Rural Broadband: Network Planning and Spectrum Management

Submitted in partial fulfillment of the requirements
of the degree of

Master of Technology
by

Sweety Suman
Roll No. : 14307R007

Supervisors:

Prof. Abhay Karandikar

&

Prof. Prasanna Chaporkar

Department of Electrical Engineering
Indian Institute of Technology Bombay

June 2017

Dedicated to my parents

Approval Sheet

This thesis entitled **Rural Broadband: Network Planning and Spectrum Management** by Sweety Suman (Roll No. 14307R007) is approved for the degree of **Master of Technology** in **Communication and Signal Processing**.

Examiners

Kumar Appaiah
____

NKS
____

Supervisors

____

____

Chairperson

____

____

Date: 19/6/2017

Place: Mumbai

Declaration

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Sweety

Sweety Suman

Roll No: 14307R007

Date: 20th June 2017

Acknowledgement

I would like to express my sincere gratitude to my guide Prof. Abhay Karandikar for the continuous support of my M.Tech. study and research, for his motivation, enthusiasm, and immense knowledge. I would also like to thank my co-guide Prof. Prasanna Chaporkar for his invaluable guidance, patience and suggestions throughout my thesis work. It was their motivation and inspiration which led my initial steps in research. During the last three years, my approach towards problem solving and technical writing has been shaped and polished by them. Their enthusiasm has been a source of constant motivation for me throughout my stay at IIT Bombay. I attribute the level of my research work entirely to their encouragement and support.

I would like to thank all my fellow Wireless Networks (WiNet) and Information Networks (InfoNet) lab members for being helpful, supportive and making the lab a wonderful place to carry out research. I would also like to thank Meghna Khaturia, Shubham Saha and Sadaf Ul Zuhra for their invaluable help and support in carrying out my research work.

Finally, I must express my very profound gratitude to my parents for providing me with unfailing support and continuous encouragement throughout my years of study. I am extremely fortunate to be their daughter, and will always remain indebted to them. This accomplishment would not have been possible without them. I dedicate this thesis to them!

Sweety Suman

Roll Number: 14307R007

Date: June 19, 2017

Abstract

Rural areas in the developing countries are predominantly unconnected as it is not viable for operators to provide broadband access in these areas. To solve the problem of poor broadband penetration in rural areas, we propose a wireless *middle mile* Third Generation Partnership Project (3GPP) Long Term Evolution Advanced (LTE-A) network using TV white space to connect villages to an optical Point of Presence (PoP) located in the vicinity of a rural area. We design a genetic algorithm based tool which can be used for network planning. We consider Registered Shared Access (RSA) as a feasible regulation scheme to access the TV white space. We discuss the spectrum sharing among multiple operators under (a) static network load and (b) dynamic network load conditions. We design a Fairness Constrained Channel Allocation (FCCA) scheme based on graph theory for the first case. For the second case, we model spectrum sharing as hierarchical resource allocation problem with inter-operator resource allocation in the first stage and then intra-operator resource allocation in the second stage. We present a novel idea of allocating resources in the form of orthogonal time and frequency (TF) blocks. For inter-operator resource allocation, we propose two algorithms which achieves fair demand aware resource allocation to the operators. The first algorithm is designed using the concept of *Virtual Clock Scheduling* [1] while the second is based on the *Weighted Fair Queuing* [2]. These algorithm takes the demand from the operator as input and returns the resource allocation vector for each operator as output. We show that both of these algorithm ensures long term as well as short term fairness in terms of resource allocation. For intra-operator resource allocation, we propose an optimal as well as graph theory based sub-optimal solution. We simulate this scenario in MATLAB [3] and present the simulation results to assess the performance of the algorithms. We demonstrate that the proposed hierarchical resource allocation scheme is adaptable to network load and thus resulting into efficient spectrum utilization in most scenarios.

Contents

List of Figures

Chapter 1

Introduction

The world has seen a vast growth in communication technology and yet 52% of the global population is still unconnected [4], majority of which live in developing countries. For example, in India, only 8% of 1.25 billion population has broadband connectivity [5]. The broadband penetration in the rural areas of developing countries is even worse due to high cost of infrastructure, difficult terrain, sparse population density and low Average Revenue per User (ARPU). A low cost broadband access to the end users in these areas can be provided by deploying Wi-Fi Access Points (APs). However, laying fiber to backhaul each and every Wi-Fi AP becomes infeasible as it is time consuming and expensive. If an optical Point of Presence (PoP) is located in the vicinity of a rural area, then a wireless *middle mile network*, as proposed in [6], can be established to connect the optical PoP to the WiFi APs in the villages.

1.1 Middle-mile using TV UHF band

A possible solution for connecting the PoP to the APs is to use TV UHF band in the middle mile network as it is highly underutilized in many developing countries. In India, more than 100 MHz of TV UHF band (470-585 MHz) is unused (commonly referred to as TV white space) [7]. This is in contrast to the developed countries where only small sporadic gaps are available in the TV UHF band. Owing to the propagation characteristics of this band, it is possible to obtain large coverage area even with low power transmission. This will enable the use of renewable energy sources which is a highly desirable feature to develop an affordable technology for rural areas. Consequently, the operators can be encouraged to deploy a middle mile network in these areas. However, a middle mile network using the TV UHF band is not a plug and play solution. As multiple operators have to coexist in the same band, there will be huge interference among them which will lead to low spectral efficiency. Hence, it is important to design a spectrum sharing scheme which not only increases the spectral efficiency but also guarantees a fair share of spectrum to the operators. The major challenge in designing the above scheme is that it should be based on trivial information which can be easily availed from operators since they will be unwilling to share sensitive information.

Conventionally, underutilized spectrum can be accessed in two ways viz. *licensed* or *unlicensed*. If this band is used under a *licensed* regime, the operators are discouraged to provide broadband services in rural areas due to low ARPU as compared to the very high cost of the band. If this band becomes *unlicensed*, the interference among operators is difficult to manage due to good long distance propagation characteristics of this band. Thus, in [6], the authors have proposed Registered Shared Access (RSA) as a possible scheme. Under this scheme, an operator has to register itself with a central entity called *Spectrum Manager (SM)*, before using this band and might have to pay a usage fee. The SM allocates resources to the operators according to some resource allocation scheme. We also discuss the network planning in case of single operator deployment.

1.2 Proposed solutions for Spectrum Sharing

The spectrum sharing problem among multiple operators can be modeled as hierarchical resource allocation problem. In the first stage, the SM allocates resources to the operators and in the second stage operators has to distribute the allocated resources among its base stations, referred to as evolved NodeBs (eNBs) in LTE standards. We propose two schemes for inter-operator resource allocation, which can be followed by SM for fair resource allocation among operators. Along with this, we also propose a solution for intra-operator resource allocation among eNBs of any operator.

1.2.1 Inter-operator resource allocation

We propose two schemes to solve inter-operator resource allocation problem. The first scheme is well suited for the network where load variation over time is less or negligible.

As per this scheme, the available resource is statically allocated among the participating operators based on their network topology. We present a topology aware spectrum sharing algorithm which performs fair resource allocation to the operators. Fairness in resource allocation is important to prevent the conflict among participating operators. Fair resource allocation can be defined as equal distribution of available resources among operators, if equal priority is given to each operator. We demonstrate that the proposed scheme guarantees long term fairness among operators.

The other scheme is designed for the network where load condition varies with time. For better spectrum utilization in such network, the resource allocation should be dynamic. This scheme allows dynamic resource allocation by considering demand from individual operator and thus ensuring short term fairness. This scheme adapts itself to provide fair resource allocation even in case of bursty traffic conditions. Even when SM doesn't give equal priority to all operators, this scheme can be altered to allocate resources to the operators in weighted fair manner. Since the demand from the operator is taken as input so there may be the case when some operator may lie and thus ask for fake demand to the SM. It is very important that resource allocation scheme should be immune to all such incidences. As per the proposed scheme, the operators with fake demand gets punished by less resource allocation while other operator gets their fair share. Hence, this scheme encourages the operators to ask for true demand only.

1.2.2 Intra-operator resource allocation

Along with inter-operator spectrum sharing, we also discuss the optimal solution for intra-operator resource allocation. Each operator has to allocate resources to its base station which in turn serves the end users. We model the intra-operator resource allocation as constrained Binary Integer Linear Program (BILP). Since, BILP is computationally very expensive for large network so we propose an easily implementable and inexpensive graph theory based solution. We demonstrate that the performance of the proposed solution is comparable to the original BILP solution.

1.3 Organization

In this thesis, we consider a Long Term Evolution Advanced (LTE-A) network operating in sub-GHz TV UHF band. We design a network planning tool in Chapter 2. In Chapter 3, we discuss the system model of middle-mile access network using sub-GHz TV UHF band. We solve the spectrum sharing problem in two scenarios, (a) when the network load is static and (b) when the network load is dynamic. The static load case is dealt in Chapter 4 and dynamic load case is dealt in Chapter 5. In Chapter 4, we formulate the spectrum sharing problem as the maximization of the system throughput while maintaining the fairness among operators. We propose a graph theoretic technique to allocate multiple channels to the operators. Also, we assess the performance of the proposed algorithm using ns-3 simulation results and compare the same with few other coexistence approaches in Chapter 4.

For the second scenario, we model spectrum sharing as hierarchical resource allocation problem with inter-operator resource allocation first and then intra-operator resource allocation in Chapter 5. For inter-operator resource allocation, we propose two algorithm to achieve optimal dynamic resource allocation among operators. The available spectrum resource is represented in terms of orthogonal time and frequency blocks. The first algorithm is designed using the concept of *Virtual Clock Scheduling* [1] while the second is based on the *Weighted Fair Queuing* [2]. We show that both these algorithm ensures long term as well as short term fairness in terms of resource allocation. Also, for intra-operator resource allocation, we propose an optimal as well as graph theory based sub-optimal solution. We present the results of MATLAB [3] simulations to assess the performance of the hierarchical resource allocation technique in Chapter 5.

Chapter 2

Middle-mile Network Planning for Single Operator

In this chapter we discuss a special case when government deploys the network instead of auctioning the band to operators. This use case can be considered as single operator scenario where monitoring of spectrum usage is not required. Though there is no other operator to share the spectrum with, there will be a need to plan the network so that interference among eNBs can be minimized. We present a Genetic Algorithm (GA) based network planning tool in further sections.

Given, a rural scenario where fiber PoPs are present at GPs and middle-mile is required to connect GP to villages. The objective of the tool is to provide connectivity to maximum number of villages. In order to do so, we must design an algorithm which efficiently connects the villages to the PoPs. The pre-requisites for designing the tool are the following:

- Geographical location of PoPs at Gram Panchayat : PoPs corresponds to the eNBs
- Geographical location of villages : Villages are equivalent to end users
- Throughput requirement at the village : This is calculated using population data of rural areas
- Physical layer specifications :
  - Transmit power levels
  - Available bandwidth

– Pathloss model

Owing to the good propagation characteristics of TV UHF band, there is high probability of interference among eNBs. To investigate this issue, we analyzed the rural area data to understand the geographical distribution of PoPs. We collected the PoP and village locations of some districts and studied the average cell radius of GPs. We also studied the average inter-site distance between PoPs. We concluded that average inter site distance between PoPs is approximately 2 km and the average cell radius is 2.5 km. Since the inter-site distance is less than the cell radius, there will be huge interference if eNBs are installed at all PoPs. Hence, we need to design the network intelligently, as placing eNBs at each PoPs is not the solution. We assume all the above mentioned data are available to design the tool.

2.1 Genetic Algorithm based Tool Design

In the previous section, we concluded that installing eNBs at each PoP is not the optimal solution. Now, given all the data, there are two parameters which we need to find optimally for network planning. First, to choose the optimal set of locations where eNBs can be installed. Second, the optimal transmit power level of these eNBs. The main objective is to meet the throughput requirement of villages by placing eNBs optimally. This is an combinatorial optimization problem which cannot be solved in polynomial time for large networks. Hence, we use genetic algorithm to make intelligent move over the search space. In this section, we propose a genetic algorithm based tool which takes the pre-requisite data as input and returns the optimal transmit power of eNBs. This tool is based on two algorithms, first calculating utility for given topology and second genetic algorithm. We discuss in details in the further sections.

2.1.1 Utility Function

For a given topology, this function calculates the maximum number of villages which can be served by eNBs at GPs. The transmit power of eNBs, its location, village centroids and throughput requirement of villages are required as input to this function. During initialization, reference signal received power (RSRP) is calculated for all possible GP-village pair. This data is further used to connect a village to the best match GP using following steps:

- Choose max RSRP GP-village pair and then perform the next steps on this pair,
- Map the throughput requirement of village in terms of resource block(RB). Check whether the number of available RBs at GP is greater than the requirement of village,
- If no, then delete this entry of GP-village pair from the data,
- If yes, then connect the village to the GP and increase the counter which maintains the count of connected village,
- Repeat the same steps until all feasible connections are exhausted i.e. either resources at GPs are exhausted or all villages are connected.

This function returns the number of villages which are successfully connected to the eNBs at GPs. While allocating resources to the villages, we assume 100% reuse of available bandwidth among eNBs. The flowchart of algorithm shown in Figure 2.1.

2.1.2 Genetic Algorithm (GA)

GA is a method for solving combinatorial optimization problems based on a natural selection process [8]. GA mimics the biological evolution. The algorithm repeatedly updates a population of individual solutions based on cost returned. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. We use GA to obtain the optimal set of eNBs as well as its transmit power.

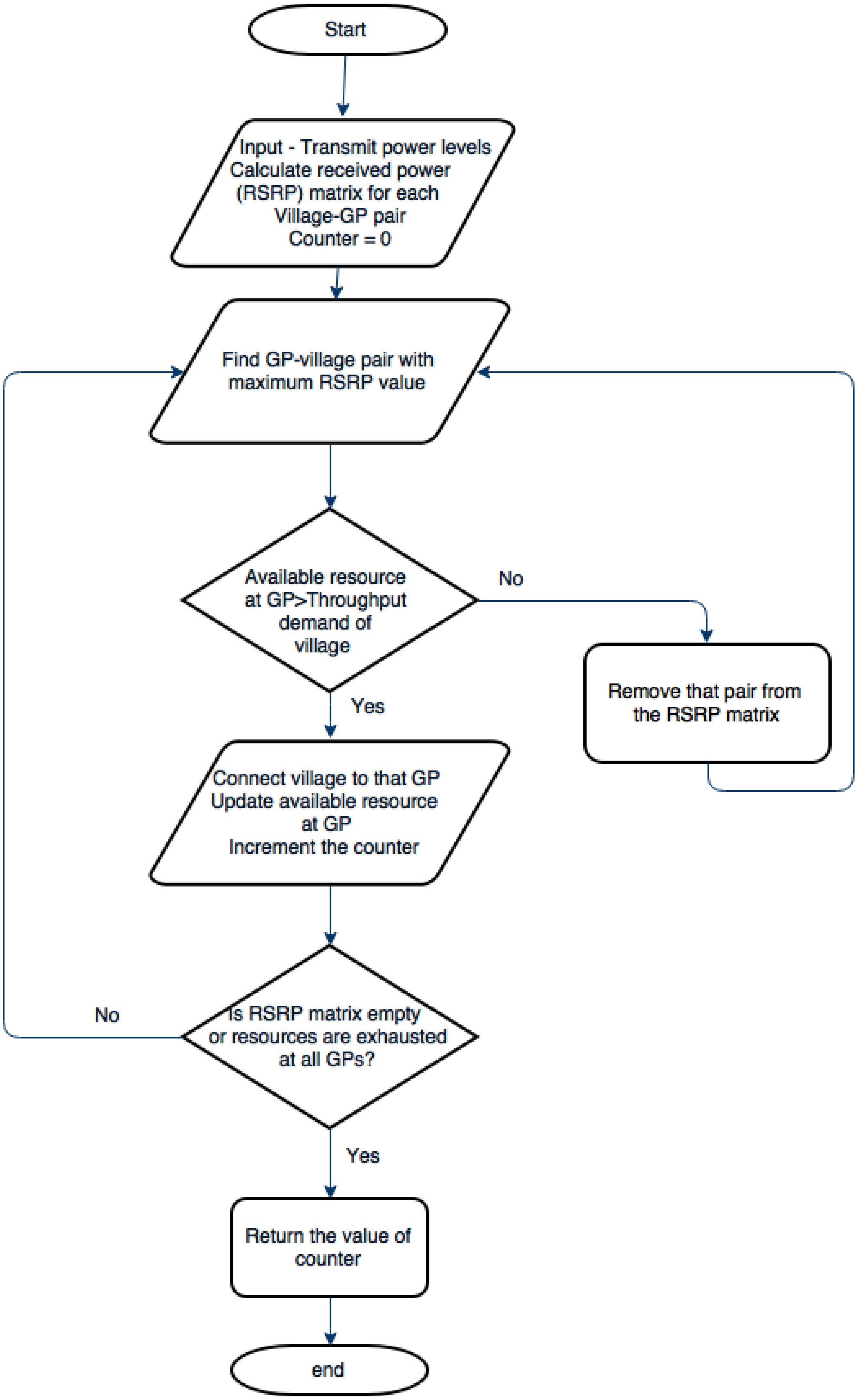

Figure 2.1: Flowchart of algorithm to calculate utility.

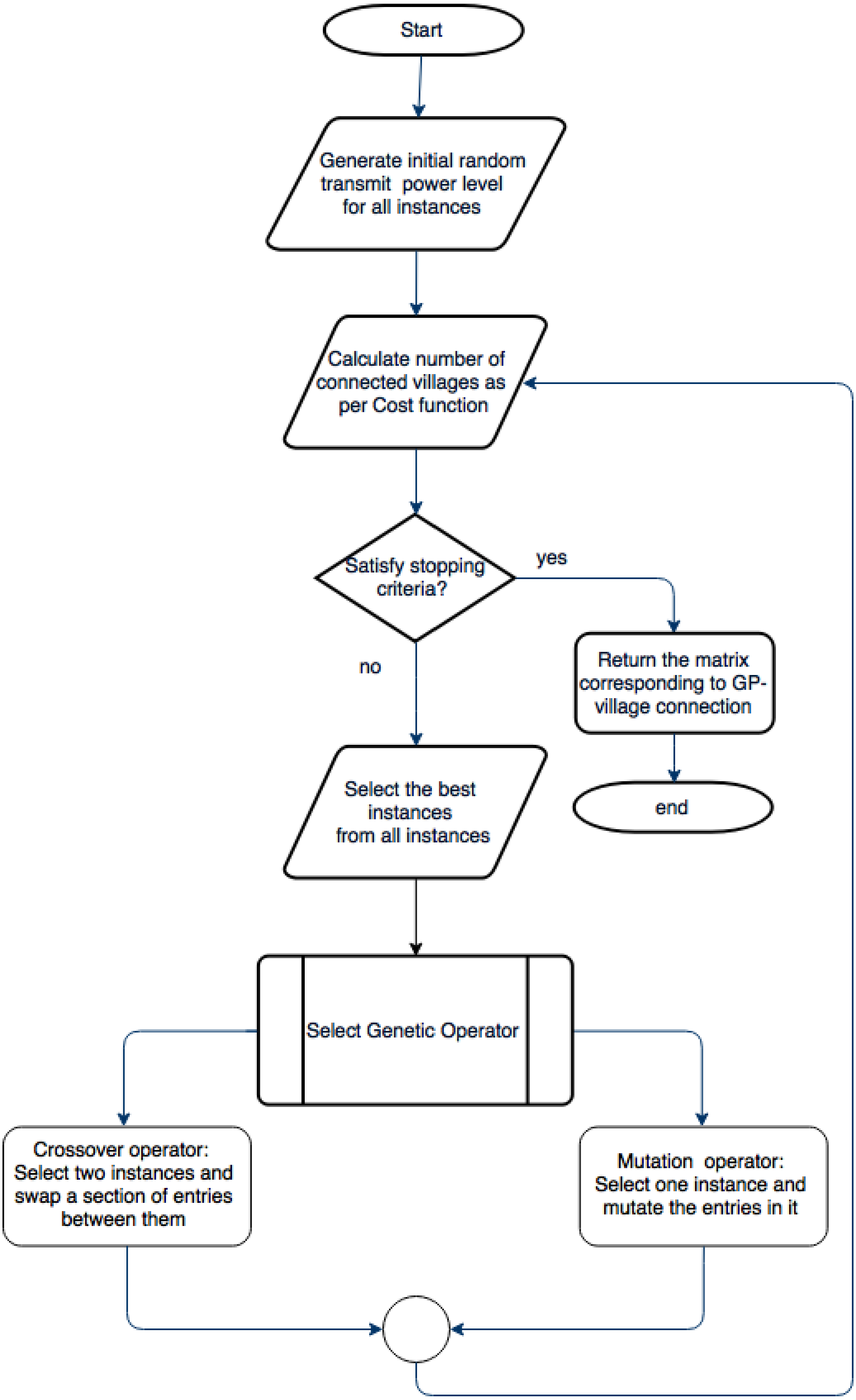

Figure 2.2: Flowchart of genetic algorithm.

Figure 2.2 shows flowchart of genetic algorithm. In our case, selecting population is same as choosing the power levels of eNBs. In the standard genetic algorithm fitness of each set of population is compared to choose the new population. Here, we have used the utility function to calculate the fitness of the population, fitness is equivalent to the number of successfully connected villages for a given topology. Every time, a new population is selected by mutating the fittest population set of previous state. In this way, genetic algorithm performs intelligent search over the possible combinations of eNBs.

2.2 Simulation Results

We tested the tool for various rural scenarios by collecting data from different districts. But, here for simplicity we discuss the performance of tool for one district only. The results of the tool for this district are as follows:

- Number of GPs where eNBs are installed : 100
- Number of GPs where eNBs are not installed : 86
- Number of villages which are connected : 197
- Number of villages which remain unconnected : 15
- Available transmit power levels : [18, 24, 36] dBm

Figure 2.3 shows the output of the tool for this district. In the figure, BS denotes the eNBs used in our discussion. We can observe from the results that out of 186 PoPs or GPs, eNBs are need to be installed on only 100 GPs. This is as per our discussion in previous section. Due to the good propagation characteristics of TV UHF band, installing eNBs at few GPs only are enough to provide connectivity to most of the villages.

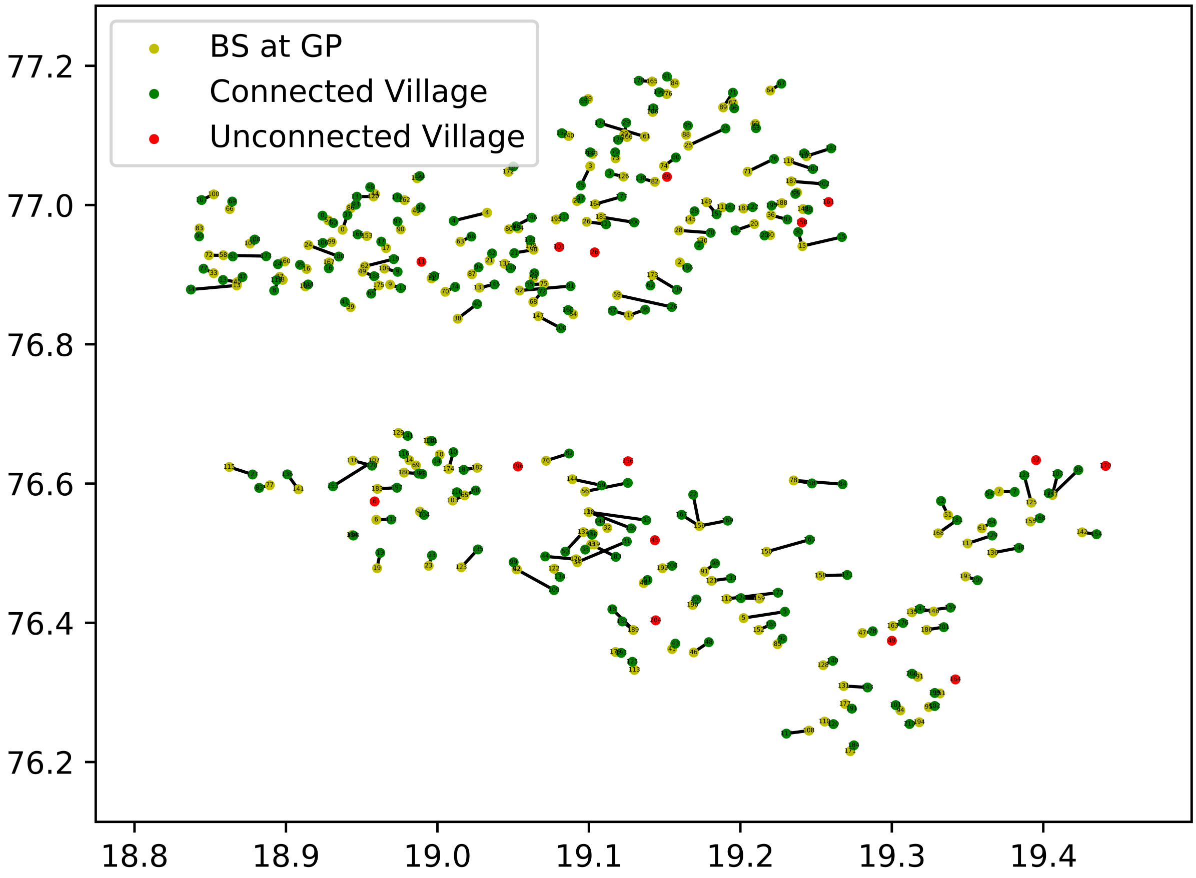

Figure 2.3: Output of the tool showing GP village connectivity (to scale).

2.3 Conclusions

We presented tool design for middle-mile network planning. We have also presented the results obtained from testing the tool on real GP village data. We can conclude that using GA ensures fast convergence of search and also provides sub-optimal solution.

Chapter 3

Multi-operator Middle-mile Network Architecture

One of the promising solution to provide broadband connectivity in rural areas is deployment of *middle mile* LTE-A network operating in TV UHF band. Owing to the good propagation characteristics of this band, it is possible to provide large coverage area even by deploying small number of low power base station. Also, these low power base station can be operated using renewable energy sources and thus reducing the cost of network deployment. This encourages multiple operators to deploy their network to provide broadband services. In this chapter, we will discuss the multi-operator *middle mile* LTE-A network architecture in details. We will also discuss the best suited regulation scheme for spectrum sharing among multiple operators in the given rural setup.

3.1 Network Architecture

We consider a *middle mile* LTE-A network working in TV UHF band. We assume that a portion of this band is available for providing wireless broadband connectivity to the rural areas. This portion is divided into multiple orthogonal channels. A frequency band in an LTE-A system is divided into sub-carriers which are spaced 15 kHz apart. Here, we define channel as a group of sub-carriers occupying a certain bandwidth. We assume that these channels are identical, i.e. they have the same bandwidth. The network architecture is shown in Figure 3.1.

The network comprises of a central entity called *Spectrum Manager (SM)* which is

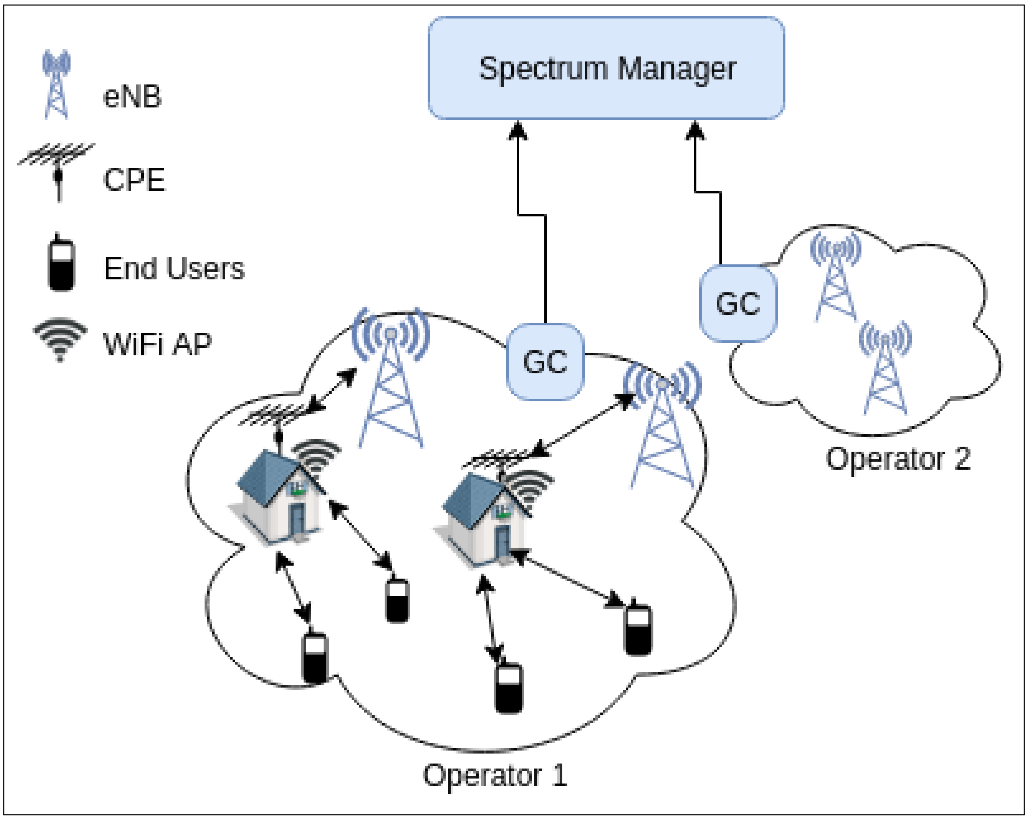

Figure 3.1: Overview of the middle mile network

responsible for channel allocation to the operators. In a specific area, multiple evolved NodeBs (eNBs) are deployed, preferably, in the vicinity of an optical PoP. Each operator has an entity called Gateway Controller (GC) which acts as an interface to communicate with the SM. Multiple LTE-A Customer Premise Equipments (CPEs) are served by each eNB. A CPE connects to one or many WiFi APs installed in a village. An end user accesses broadband services through a WiFi AP. Without loss of generality, assume that the end users are uniformly distributed in a given area. We consider *Registered Shared Access* (RSA) as the regulation scheme adopted by SM.

3.2 Registered Shared Access (RSA)

Under RSA scheme, the operator registers itself with the SM to access the band. Each operator is connected to a distributed SM through gateway controller (GC). GC is responsible for collecting the topology information and communicating it to the SM. Using this information, SM allocates channels from the available band to the operators. We assume that the operators may provide their network details (eNB location, transmit

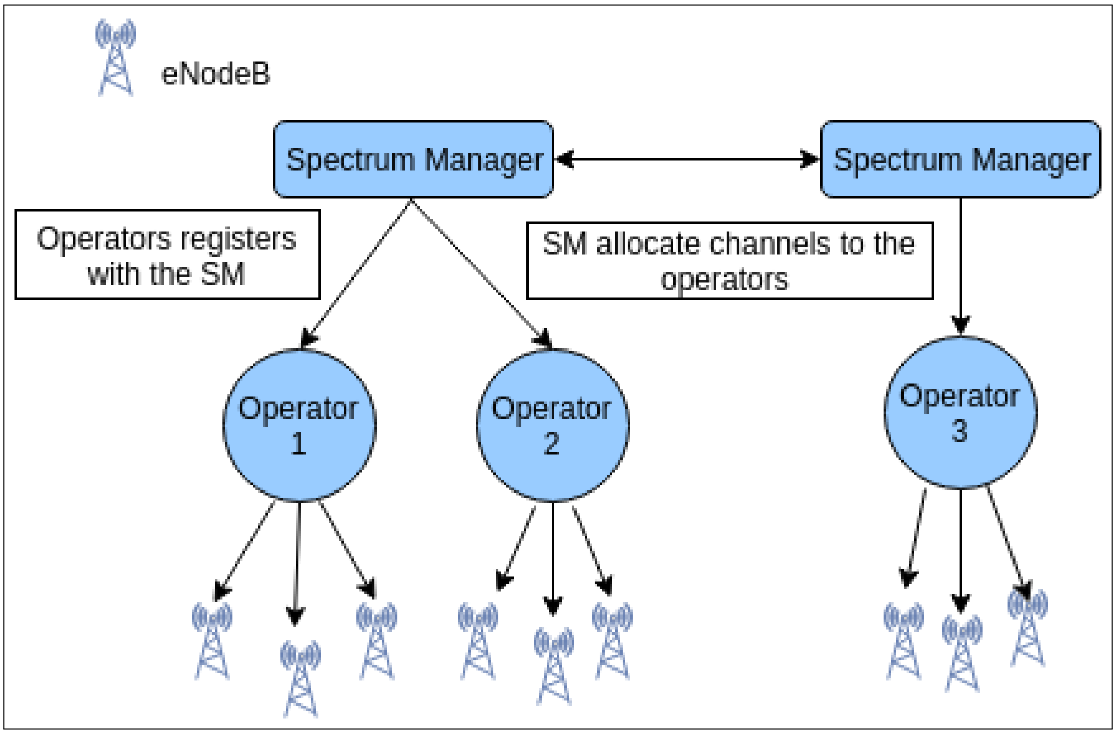

Figure 3.2: Registered Shared Access in an LTE-A network.

power etc.) to the GC. There is no direct exchange of information among the operators. The SM can allocate multiple channels to an operator, such that multiple operators can use the same channel leading to the spatial reuse of channels. The channel allocation information is communicated to an eNB of an operator through its GC. The complete architecture of RSA is shown in Figure 3.2.

When the operators share their network topology with the SM, then each eNB can be treated as an independent network identity. We assume that the SM treats all operators equally. As we have considered that the end users are uniformly distributed in a given area, average throughput requirement at each eNB is equal. Hence, an operator gives equal priority to all its eNBs which ultimately boils down to the conclusion that SM gives equal priority to eNBs. We study this topology aware spectrum sharing problem with respect to an eNB irrespective of the operator it belongs to in the next chapter.

3.3 Literature Review

The problem of spectrum sharing among operators has been widely studied from the context of heterogeneous networks. In [9] and [10] spectrum sharing is studied for dense small cell network of two operators. In [9], operators broadcast their spectrum occupancy information which allows small cells to access the available spectrum pool. While in [10], each operator reports its interference level to the spectrum controller and the controller allocates resources from the pool to the small cells using graph or clustering approach. Also, there are many work in the literature which considers spectrum sharing problem as optimization problem with various constraints, and utilizes different optimization tools to solve the objective function. In [11] and [12], heuristics based graph coloring algorithm is used for channel allocation to the network such that overall system throughput can be maximized. All these works require coordination among operators which in general, is infeasible as operators are unwilling to share sensitive information. In some of the work in literature, authors have studied this problem using game theory approach. In [13], two operators dynamically share the spectrum by playing a non-zero sum game. This work considers both centralized and distributed system models with dynamic spectrum pricing based on demand. In [14], the authors have modeled spectrum sharing among operators as a non-cooperative repeated game. An improvement in spectrum efficiency is observed for a two operator small cell network under this model. The main concern with game theory based models is that it may result in inefficient Nash Equilibrium depending on the utility function selected by the operator. Moreover, the schemes discussed in [13, 14] do not guarantee fairness and are also difficult to implement in practical scenario. As the network size increases the convergence of these models become slow, leading to performance degradation. All the above work in literature discusses the spectrum sharing among only two operators. Generalization to multiple operators has not been widely studied in literature and is a challenging problem that we tackle in this work.

Chapter 4

Inter-operator Static Spectrum Sharing

In the previous chapter, we discussed architecture of middle mile network where multiple operators share the TV UHF spectrum under registered shared access (RSA) scheme. With the same context, we will discuss the multi-operator spectrum sharing in this chapter. We will formulate the spectrum sharing problem as a constrained optimization problem which maximizes the system throughput along with the fairness constraint. We will show that it is a combinatorial optimization problem which is very expensive for large networks. Hence, we will propose a heuristics based graph theoretic channel allocation algorithm to solve the optimization problem sub-optimally. The proposed algorithm can be easily implemented for large network. We will also present the throughput performance of the proposed algorithm by simulating the multi-operator network in ns-3 [15].

4.1 System Model

Consider a set $\mathcal{K} = \{1, 2, ..., K\}$ representing total number of eNBs belonging to all the operators in the network. Let $\mathcal{L}_k = \{1, 2, ..., L_k\}$ be the set of L_k CPEs served by the eNB$_k$. The set of channels available at the SM is given by $\mathcal{M} = \{1, 2, ..., M\}$ with M channels. Also, let $\mathcal{M}_k \subset \mathcal{M}$ be the set of channels assigned to eNB$_k$. The eNB$_k$ schedules Resource Blocks (RBs) from its allocated channel or channels to its L_k associated CPEs in a proportional fair manner. Here, an RB is a resource unit in LTE-A representing 180 kHz in frequency and 0.5 ms of time. The problem of scheduling RBs to multiple

UHF-CPEs is insignificant to this work. Hence, any scheduling scheme can be used as we perform comparative analysis of all spectrum sharing schemes under the same user scheduling.

Before proceeding further, we will discuss about some terminologies which will be required in problem formulation.

Interference State :

The sub-GHz TV UHF band has good long distance propagation characteristics which results into large coverage area of an eNB. Thus, the eNBs will interfere with each other with a very high probability. For simplicity, we consider the *Protocol Interference Model* [16] to model the interference between eNBs. In accordance with this model, the two eNBs interfere with each other if they are operating on the same channel and the euclidean distance between them is less than a certain threshold. The protocol model formulates interference state as a binary symmetric matrix where each element of the matrix indicates whether the two eNBs interfere with each other.

Let $C = \{c_{k,j} | c_{k,j} \in \{0, 1\}\}_{K\text{x}K}$ be a binary symmetric KxK matrix where $k, j \in \mathcal{K}$, represents the interference state such that:

$$c_{k,j} = \begin{cases} 1, \text{if eNB}_k \text{ and eNB}_j \text{ interfere} \\ \quad \text{with each other,} \\ 0, \text{otherwise.} \end{cases}$$

Allocation Matrices :

The SM allocates channel to the eNBs depending on the interference state of the network. In addition to allocating channel, SM also defines the mode in which the channel has to be used. The mode can be shared or dedicated. If the mode of a channel assigned to an eNB is dedicated, then that channel will not get allocated to its neighbours. If the mode of the assigned channel is shared, then it has to be shared with the neighbours using some sharing mechanism. The channel allocation is defined by the two matrices A and B which are defined as follows:

- *Channel Allocation Matrix (A):* We define channel allocation matrix as $A = \{a_{k,m} | a_{k,m} \in \{0,1\}\}_{K \text{x} M}$ where $k \in \mathcal{K}$ and $m \in \mathcal{M}$ such that:

$$a_{k,m} = \begin{cases} 1, \text{if channel } m \text{ is assigned to eNB}_k, \\ 0, \text{otherwise.} \end{cases}$$

- *Mode Allocation Matrix (B):* Let $B = \{b_{k,m} | b_{k,m} \in \{0,1\}\}_{K \text{x} M}$ is a K by M binary matrix where $k \in \mathcal{K}$ and $m \in \mathcal{M}$. B represents the mode of operation on the allocated channel:

$$b_{k,m} = \begin{cases} 1, \text{if allocated channel } a_{k,m} \text{ is to be shared,} \\ 0, \text{otherwise.} \end{cases}$$

SM assigns a single or multiple channels to an eNB. In case of multiple channels, they can be contiguous or non-contiguous. When multiple non-contiguous channels are allocated, aggregation is required for cross channel scheduling.

- **Carrier Aggregation (CA) :** Carrier Aggregation is a feature of LTE-A, used to increase the bandwidth. Using this, it is possible to schedule transmission over more than one carrier. As per 3GPP LTE-A standard, each aggregated carrier is referred to as a component carrier [17]. These carriers can be contiguous or non contiguous elements of frequency band. We have utilized this feature to support scheduling over non contiguous channels.

- **Listen Before Talk (LBT) :** When the mode of the allocated channel is shared, Listen Before Talk (LBT) is used for sharing the channel. LBT is a mechanism in which a radio transmitter performs Clear Channel Assessment (CCA) to check if the medium is idle. The energy in the channel is measured and compared with the Detection Threshold (DT). If the energy level is greater than DT, the channel is assumed to be busy and the transmitter defers the transmission. If the energy in the channel is lower than DT, then the channel is assumed to be idle and the transmitter has to backoff for a random number of slots. Here, slot is basic unit of time in LBT. Even when the backoff counter reduces to 0, the transmitter can transmit only if the channel is still idle. Once the trasnmitter gets access to the channel, it can transmit for a fixed duration which is termed as Transmit Opportunity (TxOp).

The LBT mechanism is widely discussed for the coexistence between LTE-A and Wi-Fi system [18]. We have used LBT for the coexistence among LTE-A systems in this work.

Expression for Throughput and Fairness :

Once the channel allocation is done by the SM, an eNB allocates the RBs from the allocated channels to its associated CPEs in a proportional fair manner. The sum rate at the eNB$_k$ is given by:

$$T_k(A,B) = \sum_{i \in \mathcal{L}_k} R_{k,i}(A,B), \tag{4.1}$$

where $R_{k,i}$ is the throughput of CPE$_i$ served by eNB$_k$. A and B are the allocation matrices as described above. We quantify the fairness F of the system using Jain's Fairness Index (JFI) as below:

$$F = \frac{\left(\sum\limits_{k=1}^{K} T_k(A,B)\right)^2}{K \times \sum\limits_{k=1}^{K} T_k(A,B)^2}. \tag{4.2}$$

4.2 Problem Formulation

The spectrum sharing problem can be modeled as system throughout maximization subject to a fairness constraint. We define system throughput as the expected sum rate of eNBs deployed by all operators. Mathematically, the problem can be stated as follows:

$$(A^\star, B^\star) = \arg\max_{A,B} \left(\sum_{k=1}^{K} T_k(A,B) \right), \tag{4.3}$$

subject to $\quad F > \delta$

$$\begin{aligned} \text{where } A &= \text{Channel Allocation Matrix}, \\ B &= \text{Mode Allocation Matrix}, \\ F &= \text{Fairness Index}, \\ \delta &= \text{Constrained value of fairness}. \end{aligned}$$

In a multi-operator scenario, there is a high probability that an operator will act greedily. Therefore, it is very critical to maintain fairness among operators. Ideally, the value of δ should be equal to 1. However, if we give more preference to the fairness, the system throughput will be compromised. Hence, we choose the above δ equal to 0.75 to strike a balance between throughput and fairness. There are two major challenges in obtaining an optimal solution of this problem. Firstly, this is a combinatorial optimization problem which is known to be NP-complete. Secondly, to determine an optimal solution, a closed form expression for throughput is required at the eNB. The mathematical expression for LBT throughput can be obtained only for a network which forms a complete graph. In our case the network graph is not complete. Therefore, in the following section, we propose a heuristic based graph theoretic algorithm to solve the above problem sub-optimally.

4.3 Graphical Model

The system can be modeled as a conflict graph $G(V, E)$ where V denotes vertices and E denotes edges. In the traditional *Graph Coloring* problem, colors are to be assigned to the vertices such that vertices with an edge between them cannot get the same color. In our system, V represents set of all eNBs in the system. E represents set of edges denoting interference among eNBs i.e. an edge between any two vertices implies that vertices are interfering with each other. Here, $E := \{(k, j) | c_{k,j} = 1, \ \forall k, j \in \mathcal{K}\}$ where $c_{k,j}$ is an element of interference matrix, C defined in Chapter 3. The colors represent the available set of channels denoted by $\mathcal{M}$.

4.4 Fairness Constrained Channel Allocation

We now present an extension of the traditional graph coloring technique. We propose an algorithm which takes graph G as an input and outputs the allocation matrices. Here, G is the graph representing network as discussed above. Note that, we have considered fixed numbers of colors i.e. the available bandwidth is divided into 4 channels. Since the PoPs are sparsely distributed in a rural area and the eNBs are installed near PoPs there is very less probability that the network graph cannot be colored with certain fixed number of colors. In this method, the channels are assigned to the eNBs according to two sub-algorithms which are described next.

1. *Multiple Dedicated Channel Allocation (MDCA)*: In this sub-algorithm, multiple

dedicated channels are assigned to an eNB by using greedy graph-coloring method iteratively. It is possible to assign multiple channels to an eNB if the total number of neighbours of an eNB is less than the total number of channels.

2. *One Dedicated Rest Shared Channel Allocation (ODRS-CA)*: In this sub-algorithm, the channel assignment is done in two steps. In the first step, a single dedicated channel is assigned to each eNB. Then, the set $\mathcal{N}_k$, containing all the channels which are not assigned to the neighbours of eNB_k is obtained. In the second step, all the channels contained in $\mathcal{N}_k$ are assigned to eNB_k in shared mode.

For a given network topology, the output of the above mentioned sub-algorithms are compared to decide the final channel allocation as described in Algorithm 1.

4.4.1 Illustrative examples of FCCA

We explain the behaviour of the proposed algorithm using examples. The channel assignment using MDCA algorithm is shown in Figure 4.1 (left) and using ODRS-CA algorithm is shown in Figure 4.1 (right). The dedicated channels are denoted by bold numbers, otherwise the channels are to be shared. The channel assignment done by MDCA algorithm is biased towards vertex 1 as it gets 2 channels. In contrast to MDCA algorithm, the ODRS-CA algorithm gives one dedicated and one shared channel to all. This improves the system fairness with a very little compromise in throughput. The compromise in the throughput occurs due to the sharing of the channel between three vertices.

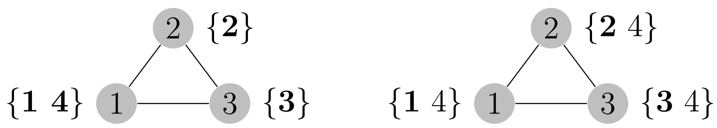

Figure 4.1: Graph representing the channel allocation for MDCA (left) and ODRS-CA (right) sub-algorithm

We now show a topology where MDCA performs better than ODRS-CA. Consider an example shown in Figure 4.2. The MDCA algorithm assigns 2 dedicated channels to all vertices as shown in Figure 4.2 (left) and is completely fair. The ODRS-CA algorithm is not equally fair as vertex 2 shares 2 channels with its two neighbours while vertex 1 and 3 gets 2 shared channels which they have to share with only one neighbour. The overall

Algorithm 1 Fairness Constrained Channel Allocation (FCCA)

Require: Graph G

$\delta = 0.75$

Sub-Algorithm 1 : MDCA

while $\mathcal{N}_k$ is non empty for all K **do**

  for each k from 1 to K **do**

    find $\mathcal{E}_k$, the set of channels assigned to neighbours of k

    obtain $\mathcal{N}_k = \{\mathcal{M}\} \setminus \{\mathcal{E}_k\}$ set of feasible channels for eNB$_k$,

    $q \leftarrow \min \mathcal{N}_k$, $a_{k,q} \leftarrow 1$, $b_{k,q} \leftarrow 0$

  end for

end while

$T_1 \leftarrow T(A, B)$, $F_1 \leftarrow F(A, B)$, $A_1 \leftarrow A$, $B_1 \leftarrow B$

Sub-Algorithm 2 : ODRS-CA

for each k from 1 to K **do**

  find $\mathcal{E}_k$

  obtain $\mathcal{N}_k = \{\mathcal{M}\} \setminus \{\mathcal{E}_k\}$

  $q \leftarrow \min \mathcal{N}_k$, $a_{k,q} \leftarrow 1$, $b_{k,q} \leftarrow 0$

end for

for each k from 1 to K **do**

  find $\mathcal{E}_k$

  obtain $\mathcal{N}_k = \{\mathcal{M}\} \setminus \{\mathcal{E}_k\}$

  $a_{k,q} \leftarrow 1$, $b_{k,q} \leftarrow 1 \quad \forall q \in \mathcal{N}_k$

end for

$T_2 \leftarrow T(A, B)$, $F_2 \leftarrow F(A, B)$, $A_2 \leftarrow A$, $B_2 \leftarrow B$

Result: Check F_1 and F_2 and choose $(A^\star, B^\star)$ such that the fairness is greater than δ. If both are greater than δ then choose $(A^\star, B^\star)$ corresponding to $\max(T_1, T_2)$. If both are less than δ, then choose $(A^\star, B^\star)$ coresponding to the algorithm with better fairness.

return A^*, B^*

system throughput is also less in ODRS-CA, as the vertex 2 shares 2 channels with the two vertices. Hence, MDCA algorithm is better.

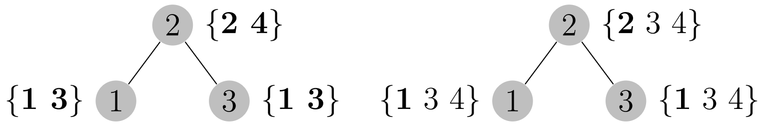

Figure 4.2: Graph representing the channel allocation for MDCA (left) and ODRS-CA (right) sub-algorithm

As seen by the above two contrasting examples, one of the two sub-algorithms performs better depending on the system topology. Hence, we use a combination of two sub-algorithms to obtain better system fairness.

4.5 Performance Evaluation of LTE with LBT

Firstly, we compute the coverage radius of an eNB operating in TV UHF band. To the best of our knowledge there is no literature available which establishes the same result. Further, we also evaluate the performance of LTE with LBT in different network topologies.

4.5.1 Coverage Radius of eNB working in TV UHF band

The coverage radius of a transmitter is defined as the maximum allowed distance between the transmitter and the receiver such that they can communicate. We calculate the coverage radius of an eNB operating in sub-GHz TV UHF band using the equation:

$$RS = P_t + G_t + G_r - PL(d, h_t, h_r, f_c) - CL - NF, \tag{4.4}$$

where P_t, G_t and G_r are the transmit power, the transmitter antenna gain and the receiver antenna gain respectively. $PL(d, h_t, h_r, f_c)$ is the pathloss which is function of distance d between transmitter and receiver, the transmit antenna height h_t and the receiver antenna height h_r and operating frequency f_c. CL is the cable loss and NF is the receiver noise figure. Here, RS is receiver sensitivity as specified in an LTE-A system. We use Hata model [19] as the pathloss model as it is best suited for Suburban Areas. For the values of the parameters given in Table 4.1, the coverage radius of eNB is approximately 3 km.

Table 4.1: Simulation Parameters

Parameters	**Values**
Frequency Band	500-520 MHz
Transmit Power (P_t)	18 dBm
Receiver Sensitivity (RS)	-101 dBm [20]
Cable Loss (CL)	2 dB
Receiver Noise Figure (NF)	7 dB
Transmitter Antenna Gain (G_t)	10 dB
Receiver Antenna Gain (G_r)	0 dB
Transmitter Antenna Height (h_t)	30 m
Receiver Antenna Height (h_r)	5 m
Slot Time	9 μs
Transmit Opportunity ($TxOp$)	10 ms
Detection Threshold	-62 dBm
Simulation Time	1 s

4.5.2 Throughput performance of LTE with LBT

We compare the system throughput performance of two schemes i) LTE with no co-existence mechanism and ii) LTE with LBT as coexistence mechanism in two different network topologies. The system throughput are obtained from ns-3[15] simulations as per the parameters given in Table 4.1

Topology with two interfering eNBs

We consider two eNBs deployed in a specific area as shown in Figure 4.3. The CPEs are uniformly distributed within the cell area. The system throughput is obtained by taking average over 100 such instances.

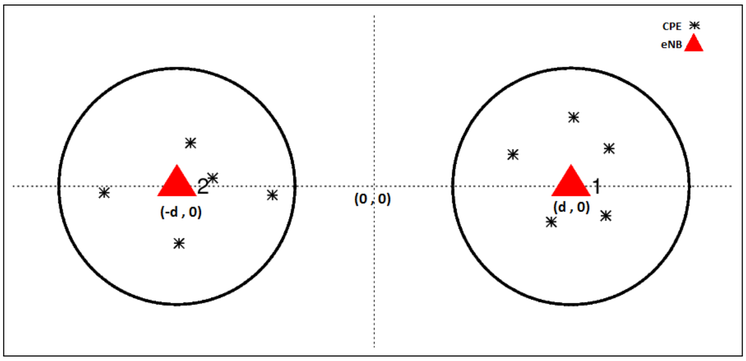

Figure 4.3: Network topology with two eNBs.

In order to study the effect of interference we plot the system throughput versus variable distance, d. Clearly in Figure 4.4, LTE with LBT as coexistence mechanism performs better than LTE with no coexistence mechanism. However, after certain value of distance d, the interference between two cells decreases and hence, the performance of LTE with no coexistence improves.

Topology with four interfering eNBs

We now consider network topology with four eNBs deployed in a specific area as shown in Figure 4.5. The CPEs are uniformly distributed within the cell area. In this case also, the system throughput is obtained by taking average over 100 such instances. Similar to previously discussed case, the system throughput performance of LTE with LBT as coexistence mechanism is better than LTE with no coexistence mechanism 4.6.

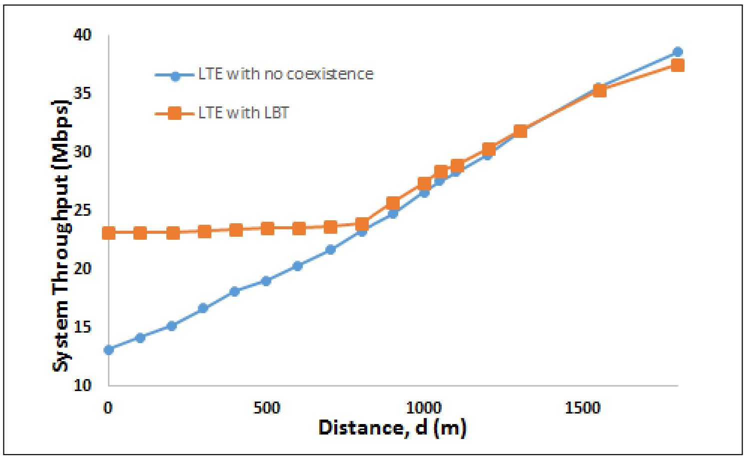

Figure 4.4: System Throughput performance when two eNodeBs interfere with each other, under two schemes: i) LTE with no coexistence mechanism ii) LTE with LBT as coexistence mechanism.

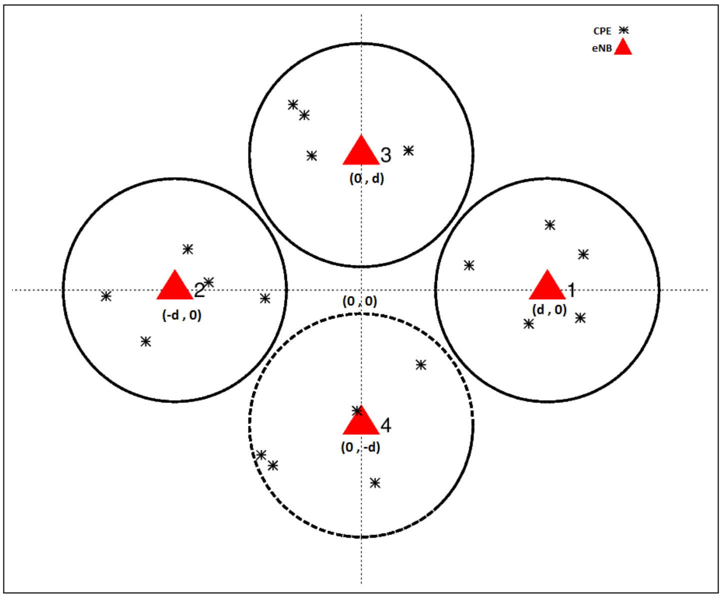

Figure 4.5: Network topology with four eNBs.

Clearly, LTE with LBT as coexistence mechanism outperforms LTE with no coexistence mechanism in both the topologies. From the above two scenario it can be concluded that LBT can be used as one of the solution for coexistence of multiple operators in sub-GHz TV UHF band. In the proposed FCCA algorithm, we have discussed the application LBT as coexistence mechanism depending upon the network topology.

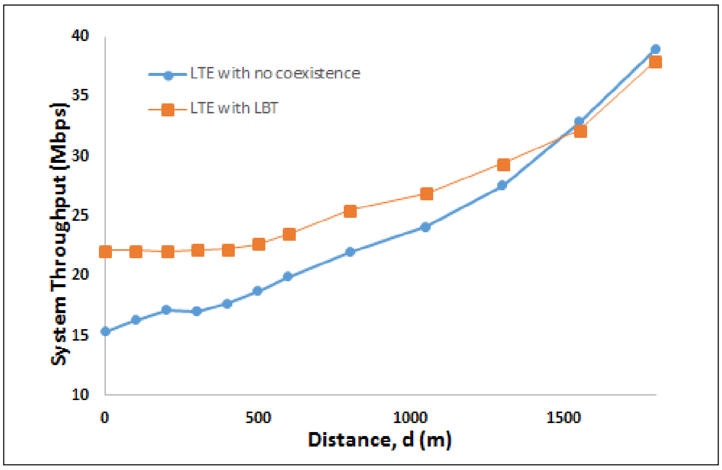

Figure 4.6: System Throughput performance when four eNodeBs interfere with each other, under two schemes: i) LTE with no coexistence mechanism ii) LTE with LBT as coexistence mechanism.

4.6 Performance Evaluation of FCCA

In this section, we present the results of ns-3 [15] simulations to assess the performance of FCCA algorithm. We also compare the proposed approach with few other coexistence approaches.

4.6.1 Scenario description of multi-operator network

We assume that a portion of 20 MHz in sub-GHz TV UHF band is available. This portion is further divided into 4 orthogonal channels of 5 MHz each. All channels are assumed

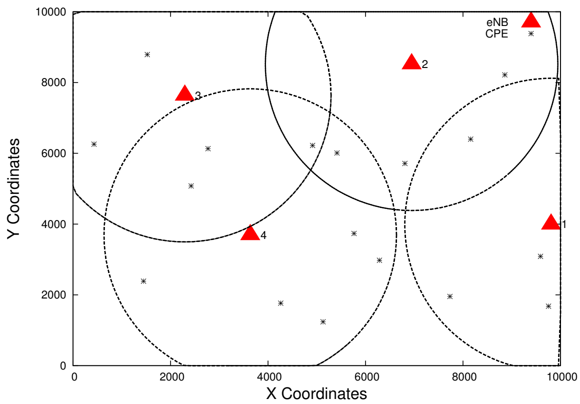

Figure 4.7: An example topology of the network.The eNBs are deployed uniformly at random in an area of 100 km^2. CPEs are distributed randomly within the coverage area of eNBs.

to be identical. The eNBs are deployed uniformly at random in an area of 100 km^2 as shown in Figure 4.7. The CPEs are distributed uniformly within the coverage area of an eNB. Each eNB is assumed to serve 5 stationary CPEs. For constructing the conflict graph using protocol interference model, we consider a distance of 4 km between eNBs. If the distance between eNBs is less than 4 km, then they interfere with each other. We perform ns-3 simulations over 100 random topologies. All the performance metrics are averaged over such realizations. The simulation parameters are given in Table 4.1. Note that, CPEs are stationary hence fast fading is not considered. We consider only saturated downlink transmission in this work i.e. at each eNB, same saturated traffic is generated for each of the associated CPEs.

4.6.2 Simulation Results

We analyze three performance metrics to assess the performance of the proposed FCCA algorithm: a) *Spectral Efficiency* b) *Average System Throughput per eNB* and c) *Jain's Fairness Index.* The performance of these metrics are observed with respect to an increase in the network density i.e. we increase the number of eNBs from 3 to 10 in a fixed area of 100 km^2. Spectral Efficiency is defined as the information rate that can be transmitted over a given bandwidth in a specific network. It provides the information about how efficiently a limited bandwidth is utilized. In our results we present spectral efficiency per eNB which is measured in bits/s/Hz/eNB. We have used Jain's Fairness Index to quantify how fairly the available band is shared among eNBs.

In Figure 4.8 and 4.9, we compare the spectral efficiency and the average system throughout of FCCA with two other schemes i) LTE with no-coexistence mechanism ii) LTE with LBT as the coexistence mechanism. Clearly, the FCCA algorithm outperforms both the schemes in both the metrics. In the first scheme, the entire 20 MHz band is used by all eNBs without any coexistence mechanism. Due to interference among the eNBs, the spectral efficiency is very poor. In the second scheme, the entire 20 MHz band is shared among all the eNBs using LBT. Here, the performance is poor as the transmission time is wasted in contention. The FCCA algorithm performs better than the above two schemes as it considers the topology for allocating the channels. As shown in Figure 4.10, the fairness of the FCCA algorithm is also better than the other two schemes. The proposed algorithm guarantees an excellent fairness index of 0.76 even in

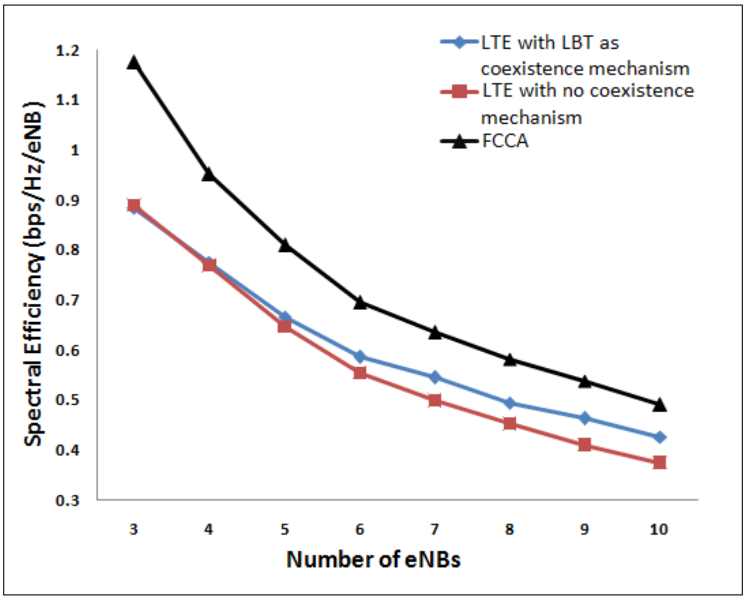

Figure 4.8: Comparative analysis of Spectral Efficiency of eNB vs. number of eNBs deployed in 100 km^2 area for the three schemes i) LTE with no coexistence mechanism ii) LTE with LBT as coexistence mechanism and iii) FCCA.

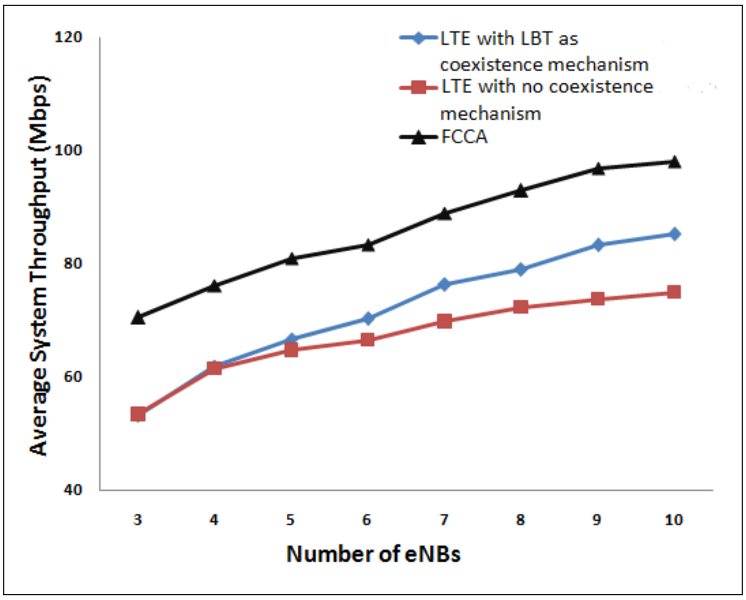

Figure 4.9: Comparative analysis of System Throughput vs. number of eNBs deployed in 100 km^2 area for the three schemes i) LTE with no coexistence mechanism ii) LTE with LBT as coexistence mechanism and iii) FCCA.

the case 10 eNBs per 100 km^2.

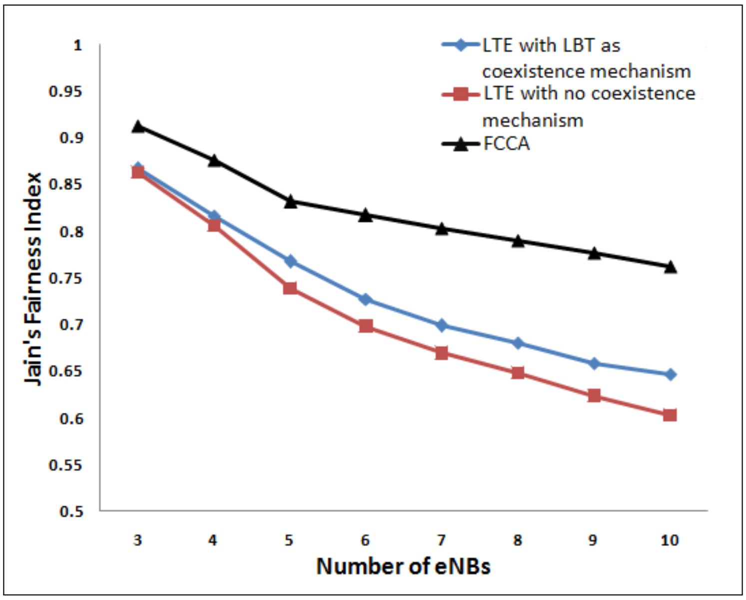

Figure 4.10: Comparative analysis of JFI vs. number of eNBs deployed in 100 km^2 area for the three schemes i) LTE with no coexistence mechanism ii) LTE with LBT as coexistence mechanism and iii) FCCA

4.6.3 Average Throughput vs Demand

Now, we compare the average system throughput obtained using the proposed algorithm with the throughput demand generated in a typical rural setting. Let us consider a scenario in which there are 5 optical PoPs in an area of 100 km^2. We assume that there are 10 villages in the given area and each PoP serves 2 villages. Assume that the average population of a village is 1000. We also assume that, there is one subscriber per household i.e. one person in a house of 5 will subscribe to broadband service. Consider a minimum broadband speed of 2 Mbps with the contention ratio of 1 : 50. Thus, the average throughput requirement under the above scenario is (1000 people$\times$10 villages$\times$2 Mbps)/(50×5) = 80 Mbps. If 5 eNBs are deployed at the 5 optical PoPs, the average throughput demand that can be served is approximately 83 Mbps. Hence, the average throughput requirement of the above setting can be easily met.

4.7 Conclusions

In this chapter, we have discussed channel allocation algorithm for multi-operator network. We have proposed FCCA algorithm which perform fair channel allocation among eNBs. We have also analyzed the performance of FCCA using ns3 simulations. The results demonstrate that it increases both the spectral efficiency and the fairness among operators in a network. We have also compared the obtained average throughput with the throughput demand generated by a typical rural setting. We note that the proposed scheme easily meets the throughput demand generated in a rural area.

Chapter 5

Inter-operator Dynamic Spectrum Sharing

In the previous chapter, we have discussed the spectrum allocation problem among multiple operators under RSA scheme, with an assumption that the network topology is known to the SM. Generally, the operators are unwilling to share the network topology information so this assumption is not feasible in all practical scenario. Hence, in this chapter, we explore the spectrum sharing problem from the perspective of operator when its network topology is hidden from the SM. This assumption results into less information exchange between operators and the SM, which is desired by the operators in general. We model the multi-operator spectrum sharing problem as hierarchical resource allocation problem as shown in Figure 5.1. In the first stage, inter-operator resource allocation is done by the *Spectrum Manager (SM)*, and then in the second stage, the operators distribute the allocated resources among its evolved NodeB (eNBs). Moreover, the algorithm discussed in Chapter 4 considers saturated load at each eNB of the operator, which is also a rare assumption. In this chapter, we discuss a more practical scenario where each operator's network load varies with time. For better spectrum utilization in such scenarios the resource allocation scheme needs to be dynamic. Hence, we propose a dynamic resource allocation scheme which takes demand from the operator as the input while allocating resources. We also discuss intra-operator resource allocation problem and propose a graph theory based algorithm to solve the same. The design and the implementation of the proposed resource allocation schemes are discussed in further sections.

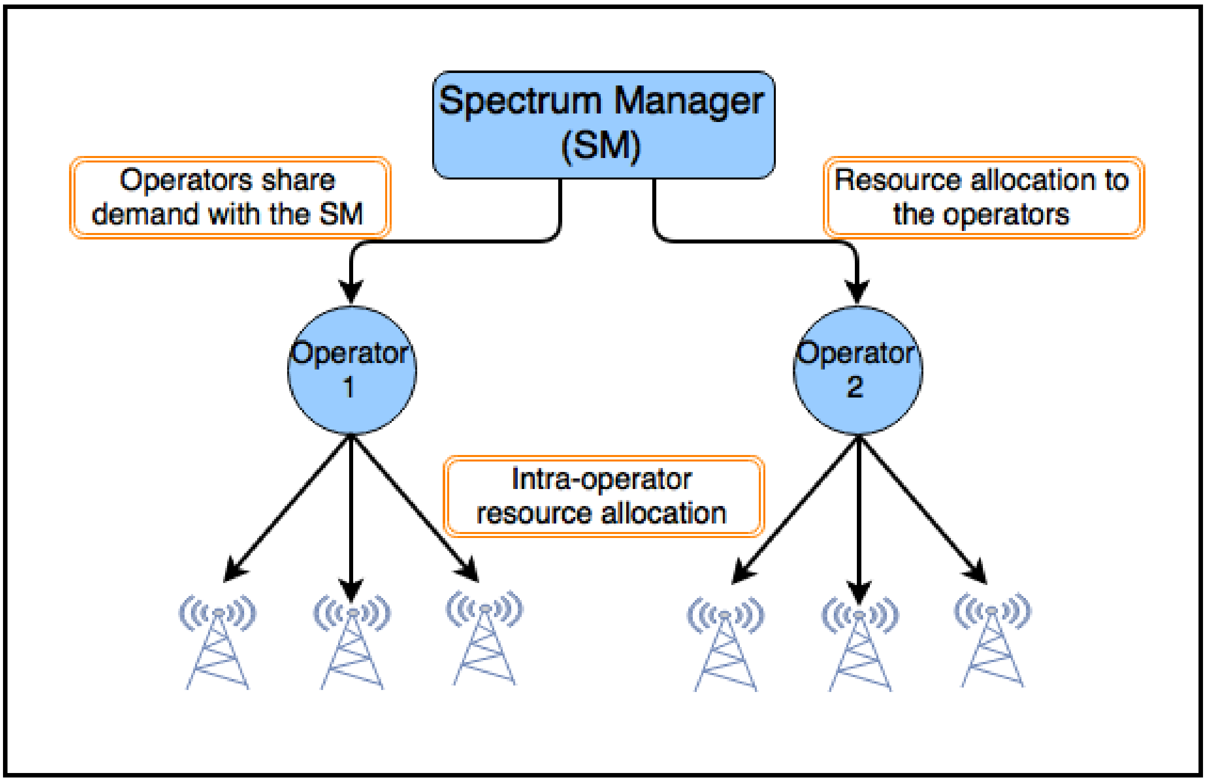

Figure 5.1: Hierarchical resource allocation.

5.1 Network Architecture

We consider dense deployment of middle mile LTE network operating in TV UHF band, same as discussed in Section 3.1. Without loss of generality, we assume that the network topology of each operator is hidden from the SM. We consider the time varying load in each operator's network. Given a network topology, each operator evaluates the spectrum resource requirementof its network, periodically after every fixed interval. This resource requirement or the demand is conveyed to the SM via operator's *gateway controller(GC)*. The demand is the only information that an operator has to share with the SM. The SM allocates the resources to the operators dynamically depending on their demand.

Before proceeding further, we discuss some of the concepts which are required for a better understanding of the proposed algorithms.

Scheduling Frame Structure

We consider resource allocation in terms of both frequency band and time slot, unlike the static channel allocation scheme where only fixed frequency bands are allocated. We assume that a portion of TV UHF band is made available for deploying middle mile network. Let the bandwidth of this portion be B. This bandwidth is further divided into four orthogonal channels. We assume that for a given network topology, these channels are identical i.e. they have same propagation characteristics. The resource allocation is done after every fixed interval called *scheduling interval*. Each scheduling interval is further divided into five slots in time domain.

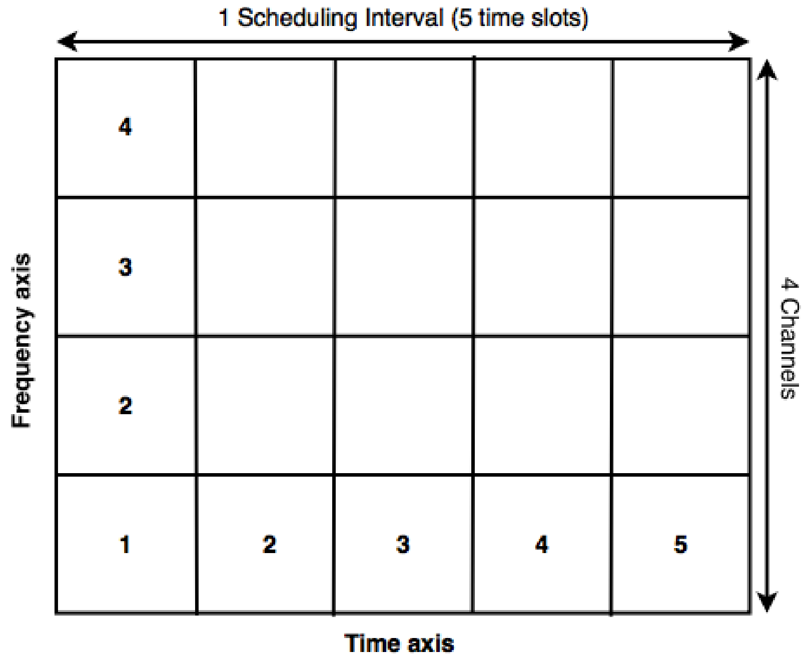

Figure 5.2: Scheduling frame structure.

The combination of one time slot and one channel at a time, forms one *time frequency (TF) block*. Each TF block corresponds to a certain data rate depending on the channel conditions. Figure 5.2 shows the complete structure of scheduling frame. The demand from each operator is received by the SM in the beginning of each scheduling interval. Also, the resource allocation for the scheduling interval is done by the SM in the beginning itself. From now onwards in this work, we represent both the demand and the resource allocation in terms of TF blocks.

5.2 System Model

We consider a set $\mathcal{M} = \{1, 2, ..., M\}$ denoting the set of operators whose network is deployed in a given area. Each operator deploys multiple eNBs depending on the end user distribution. Consider a set $\mathcal{N}_i = \{1, 2, ..., N_i\}$, representing the total number of eNBs belonging to an operator i. The eNBs of each operator serves multiple end users. In this work, we will not delve into the user scheduling process at eNB. We assume that eNBs perform optimal resource allocation to the end users. Since each TF block in the scheduling frame corresponds to a certain data rate, all the data rate requirement in the network is converted in the form of TF blocks. Let $\mathcal{L} = \{1, 2, ..., L\}$ represent the total number of TF blocks available in a scheduling frame. Consider a binary resource allocation matrix Y, such that

$$y_{i,k} = \begin{cases} 1, \text{if TF block } k \text{ is assigned to operator } i, \\ 0, \text{otherwise.} \end{cases} \tag{5.1}$$

Each operator compute the demand of its network in terms of TF blocks and asks SM for that many TF blocks. Let Δ represent the demand vector obtained at the SM such that Δ_i denotes the demand of operator i. Next, we discuss the resource allocation algorithms.

5.3 Resource Allocation Algorithms

We propose two algorithms for fair spectrum sharing in multi-operator network discussed in Section 5.1. Given the demand vector Δ obtained from the operators in terms of TF blocks, the SM can implement any of these algorithms to achieve efficient spectrum utilization in the system. We discuss the design and implementation of these algorithms in the next section.

5.3.1 Virtual Clock based Algorithm

The main idea of our algorithm is inspired from the *Virtual Clock* scheduling algorithm. Before exploring our algorithm, we discuss some of the basic concepts of Virtual Clock scheduling algorithm. This algorithm was studied for the first time in [1] for data traffic control in high speed networks. This algorithm was designed to achieve isolation among multiple flows along with the flexibility of statistical multiplexing at the switch in the network. The algorithm schedules active flows in the network in such a way that scheduling resembles the Time division Multiplexing (TDM) systems. The resemblance with TDM systems ensures isolation among flows and the scheduling of active flows only ensures statistical multiplexing. As per the algorithm, the switch assigns a virtual clock to each flow in the network. The virtual clock of the flow ticks after every packet arrival in that flow, with the tick step set equal to the mean inter-packet gap. Thus, the virtual clock reading of the flow denotes the expected packet arrival time in that flow. Now to emulate the TDM systems, the packets are stamped with the virtual clock reading of the flow and transmission is scheduled according to the stamped value.

To imitate the virtual clock scheduling algorithm in our setup, we treat each of the operator as different flows and the demand from the operators as packet arrival in that flow. The implementation outline of the algorithm is sketched below.

- Initialization : Set Virtual Clock of each operator equal to the real time i.e.
  $VC_i \leftarrow$ real time;

- At each scheduling instant repeat the following steps:

  1. For each operator i, given demand of Δ_i blocks, repeat these steps Δ_i times
     (a) Update the virtual clock of operator i,
     $VC_i \leftarrow max$ (real time, VC_i)
     (b) $VC_i \leftarrow (VC_i + Vtick_i)$, where $Vtick_i = 1/Share_i$,
     If we assume equal priority is given to all operators, then
     $Share_i = \frac{\text{Total available resource}}{\text{Total number of operators}}$,
     (c) store the tuple $(VC_i,\, i)$ in the stamp list,
  2. Tag the available TF blocks in the scheduling frame with the operator's id i in the increasing order of stamp values stored in the stamp list;
  3. Store the tagged TF blocks in the allocation matrix Y;
  4. Keep the track of the virtual clock value (VC_i) of each operator for the next scheduling instant.

In the beginning of each scheduling interval, SM receives the demand vector Δ and then runs this algorithm to obtain resource allocation matrix Y. Each row of matrix Y is a binary vector which denotes the orthogonal time and frequency block allocated to an operator. This row vector is shared with the respective operators via GC. After receiving the row vector, the operators can serve the end users in the assigned TF blocks until the next scheduling instant. In the next scheduling instant, the operators again generate the demand and ask for the resources to the SM. Also, this algorithm provides flexibility to control the resource allocation among operators, i.e. if any operator behaves absurdly and ask for more resources than its fair share for long time, then that operator is penalized. This check is provided by following line of codes of virtual clock algorithm:

- After certain scheduling instant, upon receiving the demand from operator i,
  - ($VC_i >$ real time) indicates that the operator has been asking for more resources than the fair share. If VC_i is ahead by more than a threshold value (assumed constant 50 in this work), then do not serve that operator untill this gap between VC_i and real time is recovered.
  - If ($VC_i <$ real time), then $VC_i \leftarrow$ real time.

The virtual clock based allocation algorithm ensures long term fairness in the system but it fails in achieving fair allocation at every scheduling instant.

5.3.2 Weighted Fair Queuing based Algorithm

To overcome the shortcoming of previous algorithm, we propose another algorithm which can ensure both short term and long term fairness in the system. The main concept of this algorithm is derived from *Weighted Fair Queuing (WFQ)* systems [2]. In the packet switched network, WFQ is used to allow multiple flows to share the link in a fair manner, such that a minimum bandwidth guarantee can be provided to each flow. Each flow in the network is assigned a weight which indicates the priority order of the flow. While scheduling packet transmission, the link bandwidth is divided among the active flows in the ratio of their weights. As per WFQ, bandwidth allocation among active flows at any scheduling instant is independent of allocation in previous scheduling instant. This way of allocating resources i.e. independent of past allocation guarantees short term fairness in the system.

In the similar fashion, we design an algorithm for resource allocation in multi-operator system where the spectrum resource is allocated to the operators based on the weights assigned to them. For simplicity, we consider equal weight assignment to each operator. The implementation detail of the algorithm is discussed below.

- Initialization : Set the *pointer* value equal to the first operator to be served, it can be chosen randomly;

- At each scheduling instant repeat the following steps,

  1. Store the index of the operator to be served in this scheduling instant from the *pointer* variable, i.e. $i \leftarrow pointer$,
  2. Given the demand Δ_i of each operator i, calculate the weighted fair share, $Share_i$, of each operator. For any operator i, its weighted fair share can be defined as
     $Share_i = \frac{w_i}{\sum\limits_{i=1}^{M} w_i}$ where w_i denotes weight assigned to operator i.
  3. Repeat the following steps for each operator i:
     (a) if the demand Δ_i of operator i is non zero, then allocate the resources to the operator i corresponding to its weighted fair share,
     (b) update the row of allocation matrix Y corresponding to the operator i,
     (c) update the value of i as follows,
     $i \leftarrow \mathrm{mod}\ (i + 1, \mathrm{N})$
  4. Store the updated value of pointer variable for the next scheduling instant,
     $pointer \leftarrow \mathrm{mod}\ (i + 1, \mathrm{N})$.

SM receives Δ and runs the algorithm to obtain Y in the beginning of each scheduling interval. The algorithm returns the allocation matrix Y whose rows correspond to allocation vector of the operators. The allocation or row vector is conveyed to the respective operators via GC. Although we assumed equal weight assignment to each operator, but this algorithm gives the flexibility to allocate resources to the operators, in any priority order. WFQ based algorithm ensures fair resource allocation at each scheduling instant.

Till now, we have discussed inter-operator resource allocation algorithms with an assumption that, the demand from the operators are available at the SM. But computing the demand for a given network topology is in itself a hard problem, which needs to be studied. We study the demand evaluation within each operator network in the next section.

5.4 Intra-operator Spectrum Sharing

There are two major problems with intra-operator spectrum sharing, which we discuss in the following sections. The first problem is to compute the total demand of the network in terms of TF blocks. And the second problem is distribution of resources among eNBs of an operator. Once, the SM allocates resources to the operators, the operator has to optimally distribute the resources among its eNBs.

5.4.1 Intra-operator system model

As discussed in Section 5.2, we consider each operator deploys multiple eNBs in a given area, to serve the end users. Each eNB in an operator's network is assumed to predict the throughput requirement from the past learning of end user experience. This throughput requirement is further converted in terms of TF blocks. Let D be the demand vector corresponding to the eNBs of an operator, where d_j is an element of vector D, denoting demand of the eNB$_j$. After resource allocation at the SM, each operator receives a certain number of TF blocks. Consider a set $\mathcal{R}_i = \{1, 2, ...R_i\}$ representing the set of TF blocks allocated to an operator i such that $\mathcal{R}_i \subset \mathcal{L}$. Let $x_{j,k}$ denote an element in the resource allocation matrix X corresponding to an operator i, such that $\forall j \in \mathcal{N}_i$ and $k \in \mathcal{R}$,

$$x_{i,j} = \begin{cases} 1, \text{if TF block } k \text{ is assigned to eNB}_j, \\ 0, \text{otherwise.} \end{cases} \tag{5.2}$$

5.4.2 Demand Evaluation

We present the two solutions which can be used by an operator to compute the demand of its network. The first solution is based on an optimization technique. Even though, this solution gives the best result, it cannot be used in practice as optimization technique is very expensive and infeasible for large network. Hence, we present a second solution, based on graph theory, which gives sub-optimal results.

Using Optimization Technique

For a given network topology, to evaluate the total demand of the network, the operator cannot just sum up the demands of all eNBs as it will result into resource wastage. To achieve efficient spectrum utilization, an operator has to compute the optimal number of TF blocks, considering the fact that these blocks can be reused among the non-interfering eNBs within its network. The interference between two eNBs is modeled using the *Protocol Interference Model* discussed in Chapter 4.

The problem of computing the minimum number of TF blocks required to fulfill the demand of all eNBs in the network, can be modeled as a linearly constrained optimization problem. Let, $\mathcal{A} = \{1, 2, ...A\}$ represent the set of TF blocks required by all eNBs of an operator i such that $A = \sum_{j=1}^{N_i} d_j$. The mathematical representation of the optimization problem for an operator i can be expressed as follows:

$$\min_{X} \left(\sum_{j=1}^{N_i} \sum_{k=1}^{A} x_{j,k} \right), \tag{5.3}$$

$$\text{subject to} \sum_{k=1}^{A} x_{j,k} \geq d_j \quad \forall j \in \mathcal{N}_i, \tag{5.4}$$

$$\text{and} \sum_{l \in \mathcal{I}(j)} x_{l,k} \leq 1 \quad \forall k \in \mathcal{A} \text{ and } j \in \mathcal{N}_i. \tag{5.5}$$

where $\mathcal{I}(j)$ represents the set of eNBs interfering with eNB$_j$. Here, the constraint 5.4 ensures that the demand of each eNB in the network is fulfilled and the constraint 5.5 is to make sure that TF blocks are not reused among the interfering eNBs in the network. This optimization problem can be solved using Binary Integer Linear Programming (BILP). The ouput of the optimization problem is the total number of TF blocks required for the network of an operator i. We assume that each operator solves this optimization problem to obtain the optimal demand of its network, which is then conveyed to the SM for resource allocation.

Using Graph Theoretic Technique

We model the network of an operator as a conflict graph $G(\mathcal{V}, \mathcal{E})$ where $\mathcal{V} = \{1, 2, ..., V\}$ denotes the set of vertices and $\mathcal{E} = \{1, 2, ..., E\}$ denotes the set of edges. In our system, $\mathcal{V}$ represent the set of all eNBs in the network. $\mathcal{E}$ represent the set of edges denoting interference among eNBs i.e. an edge between any two vertices implies that vertices are interfering with each other. The demand d_j of the eNB$_j$ indicates the minimum number of color which needs to be assigned to vertex j. So given a graph $G(\mathcal{V}, \mathcal{E})$ and demand vector D, this problem can be modeled as an extension of pre-emptive version of *sum multi-coloring (SMC)* problem discussed in [21]. The objective is to color each vertex j with d_j colors, so as to minimize the maximum of the color index assigned to each vertex, while assigning distinct colors to adjacent vertices. We use the concept of greedy graph coloring algorithm discussed in [22] to design the algorithm for our setup. Let $\mathcal{R} = \{1, 2, ..., R\}$, represent the set of available colors. Assume that there are sufficient colors in the set $\mathcal{R}$ to color the graph. The pseudocode of the algorithm is described in Algorithm 2.

Algorithm 2 Algorithm to compute the number of colors

Require: Graph G,

Sort the vertices of G by non decreasing demand and store the sorted list in $\mathcal{V}$

for each j from 1 to V **do**

find $\mathcal{F}_j$, the set of colors assigned to neighbors of j,

obtain $\mathcal{G}_j = \{\mathcal{R}\} \setminus \{\mathcal{F}_j\}$, set of feasible colors for vertex j,

sort the set $\mathcal{G}_j$ by increasing order of color index,

assign d_j colors from the set $\mathcal{G}_j$ to the vertex j,

end for

Result: Return the total number of colors used in coloring the graph.

The Algorithm 2 returns the total number of colors required to color the graph. This total number of colors represent the demand of the network in terms of TF blocks.

Comparison of Optimization and Graph Theoretic technique

Consider a randomly generated graph with 10 nodes such that each node has some random demand i.e. each node requires a certain number of colors. We simulate this model in MATLAB and study the performance of these technique by varying the number of edges in the graph. Each result is obtained by taking an average over 100 random topologies. The minimum number of colors required to color the graph, such that demand of each node is satisfied is same in both techniques for sparse graphs as shown in Figure 5.3. Obviously for dense graphs, optimization technique outperforms graph theoretic technique. Figure 5.4 shows time taken by both technique to solve the graphs of different density. The elapsed time of optimization technique is very high compared to graph theoretic technique.

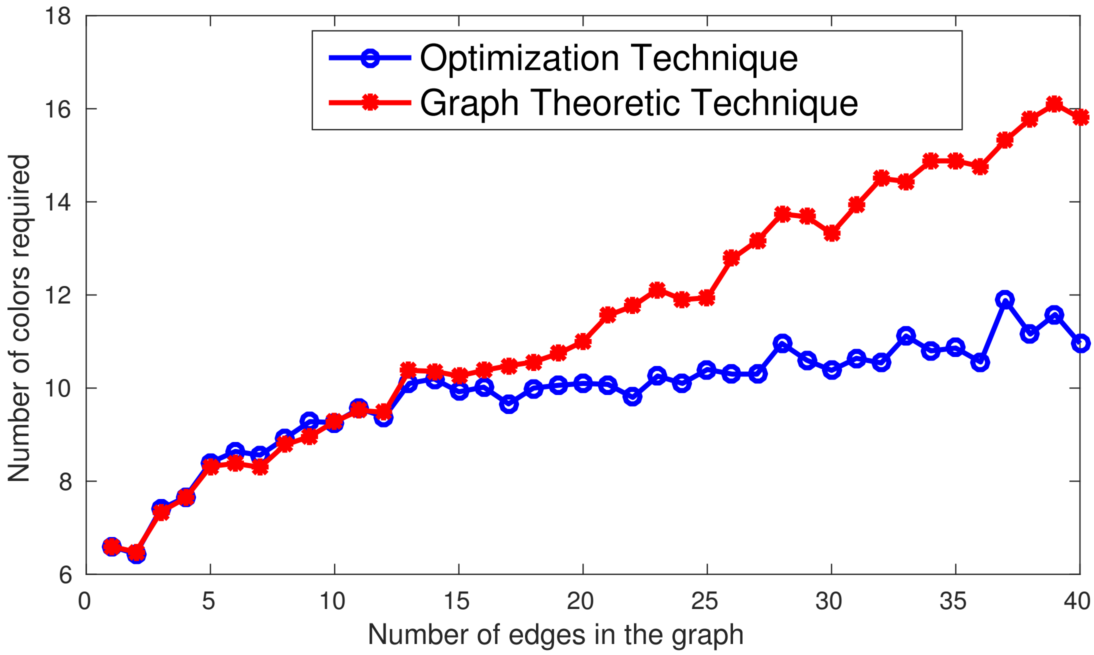

Figure 5.3: Comparison of number of colors required for color a graph using optimization and graph theoretic technique, in a network with 10 nodes.

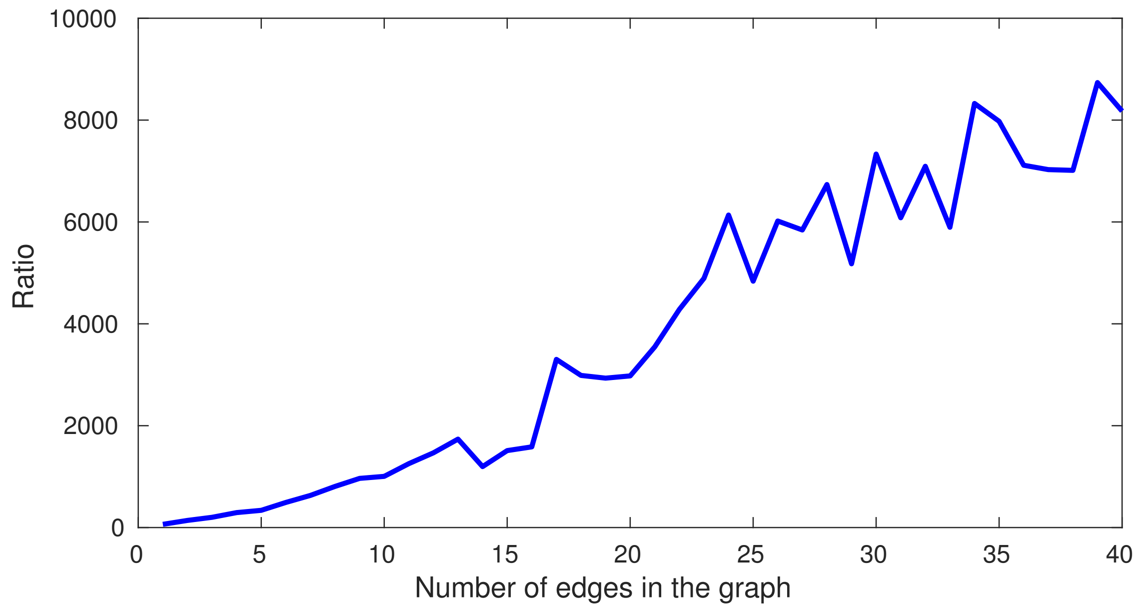

Figure 5.4: Ratio of elapsed time to color a graph using optimization and graph theoretic technique, in a network with 10 nodes.

5.4.3 Intra-operator Resource Allocation

In this section, we present two solutions, which can be used by an operator to compute the resource allocation matrix for its eNBs. The first solution is based on optimization technique while the second technique is based on graph theory.

Using Optimization Technique

Now we discuss the problem of intra-operator resource allocation i.e. the resource allocation among eNBs of an operator. After receiving the resources from the SM, each operator has to distribute the resources among its eNBs which in turn serves the end users. Before discussing further, let us first define a term, *node utility* which is the ratio of demand to the allocated resources, denoted by ρ, such that

$$\rho_j = \frac{D_j}{\sum_{k=1}^{R_i} x_{j,k}} \quad \forall j \in \mathcal{N}_i.$$

where R_i is the total number of TF blocks allocated to the operator i. The node utility, ρ is associated with each eNB$_j$, representing its resource utilization. For a given topology, the objective of the intra-operator resource allocation is to minimize the maximum node utility of the network under the given reuse constraint. This problem can be mathematically modeled as follows:

$$\min_{X} \max_{j} \rho_j, \tag{5.6}$$

$$\text{subject to} \quad \text{and} \sum_{l \in \mathcal{I}(j)} x_{l,k} \leq 1 \quad \forall k \in \mathcal{R}_i \text{ and } j \in \mathcal{N}_i, \tag{5.7}$$

where $\mathcal{I}(j)$ represent the set of eNBs interfering with the eNB$_j$. Here the constraint 5.7 is to make sure that TF blocks are not reused among the interfering eNBs in the network. This is a binary non linear optimization problem. Due to the non availability of an optimization tool to solve this binary min-max problem, we have reduced this problem to a linearly constrained optimization problem. The reduced form is given below:

$$\max T, \tag{5.8}$$

$$\text{subject to } T \leq \frac{1}{\rho_j} \; \forall j \in \mathcal{N}_i, \tag{5.9}$$

$$\text{and} \sum_{l \in \mathcal{I}(j)} x_{l,k} \leq 1 \quad \forall k \in \mathcal{R}_i \text{ and } j \in \mathcal{N}_i. \tag{5.10}$$

where T is a scalar variable and $\mathcal{I}(j)$ represents the set of eNBs interfering with the eNB$_j$. Now this reduced problem can be easily solved using BILP tools. The output of the optimization problem gives the allocation matrix X for an operator i.

Using Graph Theoretic Technique

As discussed in Section 5.4.2, here also, we model the network of an operator as a conflict graph. If R denotes the total number of TF blocks allocated to the operator, then the total number of available colors to color the graph will also be R. Let $\mathcal{R} = \{1, 2, ..., R\}$ denotes the set available colors. Given, a graph and the color set, we want to design a multi-coloring algorithm which can assign the available colors to the vertices in the fair manner. Here, the objective is to color the vertex with available colors, so as to maximize the minimum number of colors assigned to each vertex, while assigning distinct colors to adjacent nodes. Let C be the binary color assignment matrix such that,

$$c_{i,j} = \begin{cases} 1, \text{if color } i \text{ is assigned to vertex } j, \\ 0, \text{otherwise.} \end{cases} \tag{5.11}$$

The Algorithm 3 returns color assignment matrix C for a graph. The matrix C is same

Algorithm 3 Algorithm to compute color assignment matrix

Require: Graph G, Total colors R

while available colors, R, does not gets exhausted **do**

Sort the vertices of G by non decreasing demand and store the sorted list in $\mathcal{V}$

for each j from 1 to V **do**

find $\mathcal{F}_j$, the set of colors assigned to neighbors of j,

obtain $\mathcal{G}_j = \{\mathcal{R}\} \setminus \{\mathcal{F}_j\}$, set of feasible colors for vertex j,

sort $\mathcal{G}_j$ and assign the first color from $\mathcal{G}_j$ to the vertex j,

update the channel assignment matrix, and demand as follows:

$c_{i,j} = 1$, where $i = \min \mathcal{G}_j$ and $d_j = d_j - 1$

end for

end while

Result: Return the color assignment matrix C.

as the allocation matrix X used in intra-operator resource allocation.

Comparison of Optimization and Graph Theoretic technique

We consider the same simulation model as discussed in the Section 5.4.2, with the only difference that number of nodes is 5. We have taken small number of nodes only considering the fact that optimization technique is very expensive for large graphs. Here, we need to find the optimal coloring scheme so that colors are assigned to the nodes in fair manner. We compute the fairness index in terms of ratio of colors assigned to the colors required by the node. The comparison of fairness index for two techniques is shown in Figure 5.5. The figure shows the marginal decrease in the performance in case of graph theoretic technique compared to the optimization technique. Figure 5.6 shows time taken by both the techniques to solve the graphs of different density. The elapsed time of optimization technique is very high compared to graph theoretic technique. This time complexity of optimization technique makes it infeasible to solve large graphs.

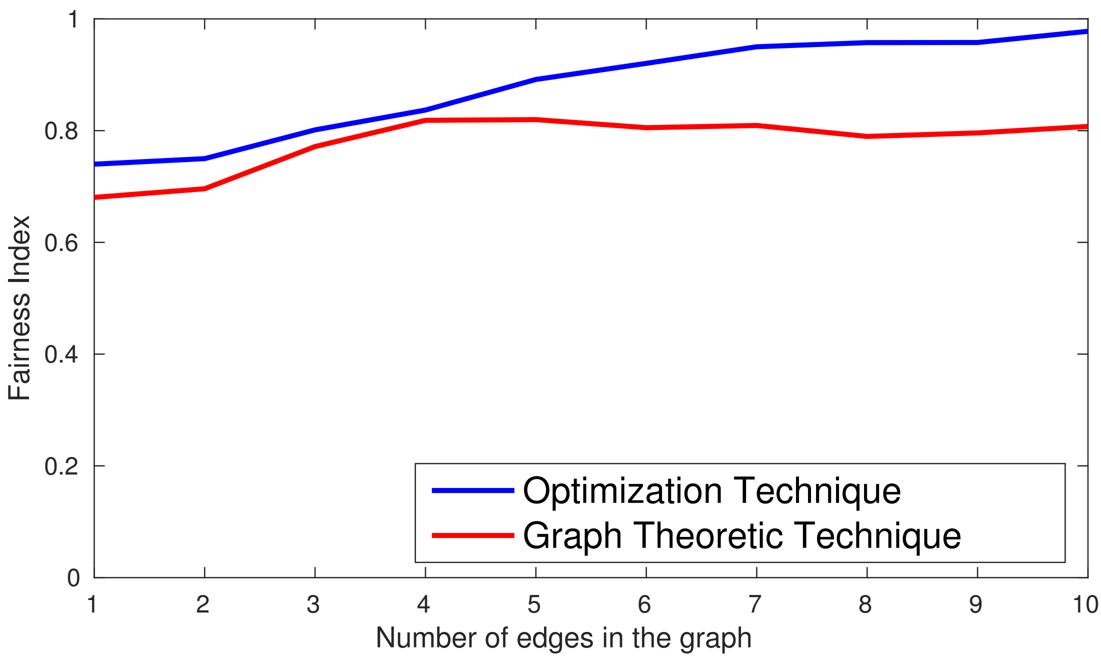

Figure 5.5: Comparison of fairness index obtained by coloring a graph using optimization and graph theoretic technique, in a network with 5 nodes.

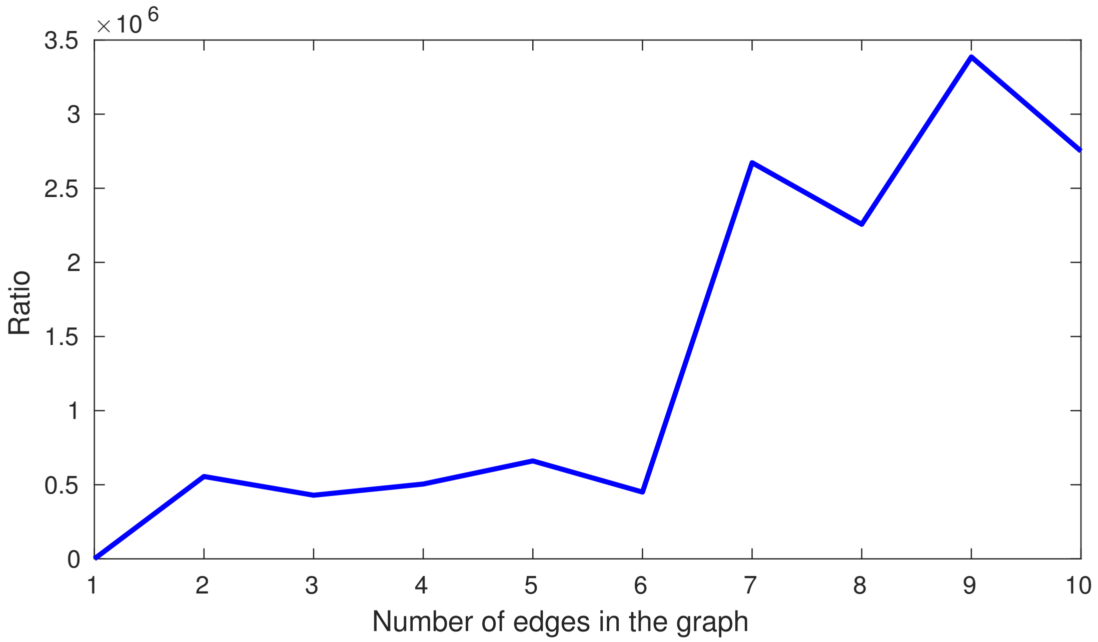

Figure 5.6: Ratio of elapsed time to color a graph using optimization and graph theoretic technique, in a network with 5 nodes.

5.5 Performance Evaluation

In this section, we present the results of MATLAB [3] simulations to analyze the performance of the proposed algorithms. We model multiple scenarios in MATLAB to study the behavior of both inter-operator and intra-operator algorithm. In all scenarios, we assume that total system bandwidth is 20 MHz, centered around 510 MHz frequency. SM divides this bandwidth into four orthogonal channels, each of 5 MHz bandwidth. Further we assume that for a given network topology, these channels are identical i.e they have the same propagation characteristics. Each scheduling interval comprises of 5 time slots in time domain. 1 time slot corresponds to 1 minute in time frame. For a given area, multiple operators deploys their eNBs in uniformly at random fashion. SM allocates resources to the operators in the beginning of each scheduling instant depending on their demand. For intra-operator resource allocation, each operator construct the conflict graph using protocol interference model. The threshold distance between eNBs for constructing an edge in the conflict graph is 4 km, i.e. if the distance between eNBs is less than 4 km, then they interfere with each other. An eNB serves multiple end users which are placed randomly within its coverage area. We assume that end users are stationary. Without loss of generality, we assume that all users are not always active, they switch between active and sleep mode. The arrival process of the active users in the system is modeled as poisson process with expected mean λ. Each active user download a file of fixed size and then switch back into sleep mode after successful download. Given a network topology, the threshold value of λ can be calculated as follows

$\lambda_{th} = (\text{System Capacity})/(M * N * F)$,

where F is fixed file size which users download. Before discussing the simulation scenario and results in details, let us discuss the performance metrics which we use to assess the performance of the proposed algorithm.

1. **Convergence:** To check the convergence of the algorithm, we study the evolution of number users in the system with time. Since the resources are allocated dynamically, depending on the demand from the operators, the number of users in the system should settle down with time if the network load does not exceeds the system's capacity.

2. **Fairness Index:** The resource allocation algorithm needs to be fair so that conflict among operators can be avoided. We define fairness in terms of utility which represents satisfaction level of operators. Without loss of generality the utility of an operator can be defined as

$$U_i = \begin{cases} R_i/\Delta_i, & \text{if } R_i < \Delta_i, \\ 1, & \text{otherwise.} \end{cases} \tag{5.12}$$

   where R_i denotes the allocated resources to the operator i and Δ_i is the demand of operator i. Then, from the fair allocation point of view, the fairness metric, F can be defined as,

$$F = \frac{\left(\sum_{i=1}^{M} U_i\right)^2}{M \times \sum_{i=1}^{M} U_i^2}. \tag{5.13}$$

   where M represent the total number of operators in the system. We use the fairness metric F to compare the performance of allocation algorithms.

3. **Backlogged Users:** For this metric, we calculate the cumulative number of users, which are not served in the same instant, in which they have arrived in the system.

This metric captures the delay observed by the users in the system. We show the variation in the number of backlogged users in the system for different values of mean user arrival rate.

4. **Delay Fairness:** This metric captures the fairness of resource allocation among eNBs in the system irrespective of operators. We calculate the fairness metric in terms of user delay observed in each cell as per the equation 5.13.

5.5.1 Simulation Results

In this section, we discuss the simulation scenario and results in details.

Scenario 1:

Let us consider a scenario, where multiple operator deploys its network in a given area, in such a way that each eNB interferes with all other eNBs irrespective of operator. Since each eNB interferes with all other eNBs, SM treats each eNB as an independent operator while allocating resources. The simulation parameters are given in Table 5.1. We perform simulations of this topology for two values of λ. In the simulation model, we assume that all eNBs are equally loaded and hence the same value of λ is taken for all eNBs.

As can be observed from Figure 5.7 and 5.8, the system converges fast in both the cases. This ensures bounded user delay in the system. The convergence time of first case is 3 hours, and for second it is 5 hours. The convergence time increases as the value of λ become closer to the threshold value.

Table 5.1: Simulation Parameters

Parameters	**Values**
Frequency Band	500-520 MHz
Number of operators	5
Number of eNBs/operator	10
Scheduling interval	5 min
Channel bandwidth	5 MHz
Slot time	1 min
File Size (F)	20 Mb
Simulation Time	3×10^5 sec
System Capacity	62×10^6 Mbps
λ_{th}	0.62/eNB/sec

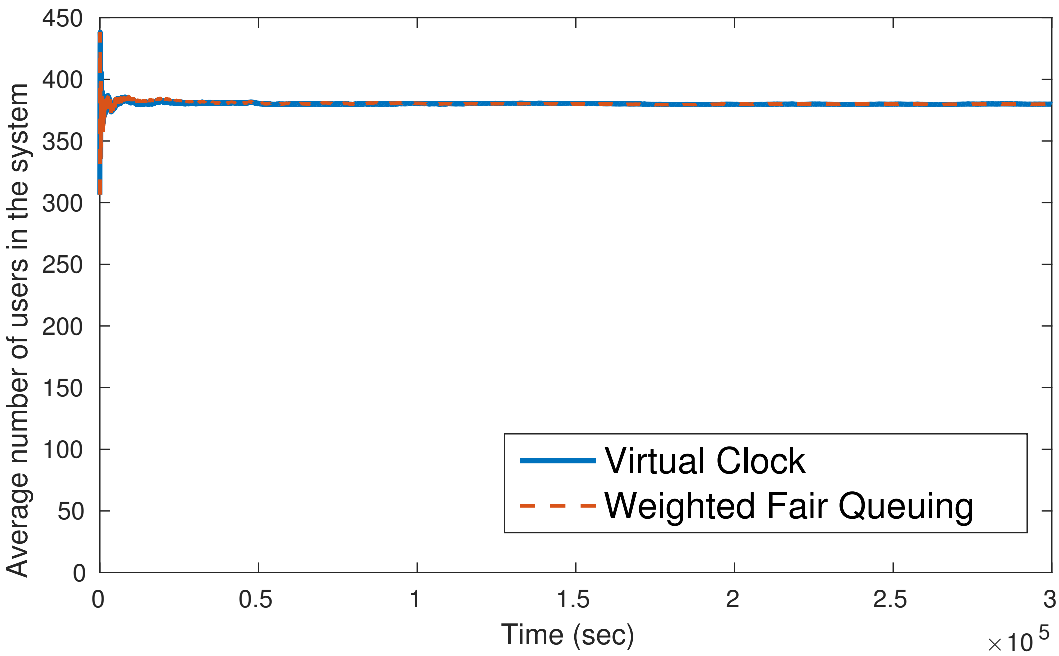

Figure 5.7: Convergence of virtual clock and weighted fair queuing based algorithm with time when $\lambda = 0.66\lambda_{th}$.

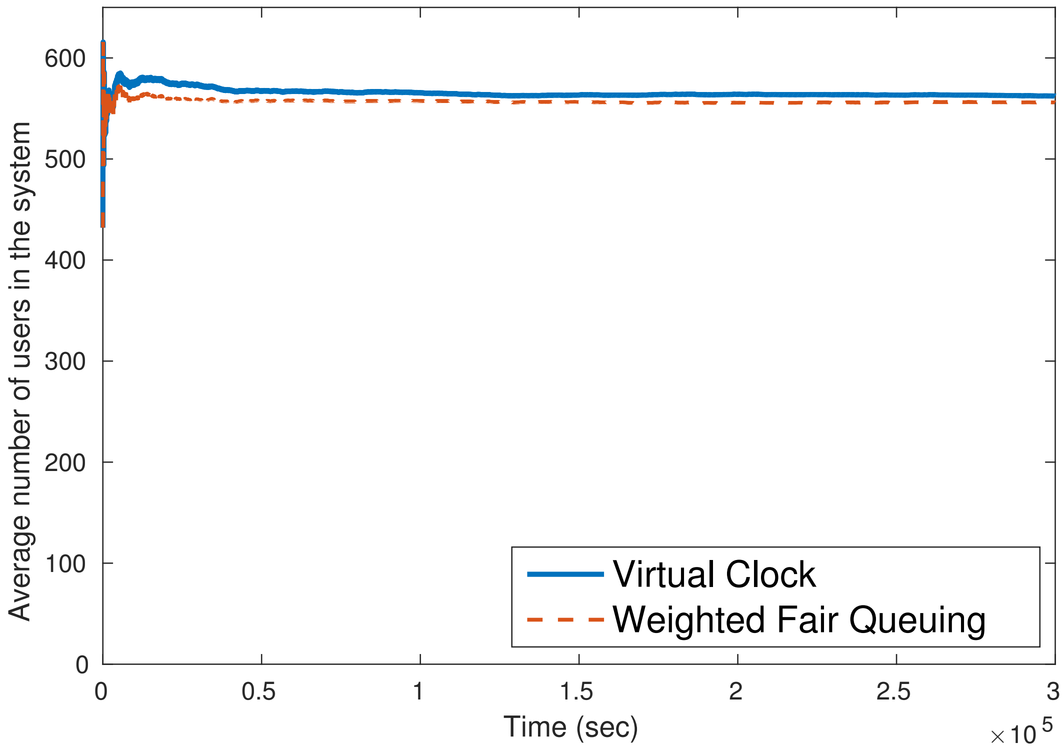

Figure 5.8: Convergence of virtual clock and weighted fair queuing based algorithm with time when $\lambda = 0.92\lambda_{th}$.

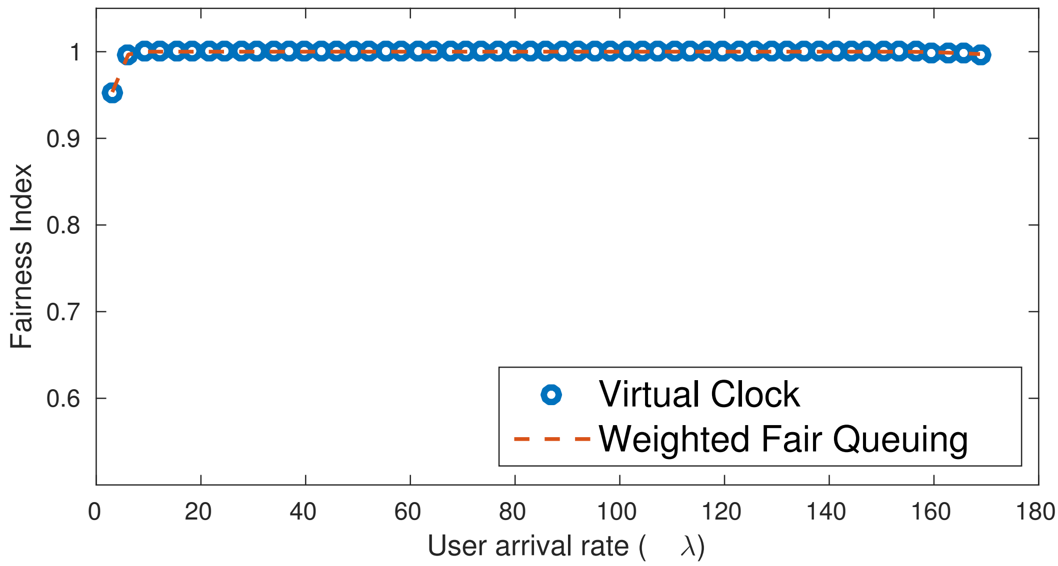

Figure 5.9: Average Fairness Index of virtual clock and weighted fair queuing based algorithm with varying λ.

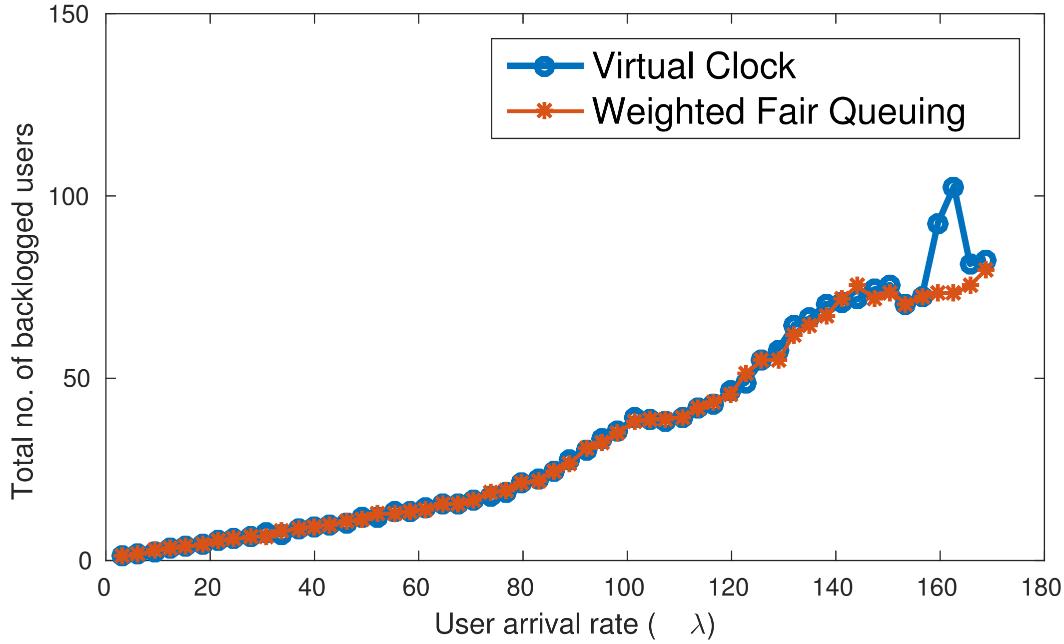

Figure 5.10: Total number of backlogged users in the system with varying λ, when virtual clock and weighted fair queuing based algorithm is used.

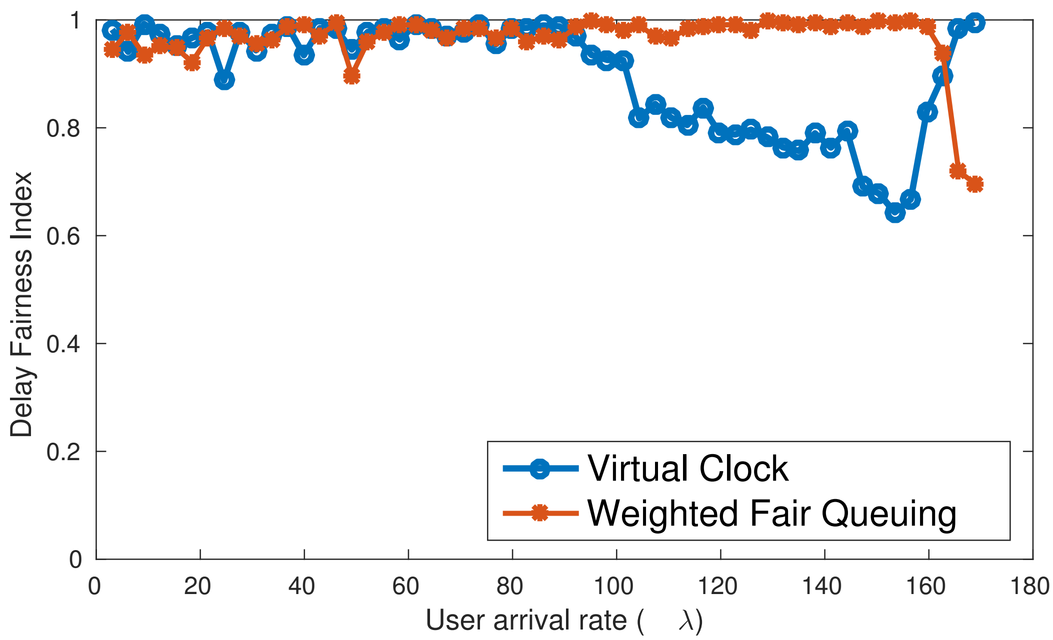

Figure 5.11: Average Delay Fairness Index of virtual clock and weighted fair queuing based algorithm with varying λ.

Figure 5.9 shows variation in average fairness index with λ. For each value of λ, the system is run for simulation time and fairness metric is calculated at each scheduling instant as per equation 5.13. The average value of obtained fairness index gives long term fairness index of the system. In this figure, long term average fairness index is plotted against λ. It can be observed from the figure that both virtual clock and weighted fair queuing based algorithm perform equally fair for all value of λ. Figure 5.10 shows, how the total number of backlogged users in the system varies by increasing λ. As the value λ become closer to the threshold the number of unserved users in the system starts increasing. But, finite and small number of backlogged users in the system indicates the bounded delay property of the resource allocation algorithm. Next, to ensure fair delay among end users of each eNB, we plot delay fairness versus λ in Figure 5.11. We conclude that the weighted fair queuing algorithm performs better than the virtual clock algorithm for larger values of λ. While, for λ closer to the threshold, both the algorithms behaves abruptly. This behavior is justified, as, the system become unstable when the value of λ reaches to the threshold value.

Scenario 2:

Consider a multi-operator network deployment in a given area. Let 5 operators deploys their network, with 10 eNBs of each operator. The topology is assumed such that not every eNB interferes with every other eNBs. Each operator evaluates the demand of its network and inform it to the SM. Depending upon the demand of operators, SM allocates the resources in the beginning of each scheduling instant. Since the network is big, we use graph theoretic technique instead of optimization technique, for both demand evaluation and intra-operator resource allocation. The rest of the simulation parameters are as per Table 5.1. In this scenario also, we assume that all eNBs are equally loaded and hence the same value of λ is taken for all eNBs. All the performance metrics are evaluated by taking an average over multiple random topologies of each operator.

The convergence of the resource allocation algorithm with time, is shown in Figure 5.12 and 5.13 for different values of λ. Even in this scenario, the system converges fast for both algorithms. This ensures bounded user delay in the system. The convergence time of first case is 2 hours, and for second it is 4 hours. The convergence time increases as the value of λ become closer to the threshold value.

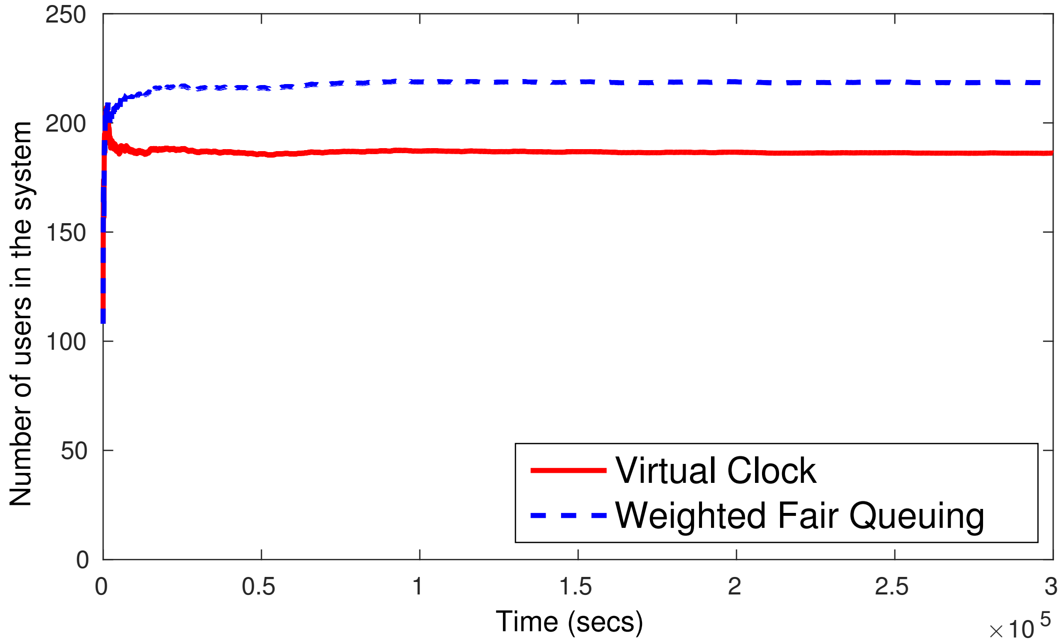

Figure 5.12: Convergence of virtual clock and weighted fair queuing based algorithm with time when $\lambda = 0.35\lambda_{th}$.

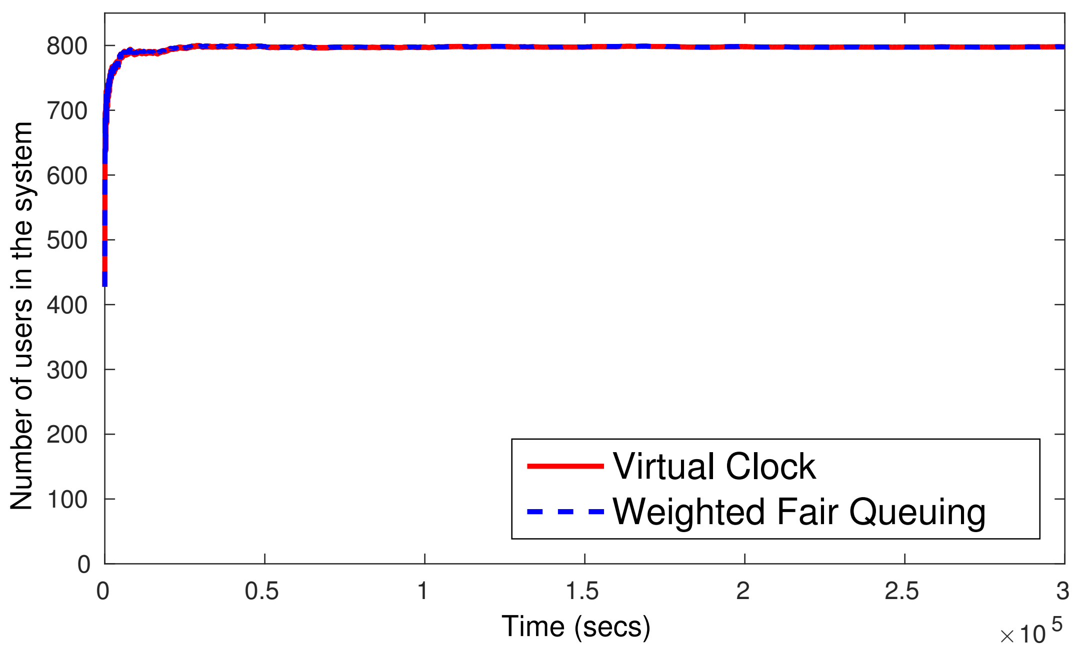

Figure 5.13: Convergence of virtual clock and weighted fair queuing based algorithm with time when $\lambda = 0.92\lambda_{th}$.

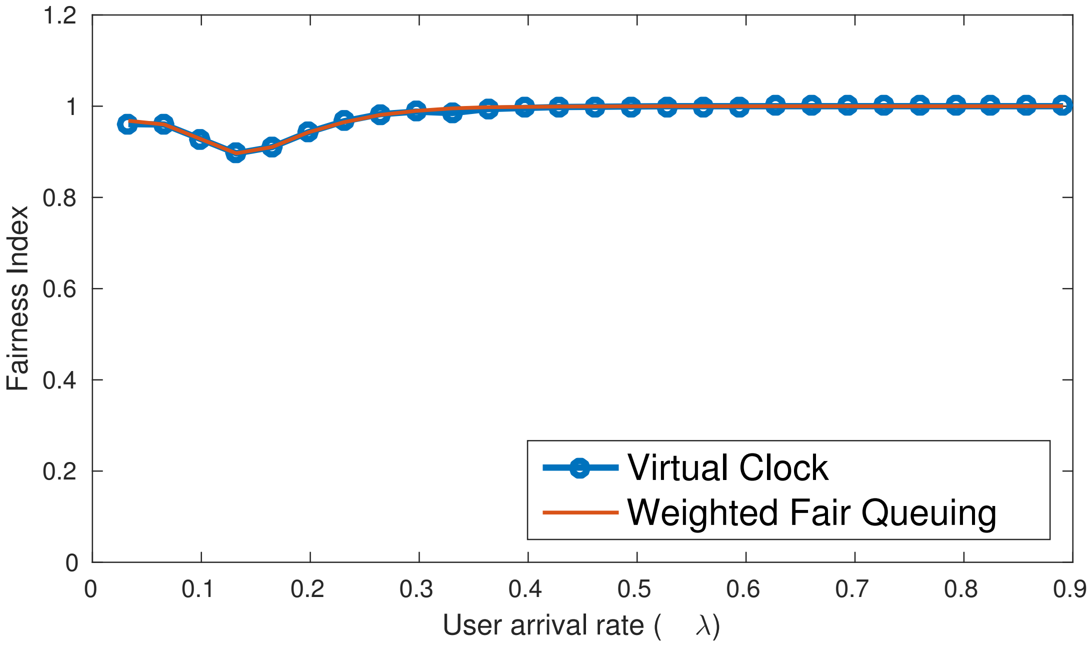

Figure 5.14: Average Fairness Index of virtual clock and weighted fair queuing based algorithm with varying λ.

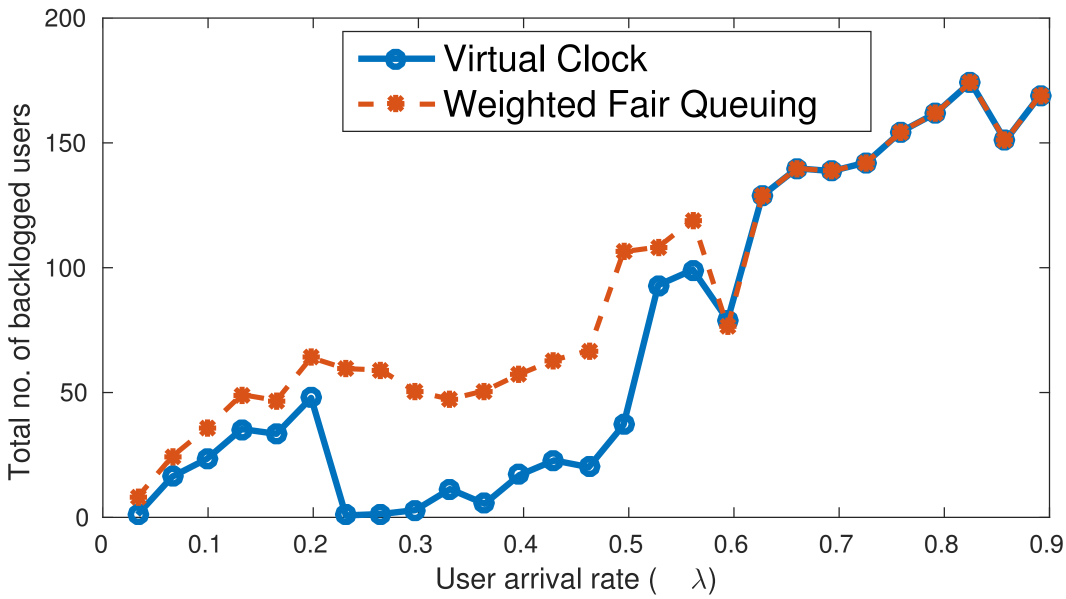

Figure 5.15: Total number of backlogged users in the system with varying λ, when virtual clock and weighted fair queuing based algorithm is used.

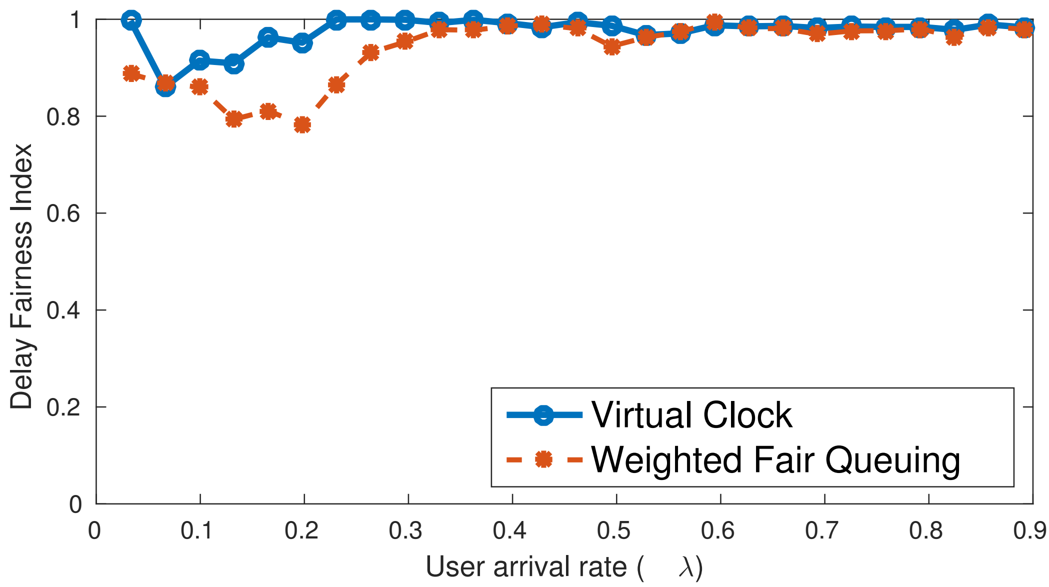

Figure 5.16: Average Delay Fairness Index of virtual clock and weighted fair queuing based algorithm with varying λ.

We calculate an average over 100 random topologies of the network for comparing other performance metrics. Figure 5.14 shows the variation of long term average fairness index with λ. The average value of fairness index obtained after running the simulation for long time, gives average fairness index of the system. It can be observed from the figure that both the virtual clock and weighted fair queuing based algorithm perform equally fair for all value of λ. Figure 5.15 shows, how the total number of backlogged users varies with λ. As the value λ become closer to the threshold the number of unserved users in the system starts increasing. But finite and small number of backlogged users in the system indicates bounded delay property of the resource allocation algorithm. Next, to ensure fair delay among end users of each eNB, we plot delay fairness versus λ in Figure 5.16. The behavior of both algorithm is same for all values of λ, and they perform equally fair. These values of delay fairness in the system, indicates that the intra-operator resource allocation using graph theoretic technique is also fair.

Scenario 3:

Till now, we have considered only those scenarios, where λ is constant with time, but this is not true in general. In this section, we study the performance of the algorithm under a more practical scenario, i.e. when the mean network load varies with time and the traffic pattern of each operator is different. Consider a scenario of spectrum sharing between two operators, when one operator serves users in residential area and other serves users in business area. We model the traffic pattern of these areas as discussed in [23]. Figure 5.17 and 5.18 shows the user traffic pattern and the users served by eNBs deployed in business areas during hours of the day. Figure 5.19 and 5.20 shows the same for eNBs deployed in residential areas. Here, we have taken moving average of the number of users to smoothen out the graph. As can be observed from the figures, the proposed hierarchical resource allocation scheme quickly adapts the traffic pattern of the network irrespective of which algorithm is used at the SM. Both virtual clock based and weighted fair queuing based algorithm performs equally well in dynamically allocating resources to the operators.

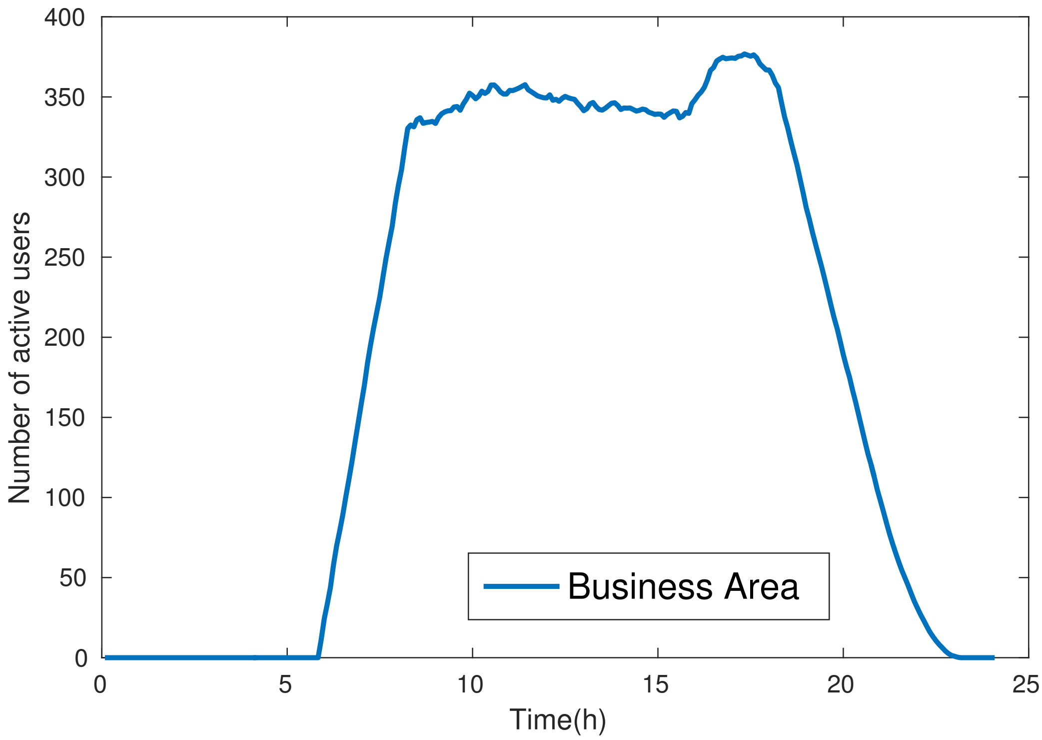

Figure 5.17: User traffic pattern experienced by eNBs deployed in business areas during hours of the day.

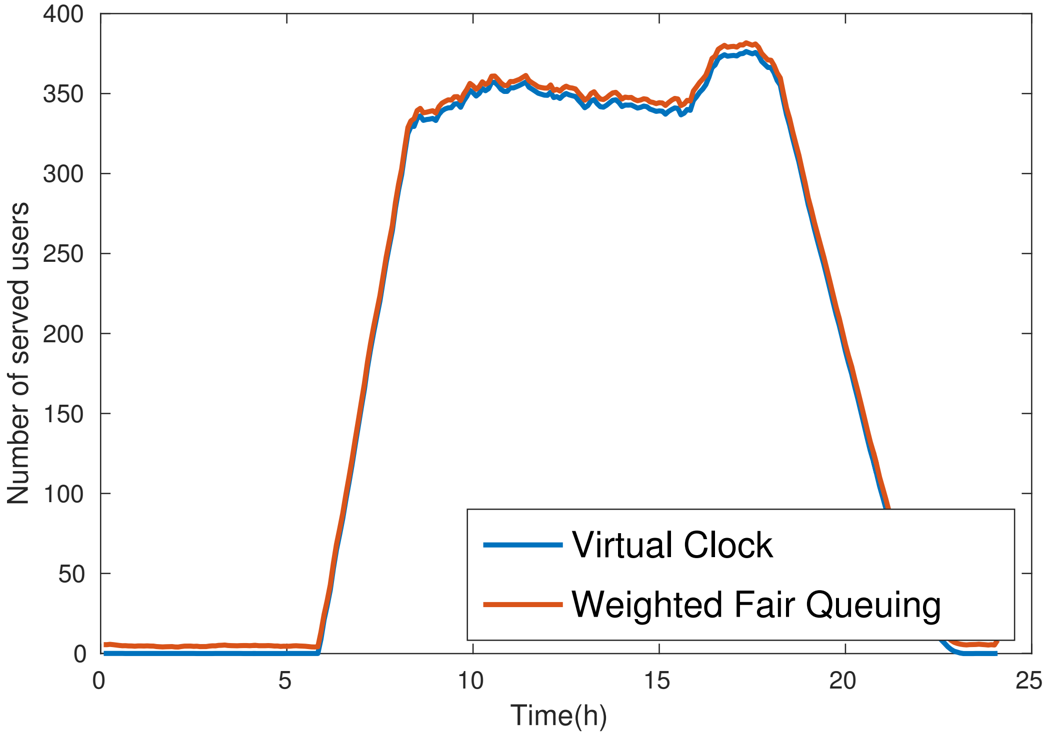

Figure 5.18: Users served by eNBs, deployed in business areas during hours of the day.

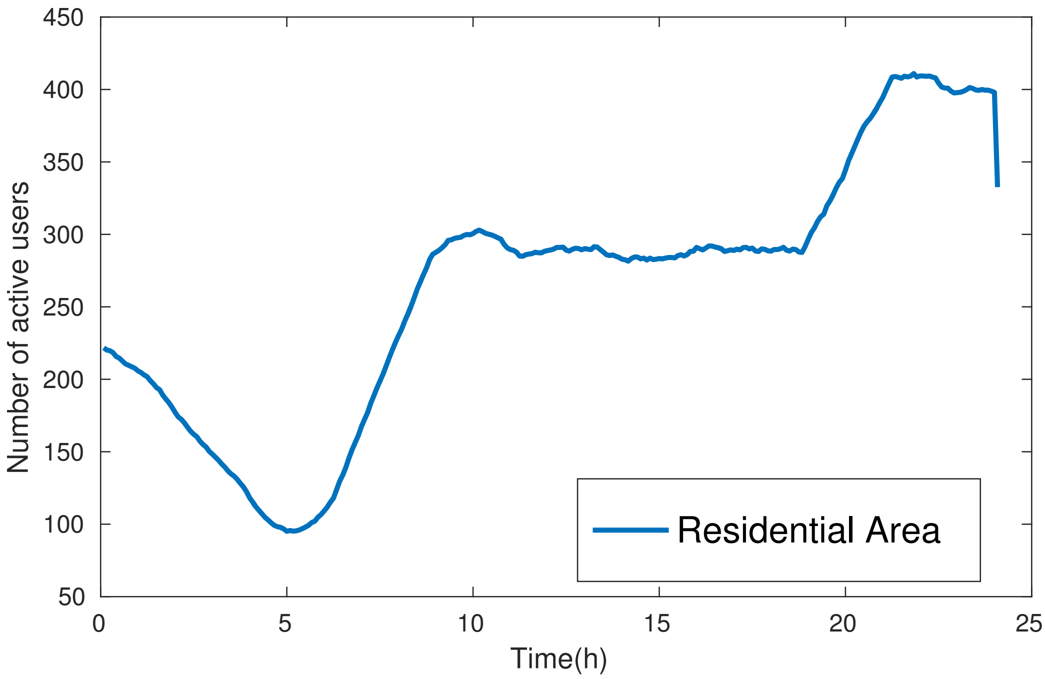

Figure 5.19: User traffic pattern experienced by eNBs deployed in residential areas during hours of the day

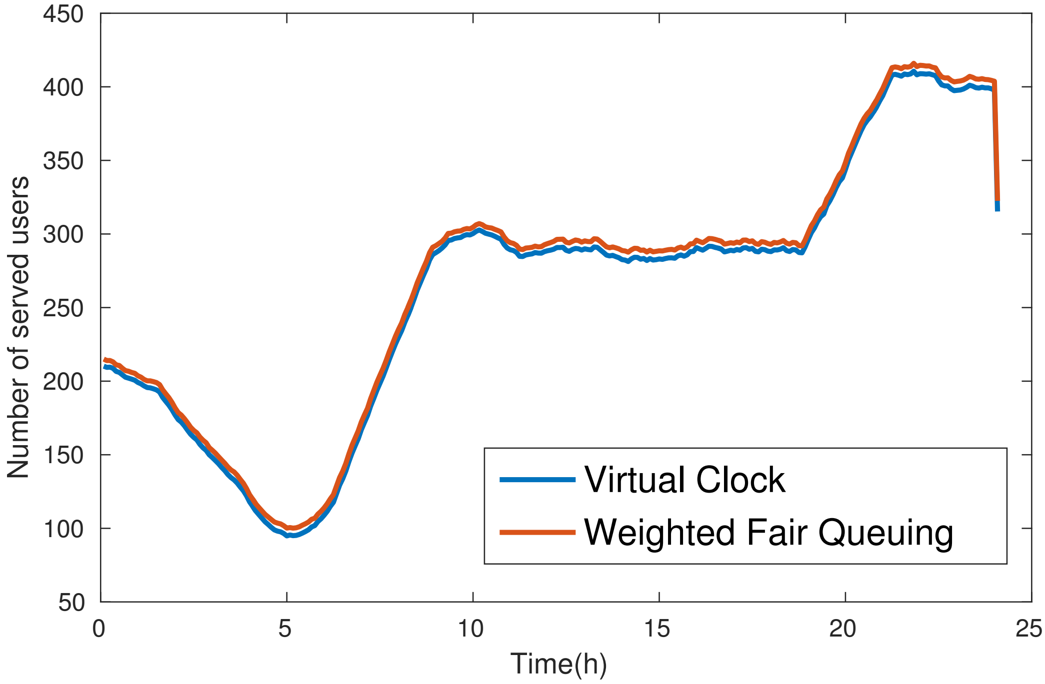

Figure 5.20: User served by eNBs, deployed in residential areas during hours of the day.

Scenario 4:

Next, we discuss a scenario when an operator asks for fake demand to the SM. Ideally the resource allocation algorithm should perform fair resource allocation irrespective of the behavior of the operators. But since, the proposed algorithm allocates resources according to the demand of the operators so it is important to study the behavior of the system in such scenario. Let us consider that two operator A and B, shares the common spectrum as per RSA scheme. We assume that the value of λ for each operator is less than the threshold value. In such scenario, if the demand of operator is fulfilled and yet resources are available at the SM, then the SM allocates this extra resource equally among the operator. Let, operator B behaves greedily and asks for more resources than its fair share, at every scheduling instant. Now we discuss the behavior of virtual clock and weighted fair queuing algorithm in this scenario.

- Weighted Fair Queuing based Algorithm :

  Figure 5.21 shows the evolution of number of users in the system for both cases, first when operator B asks for true demand and second when it asks for fake demand. Due to the fake demand from operator B in second case, the SM allocate more resources to it compared to the first case. This will lead to increase in number of users in the system as well as in operator A network. Also, Figure 5.22 and 5.23 shows the variation in number of users in operator A and operator B network respectively. This algorithm allocates extra resources to the operator B instead of penalizing it, which leads to unfair resource allocation.

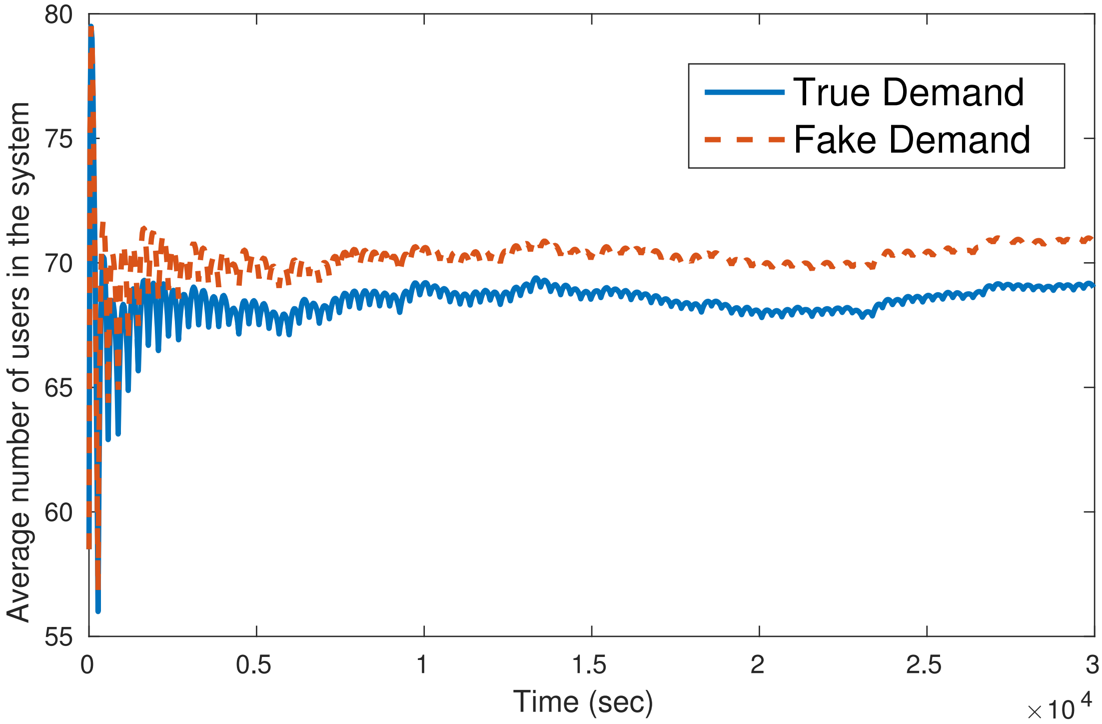

Figure 5.21: Time averaged value of number of users in the system with time.

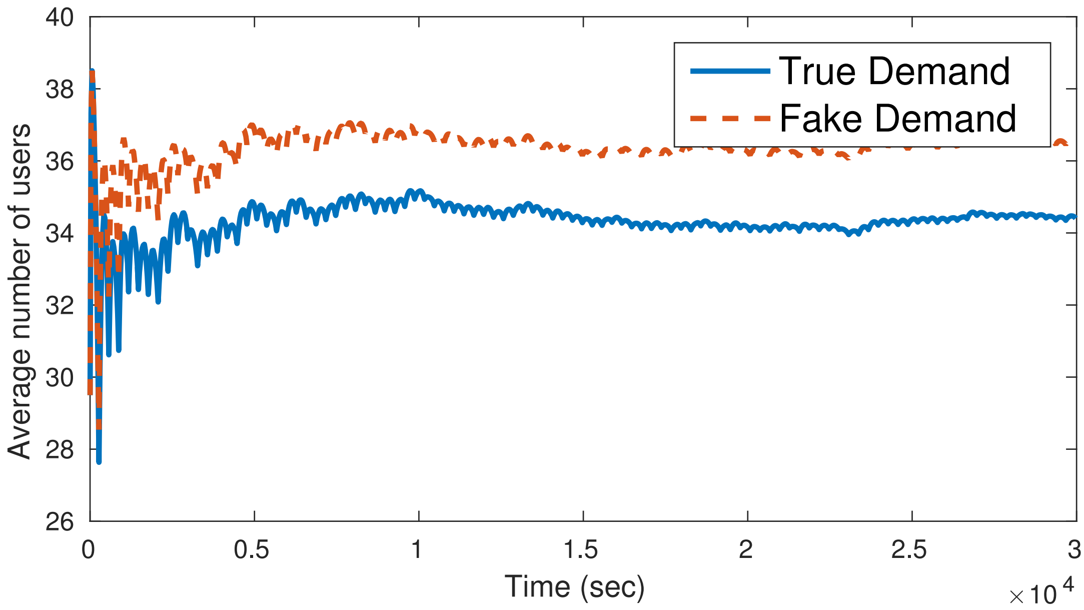

Figure 5.22: Time averaged value of number of users in the operator A network with time.

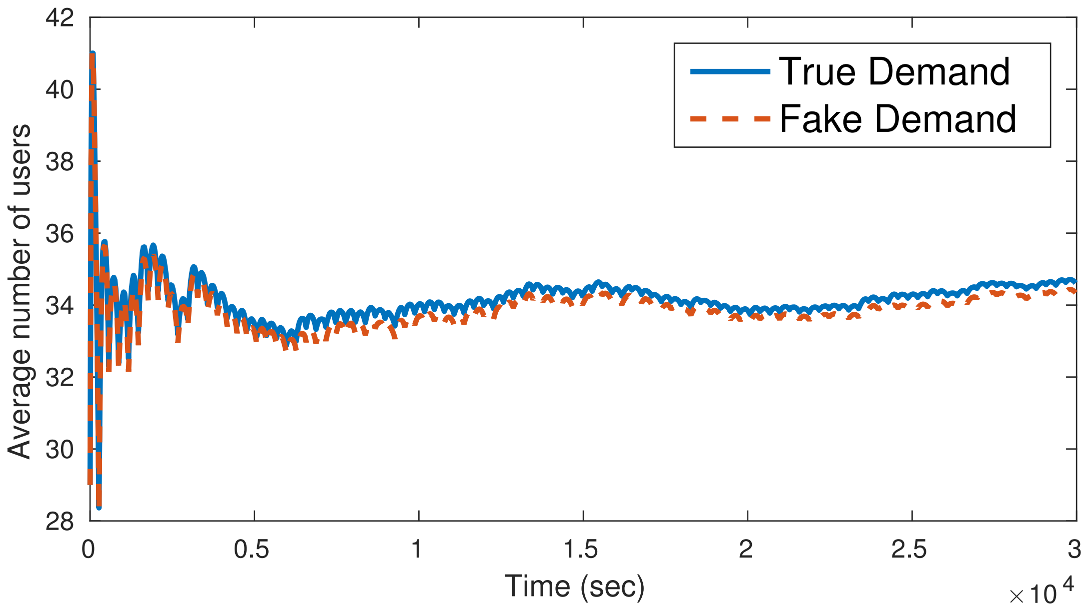

Figure 5.23: Time averaged value of number of users in the operator B network with time.

- Virtual Clock based Algorithm

  Figure 5.24 shows the evolution of total number of users in the system for both fake demand and true demand case. It can be observed that the total number of users in the system increases exponentially when operator B asks for fake demand. Due to fake demand, the value of virtual clock of operator B shoots up and when this value reaches a certain threshold, no resources will be allocated to it. This leads to the users getting queued up in operator B's network. In Figure 5.25 and 5.26, we observe that after a certain time, the number users in operator B network increases exponentially while it remains same for operator A. As per this algorithm, once the virtual clock value of any operator reaches far ahead than real time, the further demands from that operator is dropped assuming it as fake demand.

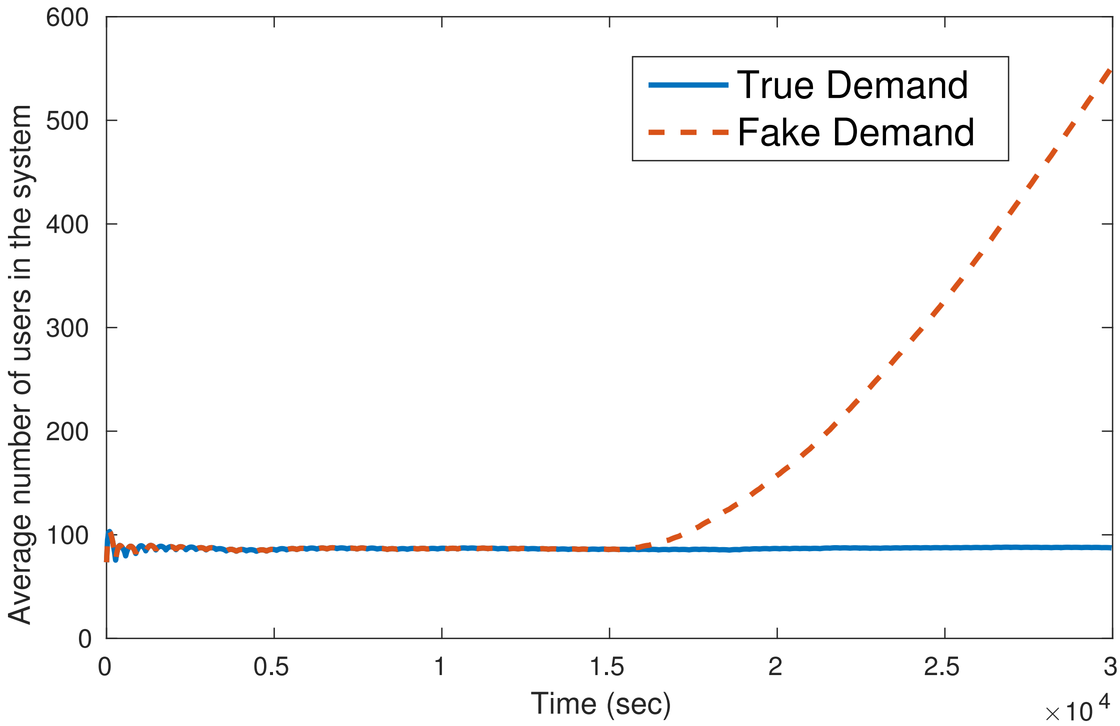

Figure 5.24: Time averaged value of number of users in the system with time.

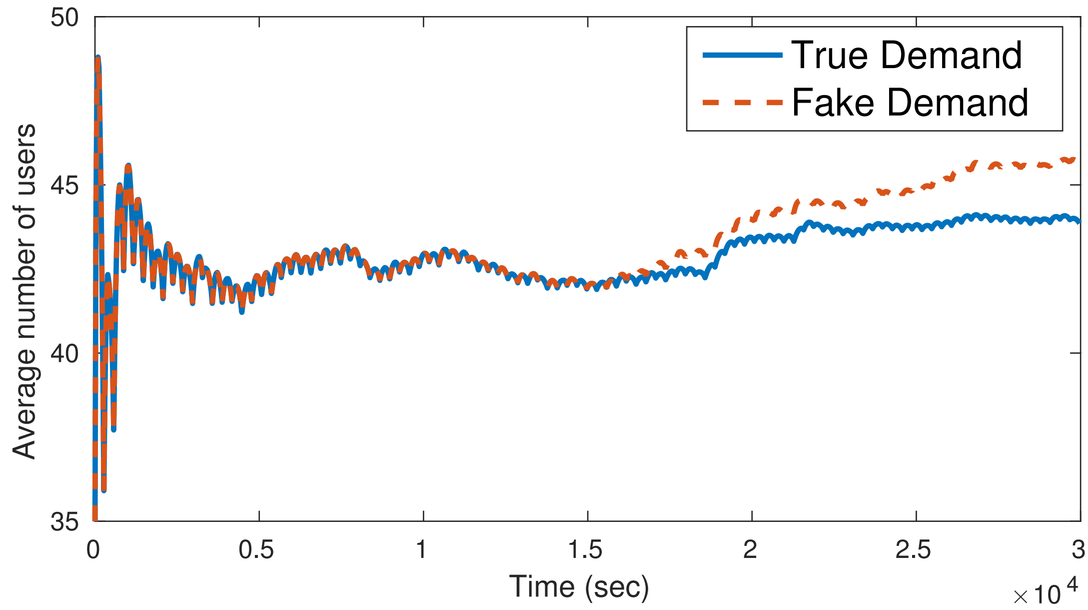

Figure 5.25: Time averaged value of number of users in the operator A network with time.

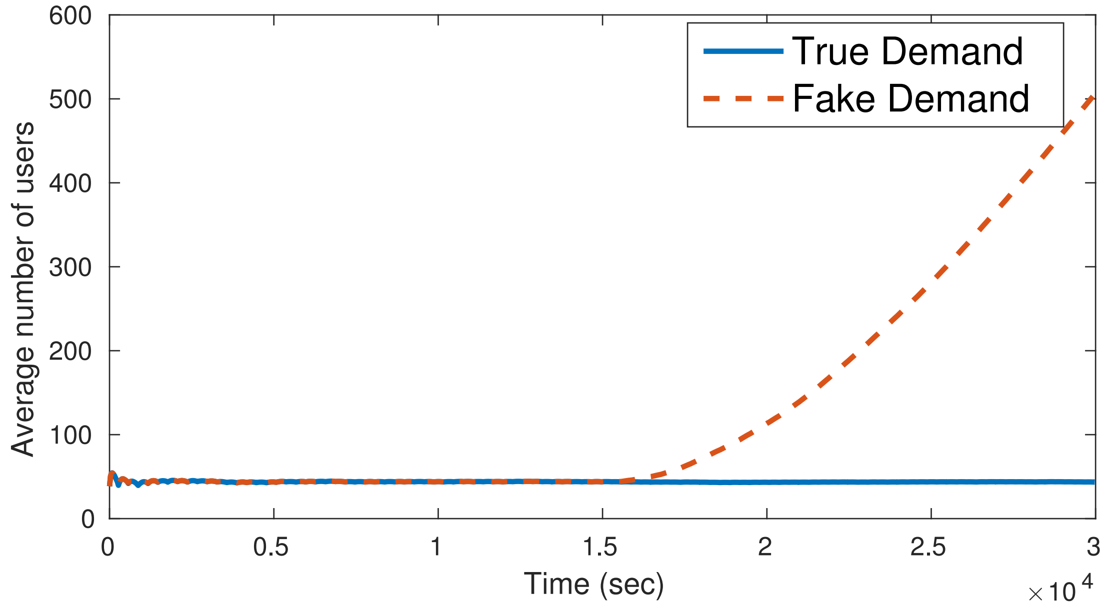

Figure 5.26: Time averaged value of number of users in the operator B network with time.

We can observe from the graph that the number of users in operator A network is not affected by the fake demand from operator B. Also, the operator B which asks for the fake demand is getting penalized. Hence, we conclude that the proposed virtual clock based resource allocation algorithm encourages operators to ask for true demand only.

Scenario 5:

In any practical scenario, the network load is different at each eNB irrespective of operators. Basically, the network load is function of user base and operator deploys their network depending on the user demand in the given area. To imitate such practical scenario in MATLAB, we have modeled a given area as grids, where each grid point corresponds to certain value of λ. The value of λ_{th} is uniformly distributed among all grid points. eNBs of different operators are dropped uniformly at random in that area. We assume an area of 20×20 km^2, 5 operators and each operator deploys 10 eNBs. The coordinates of the eNBs in an area is shown in Figure 5.27.

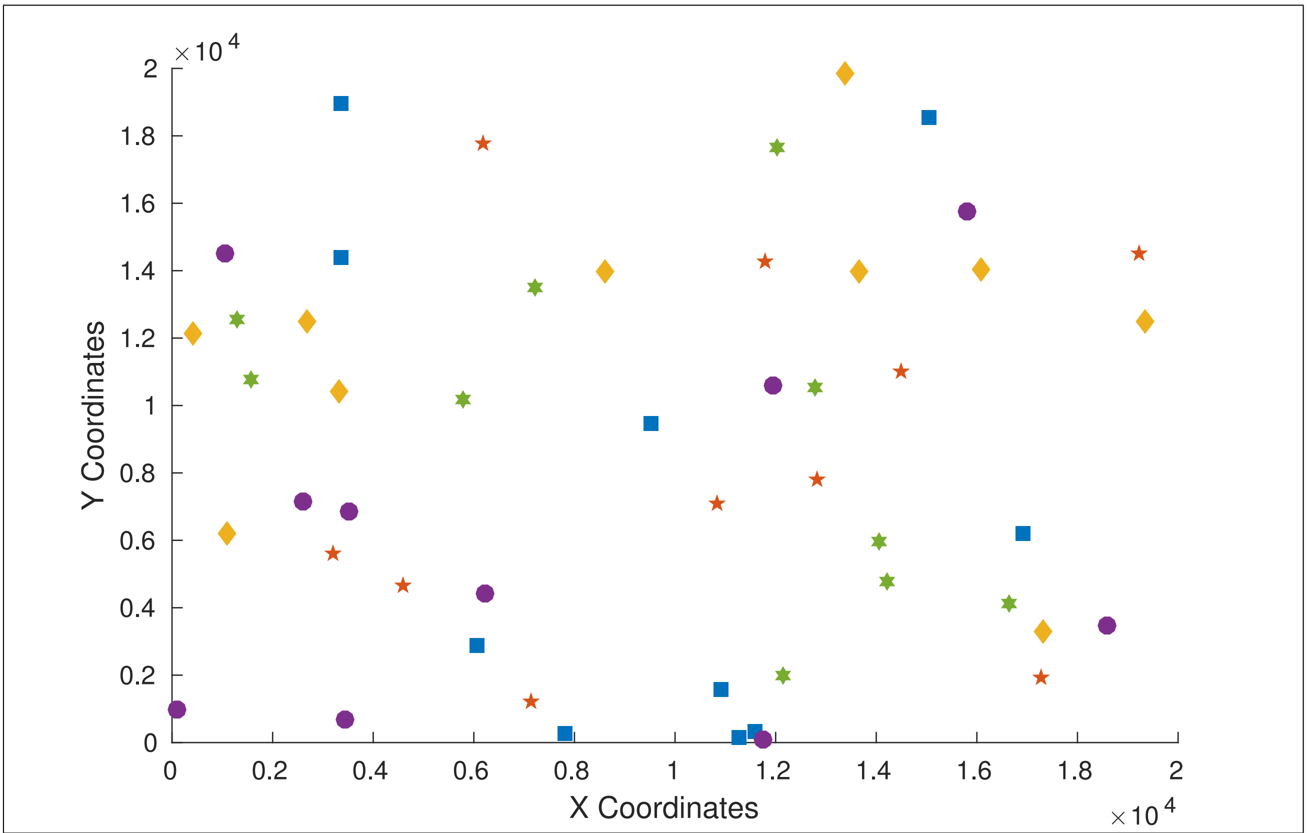

Figure 5.27: coordinates of eNBs deployed by multiple operators.

We assume that each grid point connect to the nearest eNB, and each eNB serves different number of grid points. The demand at any eNB is computed by summing up the λs of grid points connected to that eNB. Hence, in this scenario each eNB has different network load depending on the density of eNBs deployment.

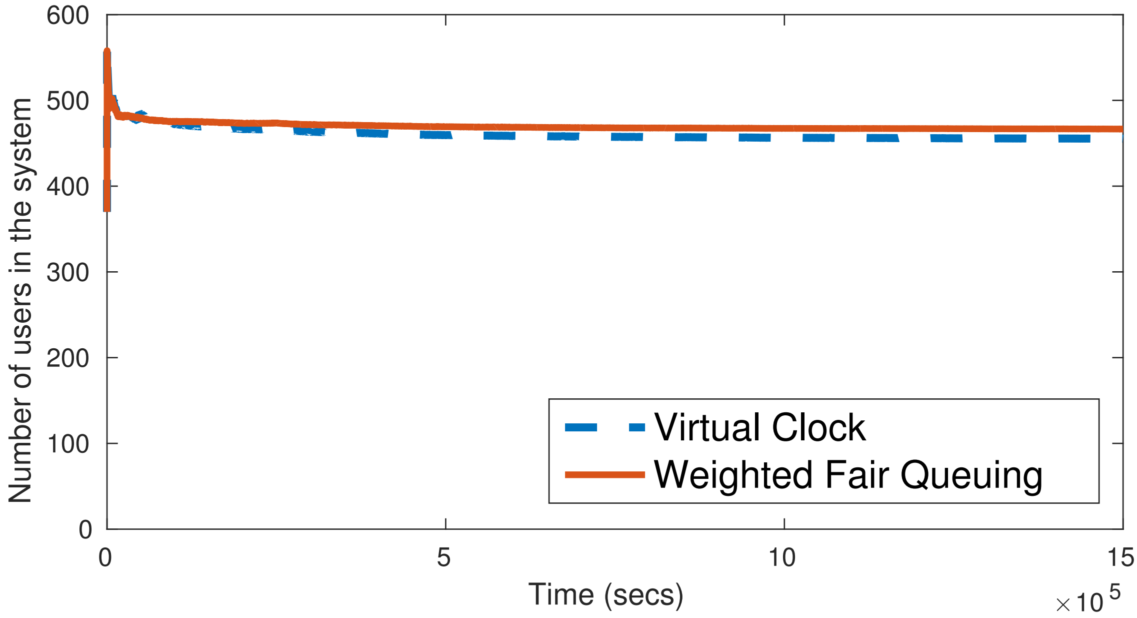

Figure 5.28: Convergence of virtual clock and weighted fair queuing algorithm with time.

In Figure 5.28, it is observed that the number of users in the system converges with time in both virtual clock weighted fair queuing algorithm. This fast convergence ensures bounded user delay in the system. We conclude, that the proposed hierarchical resource allocation algorithm adapts to the network load variation at each eNB along with the demand variation at the operator level.

5.6 Conclusions

In this chapter, we have modeled the spectrum sharing problem as hierarchical resource allocation problem. In the first stage the SM allocates resources to the operators according to their demand. After this in the second stage, operators distribute the allocated resources among its eNBs which in turn serves the end users. We have presented two algorithm which can be implemented at SM for dynamic resource allocation to the operators based on their demand. We analyzed the performance of these algorithm and concluded that both algorithm performs equally fair resource allocation and quickly adapts to the network load variation.

Chapter 6

Conclusions and Future Work

6.1 Summary

We have discussed the problem of poor broadband penetration in rural areas of developing countries. The TV white space scenario in developing countries is much unlike those in developed countries. The availability of underutilized spectrum in sub-GHz TV UHF band is significant in these countries in contrast to developed countries where only sporadic spectrum gaps are available. In this report, we have explored the application of sub-GHz TV UHF band for middle mile access to provide broadband to rural areas. We have proposed a *middle mile* LTE-A network operating in sub-GHz TV UHF band. For single operator deployment, we have designed a network planning tool based on Genetic Algorithm. Further, assuming *registered shared access* as one the possible regulation scheme, we have studied multi-operator spectrum sharing with (a) static network load and (b) dynamic network load.

For static network load case, we have presented a centralized graph theory based channel allocation algorithm with a novel concept of allocating a combination of shared and dedicated channel to an eNB. We have assumed that the operators share their topology information with the SM. The performance of the algorithm is studied using ns-3 simulations. The results demonstrate that it increases both the spectral efficiency and the fairness among operators in a network. We have also compared the obtained average throughput with the throughput demand generated by a typical rural setting. We note that the proposed scheme easily meets the throughput demand generated in a rural area.

For dynamic network load case, we have modeled the spectrum sharing problem as hierarchical resource allocation problem. In the first stage the SM allocates resources to the operators according to their demand. After this in the second stage, operators distribute the allocated resources among its eNBs which in turn serves the end users. In order to incorporate the dynamism of network load, we have presented a novel idea of resource allocation in the terms of orthogonal time and frequency (TF) blocks. We have presented two algorithm which can be implemented at SM for dynamic resource allocation to the operators based on their demand. The first algorithm is based on the concept of virtual clock algorithm and the second is based on weighted fair queuing algorithm. We analyzed the performance of these algorithm and concluded that both algorithm performs equally fair resource allocation and quickly adapts to the network load variation. We have modeled the second stage of resource allocation as an optimization problem which maximizes the minimum resources allocated to each eNB in an operator's network. Due to the time complexity of the optimization problem it is not feasible to solve it for larger network, hence we have presented a graph theory based multi-coloring algorithm for allocating resources to the eNBs. We have assessed the performance of proposed algorithm by modeling various scenarios in MATLAB. The results shows that the proposed algorithm ensures efficient spectrum utilization along with fair spectrum sharing for dynamic load scenarios. Also, this algorithm enables SM to penalize the operators which asks for fake demand, hence encouraging the operators to ask for true demand.

6.2 Future Work

In this work, we have demonstrated that the proposed virtual clock based algorithm makes system immune to the fake demand scenarios and thus allows the SM to penalize such operators. In order to penalize the operator, the SM has to choose a threshold parameter. We have assumed this parameter as constant in this work. The proper tunning of this parameter needs to be investigated further for different use cases. We discuss one such use case here. An operator can predict its virtual clock value as the virtual clock of each operator is independent of other operators. Using this information it can predict the threshold value also. Now, the operator may generate fake demand in such a way that its virtual clock doesn't exceed by threshold value. Thus, by generating fake demand in controlled way, an operator can make this fair resource allocation algorithm to fail. Here, all this is possible because of independent nature of virtual clock. In order to avoid such scenarios, other techniques like Random Early Drop (RED), needs to be explored to make the system more robust.

Bibliography

[1] L. Zhang, "Virtual clock: A new traffic control algorithm for packet switching networks," in *In Proc. ACM SIGCOMM*, pp. 8–18, 1990.

[2] A. K. Parekh and R. G. Gallager, "A generalized processor sharing approach to flow control in integrated services networks-the multiple node case," in *INFOCOM '93. Proceedings.Twelfth Annual Joint Conference of the IEEE Computer and Communications Societies. Networking: Foundation for the Future, IEEE*, pp. 521–530 vol.2, 1993.

[3] "`https://in.mathworks.com/products/matlab.html`."

[4] "`http://www.broadbandcommission.org/documents/reports/bb-annualreport2016.pdf`."

[5] "`http://www.trai.gov.in/WriteReadData/PIRReport/Documents/Indicator-Reports-Mar12082015.pdf`."

[6] A. Kumar and A. Karandikar and G. Naik and M. Khaturia and S. Saha and M. Arora and J. Singh, "Toward enabling broadband for a billion plus population with TV white spaces," *IEEE Communications Magazine*, vol. 54, pp. 28–34, July 2016.

[7] G. Naik and S. Singhal and A. Kumar and A. Karandikar, "Quantitative assessment of TV white space in India," in *2014 Twentieth National Conference on Communications (NCC)*, pp. 1–6, Feb 2014.

[8] "`https://en.wikipedia.org/wiki/Genetic_algorithm`."

[9] A. Alsohaily and E. S. Sousa, "Spectrum sharing LTE-advanced small cell systems," in *2013 16th International Symposium on Wireless Personal Multimedia Communications (WPMC)*, pp. 1–5, June 2013.

[10] Y. Teng and Y. Wang and K. Horneman, "Co-primary spectrum sharing for denser networks in local area," in *2014 9th International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM)*, pp. 120–124, June 2014.

[11] M. Vishram and L. C. Tong and C. Syin, "List multi-coloring based fair channel allocation policy for self coexistence in cognitive radio networks with QoS provisioning," in *2014 IEEE REGION 10 SYMPOSIUM*, pp. 99–104, April 2014.

[12] Wei Wang and Xin Liu, "List-coloring based channel allocation for open-spectrum wireless networks," in *VTC-2005-Fall. 2005 IEEE 62nd Vehicular Technology Conference, 2005.*, vol. 1, pp. 690–694, Sept 2005.

[13] H. Kamal and M. Coupechoux and P. Godlewski, “Inter-operator spectrum sharing for cellular networks using game theory,” in *2009 IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 425–429, Sept 2009.

[14] B. Singh and K. Koufos and O. Tirkkonen and R. Berry, “Co-primary inter-operator spectrum sharing over a limited spectrum pool using repeated games,” in *2015 IEEE International Conference on Communications (ICC)*, pp. 1494–1499, June 2015.

[15] “https://www.nsnam.org.”

[16] Jain, Kamal and Padhye, Jitendra and Padmanabhan, Venkata N. and Qiu, Lili, “Impact of Interference on Multi-hop Wireless Network Performance,” in *Proceedings of the 9th Annual International Conference on Mobile Computing and Networking*, MobiCom ’03, (New York, NY, USA), pp. 66–80, ACM, 2003.

[17] “http://www.3gpp.org/technologies/keywords-acronyms/101-carrier-aggregation-explained.”

[18] “https://portal.3gpp.org/desktopmodules/Specifications/SpecificationDetails.aspx?specificationId=2579.”

[19] M. Hata, “Empirical formula for propagation loss in land mobile radio services,” *IEEE Transactions on Vehicular Technology*, vol. 29, pp. 317–325, Aug 1980.

[20] “http://www.etsi.org/deliver/etsi_ts/136100_136199/136104/11.02.00_60/ts_136104v110200p.pdf.”

[21] Mohammad R Salavatipour, “On sum coloring of graphs,” *Discrete Applied Mathematics*, vol. 127, no. 3, pp. 477 – 488, 2003.

[22] Amotz Bar-Noy and Magns M. Halldrsson and Guy Kortsarz and Ravit Salman and Hadas Shachnai, “Sum Multicoloring of Graphs,” *Journal of Algorithms*, vol. 37, no. 2, pp. 422 – 450, 2000.

[23] F. Xu, Y. Li, H. Wang, P. Zhang, and D. Jin, “Understanding mobile traffic patterns of large scale cellular towers in urban environment,” *IEEE/ACM Transactions on Networking*, vol. 25, pp. 1147–1161, April 2017.