite number of data subcarriers per symbol time and maximum BS transmission power are considered. Connection assignments and operation modes are transformed to decision variables, which from the solution, reveal information about BSs' operation modes and serving assigned users. BSs running in sleep mode provide little service area with a very basic sleeping power level. As it is expected that our model is able to adapt to instant traffic demand growth, our scheme is developed to run every certain period (1 second), and the users blocked have the right to regain services for next time periods. Thus, an efficient computation method which allows timely adaptation to traffic demand change is required for the network topology. Since ILP problems are NP-hard, we derive heuristic algorithm to obtain near-optimal solution as a practical solution which is computationally trackable.

The contributions of this paper are summarized as follows: 1) To the best of our knowledge, this is the first work which identify an optimization framework for the spectrum-energy efficiency maximization problem for the WMA networks, where cell zooming, BS sleep mode and user migration are jointly considered unlike previous works optimizing only energy consumption or spectrum efficiency separately. 2) We provides a mathematical model for the spectrum-energy efficiency maximization problem with a consideration on the affecting factors in the communication environment such as the link budget and demands in terms of data subcarriers on spectrum. The outcomes of interest include the optimal associations between BSs and SSs and the operation modes of BSs.

Due to the fractional objective function in the first developed mathematic formulation, finding an optimal (near-optimal) solution is challenging. We transform the developed formulation into an Integer Linear Programming (ILP) such that the resultant optimization problem can be solved by CPLEX-a well recognized optimization package for solving ILP. To avoid the exponential computation time for solving the ILP, a heuristic approach is devised that can obtain the near-optimal solution in polynomial time. A timely response by our heuristic algorithm is able to cope with the growth of traffic demands. A series of case studies are conducted to verify the optimization framework and demonstrate the significant performance benefits of the spectrum-energy model.

The remainder of this paper is organized as follows: we review the related work in Section 2. The system model is presented in Section 3. In Section 4, the ILP model is proposed. In Section 5, a heuristic approach is proposed to enhance the computation efficiency, followed by numerical experiments in Section 6. Section 7 concludes this paper.

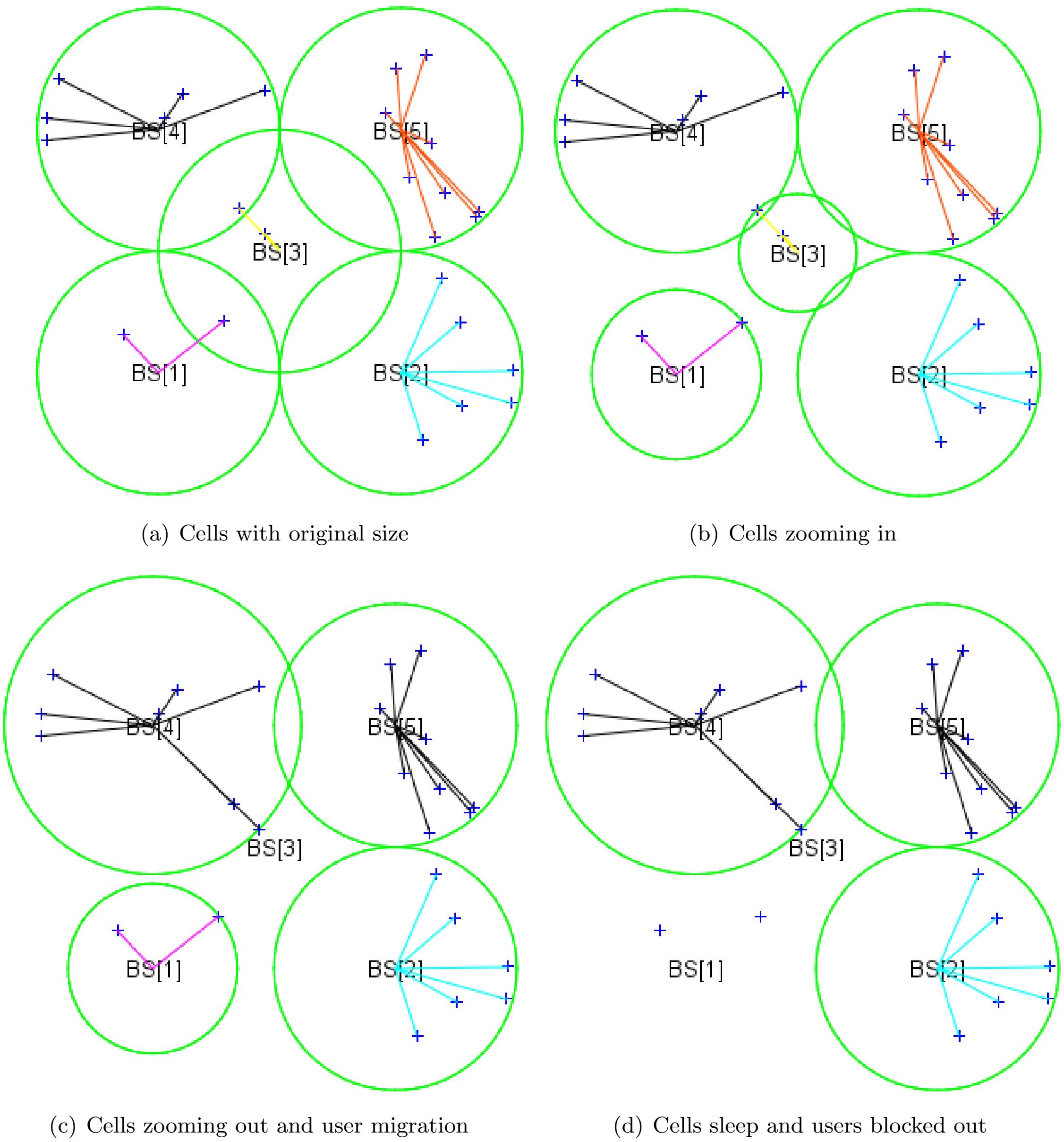


Figure 1.1: Examples of cell zooming operations

CHAPTER 2. REVIEW OF LITERATURE

Some studies look for reducing power or enhancing energy efficiency from the contribution in a network accommodating macro BS and micro BS. The papers of [Richter et al. (2009); Arnold et al. (2010)] 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 [Badic et al. (2009)] 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 [Niu et al. (2010)] proposes centralized and distributed algorithms to verify the reduction of power consumption of a cellular network with cell zooming. The authors of [Correia et al. (2010)] tackle the problem from the angle of BS components, stating that advanced power amplifiers can save energy. In [Onireti et al. (2012)], the uplink of coordinated multi-point system is considered and the energy efficiency gain is examined over the non-cooperative system. Their energy consumption model mainly benefits cell-edge communication.

During off-peak periods the system is probably over-provisioned by surplus energy. BSs might have no users, for instance. In such circumstance, if the BSs can be switched into sleep mode, the energy consumption can be reduced consequently. The traffic load fluctuation implies that some BSs do not necessarily stay in active mode when the traffic load is light to save the energy. There have been many switching on/off schemes proposed in both academia and industry [Marsan et al. (2009); Chiaraviglio and Torino (2008); Zhou et al. (2009); R3-100162 (2010)]. While other green cellular network studies concentrate on limiting energy consumption on macro BSs [Kelif et al. (2010); Saker et al. (2010); Oh and Krishnamachari (2010)] or improving spectrum efficiency [Xiong et al. (2011)], we focus on jointly optimizing the energy consumption and the spectrum efficiency. To decide which cells can be switched into sleep mode without a violation of the blocking probability, two aspects should be taken into account. First, the cells that stay on must provide necessary radio coverage. Secondly, in any cell bandwidth demands from served users must be satisfied.

This paper investigates the problem of energy consumption and spectrum efficiency together of the wireless network where cell sizes can vary, BSs can operate in sleep mode and blocking probability are characterized. The problem is formulated as an ILP model which aims at maximizing spectrum-energy efficiency with adaptability to traffic demand growth due to special events, emergency response, or newly emerging hot spots that generate large traffic demands. Different from previous works, instead of settling the certain time during hours to turn on and switching off BSs, we realize that BSs operate in their operation modes in the flexible time period (1 second by default).

CHAPTER 3. PROBLEM FORMULATION

In this section, a practical scenario in a broadband wireless communication system which manages multiple users and BSs is considered. A number of users exists within a BS's coverage area, each of which submits a traffic demand. Without loss of generality, we assume that the users are randomly distributed in the cells, and the traffic demand is a random distribution as well. In this study, the determination of BS-SS associations is the selection from a set of BSs. The goal is to (i) maximize the spectrum-energy efficiency, (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 while considering the predefined blocking probability. The notation taken in the problem are listed in Table 3.1.

We discuss the user and BS types in our scenarios, and the operation strategies of BSs are illustrated. The important factors related to power and data subcarrier are evaluated also, including the link budget. Spectrum-energy efficiency is defined as delivered bandwidth over the data subcarrier number per energy consumed in the unit of Joule.

3.1 The Green Wireless Access Network Architecture

3.1.1 User Device and Base Station

With regard to the parameters of user devices and base stations, the profiles of the Mobile CPE (customer premises equipment) and BS are given in Table 3.2 [Lannoo et al. (2007)], where Tx, Rx stand for transmitter and receiver, respectively. The six parameters are used for the link budget calculation in the optimization model.

3.1.2 Operation Strategy

In each cell, the BS transmits common control signals and data signals to users, and users can receive high quality signals from it. It is typical that planners assume BSs run with the roughly same range, consuming a similar power level. However, radio coverage is changeable by tuning the transmission power level. The cell dimension is determined by the distance between the BS and the farthest user it serves.

With cell zooming operations as in Fig. 1.1, there is potential to reduce the energy consumption and balance the traffic load. It is a wireless access network with five cells where the central cell is surrounded by four neighboring cells. BSs are located at the respective center of the cells; users are randomly distributed in the cells, denoted by the plus signs. When users are nearly at the centers of cells, cells can zoom in to reduce the cell size and therefore lower the power consumption (Fig. 1.1(b)).

On the contrary, if cells are working in sleep mode, the neighboring cells can zoom out to take over migrated users and avoid possible coverage hole (Fig. 1.1(c)). If the neighboring cells cannot zoom out to cover more users due to the finite resources of energy and subcarriers, cells can also choose to sleep to reduce the energy consumption and block out users as in Fig. 1.1(d). When a BS is in sleep mode, the energy consumption is comparatively low. Sleeping BSs can contribute the major reduction of energy in green wireless networks. A BS in sleep mode has no coverage, and its neighbor cells can zoom out to guarantee the coverage if necessary. There will be no blocked out users if the blocking rate is set to zero. It is assumed that a BS consumes 8 Watts in sleep mode [Niu et al. (2010)], and a basic 68.73 Watts in active mode plus the energy to serve users [Klessig et al. (2011)].

3.1.3 Definition of Blocking Probability

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

$$P_b = \frac{\sum \# \, users \ not \ obtaining \ connections}{\sum \# \, users \ requesting \ services} = \frac{N - \sum a_{mn}}{N} \tag{3.1}$$

3.2 Link Budget

To reach the user at a certain location, a BS has to send out the signal which is strong enough with the necessary transmission power level. The received signal at the user needs to be higher than the threshold which can guarantee the desired data rate. Signals usually suffer the attenuation due to the propagation gains and miscellaneous losses between BSs and users. Considering all of the gains and losses, a link budget can be used to calculate the power level arriving at the user device, P_{rx}, given the transmitter power output from the BSs, P_{tx} in dBm. Fundamentally, a link budget equation is [Klessig et al. (2011)]

$$P_{rx} = P_{tx} + G_{tx} - A_{pl} + G_{rx} - A_m \tag{3.2}$$

where:

G_{tx} = DL T_x antenna gain + other DL T_x gain (dBi)

G_{rx} = DL R_x antenna gain + other DL R_x gain (dBi)

A_{pl} = path loss (dB)

A_m = miscellaneous losses (link margin, diffraction loss, connector loss, trees, rain, walls, glass, body loss, etc.) (dB)

Conversely, given P_{rx}, the needed transmission power levels, P_{tx} from BSs can be learned from Eq. (3.2). To know the value of required P_{rx}, receiver sensitivity, (S_R), is introduced as the minimum received power threshold at which point the desired Bit Error Rate (BER) can be achieved at the user. Since different modulation request for different receiver sensitivity, to know the receiver sensitivity value for the modulation, the following equation is used.

$$S_R = Implementation \ Losses + R_x \ Noise \ Figure + Thermal \ Noise + R_x \ SNR \tag{3.3}$$

The receiver sensitivity is regarded as the desired minimum power at the user for a guaranteed signal strength [Afric et al. (2006)]. For each modulation, Eq. (3.2) can be used for computing P_{tx} as

$$S_R = P_{tx} + G_{tx} - A_{pl} + G_{rx} - A_m \tag{3.4}$$

In Eq. (3.4), G_{tx} and G_{rx} are the downlink transmitter and receiver gains from Table 3.2. As the BS antenna is assumed to transmit ideally, feeder losses, connector losses and jumper losses are not considered in our study. In Eq. (3.3), S_R is affected by the factors whose values can be usually assumed in the simulation [Lannoo et al. (2007); Forum and Certified (2006)], and are designated in Table 3.2 and 3.3 [Marks and Marks (2004); Lannoo et al. (2007)].

The receiver sensitivity values can be estimated for different SNR. For example, for a user within the channel bandwidth of 10MHz, the thermal noise is -104 dB. From Table 3.3, for a user whose bandwidth requirement is 3.44 Mbps, we select 16QAM-1/2 as its modulation scheme. As a result, the receiver SNR will be determined to 16.4 dB with a noise figure of 6 dB based on Table 3.2. Considering the implementation loss of 2 dB, the receiver sensitivity in dBm can be carried out as

$$S_R = -104 + 6 + 16.4 + 2 = -79.6 \tag{3.5}$$

For users requesting different data rates, the modulation selection and receiver sensitivity (S_R) are listed in Table 3.3. The following description discusses the terms of A_{pl} and A_m in Eq. (3.4). We consider fast fading margin and building penetration loss in A_m, whose values are assumed in simulation as well [Lannoo et al. (2007)].

3.2.1 NLoS Path Loss

In the COST-231 Hata model, the basic non-line-of-sight (NLoS) path loss is [Plitsis (2003)]

$$L_{mn}^{NL} = 46.3 + 33.9 \log BW - 13.82 \log h_b + (44.9 - 6.55 \log h_b) \log d_{mn} - a(h_m) + C_m$$

where

$$a(h_m) = (1.1 \log BW - 0.7) h_m - (1.56 \log BW - 0.8)$$

$$C_m = \begin{cases} 0, \text{ for rural and suburban areas} \\ 3, \text{ for urban areas} \end{cases}$$

Four parameters effect the estimation of the path loss in this model: BW is the channel bandwidth in MHz, h_b is the base station antenna height in meter, h_m is the receiver antenna height in meter and d_{mn} is the distance between the BS and user in kilometer [Plitsis (2003)].

3.2.2 LoS Path Loss

The COST-Walfisch-Ikegami model is applied to the line-of-sight (LoS) path loss [Report (1999)].

$$L_{mn}^{L} = 42.6 + 26 \log d_{mn} + 20 \log BW \tag{3.6}$$

In our work, it is assumed the BS antenna height is 30 m and the antenna height at end user is 1 m [Lee et al. (2008)]. From Eq. (3.4), the minimum downlink transmission power towards each user can be known as

$$P_{tx} = S_R - G_{tx} + A_{pl} - G_{rx} + A_m \tag{3.7}$$

where:

$A_{pl} = L_{mn}^{NL}$, L_{mn}^{L} (depends on d_{mn})

G_{tx}, G_{rx}, BPL, S_R and A_{pl} can be obtained from Table 3.2, 3.3 and 3.4 [Lannoo et al. (2007)], Eq. (3.6) and (3.6), respectively. Thus, Eq. (3.7) allows us to compute the value for T_{mn} in Section 4 as the transmission power between a BS m and a user n.

3.3 Data Subcarrier

Since the available spectrum span is finite in wireless communication, the number of subcarriers to transmit the actual data stream within the span is also limited. To measure the spectral efficiency, it is critical to understand the sufficient number of data subcarriers for each user. For this purpose, we consider the following equation [Chen and de Marca (2008)].

$$\begin{aligned} \mathit{DL\ bit\ rate} &= BW \cdot q \cdot \frac{\#\ \mathit{data\ subcarriers}}{\#\ \mathit{FFT\ size}} \cdot \\ &\quad \mathit{data\ bits/symbol} \cdot \frac{1 - \mathit{overhead}}{1 + \mathit{guard\ time}} \cdot \mathit{TDD\ down/up\ ratio} \end{aligned} \tag{3.8}$$

, where the DL bit rate ($\rho_n, \forall\, n\, \epsilon\, \mathbb{N}_{\mathbb{SS}}$) is regarded as the bandwidth requirement in Table 3.3. Both of the channel bandwidth (BW) and the modulation scheme determine the bandwidth capacity in Eq. (3.8). And the user bandwidth requirement influences the modulation selection. BPSK-1/2 is more robust but achieves a smaller data rate. On the other hand, 64QAM-3/4 is less robust but achieves a higher rate. For our case, the channel bandwidth is 10 MHZ with FFT size of 1024, and q is equal to 28/25. The bit rate is also determined by the guard time (1/8 in our study), the overhead (we assume an overhead of 20%) and the TDD down/up ratio of 3. The Eq. (3.8) becomes

$$\rho_n = 10^7 \cdot \frac{28}{25} \cdot \frac{\#\ data\ subcarriers\ needed}{1024} \cdot data\ bits/symbol \cdot \frac{1-\frac{1}{5}}{1+\frac{1}{8}} \cdot 3$$

To obtain the number of data subcarriers needed during downlink frame,s Eq. (3.9) is converted to Eq. (3.9). For the example of 10 MHz in one symbol time, since the total data subcarriers is 720, the allowable number of data subcarriers to use is no more than 720. Now, we express the number of data subcarriers needed (D_n, $\forall\, n\, \epsilon\, \mathbb{N}_{\mathbb{BS}}$) as

$$D_n = \lceil \rho_n \cdot \tfrac{428.57}{10^7} \cdot \tfrac{1}{data\ bits/symbol} \rceil \tag{3.9}$$

Eq. (3.9) allows us to compute the value for D_n as the number of data subcarriers for user n in Section 4.

In advanced broadband wireless technology like WiMAX, the new coming or blocked users are able to follow the existing 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 initial ranging processes with BSs. The responses to different ranging codes message from users to BSs are required, which estimate the adjustment for energy level for each user that bears an initial ranging code. And the information number of data subcarriers to meet each user's requirements can be collected during resource allocation procedures. Accordingly, when users are able to synchronize with BSs, the information about transmit energy can be acquired then used as input to our model, except knowing the exact locations of all users.

The computation of P_{tx} and D_n in our study are actually realized before communications established, which manifests the practicality of the model. When users has been associated, they will periodically send period ranging to maintain communications between users and BSs. If the period ranging response messages contain parameters that must be adjusted such as changes of the necessary transmit energy level or bandwidth requirements, the model needs to be executed to obtain the real-time optimal solution. Eq. (3.7) and (3.9) are worked out in order to carry out our simulation model.

Table 3.1: Definitions of Important Symbols

Symbol	Definition
L_{mn}	The path loss for SS_n to connect with BS_m.
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	Basic active mode energy of BSs.
P_s	Sleep mode energy of BSs.
A_{pl}	The path loss.
P_b	The blocking probability.
BW	The channel bandwidth.
ξ_n	The building penetration loss correction for SSs.
ζ	The fading margin value.
η	The implementation loss value.
MP	The maximum transmission power for BSs.
DS_t	The maximum number of data subcarriers.
θ	The minimum necessary SS number, $\theta = N \cdot (1 - P_b)$.
$\mathbb{N}_{\mathbb{SS}}$	The set of SSs, $\lvert\mathbb{N}_{\mathbb{SS}}\rvert = N$.
$\mathbb{N}_{\mathbb{BS}}$	The set of BSs, $\lvert\mathbb{N}_{\mathbb{BS}}\rvert = M$.
$\mathbb{P}$	The set of traffic demand for SSs, $\mathbb{P} = \{\rho_n, \forall\, n \,\epsilon\, \mathbb{N}_{\mathbb{SS}}\}$.
$\mathbb{D}$	The set of data subcarrier number for SSs, $\mathbb{D} = \{D_n, \forall\, n \,\epsilon\, \mathbb{N}_{\mathbb{SS}}\}$.
$\mathbb{R}$	The set of spectrum efficiency, $\mathbb{R} = \{r_n, \forall\, n \in \mathbb{N}_{\mathbb{SS}}\}$, where $r_n = \frac{\rho_n}{D_n}$.
$\mathbb{T}$	The set of transmission energy between BS_m and SS_n, $\mathbb{T} = \{T_{mn}, \forall\, m \in \mathbb{N}_{\mathbb{BS}}, n \in \mathbb{N}_{\mathbb{SS}}\}$.
$\mathbb{S}$	The vector consists of the value of $(Pa - Ps)$ for M terms.
$\mathfrak{E}$	The total system energy consumed.
$\mathfrak{C}$	The objective value of the problem.
$\mathcal{A}$	The BS-SS association incidence matrix (decision variable), $\mathcal{A} = (a_{mn})_{M \times N}$.
$\mathcal{O}$	The BS operation mode vector (decision variable), $\mathcal{O} = (o_m)_{1 \times M}$.

Table 3.1: (Continued)

Symbol	Definition
$\mathbf{X}$	$\mathbf{X} = \{X_{mn}\} = a_{mn} \cdot o_m$.
$\mathbf{U}$	$\mathbf{U} = \{\mu_{mn}\} = a_{mn} \cdot \tau$ in the transformed model.
$\mathbf{V}$	$\mathbf{V} = \{\nu_m\} = o_m \cdot \tau$ in the transformed model.
$\mathbf{W}$	$\mathbf{W} = \{\omega_{mn}\} = X_{mn} \cdot \tau$ in the transformed model.
$\mathbf{Y}$	$\mathbf{Y} = \{y_j\} = [\mathbf{U}\ \mathbf{V}\ \mathbf{W}]$ in the transformed model.
$\mathbf{Z}$	$\mathbf{Z} = \{z_j\} = [\alpha_{mn}\ \beta_m\ \gamma_{mn}]$ in the transformed model.
$\mathbf{D}$	$\mathbf{D} = \{d_j\} = [\mathbb{T}\ \mathbb{S}]$ in the transformed model.

Table 3.2: DL CPE and Base Station Parameters

	Mobile CPE		BS with 2 x 2 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

Table 3.3: Parameters per Modulation Scheme

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

Table 3.4: BPL Corrections and Percentages for Various Area Types

Type	**Correction**	**Area Percentage**	**User percentage**
Rural	12 dB	65%	10%
Suburban	15 dB	20%	20%
Urban	18 dB	15%	70%

CHAPTER 4. SPECTRUM-ENERGY EFFICIENCY OPTIMIZATION

This section presents the optimization model for the BS spectrum-energy efficiencies operation problem. The problem is defined as follows:

Given the required energy (P_{tx}) and traffic load demands of N users, the finite number of M BSs for operations, maximum transmit energy and data subcarrier number of the BSs, and the blocking probability, the problem is to maximize the system spectrum-energy efficiency, denoted as $\mathfrak{C}$, by associating users and BSs, deploying BSs in active mode.

The model takes as inputs (1) the energy requirements of all users for all BSs, (2) the total number of user, and blocking probability, (3) the bandwidth requirements of each user. The required rates are converted to the number of data subcarriers, (4) the maximum power, data subcarriers, the basic active and sleep mode energy use of the BS. The expected output includes the network topology where connection assignments are specified with sufficient bandwidth provisions, the operation modes of BSs as well.

Let $\mathbb{N}_{\mathbb{BS}} = \{BS_0, \ldots, BS_{M-1}\}$ be the set of base stations with cardinality $|\mathbb{N}_{\mathbb{BS}}| = M$. Similarly, let $\mathbb{N}_{\mathbb{SS}} = \{SS_0, \ldots, SS_{N-1}\}$ be the set of users with cardinality $|\mathbb{N}_{\mathbb{SS}}| = N$. For any user, SS_n, its bandwidth and data subcarriers requirements are designated by ρ_n and D_n, respectively.

4.1 Decision Variables

The following decision variables define the connection assignments and BS operation modes.

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

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

a_{mn} is asserted when the connection between the BS m and the user n is assigned. o_m has a value of one while the BS m is determined to serve any number of user, and if the BS is able to turn into sleep mode, the value of o_m is set to zero.

4.2 Topology Constraint

The following constraint sends all the traffic of a user through a direct link with a BS. Each user can be served by up to one BS.

$$\sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}} a_{mn} \leq 1, \; \forall\, n \,\epsilon\, \mathbb{N}_{\mathbb{SS}} \tag{4.1}$$

For individual BS m, if the result of $\sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} a_{mn}, \; \forall\, m \,\epsilon\, \mathbb{N}_{\mathbb{BS}}$ is equal to 0, it means the BS m operates in sleep mode.

4.3 Constraints on BSs

The following constraints define the constraints on the BS domain. First, they ensure that when links are used in the solution, the overall data subcarriers which a BS use to transmit data cannot exceed the total number of data subcarriers a BS can utilize within the specified symbol time. For example, within one symbol time, for a BS operating in the channel bandwidth of 10 MHz, the usable data subcarriers are 720. In addition, based on the bandwidth requirement, the number of data subcarriers for individual MS varies. The notation of D_n indicates the amount of data subcarriers requested by user n.

For every BS providing connections, we limit the maximum transmission power level to a specific value. For various distances, based on Eq. (3.7), a link will need to 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 power level, or in active mode, consuming a basic running energy and additionally, the total transmitting power.

4.3.1 Data Subcarrier Constraint

The number of D_m is given by Eq. (3.9). We use decimal values for individual bandwidth requirement, randomly chosen from the set of the supported rates by the physical (PHY) layer (Table. 3.3). In the main topology, the total number of data subcarriers a BS serves should not be greater than the usable amount of data subcarriers (D_m) within the channel bandwidth and specified symbol time. This constraint is ensured by the following equation.

$$\sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} (a_{mn} \cdot D_n) \leq DS_t, \forall\, m \,\epsilon\, \mathbb{N}_{\mathbb{BS}} \tag{4.2}$$

For one second, there are 14000 symbols, where each symbol carries 720 data subcarriers on the 10 MHz channel bandwidth.

4.3.2 Transmitting Energy Constraint

The maximum power level, MP, which a BS can transmit on in total is deliberately restricted at the power level of 20 Watts throughout our study [Klessig et al. (2011)]. The constraint is as follows:

$$\sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} (a_{mn} \cdot T_{mn}) \leq MP, \forall\, m \,\epsilon\, \mathbb{N}_{\mathbb{BS}} \tag{4.3}$$

T_{mn} is calculated from Eq. (3.7).

4.3.3 Operation Mode Constraints

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

$$o_m \leq \sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} a_{mn}, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}} \tag{4.4}$$

$$\sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} (a_{mn} \cdot o_m) = \sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} a_{mn}, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}} \tag{4.5}$$

Eq. (4.5) is to make sure that a BS operates under active mode if it is in charge of any communication; otherwise the BS manages to sleep without supplying services. We transform the nonlinear Eq. (4.5) to the following equations in order to keep the model linear.

$$X_{mn} = a_{mn} \cdot o_m, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}}, \, n \, \epsilon \, \mathbb{N}_{\mathbb{SS}} \tag{4.6}$$

Therefore, Eq. 4.5 turns to be

$$\sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} (X_{mn} - a_{mn}) = 0, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}} \tag{4.7}$$

Eq. (4.7) is solvable by the following constraints. Q holds a number that is larger than both o_m and a_{mn}, $\forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}}, \, n \, \epsilon \, \mathbb{N}_{\mathbb{SS}}$.

$$X_{mn} \geq Q \cdot o_m - Q + a_{mn}, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}}, \, n \, \epsilon \, \mathbb{N}_{\mathbb{SS}} \tag{4.8}$$

$$X_{mn} \leq a_{mn}, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}}, \, n \, \epsilon \, \mathbb{N}_{\mathbb{SS}} \tag{4.9}$$

$$X_{mn} \geq 0, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}}, \, n \, \epsilon \, \mathbb{N}_{\mathbb{SS}} \tag{4.10}$$

$$X_{mn} \leq Q \cdot o_m, \forall m \, \epsilon \, \mathbb{N}_{\mathbb{BS}}, \, n \, \epsilon \, \mathbb{N}_{\mathbb{SS}} \tag{4.11}$$

4.3.4 Constraint on Blocking Probability

N represents the total number of users, and P_b the value of the blocking probability in Eq. (3.1).

$$\sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}, n \epsilon \mathbb{N}_{\mathbb{SS}}} a_{mn} \geq \theta \tag{4.12}$$

For the entire model, the total number of the connected users must be higher than the required number of active users, $\theta = N(1 - P_b)$.

4.4 Objective Function

The idea of finding out the deployment optimality by considering the spectrum-energy efficiency is transformed to the objective function that maximizes the ratio of spectrum efficiency over energy consumed in the system, building up an economical system where higher spectrum efficiency is supported by less energy. From the optimality, both the energy consumption and spectrum efficiency can be enhanced from the base case with conventional BSs.

4.4.1 Bandwidth

The expression for satisfied bandwidth requirement is:

$$\sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}, n \epsilon \mathbb{N}_{\mathbb{SS}}} (\rho_n \cdot a_{mn}) \tag{4.13}$$

4.4.2 Data Subcarriers

The number of the total data subcarriers taken on transmission is:

$$\sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}, n \epsilon \mathbb{N}_{\mathbb{SS}}} (D_n \cdot a_{mn}) \tag{4.14}$$

4.4.3 Energy

Supposedly, the power a sleeping BS will consume is Ps, 8 Watts [Niu et al. (2010)]; on the other hand, the energy consumed by an active BS m comes from the summation of the basic active mode power Pa, 20 Watts [Klessig et al. (2011)], plus the power exploited to serve all its users, $Pa + \sum_{n \epsilon \mathbb{N}_{\mathbb{SS}}} (T_{mn} \cdot a_{mn})$, $\forall\, m\, \epsilon\, \mathbb{N}_{\mathbb{BS}}$. The overall power consumption is expressed as:

$$\mathfrak{E} = \sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}, n \epsilon \mathbb{N}_{\mathbb{SS}}} (T_{mn} \cdot a_{mn}) + \sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}} (Pa \cdot o_m) + \sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}} [Ps \cdot (1 - o_m)] \tag{4.15}$$

The complete formula of the objective function combines the three Eq. (4.13,4.14,4.15).

$$\max \frac{\textit{Spectrum Efficiency}}{\textit{Energy Consumption}} = \max \sum \frac{\frac{\textit{Bandwidth}}{\textit{Data Subcarriers}}}{\textit{Energy}} = \frac{\sum_{m \epsilon \mathbb{N}_{\mathbb{BS}}, n \epsilon \mathbb{N}_{\mathbb{SS}}} (r_n \cdot a_{mn})}{\mathfrak{E}} \tag{4.16}$$

The objective function (4.16) maximizes the spectrum-energy efficiency in the model. The idea is to find out a system supporting high throughput with low data subcarriers and energy consumption. However, the problem of using the minimum energy to provide maximum capacity on less a number of subcarriers involves a fractional objective function which will result in computation intractability. To facilitate a more systematic and efficient computation, we reformulate the problem into an ILP, such that a software package, CPLEX is able to obtain the optimal solution.

4.5 Solving Optimization Problem with a Linear Fractional Objective Function

Eq. (4.16) has a numerator and denominator, which cannot be considered as a linear programming model with the equation in the first degree. To overcome this problem, the model must be transformed to another model that is pure linear; when the solution is found to this transformed model, the results can be recalculated back to the original model [Yemets et al. (2006); Bitran and Novaes (1973)].

Consider the following problem:

$$\begin{aligned} \max \quad & \frac{\sum_{j \epsilon J} c_j x_j + c_0}{\sum_{j \epsilon J} d_j x_j + d_0} \\ s.t. \quad & \sum_{j \epsilon J} a_{ij} x_j \leq b_i, \ \forall\, i \,\epsilon\, I \\ & x_j, \geq 0, \ \forall\, j \,\epsilon\, J \end{aligned}$$

It is assumed that the denominator is either positive or negative over the entire feasible set of x_j. To transform the above model into a regular linear programming model, variables y_j and τ are introduced and satisfy: $y_j = \tau x_j$, where $\tau = 1/(\sum_{j \epsilon J} d_j x_j + d_0) > 0$.

$$\begin{aligned} \max \quad & \sum_{j \epsilon J} c_j y_j + c_0 \tau \\ s.t. \quad & \sum_{j \epsilon J} a_{ij} y_j \leq b_i \tau, \ \forall\, i \,\epsilon\, I \\ & \sum_{j \epsilon J} d_j y_j + d_0 \tau = 1 \\ & \tau > 0 \\ & y_j \geq 0, \ \forall\, j \,\epsilon\, J \end{aligned}$$

This linear programming model is equivalent to the fractional objective model stated above, provided $\tau > 0$ at the optimal solution. The values of the variables x_j in the optimal solution of the fractional objective model are obtained by dividing the optimal y_j by the optimal τ. Furthermore, extra complexity arises as all the decision variables in our model are binary. We know that $y_j = x_j\tau$, in which case if x_j is zero, then y_j must be zero; otherwise, $y_j = \tau$ if $x_j = 1$. For this purpose, binary variables, z_j, and two constant values $Q1 > y_j$ and $Q2 > \tau$ are introduced along with the following constraints.

$$\begin{aligned} y_j &\leq Q1 \cdot z_j \\ y_j - t - Q2 \cdot z_j &\geq -Q2 \\ y_j - t + Q2 \cdot z_j &\leq Q2 \end{aligned}$$

In our problem the objective is a ratio of two linear terms, and Eq. (4.1)-(4.12) are linear. Since the value of the denominator is positive, the discussed method is applicable to our model. Eq. 4.16 can be transformed to a linear function, developing an integer linear programming model.

In order to realize the model transformation and eliminate the nonlinearity in the original model, new sets of decision variables are introduced and defined as follows:
$\mathbf{Y} = [(\mu)_{M\times N}\,(\nu)_{1\times M}\,(\omega)_{M\times N}]$ and $\mathbf{Z} = [(\alpha)_{M\times N}\,(\beta)_{1\times N}\,(\gamma)_{M\times N}]$.

The objective function is now given by

$$\max\ \mathfrak{C} = \sum_{m\epsilon\mathbb{N}_{\mathbb{BS}},n\epsilon\mathbb{N}_{\mathbb{SS}}} (r_n \cdot u_{ij})$$

subject to

$$\begin{aligned}
\sum_{m\epsilon\mathbb{N}_{\mathbb{BS}},n\epsilon\mathbb{N}_{\mathbb{SS}}} (T_{mn} \cdot \mu_{mn}) + \sum_{m\epsilon\mathbb{N}_{\mathbb{BS}}} [(Pa - Ps) \cdot \nu_m] + \tau \cdot M \cdot Ps &= 1 \\
\sum_{m\epsilon\mathbb{N}_{\mathbb{BS}},n\epsilon\mathbb{N}_{\mathbb{SS}}} \mu_{mn} &\geq \tau \cdot \theta \\
\sum_{n\epsilon\mathbb{N}_{\mathbb{SS}}} (T_{mn} \cdot \mu_{mn}) &\leq \tau \cdot MP \\
\sum_{n\epsilon\mathbb{N}_{\mathbb{SS}}} (D_n \cdot \mu_{mn}) &\leq \tau \cdot D_n \\
\sum_{n\epsilon\mathbb{N}_{\mathbb{SS}}} (\omega_{mn} - \mu_{mn}) &= 0 \\
\sum_{n\epsilon\mathbb{N}_{\mathbb{SS}}} \mu_{mn} &\geq \nu_m \\
\sum_{m\epsilon\mathbb{N}_{\mathbb{BS}}} \mu_{mn} &\leq \tau \\
\mu_{mn} + Q \cdot \nu_m - \omega_{mn} &\leq Q \cdot \tau \\
\mu_{mn} - \tau - Q \cdot \alpha_{mn} &\geq -Q \\
\omega_{mn} - \tau - Q \cdot \gamma_{mn} &\geq -Q \\
\nu_m - \tau - Q \cdot \beta_m &\geq -Q \\
\mu_{mn} - \tau - Q \cdot \alpha_{mn} &\leq Q \\
\omega_{mn} - \tau - Q \cdot \gamma_{mn} &\leq Q \\
\nu_m - \tau - Q \cdot \beta_m &\leq Q \\
\mu_{mn} &\leq Q \cdot \alpha_{mn} \\
\omega_{mn} &\leq Q \cdot \gamma_{mn} \\
\omega_{mn} &\leq Q \cdot \nu_m \\
\nu_m &\leq Q \cdot \beta_m \\
\mu_{mn} &\geq \omega_{mn} \\
\mu_{mn}, \nu_m, \omega_{mn}, \tau &\geq 0 \\
\alpha_{mn}, \beta_m, \gamma_{mn} &\ \epsilon\ \{0, 1\}, \forall\, m\,\epsilon\,\mathbb{N}_{\mathbb{BS}},\ n\,\epsilon\,\mathbb{N}_{\mathbb{SS}}
\end{aligned}$$

CHAPTER 5. HEURISTIC ALGORITHM

In this section, we introduce the heuristic approach to solve spectrum-energy efficiency problem to avoid the unsatisfactory exponential increase in the computation time taken by CPLEX. The pseudocode is shown in Algorithm 1, taking the same inputs with CPLEX and is implemented using C programming language. In the wireless communication environment the number of nodes changes rapidly and frequently; as a result, heuristic algorithms are favorable to solving the proposed optimization model.

After initialization (Line 2), the spectrum-energy efficiency values for connections between BSs and users are worked out by $\frac{r_n}{T_{mn}}$ and stored in $\mathbb{S}^{\mathbb{E}}$. The users are sorted in a decreasing order in terms of their spectrum-energy efficiency values and indexed in $\mathbb{N}_{\mathbb{SS}}$ (Line 3). The output is the solution in which the connection or disconnection between BS and user, a_{mn}, and the operation mode of BSs, o_m, are demonstrated. It is worth noticing that S^E_{mn} has a value larger than zero since the values of r_n and T_{mn} are positive.

In Lines 4-8, beginning from SS_{11}- which denotes for SS_1 the BS it connects with to have the largest spectrum-energy efficiency value, all the SSs are associated with the BSs that can provide the maximized spectrum-energy efficiency values (denoted as I^1_n). Namely, $I^1_1 = \arg\max_{\forall\, m\, \epsilon\, \mathbb{N}_{\mathbb{BS}}} S^E_{m1}$, which is stored in the set of selected BSs, $\mathbb{I}$. Then I^1_n is mapped to the BS-SS association decision variable such that $a_{I^1_1,1} = 1$. The same operation repeats for the next user. The iteration stops when all the users are assigned to BSs. The initial solution is established by assigning all the users to the BSs which are their first choices. By this method, all of the users are served by the BSs with best individual spectrum-energy efficiency values.

Lines 9-15 check if the initial solution is in conformity with the constraints of (4.2) and (4.3). If any of them is not achieved, the solution is not valid and need further improvements. Until the two constraints are not violated any more, the connection removal is done by discarding the users with the lower spectrum-energy efficiency values among all the initial active connections. The philosophy here is that since we are trying to maximize the total spectrum-energy efficiency, we keep the users causing higher spectrum-energy efficiency values active in the solution.

In Lines 16-26, if the blocking rate constraint of (4.12) is not met, for the remaining users without connections, we select the second best BSs that offer the second best spectrum-energy efficiency values. Similarly, the selected BS is then mapped to the BS-SS association decision variable. Subsequently, the validity of the two fundamental constraints at BSs is checked again, (4.2) and (4.3).

Since in the downlink transmission, BSs are the only resources to transmit signals and generate interference, the likelihood of the existence of interference between adjacent BSs is spontaneous along with the transmission. One possible way to reduce the impact of this phenomena is turning BSs into sleep mode, alleviating the effect of noise and interference. Therefore, it is another benefit of not turning on BSs so that the signal strength of their neighboring BSs can stay at the strong level. The following for-loop (Line 17-24) realizes the idea of operating BSs as less as possible without the constraint violation of the blocking probability.

Basically, this stage looks for the existence of the generation of a better objective function based on the current solution by switching BSs into sleep mode. Moving the current nodes to other BSs possibly can produce a better solution; therefore, we start from the BSs whose present cumulative objective values are regarded as distinctly inferior. Thanks to the substantial gap between the operation power usages of active and sleep modes of a BS, it is advantageous to operate as many as BSs in the sleep mode. By looking into every BSs and temporarily sweeping all its served nodes to the BSs which can accept those immigrants, our attempt is to dig out a new solution bringing out an improved objective value. Once the new improved solution is reached we substitute for the former one.

Finally, the overall system objective value can be further increased if there is any active users which can be removed. To carry out a system where the number of active connections is exactly the same with the active user number requirement, the algorithm next eliminates the active users with lower objective value to maximize the total system objective value. After this last step, the final solution is found where the output values of a_{mn} and o_m is presented. We also implement an algorithm with a similar idea.

Algorithm 1 Heuristic Spectrum-Energy Efficiency Maximization

Input: M, N, $\mathbb{N}_{\mathbb{BS}}$, $\mathbb{N}_{\mathbb{SS}}$, $\mathbb{T}$, $\mathbb{D}, \mathbb{P}$, Pa, Ps, θ, MP, DS_t;
Output: $\mathfrak{C}$, $\mathcal{A}$, $\mathcal{O}$;
1: $\mathcal{A} = zeros([M,\ N])$; $\mathcal{O} = zeros([1,\ M])$; $\mathbb{B}_m = \Phi$;
2: Calculate S^E_{mn} for connection between SS_n and BS_m;
3: Sort($\mathbb{S}^E, 'desc'$); Reorder($\mathbb{N}_{\mathbb{SS}}$);
4: **for** $n = 1$ to N **do**
5: **BestBS4SS()**; {1. Find $I^1_n = \arg \max\limits_{\forall\, m\, \epsilon\, \mathbb{N}_{\mathbb{BS}}} S^E_{mn}$, for SS_n among $\mathbb{N}_{\mathbb{SS}}$. 2. Map I^1_n to $\mathcal{A}$ such that $a_{I^1_n, n} = 1, \mathbb{B}_{I^1_n} \leftarrow n$. 3. Calculate C^U_m, C^D_m, C^E_m and C^S_m, $\forall\, m\, \epsilon\, \mathbb{N}_{\mathbb{BS}}$.}
6: **end for**
7: **for** $m = 1$ to M **do**
8: **while** $C^D_m > DS_t$ or $C^E_m > MP$ **do**
9: Find $n = \arg\min_{\forall\, n\, \epsilon\, \mathbb{N}_{\mathbb{SS}}} S^E_{mn}$;
10: $\mathbb{B}_m \leftarrow \mathbb{B}_m / \{n\}$, $a_{mn} = 0$;
11: Re-calculate C^U_m, C^D_m, C^E_m and C^S_m, $\forall\, m\, \epsilon\, \mathbb{N}_{\mathbb{BS}}$;
12: **end while**
13: **end for**
14: **while** $\sum_{\forall\, m\, \epsilon\, \mathbb{N}_{\mathbb{BS}}} C^U_m < \theta$ **do**
15: **for** $n = 1$ to N **do**
16: **if** $\sum a_{mn} = 0$ **then**
17: **SecondBestBS4SS()**;
18: **end if**
19: **end for**
20: **end while**
21: Do Lines 7-13 again
22: $\mathbb{F} \leftarrow$Sort($\mathbb{C}^S$, $'asce'$); Reorder($\mathbb{N}_{\mathbb{BS}}$);
23: **for** $m = 1$ to M **do**
24: **for** $m' = M$ to 1 **do**
25: **FindBetterEnergyConsumption()**; {1. Compute new $\mathfrak{C}$ by connecting $n\, \epsilon\, B_{F_m}$ with $BS_{F_{m'}}$. 2.Find $BS_{m'}$ that SS_n can migrate to with minimal energy consumption, $k = \arg\min_{\forall\, m'\, \epsilon\, \mathbb{N}_{\mathbb{BS}}} \mathfrak{C}$.}
26: **if** $\exists\, k$ and $C^D_m + C^D_k \leq DS_t$ and $C^E_m + C^E_k \leq MP$ **then**
27: **Migration()**; {1. $a_{kn} = 1$, $a_{mn} = 0$, $\mathbb{B}_k \leftarrow n$, $\mathbb{B}_m \leftarrow \mathbb{B}_m / \{n\}$ 2. Re-calculate C^U, C^D_m, C^D_k, C^E_m, C^E_k, C^S_m and C^S_k. 3.
28: $\mathbb{F} \leftarrow$Sort($\mathbb{C}^{\mathbb{S}}$, $'asce'$); Reorder($\mathbb{N}_{\mathbb{BS}}$).}
29: **end if**
30: **end for**
31: **end for**
32: **for** $m = 1$ to M **do**
33: **for** $m' = M$ to 1 **do**
34: **FindBetterSpectrumEnergyEfficiency()**;
35: **if** $\exists\, k$ and $C^D_m + C^D_k \leq DS_t$ and $C^E_m + C^E_k \leq MP$ **then**
36: **Migration()**;
37: **end if**
38: **end for**
39: **end for**
40: Determine BS operation modes given $\mathcal{A}$;
41: **return** $\mathfrak{C}$, $\mathcal{A} = (a_{mn})_{M \times N}$, $\mathcal{O} = (o_m)_{1 \times M}$

CHAPTER 6. RESULTS

This section presents network examples where a WirelessMAN OFDMA interface is assumed such as IEEE 802.16 or LTE. Case studies are conducted to evaluate the solution to the problem and the proposed heuristic algorithm in terms of the optimality and the computational efficiency against the optimal solution. We also demonstrate the performance benefits of minimizing energy consumption and maximizing spectrum-energy efficiency against the base cases. The performances in base cases are investigate, aiming to show the impact of optimization as well as the significant insights to optimal BS-SS association and BS operation mode in practical multi-cell-multi-users scenarios.

The main system parameters taken into account in the simulations are tabulated in Table 6.1. While we generate user bandwidth requirements, Table 6.2 expressing the basic classifications referred to. Table 3.4 displays the parameters for different types of areas for the calculation of the path loss.

The user percentages in each type of areas and the size of each area also described in Table 3.4. We also consider two types of users in the system, users which can be blocked out or not. For the users which cannot be blocked out, they will always be guaranteed to obtain services; on the contrary, the users which can be blocked out are determined whether to receive transmission by the solutions. Also, users and BSs can be placed at three different type of areas, urban, suburban and rural area, affecting the power requirements.

Without loss of generality, no coverage hole exists in base cases. Fig. 6.1(a) shows one of the network layouts considered in the case studies, 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. 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

Table 6.1: 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 transmit energy	20 (J)
Fading	Fast fading margin
FFT size	1024
Thermal noise	-104 dBm
User distribution	Random
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

objective values of our proposed algorithm are fairly close to the optimum for all the cases under consideration. Fig. 6.1(b) and 6.1(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.

6.1 Solving the Model

Fig. 6.2 displays the comparison of the case where 11 BSs are in the system with a blocking probability of 0.05%. 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 mini-

Table 6.2: Bandwidth Requirement Classifications

Class	Application	Bandwidth Guideline	
1	Multiplayer Interactive Gaming	Low	50 kbps
2	VoIP & Video Conference	Low	32-64 kbps
3	Streaming Media	Low to High	5 kbps to 2 Mbps
4	Web Browsing & Moderate Instant Messaging	Moderate	10 kbps to 2 Mbps
5	Media Content Downloads	High	>2 Mbps

mized, saving superfluous energy. It is clearly shown in Fig. 6.2(a) that for various number of users, the optimization model which mainly considers saving energy consumes low-level overall energy to sustain the system, saving energy substantially from the base cases without energy minimization scheme. As the number of users increases, the energy consumption difference is less between the scheme with conventional BSs and that with the energy saving scheme. The reason for this is since BSs have more users to cover, more transmission energy is devoted to communications. Even more, the number of BSs which can operate in sleep mode decreases as a result of rising number of requests to establish connections. For example, while 4200 users are considered, one more BS has to operate in active mode compared with a user number of 3900.

As the user number increases and the number of BSs which can be switched into sleep mode decreases, the saved energy consumption percentage is lower. By introducing the notion of zooming in/out, the cell sizes are modified to fit the user distribution, reducing the system energy consumption. The signal strength for the cell-edge users is guaranteed to be solid enough since the receiver sensitivity guarantees the BER of 10^{-6}. Moreover, because frequency reuse 1 is considered, the range of inter-cell interference are reduced. The idea of user migration will also be applied to sustain the required served user number. Switching off BSs is a win-win decision which can not only benefit the efficiencies but also reduce interference.

Fig. 6.2(b) depicts the performance improvements in terms of spectrum-energy efficiency. As expected, the base cases cannot put in satisfactory performance. Additionally, minimizing energy consumption also bring advantages subsequently due to the significant amount of saved energy. However, it is not able to achieve optimum spectrum-energy efficiency. The reason is that connections with low transmission energy could carry medium bandwidth, not weighting the efficiency in data subcarrier use while minimizing energy consumption. It doesn't take account of the consideration of deliver information efficiently. The optimization of spectrum-energy efficiency takes into account both energy consumption and spectral efficiencies. By this way, both metrics can be ameliorated. It is worthy to mention that to achieve maximum spectrum-energy efficiency, we have to sacrifice conserved energy for the sake of improved performance, making a trade-off between minimizing energy consumption and maximizing spectrum-energy efficiency.

Table 6.3 compares the objective values (i.e., percentages of saved energy, improved spectrum-energy efficiency). It is observed that the energy to be consumed can be substantially reduced (70%) when minimizing energy, compared to the system with conventional BSs operating normally with a fixed cell size; as a result, a salient economic benefit in terms of achievable energy cost reduction. On the other hand, a significant improvement on spectrum-energy efficiency can be achieved by 221%.

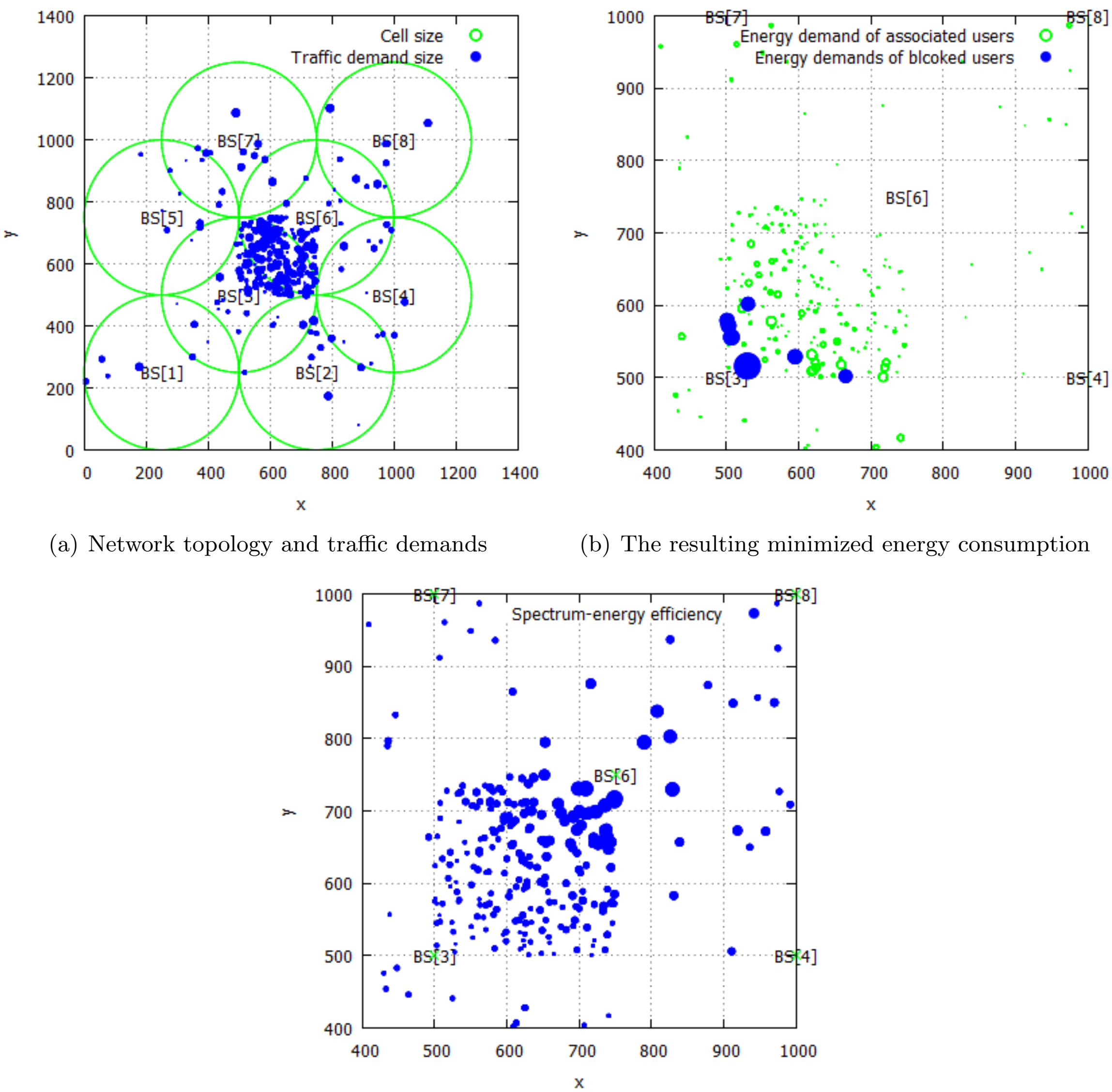
Fig. 6.3 compares each BS's various values in terms of bandwidth allocated, subcarriers used, transmitting energy and spectrum-energy efficiency with different schemes used. From Fig. 6.3(c), beside BS6 optimizing energy consumption chooses BS9 to operate in active mode. The proposed algorithm picks BS3 instead of BS5 which is one of the optimal decision to produce a best system spectrum-energy efficiency. Fig. 6.4 illustrates the different average differences in energy consumption between optimizing energy consumed and spectrum-energy efficiency offers different levels of efficiency improvements. It suggests that in the studied cases possibly the more surplus energy the model of maximizing spectrum-energy efficiency consumes, the more efficiency improvements it can lead to.

6.2 Comparison of CPLEX and Heuristic Algorithm Results

The formulation is solved by CPLEX 12.2. The results obtained by CPLEX are taken as a benchmark to evaluate the optimality gap by our proposed heuristic counterpart. The comparisons of the pairwise outcomes are measured on the identical platform, a Linux machine equipped with an 24-core processor and 24 GB memory. Fig. 6.5 shows the essential performance differences between CPLEX and the algorithm with different number of users within 11 BSs in term of energy consumption and spectrum-energy efficiency under a blocking probability on 0.05%. The results of proposed heuristic algorithm are compared against the optimal solution obtained with CPLEX. It can be seen that the proposed heuristic can provide a good solution with only slight degradation on the performance, but it is much more computationally efficient than CPLEX.

The proposed algorithm demonstrates high computation efficiency as shown in Fig. 6.6. The computation time of the proposed algorithm increases linearly with the problem size (i.e., the total number of users and BSs), while the computation time shows an exponential growth with CPLEX. More cases are considered. The problem size, the computation time and optimality gap are shown in Table 6.4. A difference of 1.26% on average is made between CPLEX and the heuristic algorithm maximizing spectrum-energy efficiency. Nevertheless, it can be seen that the complexity of solving the problem grows dramatically as the network size increases. In contrast, our proposed heuristic algorithm can solve the problem at a very fast speed. Therefore, our proposed algorithm shows a good scalability in larger scale wireless network design.

The solutions from CPLEX and our algorithm are close, however, CPLEX solves the models 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.

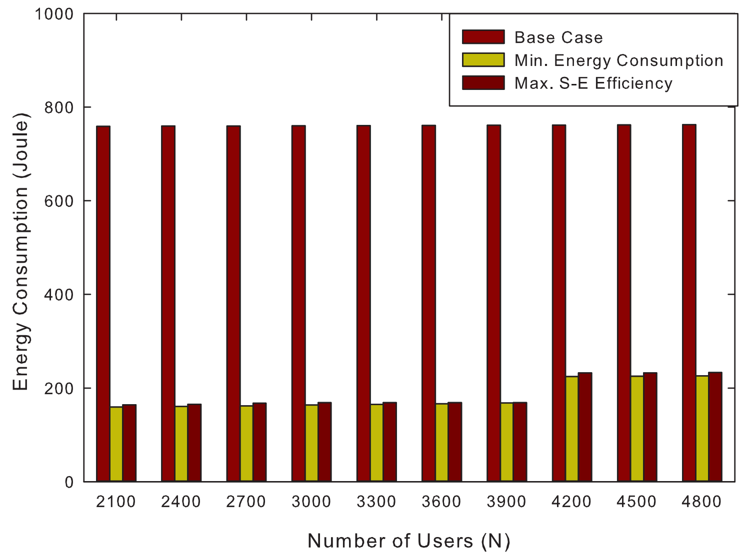


(a) Network topology and traffic demands

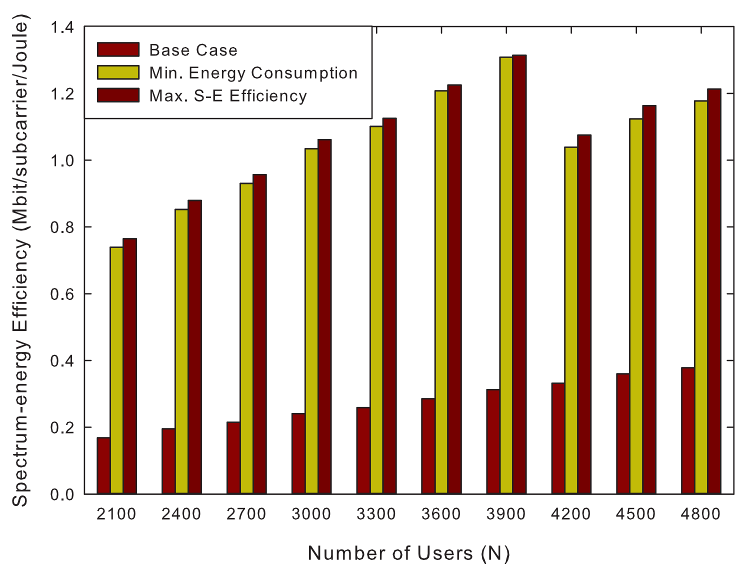
(b) The resulting minimized energy consumption

(c) The optimal spectrum-energy efficiency

Figure 6.1: Illustration of cell layout, geographical distribution of traffic demands, energy consumption and spectrum-energy efficiency for BSs in same scenario.



(a) Energy consumption versus number of users

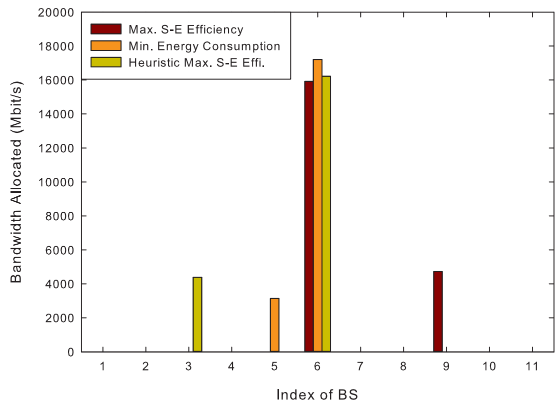


(b) Spectrum-energy efficiency versus number of users

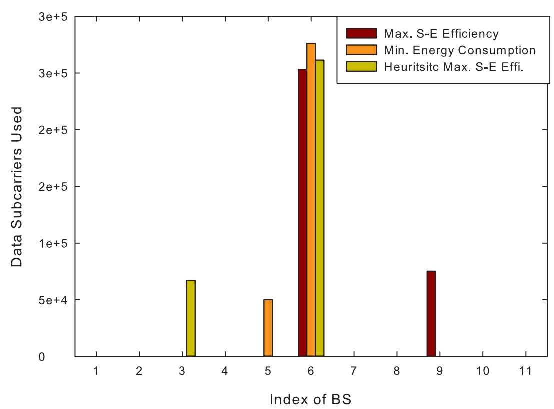
Figure 6.2: Energy consumption and spectrum-energy efficiency versus number of users with and without optimization.

Table 6.3: Objective Value Comparison

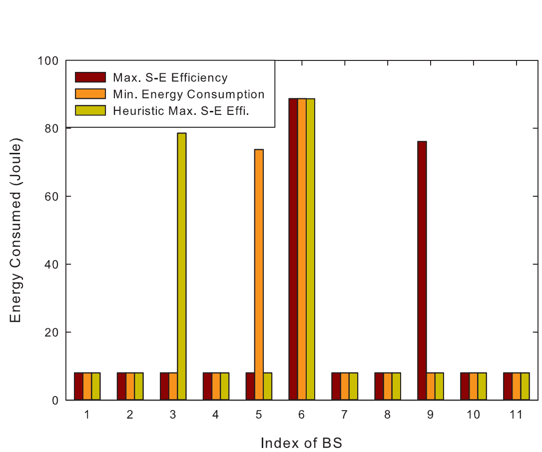
	Number of users	2100	2400	2700	3000	3300	3600	3900	4200	4500	4800
Saved Energy Consumption	Min. Energy Consumption	79%	79%	79%	79%	78%	78%	78%	71%	71%	70%
	Max. Spectrum-energy Efficiency	78%	78%	78%	78%	78%	78%	78%	70%	70%	69%
	Absolute Difference	4.64	4.42	5.75	5.06	3.89	2.46	0.72	7.56	7.43	6.99
Enhanced Spectrum-energy Efficiency	Min. Energy Consumption	340%	337%	334%	329%	325%	323%	318%	213%	212%	211%
	Max. Spectrum-energy Efficiency	355%	351%	346%	341%	334%	329%	320%	224%	223%	221%
	Absolute Difference	0.03	0.03	0.03	0.03	0.02	0.02	0.01	0.04	0.04	0.04



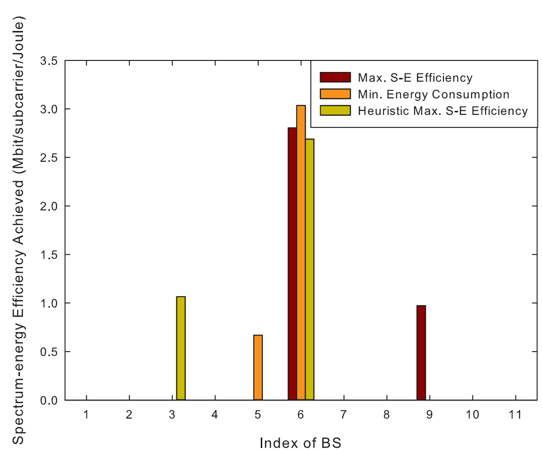
(a) Bandwidth allocated



(b) Data subcarriers used



(c) Energy consumed



(d) S-E efficiency achieved

Figure 6.3: Performance of each BS where 5700 users are deployed.

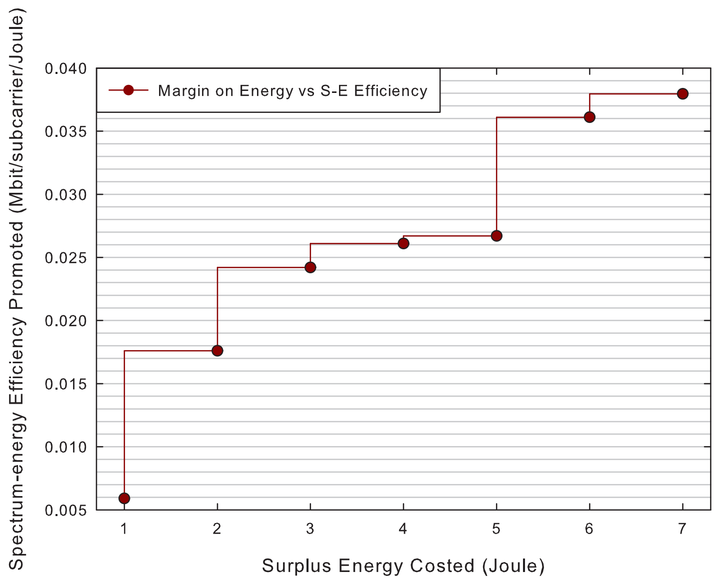
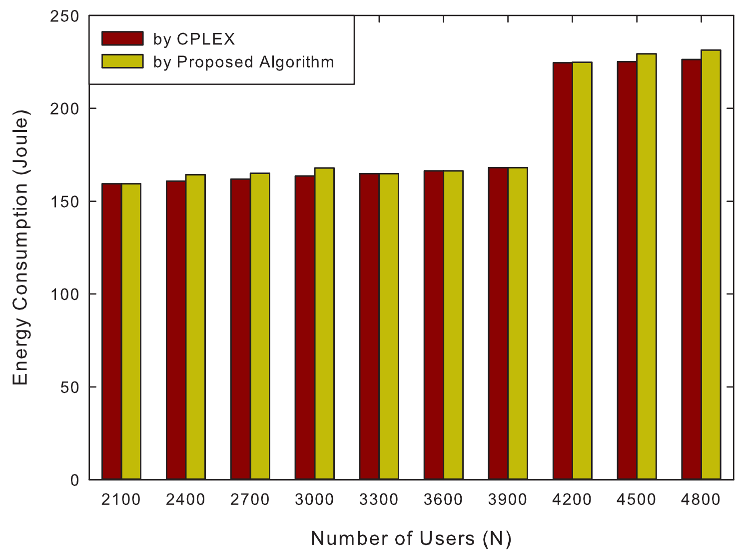


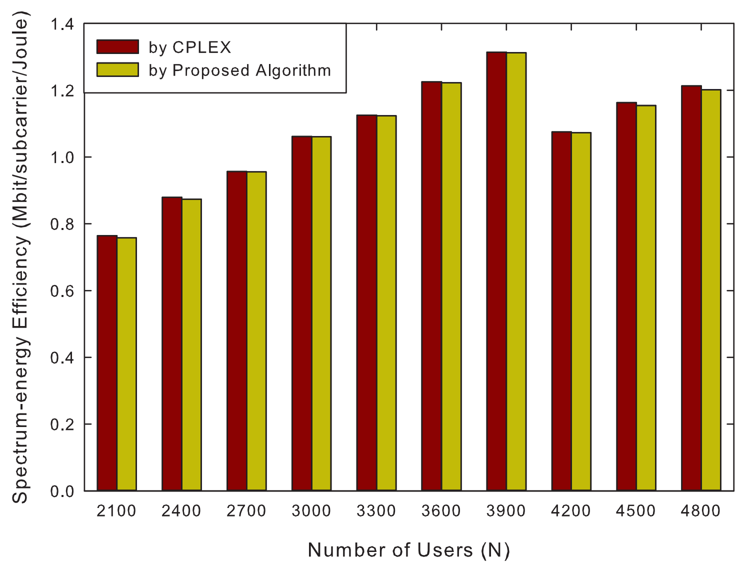
Figure 6.4: Margin on Spectrum-energy Efficiency versus Energy.

Table 6.4: Problem Size, Computation Time for CPLEX Solving the Formulation and Computation Time for Proposed Heuristic

Num. of Users	Ave. Opt. Gap	Ave. computation time (Sec)	
		CPLEX	Proposed heuristic
5100	1.21%	11953.25	0.09
5400	1.43%	22291.65	0.11
5700	1.25%	13103.97	0.11
6000	1.13%	24523.55	0.11
6300	1.38%	35286.79	0.10



(a) Energy consumption comparison



(b) Spectrum-energy efficiency comparison

Figure 6.5: The comparison of objective value of proposed algorithm against CPLEX.

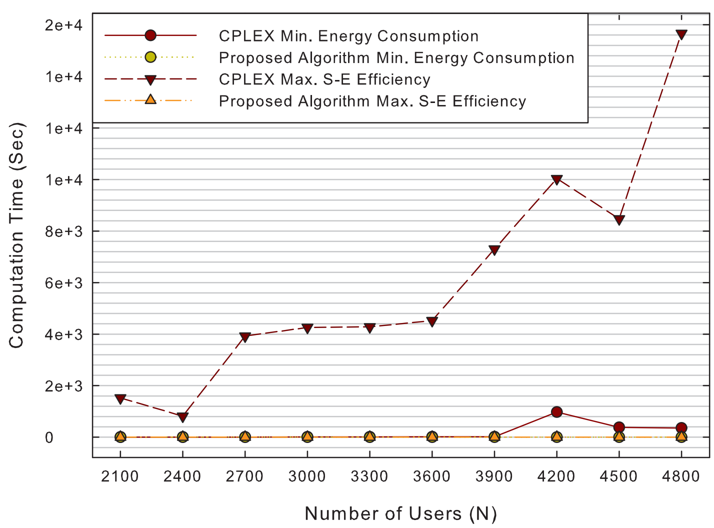


Figure 6.6: The computation time comparison between proposed algorithm and CPLEX.

CHAPTER 7. SUMMARY AND DISCUSSION

From service providers' perspective, saving energy is able to reduce electrical expenditure, and enhancing spectrum efficiency can bring profits. To increase the payoff, a network following spectral and energy efficient design is desired in wireless environments. In this paper, we have conducted a comprehensive 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 by jointly considering the cellular mechanisms, aiming at enhancing the overall spectrum-energy efficiency as well as reducing energy consumption. Maximizing spectrum-energy efficiency in present scenario is able to gain the energy saving by 69% and spectrum-energy efficiency by 221%, respectively compared to the base case equipped with conventional BSs. To make the solution on the proposed optimization problem computationally tractable, the heuristic algorithm has been developed. The framework should play an important role in the future green broadband wireless access network design by providing a guideline for the service providers in the effort of efficiency improvements.

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