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Resource Allocation in TV White Space Network Using a Novel Hybrid Firefly Algorithm

BY

Ronoh Kennedy Kibet

SUPERVISORS: DR. GEORGE KAMUCHA AND DR. TONNY OMWANSA

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Dedication

I dedicate this work to my lovely wife Verah. Thank you for your love, support and understanding my absences when I would go and spend long hours studying. I also dedicate this work to my son Lemuel Kimutai.

I also dedicate this work to my parents Mr. James Bii and Mrs Grace Bii. Thank you for your support and encouragement.

Declaration

This dissertation is my original work. It has not been presented for an award of a degree in any other university. No part of this thesis can be reproduced without the prior permission of University of Nairobi.

Ronoh Kennedy Kibet

Signature ____________________ Date __________________

This thesis has been submitted for examination with our approval as university supervisors:

Dr. George Kamucha

Signature ______________________ Date _______________________

Dr. Tonny Omwansa

Signature ______________________ Date _______________________

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Abstract

There is continued increased demand for dynamic spectrum access of TV White Spaces (TVWS) due to growing need for wireless broadband. Some of the use cases such as cellular (2G/3G/4G/5G) access to TV white spaces (TVWS) may have a high density of secondary users (SUs) that want to make use of TVWS. When there is a high density of secondary users in a TV white space network, there is possibility of high interference among SUs that exceeds the desired threshold and also harmful interference to primary users. Optimization of resource allocation (power and spectrum allocation) is therefore necessary so as to protect primary users against harmful interference and to reduce the level of interference among secondary users. Existing resource allocation optimization algorithms for a TVWS network ignore interference among SUs, use algorithms that are not computationally efficient with regard to running time or apply greedy algorithms which result in sub-optimal resource allocation.

In this study, an improved resource allocation algorithm based on hybrid firefly algorithm, genetic algorithm and particle swarm optimization (FAGAPSO) has been designed and its performance analyzed for power allocation, spectrum allocation as well as joint power and spectrum allocation. FAGAPSO is a hybrid firefly algorithm that uses final solution of PSO as its initial solution and applies particle swarm optimization concept of p_{best} and g_{best} in firefly movement as well as genetic algorithm's concept of crossover. A continuous optimization version of FAGAPSO has been applied for power allocation while a binary optimization version of FAGAPSO has been applied for spectrum allocation. A binary-continuous optimization version of FAGAPSO has been applied for joint power and spectrum allocation. For joint power and spectrum allocation, firefly algorithm was modified to solve a binary-continuous optimization problem since power allocation is a continuous optimization problem while spectrum allocation is a binary/discrete optimization problem.

Simulation was done using Matlab. The simulation environment in Matlab was developed from scratch. Cellular network offload to TV white spaces use case was considered. TVWS channels available in Nairobi CBD were considered in the simulation setup. Simulation results show that, compared to firefly algorithm, particle swarm optimization and genetic algorithm, the hybrid algorithm is able to improve the primary user signal to interference noise ratio, secondary users sum throughput and secondary users signal to interference plus noise ratio in a TV white space network. Only one algorithm considered, Spatial Adaptive Play, has better primary user signal to interference noise ratio, secondary user sum throughput and secondary user signal to interference noise ratio in a TV white space network but it has poor running time.

Keywords: *TV white spaces, cognitive radio, resource allocation, power allocation, spectrum allocation, joint power and spectrum allocation, firefly algorithm, hybrid firefly algorithm, genetic algorithm, particle swarm optimization.*

Table of Contents

List of Tables

List of Algorithms

List of Figures

List of Abbreviations and Acronyms

1G	1st Generation Networks
2G	2nd Generation Networks
3G	3rd Generation Networks
4G	4th Generation Networks
5G	5th Generation Networks
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AP	Access Point
ARPU	Average Revenue Per User
BLP	Binary Linear Programming
BPSK	Binary Phase Shift Keying
BS	Base Station
BSD	Broadcast Signal Distributors
BSS	Basic Service Set
BTS	Base Transceiver Station
CAQ	Channel Availability Query
CPE	Customer Premise Equipment
CR	Cognitive Radio
CRS	Cognitive Radio System
CSGC	Color Sensitive Graph Coloring
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance
CSMA/CD	Carrier Sense Multiple Access with Collision Detect
CVS	Contact Verification Signal
D/U	Desired to undesired ratio
DSA	Dynamic Spectrum Access
DSRC	Dedicated Short Range Communication
DTT	Digital Terrestrial TV
EA	Evolutionary Algorithm
ECC	European Communications Commission

ECMA	European Computer Manufacturers Association
EIRP	Effective Isotropic Radiated Power
FA	Firefly Algorithm
FAGAPSO	Hybrid firefly algorithm, genetic algorithm and particle swarm optimization
FAPSO	FA with initial solution of PSO
FAPSO1	FA with PSO operators
FAPSO2	FA with initial solution of PSO as well as PSO operators
FCC	Federal Communications Commission
FDMA	Frequency Division Multiple Access
FSA	Fixed Spectrum Access
GA	Genetic Algorithm
GLDB	Geo-location Database
IEEE	Institute of Electrical and Electronic Engineers
IETF	Internet Engineering Taskforce
IoT	Internet of Things
I-SMART	Interference aware Single or Multiple Accumulative Removal Technique
I-SMIRA	Interference aware Stepwise Maximum Interference Removal algorithm
ITU	International Telecommunication Union
LTE	Long Term Evolution
M2M	Machine to Machine Communications
MAC	Media Access Control
MAC	Media Access Control
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
NP	Non-deterministic Polynomial-time
NRA	National Regulatory Authority
OfCom	Office of Communication (UK)
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Acess
PAWS	Protocol Access to White Spaces
PMSE	Program Making and Special Events
PHY	Physical Layer

PSO	Particle Swarm Optimization
PT	Primary Transmitter
PU	Primary User
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RLSS	Registered Location Secure Server
SI	Swarm Intelligence
SINR	Signal to Interference Noise Ratio
SC	Secondary Cell
SCM	Single Carrier Modulation (SCM)
SDR	Software Defined Radio
SM	Spectrum Manager
SMART	Single or Multiple Accumulative Removal Technique
SMIRA	Stepwise Maximum Interference Removal algorithm
SNR	Signal to Noise Ratio
STA	Station
SAP	Spatial Adaptive Play
SU	Secondary User
TDMA	Time Division Multiple Access
TVWS	TV White Spaces
UHF	Ultra High Frequency
V2V	Vehicle to vehicle communication
VHF	Very High Frequency
WLAN	Wireless Local Area Networks
WRAN	Wireless Regional Area Network
WRC	World Radio Congress
WSD	White Space Device
WSM	White Space Map

Chapter 1: Introduction

1.1 Background

Spectrum access can either be fixed or dynamic. In Fixed Spectrum Access (FSA), the PU is granted permission to exclusively use the frequency band allocated and that frequency band cannot be varied during the period in which the license is valid. With Dynamic Spectrum Access (DSA), spectrum allocated for exclusive use to a primary user (PU) but not used by the PU, or any other idle frequency bands (such as guard bands) can be shared by different Secondary Users (SUs) as long as the interference to the incumbent (PU) by the SUs is kept to an acceptable level (Kennedy et al., 2017; Ronoh et al., 2018). DSA is a spectrum access technique in which the frequency band of operation can be changed automatically by devices with cognitive radio (CR) functionality. CR has been defined by ITU as a radio system that can scan its environment and be able to dynamically change the transceiver operating parameters such as channel of operation or transmit (ITU, 2009).

The main shortcoming of FSA is that it leads to poor utilization of radio spectrum due to different usage across various geographical regions and in different time periods (Ronoh et al., 2018). Spectrum occupancy evaluation done in various countries show that a large proportion of spectrum allocated to particular PUs is not being used (Arato and Kalecha, 2013; Mehdawi et al., 2013; Patil et al., 2011). Increasing number of devices want a pie of the spectrum and yet the usable spectrum is limited. DSA, through the use of CR is currently being embraced as a solution to these two problems of spectrum underutilization and spectrum scarcity (Kennedy et al., 2017; Ronoh et al., 2018). This is because DSA together with CR provide an efficient way for spectrum management and spectrum sharing.

Fig 1.1 shows an example of spatial reuse of spectrum between PUs and SUs. Here the primary transmitters (PTs) are the television (TV) transmitters. As can be seen from the diagram, there is an exclusion (or protection) zone around the PTs where the channel that is being used by the TV transmitter cannot be used by SUs. r_1 , r_2 , r_3 are the radii of TV transmitter coverage area. This is necessary so as to protect PUs against harmful interference.

In the diagram, the TV receivers are the PUs. The TV receivers are the ones to be protected from harmful interference. Other examples of PUs are radars and wireless microphones (Safavi-Naeini et al., 2015). Secondary Cell (SC) refers to a network of SUs under the control of one base station.

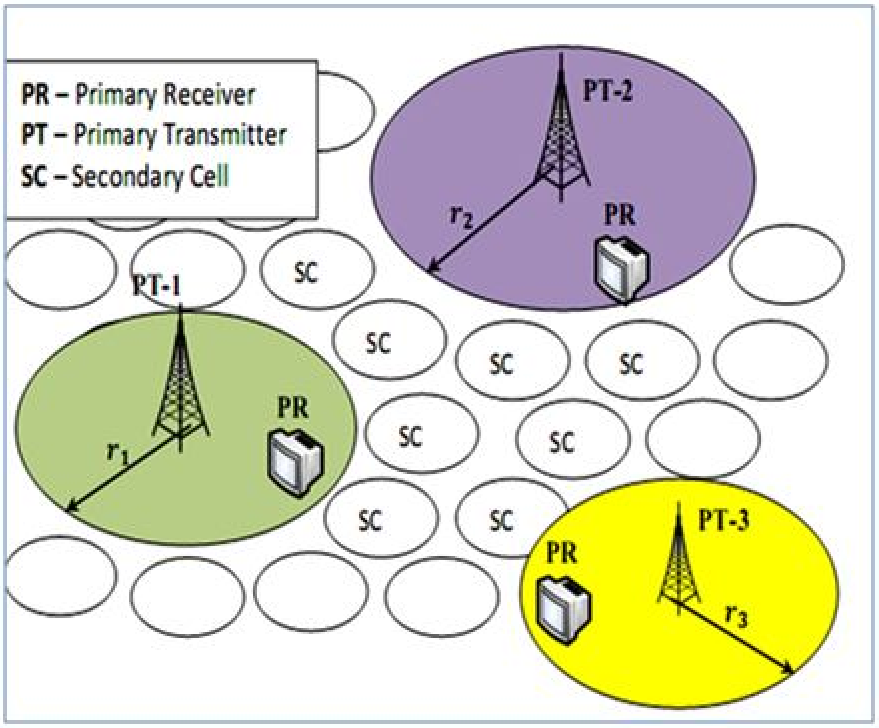

Figure 1.1: Spatial reuse of spectrum between PU and SU

Incumbent Protection

There are three main methods for incumbent (PU) protection against harmful interference: use of beacons, spectrum sensing and geo-location database (GLDB) (Nekovee et al., 2012). With the beacon method, a dedicated channel is used to give information about channels that are available for secondary use to White Space Devices (WSDs). The WSD will only transmit if it gets a beacon from a base station granting it permission to transmit in specific channels (Mangold et al., 2006). The WSD will continue to use specific channels until it receives a beacon disabling transmission in those channels. The main drawback of the beacon method is that it requires a beacon infrastructure in form of base stations to be rolled out. With spectrum sensing, the WSD uses a sensing algorithm to find out whether there is a signal from a PU in a particular channel (Nekovee et al., 2012). If a PU signal is detected on a particular channel, then the channel will not be used by the WSD. The cognitive radio system (CRS) of the WSD continuously detects current usage of the spectrum so as to know which channel is available for secondary use. The main drawback of this method is that it suffers from hidden node problem whereby an SU fails to detect nearby PUs transmissions. Spectrum sensing also do not utilize spectrum efficiently because of large protection margins required for incumbent protection (Gurney et al., 2008). GLDB is considered a better technique because it overcomes the shortcomings of the two other methods of incumbent protection (Nekovee et al., 2012). GLDB is used by a WSD to find the set of frequency channels that can be used on a secondary basis at a given area and at any given time. GLDB is populated through the use of a propagation model. The database contains estimated power levels of PUS for any point in a particular region of interest. The WSD queries a central database. The WSD provides the database with parameters such as its location, device type and antenna height. The GLDB will then use this information along with the parameters of all surrounding TV transmitters such as antenna height, transmit power and frequency of operation in order to come up with the list of available TV White Spaces (TVWS) channels that can be used by the WSD on secondary basis without causing harmful interference to the PUs. The GLDB will also give the WSD limits on the transmit power and also the time period in which each channel can be used.

TV White Spaces

TVWS is the spectrum band not being utilized by TV transmitters in the UHF and VHF band. Some of the TV spectrum has been freed by digital migration. The spectrum band which has attracted a lot interest in the DSA community is the TVWS. The main reason for this is the good propagation characteristics of the sub-1GHz spectrum (Cristian Gomez, 2013). These frequencies propagate far longer distances than that which is currently used by WiFi or WiMax. Another reason for the interest in the TV spectrum is the rather fixed and predictable spectrum assignment to TV transmitters.

TVWS, together with DSA through the use of CR devices, offers a big promise in improving broadband connectivity in developing countries (Kennedy et al., 2015). One TVWS base station is capable of serving a large area (Rural Broadband TVWS Trial in Laikipia County, Kenya, 2014). This reduces the number of required base stations resulting in lower cost of deploying a TVWS network compared to Wi-Fi or WiMax. The technology, therefore, is able to offer a lower cost of broadband access. Fig. 1.2 shows a typical TVWS network that is used for provision of wireless broadband internet. TVWS trials have been launched in South Africa (Steven, 2013), Kenya (Rural Broadband Trial, Laikipia County, Kenya: Summary findings of 12 month trial of television white spaces technologies; 2014.), Malawi (Mikeka et al., 2014), Tanzania, Ghana and many other countries worldwide. Trials have been conducted to demonstrate that TVWS technology can be used to deliver cheaper broadband services and to increase awareness of the potential of TVWS technology. Speeds of up to 16 Mbps on a single 8 MHz TV channel at distances of up to 14 kilometers were achieved in a trial in Laikipia, Kenya (Rural Broadband Trial, Laikipia County, Kenya: Summary findings of 12 month trial of television white spaces technologies; 2014.). In South Africa, a TVWS trial in Cape Town in 2013 achieved average downlink throughput, a peak downlink and uplink throughput of 2.58 Mbps, 10 Mbps and 2.7 Mbps, respectively (Steven, 2013).

Other use cases for TV white spaces are 4G (Silva et al., 2011), 5G(Chávez-Santiago et al., 2015; Demestichas et al., 2013), internet of things(IoT) (Martínez-Pinzón et al., 2016; Bedogni et al., 2013; Aijaz and Aghvami, 2015) and vehicle to vehicle communications (Adalian et al., 2014; Dawood et al. 2014; Doost-Mohammady and Chowdhury, 2012). Details of these use cases are presented in detail in Chapter 2.

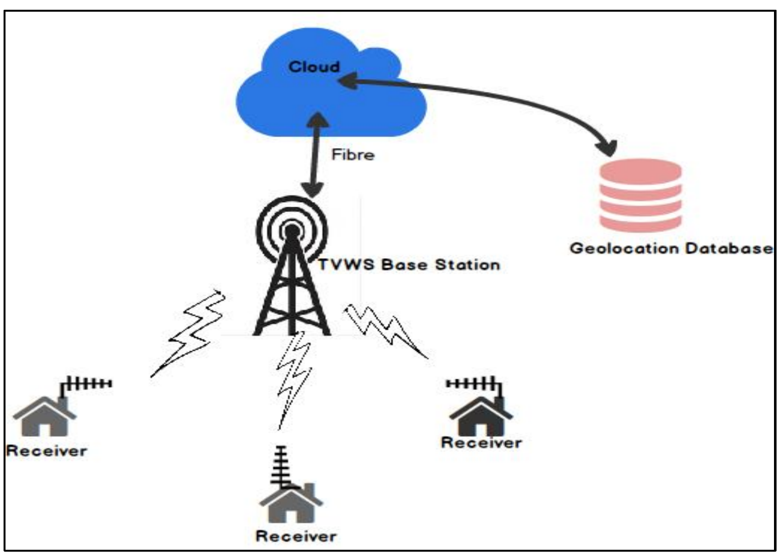

Figure 1.2: Typical TVWS network used for wireless broadband provision.

Resource Allocation in TV White Spaces

Interference becomes a major challenge in scenarios where there is a dense deployment of SUs in a TVWS network. PUs have to be protected against harmful aggregate interference from SUs. Since SUs share channels, there is need to control mutual interference among SUs so as to ensure that minimum quality of service (QoS) requirements in terms of Signal to Interference plus Noise Ratio (SINR) is met. Interference can be controlled through optimal assignment of both power and spectrum (channels) to SUs. Therefore there is need for an algorithm to optimize power and spectrum assignment to SUs. Assignment of spectrum and power to SUs is referred to as resource allocation.

Most of TVWS regulations such as those of FCC and OFCOM currently focus on assignment of channels and associated maximum power to single SUs. FCC specifies fixed maximum power to SUs and also specifies that there should be separation distance between SU and the protection zone. OFCOM allows for flexible power limits based on location probability. Currently existing IEEE standards for TVWS also focus on resource allocation to single SUs. IEEE 802.11af makes use of open loop and closed loop power control. With open loop power limitation the WSD has rigid power limitation similar to those provided by FCC regulations. In closed loop power limitation, the WSD has a more flexible power limits that depends on location, time of use and the channel. IEEE 802.22 specifies that power of Customer Premise Equipment (CPE) will be reduced in case there is interference to PU. One by one resource allocation as specified in the FCC and OFCOM TVWS regulation as well as TVWS IEEE standards will result in high interference among SUs as they do not consider interference among SUs and they do not also consider the impact of aggregate interference from SUs to PUs.

GLDB based spectrum allocation with power control mutual interference among considerations has been proposed by Xue et al. (2014). The first major disadvantage of the algorithm is that it is a greedy heuristic algorithm. Secondly, the algorithm is also designed to allocate resources one by one as SUs make request to GLDB. It is not designed to optimize resource allocation for all SUs in a network. These two features result in sub-optimal resource allocation.

GLDB based spectrum allocation with power assignment for TVWS multiple device-to-device links has also been proposed by Xue and Wang (2015). The algorithm has the following disadvantages. Firstly, the algorithm ignores adjacent channel interference. PUs may be interfered because of underestimation of interference. Secondly, the iterative power allocation algorithm makes the algorithm have high running time because it will have many iterations.

1.2 Problem Statement

It is expected there will be continued demand for DSA. There is increased demand for DSA to TVWS from vehicle to vehicle communications, 5G, 4G and IoT. This will result in secondary networks with a high density of users that will result in a problem of interference. TVWS can be used by SUs as long as the aggregate interference to the PU does not exceed a certain threshold. In a network where there is high number of devices seeking access to a secondary network, allocation of resources (power and spectrum) has to be optimized to ensure that interference constraints for PUs and QoS requirements for SUs are met.

Existing algorithms can get trapped in local optimum or allocate spectrum and power in a one by one, greedy, heuristic manner as SUs make request to the GLDB. This will result in sub-optimal resource allocation. Existing algorithms also have poor time efficiency or ignore interference among SUs. There is therefore need for an improved but efficient algorithm that can be used to optimize spectrum and power allocation for all existing users in the secondary network so as to improve throughput and SINR for SUs, maximize number of users with minimum SU SINR, and ensure minimum QoS/interference constraints at PUs are met.

1.3 Research Question

The research question of the study was as follows: "How much increment in terms throughput for secondary users and quality of service as measured by Signal to Interference plus Noise Ratio for primary users and secondary users in a geo-location database based TV White Space network with a high density of users can be achieved by using an improved algorithm to optimize spectrum and power allocation for all existing secondary users in the network?"

1.4 Research Objectives

The objectives of this study were:

1. To demonstrate the inefficiency of existing joint power and spectrum allocation algorithms.
2. On the basis of the outcome of objective 1, develop a potentially improved and efficient algorithm for optimization of power and spectrum allocation in a geo-location database based TV White Space network.
3. To evaluate the performance of the algorithm developed in 2 above.

1.5 Justification

This thesis is about designing an improved algorithm for optimization of resource allocation in a TVWS network. There has been continuous research ever since the idea of software defined radio (SDR) was proposed by Joseph Mitola in 1999 (Mitola and Maguire, 1999). It is only about a decade later that the research matured and there were then commercial applications. There are currently a number of use cases of DSA, CR and SDR. Examples of use cases are cellular networks, Internet of Things (IoT) including machine to machine (M2M) communications, rural broadband access and vehicle to vehicle communications.

As noted earlier, DSA is one of the solutions to spectrum underutilization and spectrum scarcity. DSA allows the use of underutilized spectrum with the constraint that PUs are not interfered with. Due to increased number of use cases there is need to make efficient use underutilized spectrum. Hence there is need for improved and more efficient algorithms for resource allocation in a TVWS network. In order to achieve this, there has been research on optimization of resource allocation in TVWS networks. A lot of focus has been on power allocation optimization only or spectrum allocation optimization only for GLDB based TVWS networks. There is need for joint optimization of both power and spectrum to attain more efficient use of TVWS so as to allow more devices to access TVWS. Some use cases such as cognitive access to TVWS by cellular networks have dense users in some areas that can be offloaded to TVWS. Therefore there is need to optimize resource allocation in dynamic access of TVWS even better in order to allow SUs to enjoy higher data rates while ensuring protection of PUs.

1.6 Significance

The output of this thesis can be of benefit to: GLDB service providers, TVWS service providers, cellular network providers, telecommunication regulatory authorities, IoT companies.

There have been considerations for cognitive access to TVWS by cellular (2G/3G/4G/5G) due to many subscribers with limited spectrum. Cellular companies have to pay a lot of money for spectrum. By making more efficient use of TVWS that they can access, call block rates can be lowered and users can access higher data rates without the need to buy more spectrum.

GLDB service providers such as Google or Microsoft can also incorporate the algorithm in the databases. Companies/organizations that subscribe to their database can then make more efficient use of TVWS.

IoT companies can also benefit from the algorithm. Currently there are more and more applications of IoT that will require more spectrum. There is an increased need, therefore, to optimize power and spectrum allocation to ensure that there is more efficient use of TVWS to allow more IoT devices to make use of TVWS.

The algorithm can also inform policy by national or international telecommunication organizations (e.g ITU). The regulatory agencies may require that users of TVWS perform not just spectrum or power allocation optimization but joint power and spectrum allocation in order to ensure that there is more efficient use of TVWS.

1.7 Scope of Study

In order to reduce complexity, algorithms developed consider a GLDB based TVWS secondary network under one base station i.e one cell and interference protection for a single primary user. For the same reason, fading was not considered. Failing to consider fading will not have a significant effect on the performance of the algorithms.

1.8 Thesis Organization

The remainder of the thesis is organized as follows. Literature review is presented in Chapter 2. Methodology has been elaborated in Chapter 3. Chapter 4 presents the results and an analysis of the results. The thesis is concluded in Chapter 5.

Chapter 2: Literature Review

Spectrum management has a number of stakeholders. They include spectrum standards bodies, telecom infrastructure providers, service providers, regulatory authorities, handset providers, government spectrum users, academic and industrial research organizations among others (Matinmikko et al., 2014). At the international level, International Telecommunication Union Radiocommunication (ITU-R) is responsible for global harmonization of spectrum allocation. This is done through World Radio Congresses (WRCs) that are held every four years (Matinmikko et al., 2014; Cristian Gomez, 2013). There are also regional bodies that ensure that ITU-R spectrum allocations are adhered to and that there is harmonization across a specific region. There are six regional spectrum regulatory groups recognized by International Telecommunicaiton Union (ITU). They are Asia Pacific Telecommunity (APT), Africa Telecommunications Union (ATU), Regional Commonwealth in the field of Communications(RCC), the InterAmerican Telecommunication Commission (CITEL), Arab Spectrum Management Group (AMSG) and European Conference of Postal and Telecommunications Administrations (CEPT). At the national level, spectrum management is under a National Regulation Authority (NRA). The work of NRAs is to regulate spectrum use in a country. This authorization has to be in line with ITU-R regulations. Examples of NRAs are Communication Authority of Kenya (CAK), FCC (USA), Ofcom(UK) and ICASA (South Africa). The main role of NRAs is to come up with national table of frequency allocation that specifies radio services for different frequency bands and entities that have rights to access them. NRAs also ensure that there is proper co-existence among the entities that use different frequency bands.

Due to increased demand for wireless broadband services, radio spectrum has become a scarce resource. Fixed spectrum allocation done by NRAs leave a lot of spectrum underutilized. Spectrum occupancy evaluation done in Kenya (Arato and Kalecha, 2013) , UK (Mehdawi et al., 2013), Spain (Patil et al., 2011), Singapore (Patil et al., 2011), Germany (Patil et al., 2011) and New Zealand (Patil et al., 2011) show that a large proportion of spectrum allocated to certain PUs is not being used. In fixed spectrum allocation only the user that has a license to certain spectrum band can make use of that spectrum band. This is specified in the national frequency allocation table. No other entity is allowed to access the spectrum for the duration in which the license is valid. Licenses are granted through auction, administrative or incentive pricing schemes (Cristian Gomez, 2013). Another way to access spectrum is the commons like approach when access to spectrum is open to anyone.

The idea of secondary use of spectrum was proposed so as to allow SUs make use of unoccupied spectrum by PUs with the condition that PUs are not interfered with. Secondary access to spectrum is also known as DSA. TVWS is the spectrum which is particularly attractive because of its static frequency planning and good propagation characteristics. As noted in Chapter 1, TVWS is the spectrum band not being utilized by TV transmitters in the UHF and VHF band.

SUs must have CR so as to make use of TVWS. The idea of CR was first proposed by Mitola and Maguire nearly 20 years ago (Mitola and Maguire, 1999). It is only a few years that cognitive radio research has matured into commercial applications, with the first one being TVWS devices. Cognitive radio systems (CRSs) was an agenda item in WRC-12 (Matinmikko et al., 2014). It was resolved that CRSs do not necessitate any change in radio regulations (RR).

License-exempt access and licensed shared access are the two major DSA regulation frameworks (Masonta et al., 2013; Matinmikko et al., 2014). Under License-Exempt Access (LEA), network devices can access and share spectrum anywhere and anytime without guarantee of quality of service (QoS) as long as they meet certain technical conditions and requirements (Masonta et al., 2013; Matinmikko et al., 2014) This approach has been successful in 2.4 GHz and 5 GHz of Wi-Fi. With Licensed Shared Access (LSA) or Authorized Shared Access (ASA), the incumbent or licensed primary user (PU) shares spectrum with one or more licensed secondary users (SUs) with conditions imposed on both the PU and SUs (Masonta et al., 2013; Matinmikko et al., 2014). The term ASA is commonly used in USA while LSA is used in Europe. One major advantage of ASA or LSA is that the QoS of SUs is predictable if the PU's spectrum use is stable.

TVWS trials have also been done worldwide to demonstrate the use of this technology. Following the success of TVWS trials done worldwide, some NRAs worldwide have already opened up TVWS for DSA. Example NRAs that have opened up TVWS for DSA are FCC, Ofcom and ICASA. Standards have also been developed to make use of this technology. Example standards are IEEE 802.11 af and IEEE 802.22. Already there are many TVWS use cases. Examples include rural broadband access, internet of things, machine to machine communications, cellular networks and vehicle to vehicle communications.

This chapter presents TVWS use cases, TVWS in Kenya, classification of optimization algorithms and review of literature on power allocation in a TVWS network, spectrum allocation in a TVWS network as well as joint power and spectrum allocation in a TVWS network.

2.1 TVWS Use Cases

In this section, TVWS use cases have been discussed. The following applications of TVWS have been discussed: rural broadband access, internet of things and machine to machine communications, vehicle to vehicle communications and cellular networks.

2.1.1 Rural Broadband Access

Internet penetration in Africa was estimated to be 35.2% in 2019 (Wang, 2019). Digital divide in Africa can be bridged by providing affordable internet access. Schools, businesses, libraries and clinics outside major centers or towns do not have reliable access to internet. Wired internet access is either not affordable or not economically viable in some regions in Africa especially the rural areas where the population is sparse. The cost of rolling out fiber optic-based and copper-based last mile access is uneconomical. Internet access through satellite is easier to deploy for remote and rural areas but it is not cost effective. Therefore, wireless technologies are the only conceivably viable solution for providing affordable, reliable and ubiquitous access to internet. Currently high cost of spectrum is a barrier to new entrants who cannot compete with companies that can afford to pay large amounts of money for spectrum (Kennedy et al., 2015). This lessens competition and, as a consequence, keeps the cost of internet access high. The use of TVWS in an unlicensed manner can break this barrier.TVWS trials in Africa have been conducted in Kenya, Malawi, South Africa, Ghana, Tanzania and Namibia. The objectives of the trials were (Steven, 2013):

- To demonstrate that TVWS technology can be used to deliver cheaper broadband services.
- Increase awareness of the potential of TVWS technology, not only in South Africa but also across the continent.
- To demonstrate that frequency bands, where there is very low probability of causing interference to licensed users, can be selected and used on a secondary basis.
- Demonstrate that effective bidirectional communications can occur in TVWS.
- Provide information about costs involved in the technology.
- Provide an indication as to what level of interference is experienced by licensed users and unlicensed users of the spectrum.
- Provide a running database and an assessment whether this is a method that should be used.

In Kenya, Microsoft in conjunction with the Ministry of Information and Communications of Kenya and Indigo Telecom Ltd. piloted the use TVWS for providing cheaper broadband in Laikipia in 2014. The aim of the network was to test the commercial feasibility of TVWS technology in providing low-cost broadband to communities lacking access to broadband internet connectivity (mainly rural areas where 80% of the population lives). The network covers 235 km^2 and provides broadband access to a population of about 20,000 people (three schools, local county government and a few businesses).

In a report on the project submitted to Communications Authority of Kenya (CA) (*Rural Broadband TVWS Trial in Laikipia County, Kenya*, 2014), the partners indicated that the project was extremely successful and that it demonstrated the technical viability of TVWS network. Speeds of up to 16 Mbps on a single 8 MHz TV channel at distances of up to 14 kilometers were achieved with TVWS stations operating at 2.5 Watts EIRP power. TVWS Table 2.1 summarizes the results of the Laikipia (Kenya) TVWs trial. The table shows that throughput of 7.3 Mbps was achieved at distances of up to 13 km from the TVWS base station. This shows that a single TVWS base station can cover a large area unlike WiFi which has a range of tens of meters. TVWS is, therefore, suitable for rural areas.

Table 2.1: Performance of Laikipia (Kenya) TVWS Trial

Distance from BTS(km)	Throughput (Mbps)
0.6	16
1.7	16
5.6	16
7.4	8
12.8	7.3

In South Africa, there have been TVWS trials in Cape Town and rural Limpopo. The main sponsor for the Limpopo trial was Microsoft. Other partners were Meraka Institute (South Africa), University of Limpopo and network builder Multisource. The network provides cheaper access to five secondary schools. The partners for the Cape Town trial were Google, Open Spectrum Alliance, Wireless Access Providers Association, Tertiary Education and Research Network among others (Steven, 2013). The Cape Town Trial network was located at Stellenbosch University's Faculty of Medicine and Health Sciences in Tygerberg. Table 2.2 shows the performance of a TVWS trial in Cape Town (Steven, 2013). The table shows that the mean uplink throughput is 2.75 Mbps and average downlink throughput is 2.58 Mbps. The peak downlink and uplink throughput that was achievable was 12 Mbps and 5 Mbps, respectively. The results of the Kenya and South Africa TVWS trials have demonstrated the technical viability of TVWS for providing rural broadband access.

Table 2.2: Performance of Cape Town TV White Space Trial

Dates	Average Uplink Throughput (Mbps)	Average Downlink Throughput (Mbps)
Mar 28, 2013	2	2
May 25, 2013	3.5	2
Jun 29, 2013	2.6	3
Jul 28, 2013	3	2.5
Aug 23, 2013	2.4	2.2
Sep 25, 2013	3	3.8
Average	**2.75**	**2.58**

2.1.2 Internet of Things and Machine to Machine Communications

The core concept behind Internet of Things (IoT) is that "everyday objects can be equipped with identifying, sensing, networking and processing capabilities that will allow them to communicate with each other and with other devices and services over the internet to achieve some objective" (Atzori et al., 2010). Machine to machine communications, which refers to communication of devices without any human intervention, is an enabling technology for internet of things (Aijaz and Aghvami, 2015). With IoT, high number of connected devices will create a demand for spectrum. Since spectrum is scarce worldwide, DSA and cognitive M2M communications is seen as solution to this problem. Other reasons for making use of DSA for IoT and M2M communications are (Aijaz and Aghvami, 2015):

- **Coverage problems**: Industrial, Scientific and Medical (ISM) band frequencies have limited coverage for certain IoT applications such as smart metering. M2M devices with CR functionality can be able to switch to lower frequency to alleviate the problem of coverage(Woolhouse, 2013).
- **Interference**: When unlicensed spectrum (2.4GHz and 5GHz) is used by a large number of devices, problem of interference is likely to arise(Woolhouse, 2013). There is therefore need to access other bands such as TVWS through DSA.
- **Signaling overhead and range**: Cellular networks can be used for M2M and IoT but they are not suitable because of the following two reasons. Firstly, cellular networks

are not suitable for short messages that are sent during M2M communications (Woolhouse, 2013). Such short messages will result in extremely high signaling overhead. Secondly, 2GHz spectrum band used by 3G and 4G is not suitable for M2M communications because of their relatively short range (Woolhouse, 2013).

2.1.3 Vehicle to Vehicle Communications

Vehicle to vehicle (V2V) communications is designed to allow vehicles to communicate with each other so as to improve road safety. Vehicles with sensors relay warning messages to other vehicles within their range so that drivers are able to know about traffic jam or accidents on the road.

V2V communications applications can be classified into two: safety applications and efficiency/convenience applications (Bilgin and Gungor, 2013). Safety applications of V2V communications include accident warning, lane change warning, blind spot warning, intersection warning and emergency vehicle warning. Efficiency and convenience applications include route guidance systems, transportation congestion management systems, tolling management and fleet control. In addition to V2V communications, there is also vehicle to infrastructure (V2I) communication whereby roadside infrastructure can send advertisements to vehicles or vehicles can pay toll or parking charges (Bilgin and Gungor, 2013). The communication standard for V2V communications is Dedicated Short Range Communications (DSRC). The IEEE standard for DSRC is IEEE 802.11p. DSRC has been allocated 75MHz, 20MHz, 80MHz in the 5GHz spectrum in US, Europe and Japan, respectively (Bilgin and Gungor, 2013). With V2V technology gaining popularity, the allocated spectrum DSRC will not be sufficient. Therefore there is need for additional spectrum through DSA. TVWS is attractive because of the good propagation characteristics and its static allocation (Altintas et al., 2011).

2.1.4 Cellular Networks Offload to TV White Spaces

CR can be used to develop new technologies or to advance current existing technologies. CR radio is also seen as an enabling technology for 5G systems (Demestichas et al., 2013) because it allows the use of different spectrum bands. TVWS has also been considered for wireless backhauling in 5G systems (Siddique et al., 2015). LTE, 2G and 3G are existing technologies that can benefit from CR. DSA of TVWS can be used to expand capacity of 2G/3G/4G because the current spectrum allocation worldwide is not enough to meet demand (Silva et al., 2011). DSA is currently being seen as a solution to address this problem. Offload of cellular networks traffic to TVWS has been considered due to the good propagation characteristics of the VHF/UHF spectrum band. In Kenya, for example, it has been found that there are many dropped and blocked calls during peak times with spectrum shortage being the main cause (Winston et al., 2013). The three mobile service providers in Kenya (Safaricom, Airtel and Telkom) are demanding more of the 700 MHz so as to reduce dropped/blocked calls and to be able to provide faster wireless broadband services (Winston et al., 2013). Offload of cellular traffic to TVWS on a secondary basis will require that spectrum and power allocation is optimized. Through this optimization, interference will reduce. Reduction in interference will result in improved data rates and more devices accessing the unused spectrum thus reducing possibility of call blocks.

2.2 TVWS Use and Availability in Kenya

In Kenya, TVWS has been confined to the frequency ranges of 470MHz to 694 MHz. TVWS devices operate on non-protected, non-interference and non-exclusive basis (Ngige, 2017). Before a TVWS network is installed, the devices have to be approved by CAK. In 2013, CAK granted Microsoft a trial license to operate a TVWS network with the condition that the network does not cause interference. All transmissions must cease until interference is eliminated should there be interference.

Kenya has not allowed unlicensed operation on the TVWS spectrum band. The reason given by CAK is that it was decided in WRC 15 that the UHF band will remain a broadcast band until 2023. CAK directed that any entity that is interested in providing internet through TVWS to do so through Broadcast Signal Distributors (BSDs) and that BSDs are free to seek partnerships with ISPs in providing internet through TVWS. CAK argues that provisioning of internet through TVWS in a license exempt manner like Wi-Fi is not fair to BSDs since they need to recoup their investments. Two BSDs have been given permission by CAK to deploy TVWS networks subject to availability of spectrum in different parts of the country.

Figure 2.1 shows location of TV transmitters in Kenya and their coverage. Fig. 2.2 is the legend for TV coverage. The diagram shows that there is plenty of TVWS in Kenya. There are many areas where there are no TV transmitters. The areas where the received TV signal is blue are also areas where there are white spaces because the TV signal is less than -110dBm. This can also be seen in Fig. 2.3 that show coverage maps for TV transmitters in central Kenya. The two figures were generated by CAK from ICS Telecom radio planning software.

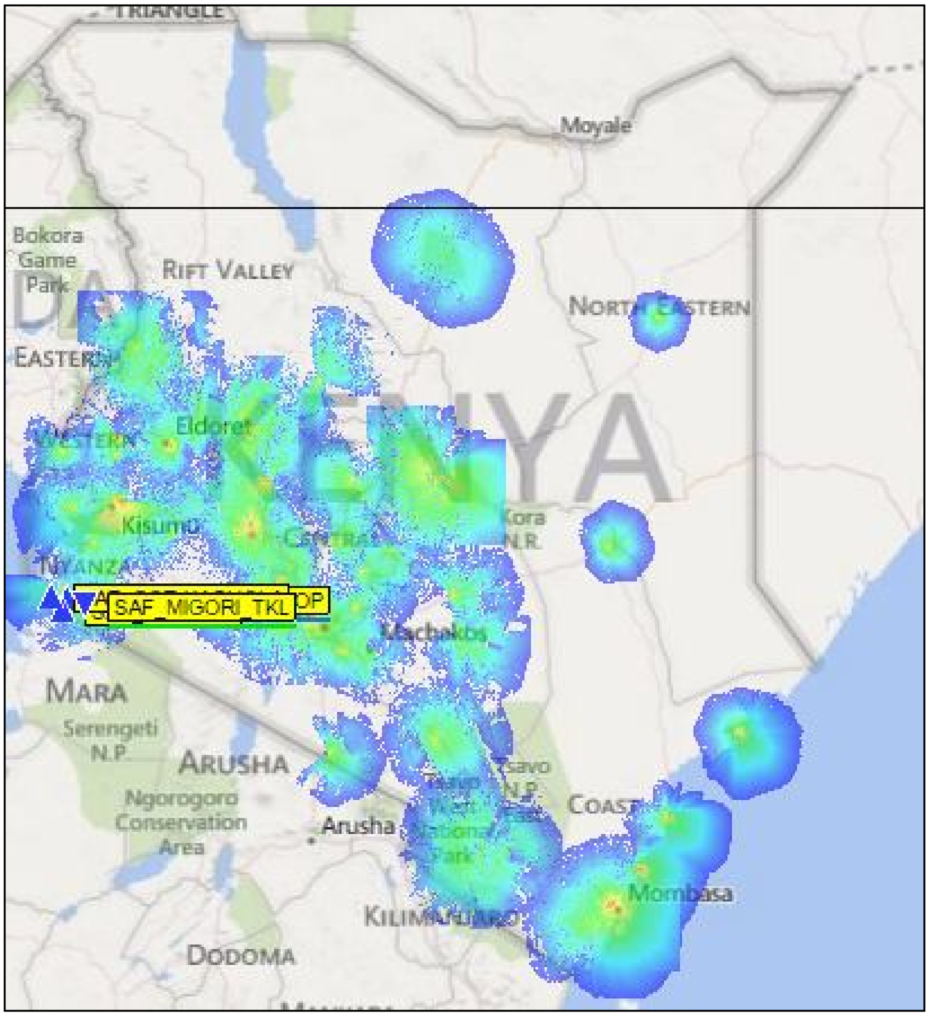

Figure 2.1: TV Transmitters Coverage Map for Kenya

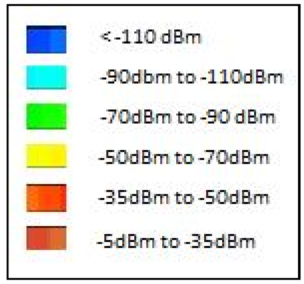

Figure 2.2: TV Signal Received Power legend

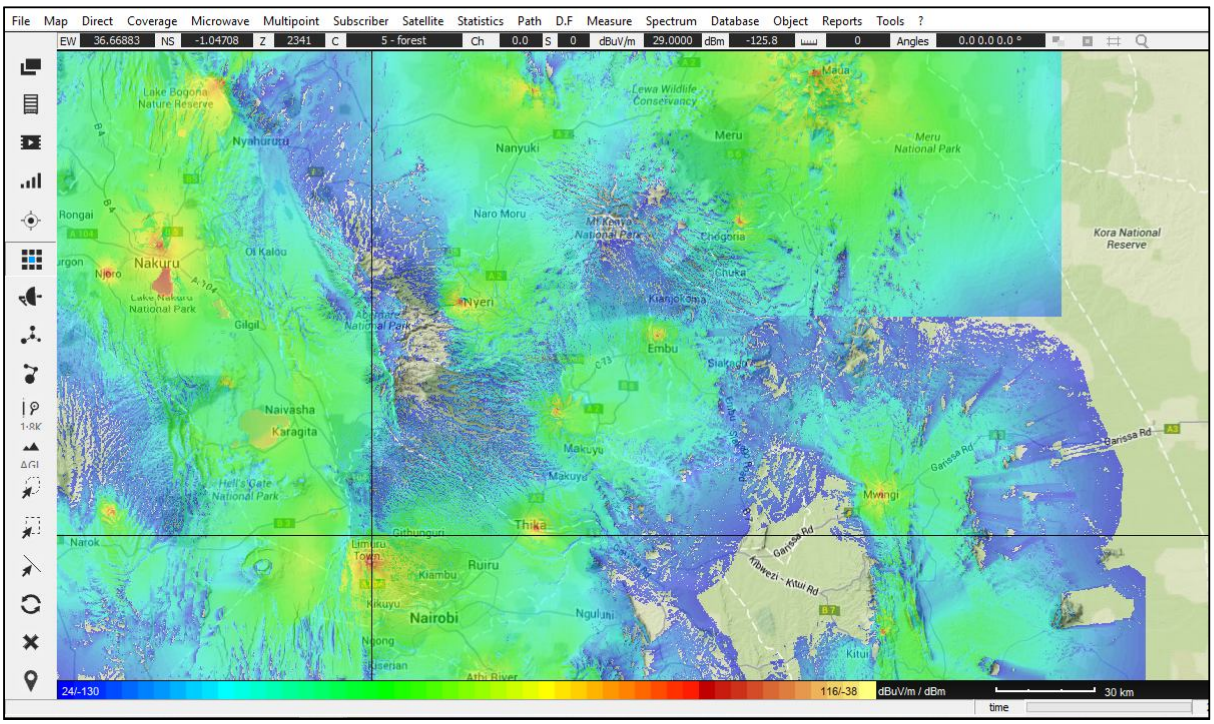

Figure 2.3: TV Transmitters Coverage Map for Central Kenya

2.3 TVWS Regulations

TVWS regulations provide guidelines for WSD power limits and allocation. Different TVWS regulations have been proposed by different countries or regions. There are three main TVWS regulations that have been proposed. They are Federal Communications Commission (FCC), Office of Communications (OFCOM) and European Communications Commission (ECC). FCC, OFCOM and ECC are the bodies tasked with regulation of radio communications in US, UK and Europe, respectively.

2.3.1 FCC Regulations

Under FCC regulations, both sensing and GLDB are specified as the methods for incumbent protection (Nekovee et al., 2012). FCC permits the use of both fixed and portable devices. Fixed devices are allowed maximum transmit power of 4 W while portable devices are allowed a maximum of 100 mW. Fixed devices must contact the GLDB to obtain channel list before operation and it has to recheck the GLDB at least once a day. FCC classifies WSDs as either mode I or mode II. Mode II devices acquire spectrum information from the GLDB and then share with mode I devices. Mode II devices have a GPS and internet connection. Mode I devices do not have internet connection and rely on Mode II devices to get information on available TVWS channels. Portable devices work in either mode I or mode II. If the portable device is operating on adjacent channel, the power should not exceed 40 mW. Sensing-only devices are allowed to operate but the transmit power is limited to 5 0mw. Sensing-only devices have to detect microphones signals with a power of -107 dBm and above.FCC specifies fixed power values for devices while for ECC and OFCOM, the transmission power is not fixed (Nekovee et al., 2012; *ECC Report on Cognitive Radio*, 2011). The use of fixed power limit to WSDs alone is not enough to protect PUs against aggregate interference from multiple SUs. In order to protect PUs against harmful aggregate interference from multiple users, FCC requires that there be a distance of protection around the TV coverage area. This is in addition to required fixed upper limit on transmission power. FCC required protection distances are summarized in Table 2.3. The protection distance depends on antenna height and whether the channel of use is co-channel or adjacent channel. FCC presume that the protection distance is enough to protect TV receivers against harmful aggregate interference (Jäntti et al., 2011). However, the use of protection distances leads to wastage of TVWS.

Table 2.3: FCC Protection Distances

Antenna Height	Required distance from TV coverage contour	
	Co-channel	Adjacent Channel
<3m	6km	100m
3-10m	8km	100m
10-30m	14.4 km	100m

2.3.2 *OFCOM Regulations*

Like FCC regulations, OFCOM provide regulations for both GLDB and spectrum sensing (Nekovee et al., 2012). OFCOM saw the benefit of both GLDB and spectrum sensing. Under OFCOM regulations, there are two types of devices: master device and slave device. Unlike FCC which specifies fixed transmit power, OFCOM allows more flexible WSD transmit power. The power is determined by the device and for each TVWS channel based on the specified levels of protection to Digital Terrestrial TV (DTT) and Program Making and Special Events (PMSE) devices. No resource allocation algorithm is provided.

2.3.3 *ECC Regulations*

ECC regulations are similar to those of OFCOM (Nekovee et al., 2012). The regulations were published in a report called Technical and Operational Requirements (*ECC Report on Cognitive Radio*, 2011). ECC regulations do not provide for protection distance for interference protection. ECC regulations instead specify certain location related power constraints. ECC regulations instead provides a link budget margin that should cater for the effects for aggregate interference from multiple SUs (Jäntti et al., 2011). ECC allows the use of adjacent channels inside the protection zone. The use of link margin will lead to wastage of TVWS. No resource allocation algorithm is provided.

2.4 Interference in a TVWS Network

Interference in TVWS networks is the main limiting factor for spectrum re-use. TVWS can be used as long as interference to the PUs does not go beyond a certain threshold beyond which there will be harmful interference to PUs. In a TVWS network interference could be due to either co-channel interference or adjacent channel interference. Co-channel interference refers to interference between two devices that share the same frequency channel. Adjacent channel interference refers to interference between two devices that occupy nearby frequency channels. In this research, both co-channel and adjacent channel interference was considered.

Studies (Jäntti et al., 2011; Obregon et al., 2011; Shi et al., 2012a; Kusaladharma and Tellambura, 2012) have shown that aggregate adjacent channel interference from a high density of mobile users using low power in multiple adjacent channels is as harmful as co-channel interference even if interference caused by each SU in a particular channel stays below the GLDB desired to undesired (D/U) ratio constraint (Jäntti et al., 2011). The desired to undesired ratio is also known as protection ratio. GLDB regulations require that the D/U ratio or protection ratio be measured at the edge of protection region (Gurney et al., 2008). These ratios are measured at the edge of protection region because TV receivers at this region are the most vulnerable since they are very close to the secondary network and they receive the weakest TV signal. This is illustrated in Fig. 2.4. Aggregate interference (co-channel and adjacent channel) at the TV receiver, both co-channel and adjacent channels should not make the protection ratio fall below the required D/U ratio threshold.

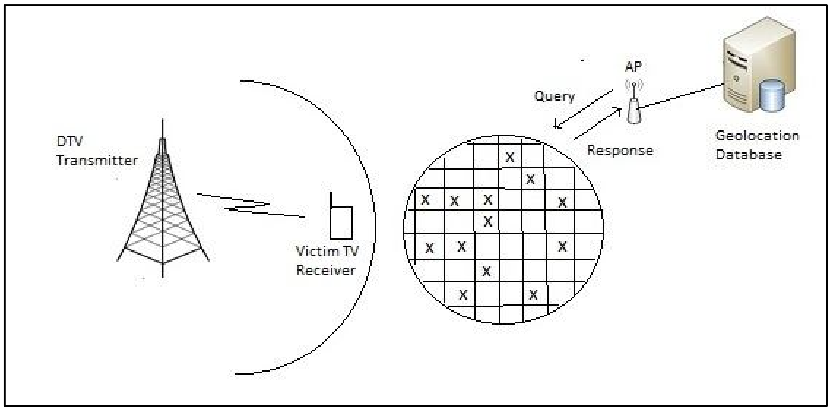

Figure 2.4: Interference scenario

The effect of adjacent channel interference in single and multiple adjacent channels has been studied through an analytical model and measurements by Obregon et al. (2011). A model for computing the maximum aggregate adjacent channel interference (ACI) that a DTV (digital TV) receiver can tolerate without experiencing degradation of service has been proposed. The authors conclude that the weighted sum of the power of all adjacent channel interferers or equivalent co-channel interference (CCI) should be kept below a certain threshold and that suitable channel allocation method may help decrease the effect of ACI (Obregon et al., 2011).

The effect of both co-channel and adjacent channel interference on the number of SUs that can be admitted into a TVWS network and effect of TV reception was studied by Shi et al. (2012b). It was found out that the aggregate effect of adjacent channel interference has a negative impact on TV reception. Linear programming was used to find the maximum number of users that can be admitted into the secondary system with co-channel interference and adjacent channel interference at the PU as the constraint. The number of SUs admitted to the network drop by almost 50% when the effect both adjacent channel and co-channel interference is considered, compared to when co-channel interference only is considered.

2.5 Optimization

This study is about optimization of resource allocation in a TVWS network. Optimization is defined as the process of finding the solution that give maximum or minimum of a function subject to a set of constraints (Rao, 2009; Omran, 2005a). Selection of values for certain parameters that satisfy all the constraints is called a feasible solution. Optimal solution refers to a feasible solution that is the best compared to other feasible solutions (Omran, 2005). Examples of optimization problems are as follows:

- Product Mix: Compute the number of products of each type to manufacture from certain parts to make maximum profits while not outstrip available parts inventory.
- Machine Allocation: Allocate production to machines with varying capacities, startup and operating cost, to meet target of production.
- Blending: Determine which raw materials from varying sources to mix to produce a substance with certain required qualities at minimum cost.
- Process Selection: Determine which of many processes (with varying speeds, costs, etc.) should be used to make a required quantity of product in a particular amount of time, at minimum cost.

2.5.1 Defining of an Optimization Problem

An optimization problem can be defined as follows:

Find $X = \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_{..} \\ x_n \end{matrix}$ which minimizes $f(X)$.

subject to:

$$g_j(X) \leq 0 \quad j = 1,2, \ldots \ldots . m$$
$$l_j(X) = 0 \quad j = 1,2, \ldots \ldots . . p$$

where X is an n-dimensional vector known as the design vector, $f(X)$ is known as the objective function. $g_j(X)$ and $l_j(X)$ are the design constraints. The design vector is made up of decision variables x_1 to x_n. Design constraints could either be equality or inequality constraints.

2.5.2 Analysis of Algorithms

An algorithm can be analyzed in terms of either space complexity or time complexity. Time complexity is the amount of time it takes an algorithm to run. Space complexity is the amount of memory an algorithm uses. A good algorithm will have both good time and space complexity. Time complexity of an algorithm can determined either experimentally or it can be theoretically analyzed in the best case, average case or worst case. Time complexity can be measured experimentally when the algorithm has been implemented. Theoretical analysis of algorithms uses a high-level description of the algorithm instead of an implementation. It characterizes running time as a function of the input size (n) and takes into account all possible inputs. Theoretical analysis allows evaluation of an algorithm independent of the hardware or software environment. Worst case analysis is often used because it is easier to analyze and also because it is crucial to applications.

2.5.3 Classification of optimization problems and algorithms

Optimization problems or algorithms can be classified as follows (Rao, 2009):

2.5.2.1 Combinatorial vs continuous

Optimization problems can be classified as either combinatorial or continuous. Optimization is classified as continuous if the decision variables are continuous. Optimization is classified as combinatorial if the decision variables are discrete. The optimization problem may also be both continuous and combinatorial. Power allocation in a TVWS network is a continuous optimization problem while spectrum allocation is a combinatorial or discrete optimization problem. Figure 2.5 also shows classification of optimization algorithms.

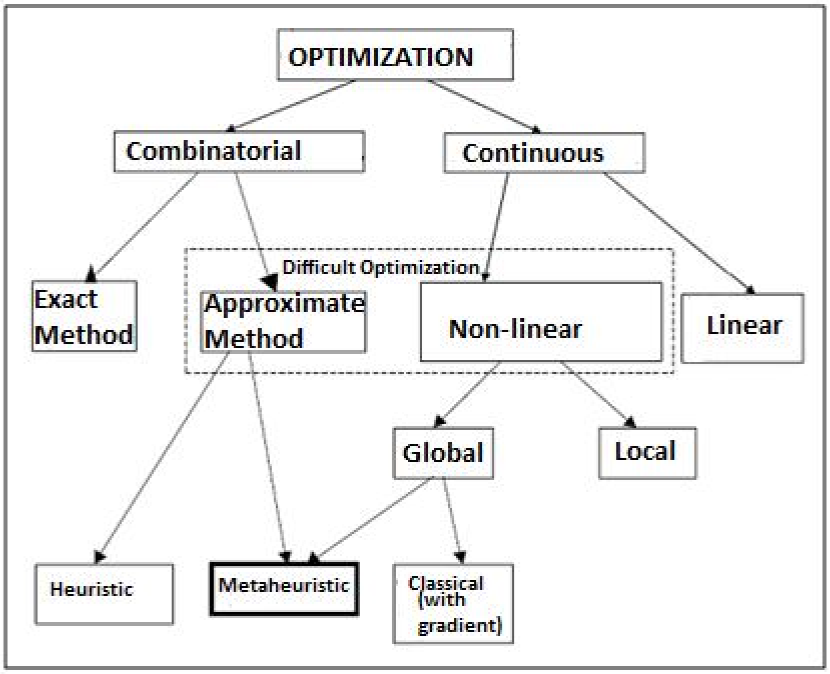

Figure 2.5: Classification of Optimization Algorithms

2.5.2.2 Exact vs approximate optimization

Exact optimization algorithm guarantees that the optimum solution will be found. Exact methods are also known as traditional optimization methods. An example of exact optimization is brute force. Brute force tries to find every possible solution in search space so that the global optimal solution is guaranteed to be found. As the search space increases, the time and space complexity for an exact algorithm increases. Exact algorithms are not suitable for NP hard optimization problems. This is because the time complexity of NP hard problem increases with problem size. Other exact algorithms are Simplex method of linear programming, divide and conquer and dynamic programming. The main disadvantage of exact algorithms or traditional algorithms is that they have poor time complexity (Woeginger, 2003).

Approximate methods are used to find near-optimal solutions for NP-hard problems in polynomial time. Approximate optimization methods are also known as stochastic optimization methods. Unlike exact methods, approximation methods of optimization find a suboptimal solution while providing an approximation guarantee on the solution quality (Festa, 2014). Approximate methods do not guarantee global optimal solution but they provide a near optimal solution. They are applied for solving intractable combinatorial optimization problems since they give a good solution quality with reasonable time complexity.

Approximate methods are classified into two: heuristic and metaheuristic. Approximate optimization algorithms are generally referred heuristics. Heuristic algorithms are specific to a problem i.e one heuristic solution to an optimization problem cannot be applied to another optimization problem. A metaheuristic algorithm is problem independent. Metaheuristic algorithms provide guidelines or a series of steps that can be applied to different optimization problems. Examples of metaheuristic algorithms are population based algorithms (genetic algorithms, firefly algorithm (FA), particle swarm optimization, Tabu search and simulated annealing

In this thesis, metaheuristic algorithms are chosen because of they are able to give good and near optimal solutions in reasonable time complexity. Other advantages of metaheuristic algorithms are as follows (Omran, 2005):

- They are easy to implement.
- They can be efficiently used in a computers with multiprocessor.
- They do not require the optimization problem function to be continuous.
- They are suitable for combinatorial optimization problems

2.5.2.3 Constrained vs non-constrained

The optimization problem may have constraints on the decision variables. If there are constraints on the decision variables, the optimization is referred to as constrained optimization. If there are no constraints on the decision variables then the optimization problem is a non-constrained one. Resource allocation in a TVWS network is a constrained optimization problem.

2.5.2.4 Single objective or multi-objective optimization

If an optimization problem has one objective function, then it is referred to as single objective optimization. If the optimization problem has more than one objective function, then it is referred to as multi-objective optimization. Single objective optimization is considered in this research.

2.5.2.5 Deterministic vs stochastic optimization

An optimization problem is stochastic if the decision variables are probabilistic. If the decision variables are not probabilistic, then the optimization problem is deterministic. Resource allocation in a TVWS network is a deterministic optimization problem if fading is not considered.

2.5.2.6 Linear vs non-linear optimization

Optimization problem is linear if the constraints or the objective function appear as linear functions. If the constraints or the objective function do not appear as linear, then the optimization problem is non-linear. Resource allocation in TVWS is a non-linear optimization problem.

2.5.2.7 Global vs local optimization

Global optimization is defined as the process of finding the optimal value of a certain function among all possible solutions whereas local optimization finds the optimal value within the neighborhood of a candidate solution. This is illustrated by an example in Fig. 2.7. In this research global optimization will be considered. In the example x_B^*, is a local optimization solution because it finds a minimum only within the neighborhood. x^* is a global optimization solution because it is the minimum value in the entire solution space.

Classical optimization falls under global optimization. The classical methods of optimization are analytical methods that are used to find the optimum solution of continuous and differentiable functions (Rao, 2009). Classical methods may utilize differential calculus in finding optimal solutions. Classical optimization techniques have limited scope in practical applications because not all functions are continuous or differentiable. Classical optimization methods will not be applied in this thesis because the functions considered are not differentiable.

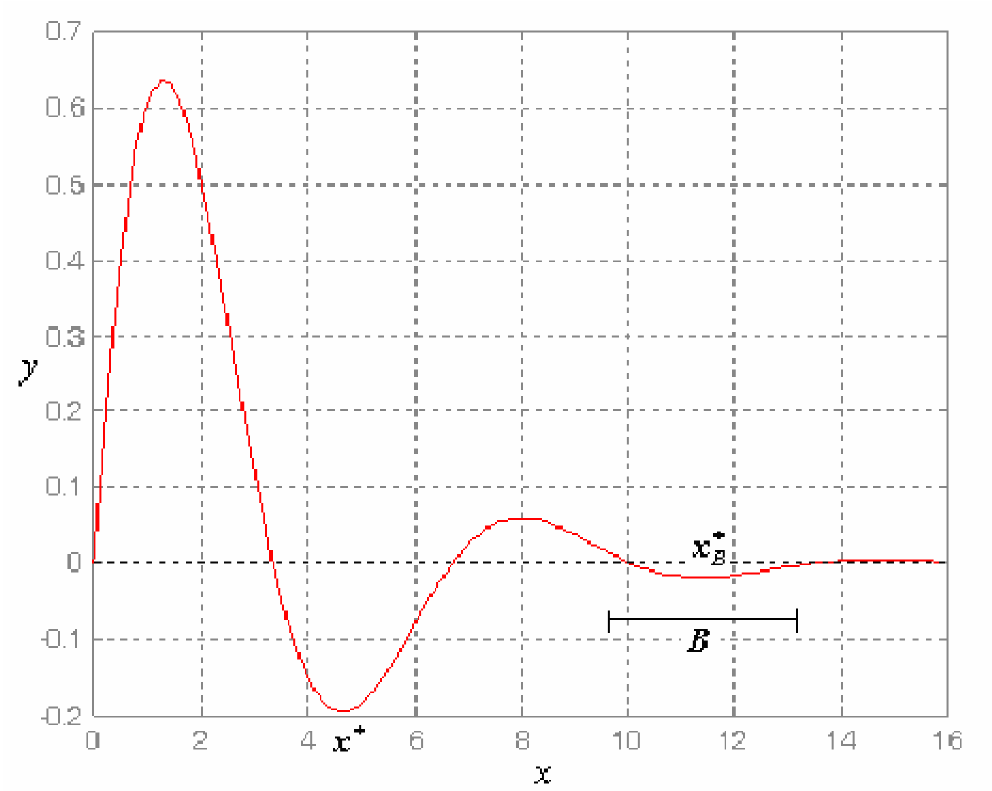

Figure 2.6: Global vs Local Optimization

2.6 Cognitive Radio Resource Allocation Optimization Algorithms

In this section, TVWS power allocation algorithms, TVWS spectrum allocation algorithms, TVWS joint power and spectrum allocation algorithms existing in literature will be discussed.

2.6.1 Power Allocation Algorithms and Methods in TVWS Networks

Limiting the transmit power is an important consideration in a TVWS network (Kennedy et al., 2017). TVWS spectrum can only be used as long as there is no harmful interference to PUs. This condition makes power allocation in TVWS networks more challenging than traditional wireless networks. Power control through a power allocation algorithm will reduce interference to PUs and among SUs.

A statistical approach for controlling aggregate interference under adjacent channel interference constraints has been proposed by Shi et al., 2012 . The proposed model allows determination of permissible secondary transmit power so as to avoid detrimental aggregate adjacent channel interference. Cumulant based log-normal approximation has been used to approximate adjacent channel interference. Only adjacent channel interference was considered. Co-channel interference outside the protection region has not been considered. Power allocation does not consider mutual interference among SUs and this will lead to poor SU QoS. Cumulant based log normal approximation is suitable when fading is considered. In order to reduce complexity, fading is not considered in this research.

Lee et al. (2011), proposed a transmit power control algorithm for a TV white space wireless network. Transmit power control was done in such a manner that the sum interference at the TV service protection contour does not exceed the D/U ratio. Lagrange multiplier was used to determine the optimal power of SUs that maximizes sum uplink throughput at the base station while ensuring that D/U threshold at the primary receiver is met. Lagrange multiplier method used is not computationally efficient. This is because Lagrange multiplier method is an exact optimization and is not suitable for NP hard problems. The work fails to address interference among SUs as the interference constraints at the SUs is not considered in the proposed power control algorithm. Failing to consider interference among SUs will result in poor QoS at SUs.

Power control for a device-to-device network has been studied by Xue et al. (2014). In a device-to-device network, devices communicate directly between themselves without going through the base station. A heuristic iterative power control algorithm with co-channel and adjacent channel interference considerations has been proposed. Interference constraints at both PUs and SUs are considered. The objective of the proposed algorithm is to maximize total system throughput through power control on each device to device link while considering interference constraints from SUs to PUs, from PUs to SUs and between SUs. Lagrange multiplier method used is not computationally efficient. This is because it is an exact algorithm.

Selén and Kronander (2012) considered the problem of finding upper power limits in which aggregate interference by SUs does not exceed the required limit. The aggregate interference was constrained so that the probability of harmful interference is below a predefined threshold. Log normal shadow fading was factored into the model by the authors. Both co-channel and adjacent channel interference was considered. Felton Wilkinson approximation was used for approximation of sum interference. An optimization problem was formulated with the objective being maximization of sum capacity. The model makes use *fmincon* function of

Matlab. *fmincon* uses the interior-point algorithm. Interior point algorithm is an exact algorithm and this makes it computationally inefficient. It is, therefore, not suitable for resource allocation in a TVWS network which is a NP hard optimization problem.

A detailed method of calculating the maximum permitted emission levels for WSDs has been presented by Karimi (2011). The proposed method provides a way to calculate location specific maximum power based on location probability. The proposed method makes use of Digital Terrestrial TV (DTT) network planning models in order to provide the GLDB with the needed parameters to perform the necessary calculations. The use of location probability is not suitable for optimization of resource allocation for all existing SUs in a network because it does not allow for approximation of aggregate interference. Only a single SU was considered. It is also applicable when fading is considered. In this research fading is not considered. In order to reduce complexity, fading is not considered in this research.

2.6.2 Cognitive Radio Spectrum Allocation Algorithms

Spectrum allocation is the process of choosing the frequency of operation for a WSD. Spectrum allocation in cognitive radio networks is a key mechanism that can be used to reduce interference. Spectrum allocation algorithms are reviewed because the problem at hand is about resource allocation in a TVWS network which incorporates spectrum allocation. It is important to know existing algorithms for spectrum allocation.

Spectrum allocation in cognitive radio is an optimization problem. This is because spectrum allocation is concerned with selecting the best operating frequency for all the devices based on a given criteria and with the constraints that there is no harmful interference to PU and that QoS constraints for the SUs are met. Example criteria that may be considered are minimization of interference or maximization of throughput, fairness or spectral efficiency. There are five different methods for solving the spectrum allocation problem. They include: graph theory, linear programming, heuristics, game theory, fuzzy logic and evolutionary algorithms (Tragos et al., 2013). Spectrum allocation is an algorithmic operation of high complexity. It belongs to the category of NP complete problems (Tragos et al., 2013).

2.6.2.1 Spectrum Allocation Based on Heuristics

Heuristic algorithms are applied where an exact algorithm is not practical due to the intractability of the problem at hand. Spectrum assignment based on heuristics have the advantages that they can easily be implemented and that they can find high quality solutions at low computational cost. A disadvantage of spectrum assignment based on heuristics is that they are problem specific. Another disadvantage is that they can get stuck in local optimum. A heuristic algorithm for spectrum assignment has been applied by Salameh et al. (2008). The problem is first formulated as integer linear programming problem. Channels with poor SINR are assigned to transmissions of short distance while channels with high SINR are assigned to more long distance transmission

2.6.2.2 Spectrum Allocation Based on Graph Theory

In some studies spectrum allocation has been abstracted as a graph coloring problem (Wang et al., 2009; Zhang et al., 2009; Zhang et al., 2010 and Ge et al., 2010; Elhachmi and Guennoun, 2016). Graph coloring allows easy representation of interference constraints among SUs. Different channels represent different colors in the graph and vertices represent different users. An effective scheduling algorithm in infrastructure based CR networks has been proposed by Nguyen and Lee (2011). The algorithm uses a heuristic greedy algorithm based on graph coloring. The scheduling algorithm has been designed in such a manner that it maximizes the spectrum utilization by the SUs without causing excessive interference to PUs. A heuristic greedy algorithm is chosen instead of mixed integer linear programming method so as to reduce computational complexity. The disadvantage of heuristic greedy algorithms is that they can get trapped in local optimum. In this research we assume that each SU interferes with every other SU in the network since a small network is considered. Graph coloring will, therefore, not be used to represent interference constraints.

2.6.2.3 Spectrum Allocation Based on Evolutionary Algorithms

Evolutionary algorithms have also been applied in spectrum allocation. A summary of the use of evolutionary algorithms for spectrum allocation in cognitive radio networks has been presented by Zhao et al., 2009. All evolutionary algorithms are metaheuristic algorithms. The work discusses the use genetic algorithm (GA), PSO, and quantum genetic algorithm. The work finds that PSO converges much faster and gives a better solution compared to GA and Color Sensitive Graph Coloring (CSGC). Performance of CSGC is found to be lower than both PSO and GA in terms of solution quality. As mentioned earlier, in this research it is assumed that each SU interferes with every other SU in the network since a small network is considered. Graph coloring will, therefore, not be used to represent interference constraints.

A spectrum allocation framework based on PSO and simulated annealing has been presented by Jie and Tiejun (2012). Simulated annealing is introduced to prevent prematurity of PSO. The work finds that PSO with simulated annealing performs better than graph coloring and greedy algorithms in terms of solution quality. Spectrum allocation using graph coloring and Ant Colony Optimization (ACO) has been presented by Koroupi et al. (2012). ACO was found to perform better than PSO and CSGC in terms of solution quality. However, the run time is higher than that of PSO. Spectrum allocation using has been explored by Anumandla et al. (2013) and Liu et al. (2014). The results of the two papers show that gives a better solution and converges to a solution faster than GA and PSO.

The advantage of evolutionary algorithms is that they are more able to escape local optimum, unlike other heuristic algorithms. Another advantage is they give reasonably good solutions with relatively lower time complexity compared to classical optimization algorithms and other exact algorithms. Despite the advantages of evolutionary algorithms, they can get trapped in a local optimum (Gaidhane and Nigam, 2018). Recent trend has been to hybridize evolutionary algorithms so as to overcome the shortcoming (Singh and Singh, 2017).

2.6.2.4 Spectrum Allocation Based on Game Theory

Game theory is a branch of applied mathematics which provides techniques for analyzing and predicting situations in which rational parties, called players, make decisions that are interdependent and that may conflict. This interdependence causes each player to consider the other player's possible decisions, or strategies, in formulating his own strategy. Game theory has been applied in many fields including engineering, economics and politics. There are two kinds of games: cooperative game and non-cooperative game. Cooperative game is a game where all players are concerned about the overall benefits and are not very worried about their own personal benefit. Thus, players fully cooperate with each other in order to achieve the highest possible overall benefit. Non-cooperative game is a game where every user is mainly concerned about his personal payoff and therefore all his decisions are made competitively and selfishly.

Game theory has also found application in wireless networks. In a wireless network, the wireless devices represent the players. Each wireless device seeks to maximize its performance at the expense of others. Game theory has been used for cognitive radio spectrum assignment by Xue and Wang (2015) and Nie and Comaniciu (2006). In cognitive radio spectrum assignment, spectrum assignment to one SU affect neighboring SUs (Tragos et al., 2013). Each SU has a set of frequency channels to choose from so as to maximize its own utility function while taking into consideration the effect on other SUs. In CR spectrum assignment, once a game has been formulated, the spectrum assignment will involve finding the optimal solution through Nash equilibrium.

The main disadvantage of using game theory for spectrum assignment is that it is difficult to formulate the spectrum assignment problem in such a way that equilibrium is achieved since equilibrium is never guaranteed (Tragos et al., 2013). In addition utility function and game formulation affect the equilibrium.

2.6.2.5 Spectrum Allocation Based on Fuzzy Logic

Fuzzy logic is a branch of computing in which the truth is not classified as 1 or 0. Truth values can take any range between 0 and 1. Fuzzy logic has found application in decision making and optimization algorithms. A fuzzy logic controller is made up of the following: fuzzy rule base, fuzzy inference engine and a fuzzy/defuzzification module. Examples of input to the fuzzy logic are arrival rate of PUs/SUs, distance between PUs/SUs and interference conflict graph(Tragos et al., 2013). The use of fuzzy logic for spectrum assignment involves using the inputs together with predefined spectrum assignment rules. Fuzzy logic has been applied to the spectrum assignment problem by Kaur et al. (2010) and Veeramakali et al. (2017). The main disadvantage of spectrum assignment based on fuzzy logic is that a great number of rules is required for spectrum assignment and this makes it a challenge for fuzzy logic because the fuzzy logic algorithm will become unscalable (Tragos et al., 2013). Another disadvantage is that the configuration of the network has to be known apriori which may not be true at all times.

2.6.2.6 Spectrum Allocation Based on Linear Programming

Linear programming has also be used for spectrum assignment (Yu et al., 2010; Anh Tuan Hoang and Ying-Chang Liang, 2008; Wang et al., 2010). Spectrum allocation is a mixed integer non-linear programming (MINLP) optimization problem (Tragos et al., 2013) that is NP hard. The spectrum assignment based on MINLP can be modified into a binary linear programming (BLP) problem that will have only binary parameters. This is applicable in cognitive radio networks because there are finite number of channels and SUs. The transformation of MINLP into BLP is done as to simplify the problem. The disadvantage of linear programming is that, being an exact algorithm, it has high computational complexity. Another disadvantage is that transformation into BLP from MINLP programming is not always guaranteed for cases when there is need to convert the problem from MINLP to BLP.

2.6.3 Joint Power and Spectrum Allocation Algorithms and Methods

In this section we look at joint power and spectrum algorithms for a TVWS network that have been proposed. Joint power and spectrum allocation in IEEE 802.11af and IEEE 802.22 are also discussed.

2.6.3.1 Joint Power and Spectrum Allocation in IEEE 802.11af

IEEE 802.11af allows only the use of GLDB for incumbent protection (Flores et al., 2013). In an IEEE 802.11af network, a device sends a channel availability query (CAQ) to registered location secure server (RLSS). RLSS operates as a local database. It contains channels available for secondary use and the permitted EIRP for those channels. RLSS serves a number of basic service sets (BSSs). It distributes operating parameters such as the channels and their associated power levels to access points (APs) and WSDs. Once a CAQ is received by the RLSS, it will respond with a white space map (WSM). The WSM contains the list of available channels and their respective EIRP. IEEE 802.11af allows for both closed loop power control and open loop power control. With open loop power limitation the WSD has rigid power limitation similar to those provided by FCC regulations. In closed loop power limitation, the WSD has a more flexible power limits that depends on location, time of use and the channel. IEEE 802.11af makes use of a spectrum manager (SM) to allocate spectrum (Flores et al., 2013). Resource allocation in IEEE 802.11af is applicable where power is assigned to SUs one by one. It does not provide an algorithm for optimization of resource allocation for all SUs existing in a TVWS network. It will result in sub-optimal resource allocation and will lead to wastage of TVWS. The use of FCC regulations under open loop power control will result in wastage of TVWS because FCC regulations require the use of protection distance as discussed in section 2.3.1.

2.6.3.2 Joint Power and Spectrum Allocation in IEEE 802.22

IEEE 802.22 allows the use of both GLDB and spectrum sensing for incumbent protection. In the IEEE 802.22 TVWS network architecture, there is an entity called spectrum manager (Cordeiro et al.; 2005, Stevenson et al., 2009). The spectrum manager (SM) makes use of spectrum sensing function and GLDB to find out the channels available for secondary use and their respective EIRP limits. The SM has three options whenever secondary use of channels may create interference:

- Reduce Customer Premise Equipment (CPE) operating power.
- If reduction in CPE powers results in unsustainable service, the CPE will be stopped from operating on that channel and will seek another channel from the spectrum manager.
- Reduce base station EIRP in order to eliminate interference.

The proposed technique is also not designed to optimize resource allocation as it seeks to ensure that specific users that request channel are allocated one with an associated power level. Power and spectrum allocation is done in an arbitrary manner with no use of an objective function. It will not be applicable in a high density network where there is need to optimize resource allocation so as to minimize interference.

2.6.3.3 Joint Power and Spectrum Allocation Based on Heuristics and Greedy Algorithm

GLDB based spectrum allocation with power control, co-channel interference and adjacent channel interference considerations has been proposed by Xue et al. (2014). The study considers a device to device (D2D) network. In D2D communication, two devices communicate directly without going through the base station. A single TV receiver, considered the most vulnerable to interference, is placed near the border of protection region. This is illustrated in Fig. 2.7. The secondary cell considered is outside the DTT protection region. The secondary network has a base station whose role is to facilitate resource sharing among the devices. The access point plays no role in relaying communications between the devices since it is a device to device network.

In the proposed algorithm, co-existence (mutual interference) among SUs is considered. Channel allocation and power control is then done in such a manner that the TV receiver and SUs SINR constraints are met. A greedy heuristic iterative algorithm is used for power control and spectrum allocation. Each SU is allocated a channel and a power level when it makes a channel request to the GLDB. Simulation results show a decrease in the number of failed links when the joint spectrum and power allocation algorithm is applied.

When two devices need to communicate, the D2D will send a request to the access point (AP). The AP will then communicate with the GLDB so as to find out the available channels and their associated power levels. The AP will then in turn send to the D2D link the available channels. The proposed algorithm is referred to as Access in Order with Best Selection (AOBS). The details of AOBS algorithm are provided in Algorithm 2.1.

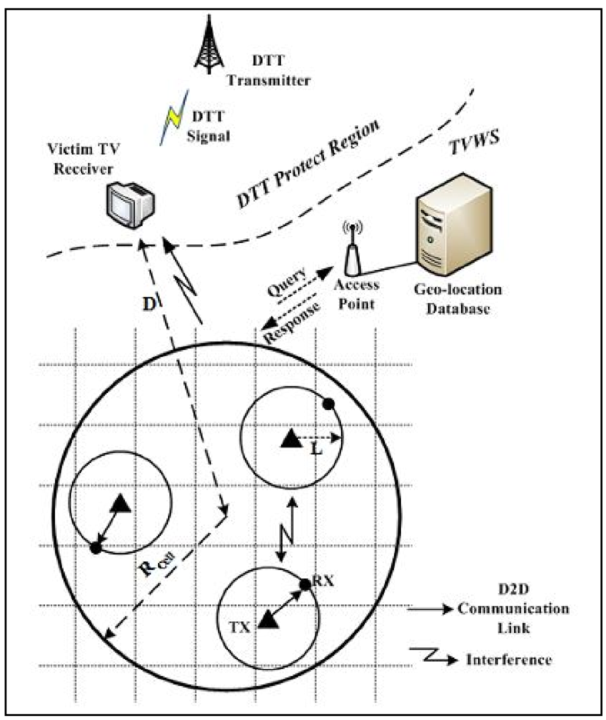

Figure 2.7: Network structure for joint power and spectrum allocation based on heuristics. Adapted from (Xue et al., 2014)

The first major disadvantage of the algorithm is that it is a greedy heuristic algorithm. Secondly, the algorithm is also designed to allocate resources one by one as SUs make request to GLDB. It is not designed to optimize resource allocation for all SUs in a network. These two features will make the algorithm result in sub-optimal resource allocation.

Algorithm 2.1: Access in Order of Best Selection

Step 1: Each link i sends a request to the access point with specific format that contains the location information before transmit signal. The power initialized the maximum value P_m.

Step 2: If $i = 1$, test the available channels one by one. For a given channel, judge whether the SINR level at the victim receiver can be accepted. If not decrease the power by a given step Δ until the SINR meets the constraint. At last, choose the channel that causes the least interference to the victim receiver for the 1st link.

Step 3: If i>1, also test the whole channels one by one. For a given channel, if the TV receiver or any former links are harmed, decrease the power level by step until the SINR conditions for the PU and D2D links are satisfied. The i^{th} link will take the channel and power it can have the highest SINR finally.

Step 4: If all the links are finished, we shall get the final power and spectrum allocation vector.

2.6.3.4 Joint Power and Spectrum Allocation Based under Fading Conditions

Selén and Kronander (2012), in addition to considering problem of finding upper power limits which aggregate interference by SUs does not exceed the required limit, also considered the problem of channel allocation under interference constraints. The aggregate interference is constrained so that the probability of harmful interference is below a predefined threshold. Log normal shadow fading is factored into the model by the authors. Both co-channel and adjacent channel interference is considered. In the presence of fading, Felton Wilkinson approximation is used to approximate the sum interference. In this research, fading is not considered. The suggested method can be used by GLDB providers to make efficient use of white spaces while ensuring PUs are fully protected. The authors simply develop the model but did propose an algorithm to solve the resource allocation problem. The model is then fed into Matlab. *fmincon* function is used for optimization of resource allocation. *fmincon* makes use of interior point algorithm which is an exact algorithm. Exact algorithms are not efficient with regard to running time.

2.6.3.5 Joint Power and Spectrum Allocation Based on Heuristics and Game Theory

As discussed previously, resource allocation to one SU affect neighboring SUs (Tragos et al., 2013) in a cognitive radio network. Each SU has a set of frequency channels to choose from so as to maximize its own utility function while taking into consideration the effect on other SUs. GLDB based spectrum allocation with power control and admission control for TVWS multiple device-to-device links has been proposed by Xue and Wang, 2015). Fig. 2.8 shows the scenario considered.

Spectrum allocation is done in greedy heuristic manner using an algorithm called spatial adaptive play (SAP). SAP is a game theory algorithm for a mixed strategy game. SMIRA algorithm is used for admission control. Only co-channel interference has been considered. Adjacent channel interference has not been considered. Resource allocation follows the steps shown in Fig. 2.9. The aim of the algorithm is to find a channel/power allocation scheme that will ensure the PU is fully protected against harmful interference and the QoS constraints (in terms of SINR) at the SUs are met. The first stage is the spectrum assignment stage. The second stage is the joint power control and admission control.

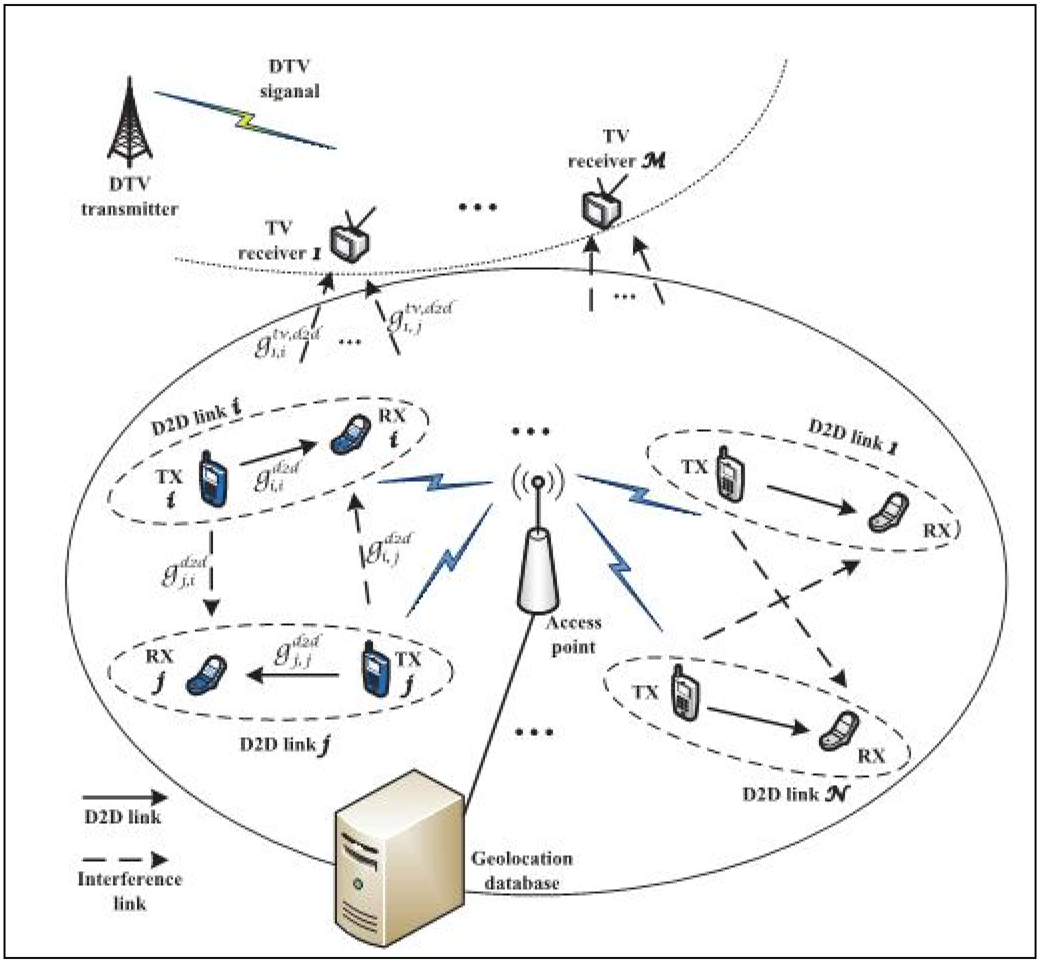

Figure 2.8: Interference scenario in a device to device communications in a TVWS network. Adapted from (Xue and Wang, 2015).

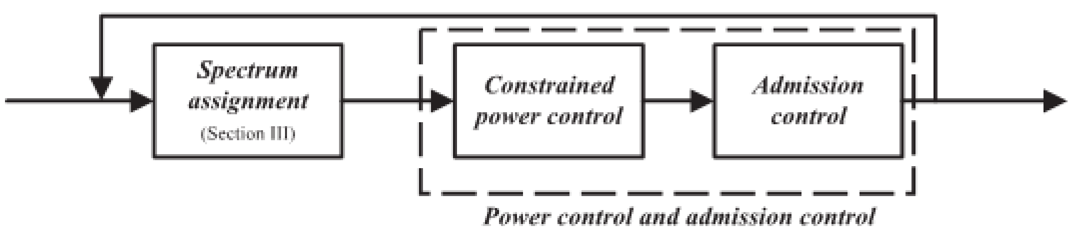

Figure 2.9: SAP Algorithm Resource Allocation Steps

SAP is used to find the optimal resource allocation instead of Nash Equilibrium (NE). This is because any utility function can have multiple NE which may not be the global optimum (Xu et al., 2012). A learning algorithm such as SAP is needed so as to achieve global optimization.

SAP allows escape from a local optimum. In SAP one player is selected to update its strategy in accordance with the mixed strategy. All other players will repeat their previous selections. In the proposed algorithm, SAP is used during the first stage of spectrum assignment. The steps have been outlined in Algorithm 2.2.

Algorithm 2.2: SAP Based Spectrum Assignment (Xue and Wang, 2015)
Step 1: Randomly assign each user a channel from the channel set with equal probability. **Step 2**: A D2D link is randomly selected. Other remaining link will repeat their last channel allocation strategy. The selected link will then test all the available channels one by one while the AP measures the objective function. The D2D link is then assigned a channel according to the following updated channel selection probability. $$q_j^{a_j=m}(k+1) = \frac{\exp\{\beta u_1(a_j = m, a_{-j})\}}{\sum_{m=1}^{M} \exp\{\beta u_1(a_j = m, a_{-j})\}}, j\epsilon\varphi, m\epsilon C \quad (2.1)$$ $\beta > 0$ is the learning parameter, u_1 is the objective function that measures interference at link j , C is the set of available channels, $m \in C$,k is the iteration number, a_j is refers to channel assigned to link j, a_{j-1} is refers to channel assigned to link j in the previous iteration, φ is the set of available links. **Step 3:** If the stop criterion (maximum number of iterations or channel allocation can be determined with channel allocation probability of more than 99%) has been met, stop; otherwise go to Step 2.

The second step in the resource allocation strategy is power control. The proposed algorithm considers a scenario where all the links can be admitted and also a scenario where not all the links can be admitted due to interference constraints at SUs and PUs. When the network load is high, not all the links can be admitted into the secondary network. Admission control, therefore, has been applied to determine the links that can be removed and those that remain in the network in a scenario where the network load is high. The algorithm aims to ensure that all the admitted links operate at their required minimum SINR through the removal of links that cause the highest interference.

An iterative power control algorithm that was proposed by Foschini and Miljanic (1993) has been applied. The focus is first on power assignment to meet the minimum SINR for all the links while ensuring that maximum power is not exceeded. The power of the D2D link i is updated according to the equation (2.2).

$$p_i(t + \Delta t) = \begin{cases} \min\left\{p_i^{max},\ p_i(t)\,\frac{\varepsilon_{i,min}^{d2d}}{\varepsilon_i^{d2d}(t)}\right\}, if\ i\ \epsilon\ \varphi \\ \qquad p_i(t) \quad , otherwise \end{cases} \tag{2.2}$$

where $p(t)$ is the instantaneous power vector at time t, $p(t + \Delta t)$ is the power vector at time $t + \Delta t$, $\varepsilon_i^{d2d}(t)$ is the instantaneous SINR of the receiving side of the D2D link at time t, $\varepsilon_{i,min}^{d2d}$ is the minimum required SINR for link i, p_i^{max} is the maximum power for link i. In the proposed algorithm, the power of each link evolved through a number of iterations so as to achieve the greatest possible SINR. In a scenario where not all the links can be admitted, the following interference measures are used to determine the link to remove:

$$\mu_i(p^\varphi) = p_i^\varphi \sum_{j\epsilon\varphi, j\neq i} f(a_i, a_j) g_{j,i}^{d2d} + \delta_n^2 \Big/ \frac{p_i^\varphi g_{i,i}^{d2d}}{\varepsilon_{i,min}^{d2d}} \tag{2.3}$$

$$v_i(p^\varphi) = \sum_{j\epsilon\varphi, j\neq i} f(a_i, a_j) g_{i,j}^{d2d} + \delta_n^2 \Big/ \frac{p_i^\varphi g_{i,i}^{d2d}}{\varepsilon_{i,min}^{d2d}} \tag{2.4}$$

where is $g_{i,i}^{d2d}$ transmitter gain of link i, $g_{j,i}^{d2d}$refers to path loss from link j to i, $g_{i,j}^{d2d}$refers to path loss from link i to j , $f(a_i, a_j)$ is the Kronecker Delta function, p_i^φ is the power assigned to link i, δ_n^2 refers to noise. $\mu_i(p^\varphi)$ quantifies the total interference that link i brings to other D2D links in φ. $v_i(p^\varphi)$ quantifies the total interference that link i receives from other D2D links in φ. If $v_i\,(p^\varphi) = 1$, it indicates that QoS constraint for D2D link i is satisfied. $I^\varphi(p^\varphi) = 1$ if all the links are supported, where $I^\varphi(p^\varphi) = \frac{1}{N}\sum_i v_i\,(p^\varphi)$. SMIRA is applied for admission control. SMIRA is applied to remove one link at the time before the power control algorithm is executed. The links that causes the most interference is identified as follows:

$$i^* = \underset{i\,\in\,\varphi}{\text{arg max}} \{\max\,(\mu_i(p^\varphi), v_i(p^\varphi))\} \tag{2.5}$$

The removal procedure is done until all the links can be supported. The entire resource allocation algorithm is summarized in the Algorithm 2.3.

Algorithm 2.3: SAP based resource allocation with Admission Control (Xue and Wang, 2015)
Step 1: Perform spectrum assignment according to Algorithm 2.2 **Step 2**: Implement iterative power control algorithm until stationary power vector is achieved. **Step 3**: Apply admission control. **Step 4**: Stop the whole algorithm

The algorithm has the following disadvantages. Firstly, the algorithm ignores adjacent channel interference. PUs may be interfered because of underestimation of interference. Secondly, the spectrum assignment will not work well when the number of channels is high because SAP algorithm will find it difficult to learn opportunities of all channels (Xue and Wang, 2015). Thirdly, the iterative power allocation algorithm makes the algorithm have high poor time efficiency and running time because it will have many iterations.

2.7 Population-based Metaheuristic Algorithms and Choice of Algorithm

In this section, population-based metaheuristic algorithms and choice of algorithm to be used for optimization of resource allocation in this thesis are discussed.

2.7.1 Population-based Metaheuristic Algorithms

Resource allocation in a TVWS network is a NP hard optimization problem. As discussed in section 2.5, metaheuristic algorithms are preferred over exact algorithms in solving NP hard problems because they provide close to optimal solutions in a good amount of time. More specifically population based algorithms are chosen for development of resource allocation algorithm. This is because population based metaheuristic algorithms are efficient for NP hard optimization problems. Another reason population-based metaheuristic algorithms are chosen is because they have ability for global exploration and local exploitation (Beheshti and Shamsuddin, 2013) in searching the solution space.

Population-based metaheuristic algorithms mimic behavior of biological entities and evolution (Goudos, 2014). They are inspired by Darwin's theory of evolution. Population-based metaheuristic algorithms perform optimization as follows: a population of individuals is initialized whereby each individual represents a possible solution to the optimization problem. Through a number of iterations the population of individual solutions is continuously improved. The best solution at the end of iteration represents the solution to the optimization problem.

Population-based metaheuristic algorithms can be used to find solutions for single objective or multi-objective optimization problems. Special type of evolutionary algorithms are swarm intelligence (SI) algorithms. Examples of swarm intelligence algorithm include PSO, FA, Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO). Popular population-based metaheuristic algorithms are described one by one.

2.7.1.1 Firefly Algorithm

FA mimics the behavior of fireflies. Firefly is an insect that flash to either attract a mate or potential prey (Fister et al., 2013). Flashing may also serve as a warning mechanism. The flashing of a firefly is rhythmic. For female fireflies the attractiveness of male fireflies depends on their brightness. The light intensity has an inverse relationship with distance. Light intensity (I) reduces as distance (r) increases according to this formula: $I \; \alpha \; \frac{1}{r^2}$. Fireflies, therefore, are visible within a limited distance. The objective function of an optimization problem can be associated with the flashing. The light intensity is determined by light intensity (brightness) I which is associated with objective function value. In an optimization problem, each firefly represents a possible solution to the optimization problem.

2.7.1.2 Particle Swarm Optimization

PSO is inspired by a flock of birds flying towards a destination. Each candidate solution is referred to as a particle(Elbeltagi et al., 2005). Each particle represents a bird in the flock. Unlike genetic algorithm, no new birds/particles are generated. The existing particles are simply improved iteratively. The birds adjust their social behavior as they move towards the destination. Birds communicate as they fly. As they communicate they identify the bird which is in the best position and then they move towards it at a certain velocity. PSO combines both local search and global search. Local search is represented by each bird learning from their own experience. Global search is represented by each bird learning from the experience of others.

2.7.1.3 Artificial Bee Colony

Artificial Bee Colony (ABC) mimics behavior of fish when foraging for food. In ABC, the position of food source represents the possible solution to the optimization problem while the quality of solution is represented by the food source (Goudos, 2014).

2.7.1.4 Ant Colony Optimization

ACO algorithm is inspired by the behavior of ants. The algorithm mimics the behavior of ants as they find a shortest way from their nest to a food source (Goudos, 2014). This is achieved by depositing and reacting to pheromones during the process of exploring the environment. The ant with the shortest path will deposit the most pheromones. Other ants will then follow the path with the most pheromones. In ACO, each ant represents a possible solution to the optimization problem.

2.7.1.5 Cuckoo Search

Cuckoo search algorithm (CSA) is based on brooding behavior of cuckoos (Joshi et al., 2017; Dash and Mohanty, 2014; Fister Jr. et al., 2014). Cuckoos lay their eggs on communal nests. In order to improve the chances of hatching of their own eggs, they remove host bird's eggs from the nest. The host bird will either throw the eggs away or desert the nest if it finds out that the eggs are not her own. Cuckoo birds may even mimic the pattern of the host bird eggs in order to reduce the chances of being discovered. Cuckoo birds may lay their eggs earlier than host bird in order to ensure that its eggs get space in the nest and that its chicks get a large portion of feed from the host bird.

In the CSA, each cuckoo lays an egg in a randomly chosen nest. Each nest represents a possible solution to the optimization problem. The idea is to replace poor solutions with new cuckoos. The best nests with good solutions will carry over to the next generation.

2.7.1.6 Genetic Algorithm

Genetic algorithm (GA) mimics evolution of biological systems (Elbeltagi et al., 2005). Each candidate solution to an optimization problem is represented by a string called a chromosome. Random solutions that represent initial chromosomes are first generated. The fitness of each of chromosome is then measured by using an objective function. In order to imitate survival of the fittest in a biological system, chromosomes will exchange information amongst each other in a random manner. The process of exchange of information is referred to as crossover. Two parents exchange information in the crossover process to create new offsprings. Just like the evolution of biological systems, the new offsprings are then mutated.

2.7.1.7 Bat Algorithm

Bat algorithm is inspired by echolocation behavior of microbats (Fister et al., 2014; Arora and Singh, 2013). Bats use echolocation to sense distance and to differentiate between prey and background barriers in some magical way. Each bat has a velocity v_i^t and a location x_i^t at each iteration t in a d-dimensional solution space. The location of each bat is considered as a solution vector to the problem of interest.

2.7.2 Choice of Algorithm

Among other population-based metaheuristic algorithms, FA is chosen because it has been found to perform better than other algorithms in terms of solution quality and convergence time (Yang; 2009, Arora and Singh; 2013). Despite its superior performance over other algorithms, FA can get trapped in a local optimum. This is because many population-based metaheuristic algorithms can have a weakness either in exploration or exploitation or both (Gaidhane and Nigam, 2018), (Singh and Singh, 2017). In order to solve this problem, hybrid of FA with other algorithms have been proposed. They are listed as follows:

- A hybrid of PSO and FA (Arunachalam et al, 2015; Kora, Rama Krishna, 2016).
- A hybrid of FA and GA (Luthra and Pal, 2011; Rahmani and MirHassani, 2014).
- A hybrid of bat algorithm and FA (Warangal et al. (2016)).
- A hybrid of cuckoo search and FA (Elkhechafi et al. (2018)).
- A hybrid of FA and ant colony optimization (Layeb and Benayad (2014)).

In this thesis, FA is hybridized with PSO and GA in order to improve quality of solution obtained by FA through improvement of its exploitation or exploration ability. PSO is chosen because, compared to other EAs, it has been found to converge more quickly and give better quality solutions (Elbeltagi et al., 2005). Crossover feature of GA is further added to the hybrid of FA and PSO to further improve the quality of the solution through diversification of the search of the solution space and hence avoidance of the problem FA of being trapped into local optimum. Detailed discussion of the hybrid FA, GA and PSO (FAGAPSO) is presented in Chapter 3.

2.8 Conceptual/Study Model

This research is about development of an improved and efficient algorithm for optimization of power and spectrum allocation in a TVWS network. As discussed in Section 2.7, power and spectrum allocation in a TVWS network is a NP hard optimization problem. Population based metaheuristics are preferred over exact algorithms such as exhaustive search because they are known to be efficient. This is because they are able to find good solutions in reasonable time complexity.

FA was chosen among other algorithms because it has been found to perform better than other algorithms in terms of solution quality and convergence time. FA was hybridized with PSO and GA in order to improve quality of solution obtained by FA through improvement of its exploitation and exploration ability. An improved performance in FA would result in improved resource allocation.

Fig. 2.10 shows the conceptual/study model for the research. The ultimate aim was to design an algorithm for joint power and spectrum in a TVWS network which is a continuous-binary. Different versions of hybrid FA/GA/PSO algorithms were evaluated separately first for spectrum allocation (consist of binary spectrum allocation matrix) and power allocation (consists of continuous power values) because metaheuristic algorithms may perform differently for continuous and combinatorial/discrete/binary optimization problems. This determined the best hybrid algorithm for joint power allocation and spectrum allocation.

The hybrid algorithm designed for power allocation is a continuous version i.e a continuous optimization problem because the design variables are continuous. The input parameters are number of channels, number of SUs, SU spectrum allocation. Simulation parameters also form part of the input. The hybrid algorithm designed for channel allocation is a binary version i.e a combinatorial/discrete optimization problem because the design variables are binary. The input parameters are number of channels, number of SUs, and SU power allocation. Simulation parameters also form part of the input. The performance of different power allocation and spectrum allocation hybrid algorithms are then compared with other FAPSO (FA and PSO) and FAGA (FA and GA) hybrid algorithms.

On the other hand, the hybrid algorithm designed for joint power and spectrum allocation is a continuous-binary version or a discrete-continuous optimization problem. The algorithm is designed after determining the best hybrid algorithms for spectrum allocation and power allocation. The input parameters are number of channels and number of SUs. Simulation parameters also form part of the input.

For the three cases, the performance of the algorithm in terms improving resource allocation in TVWS network is analyzed using the following performance metrics: SU SINR, sum throughput, PU SINR and run time.

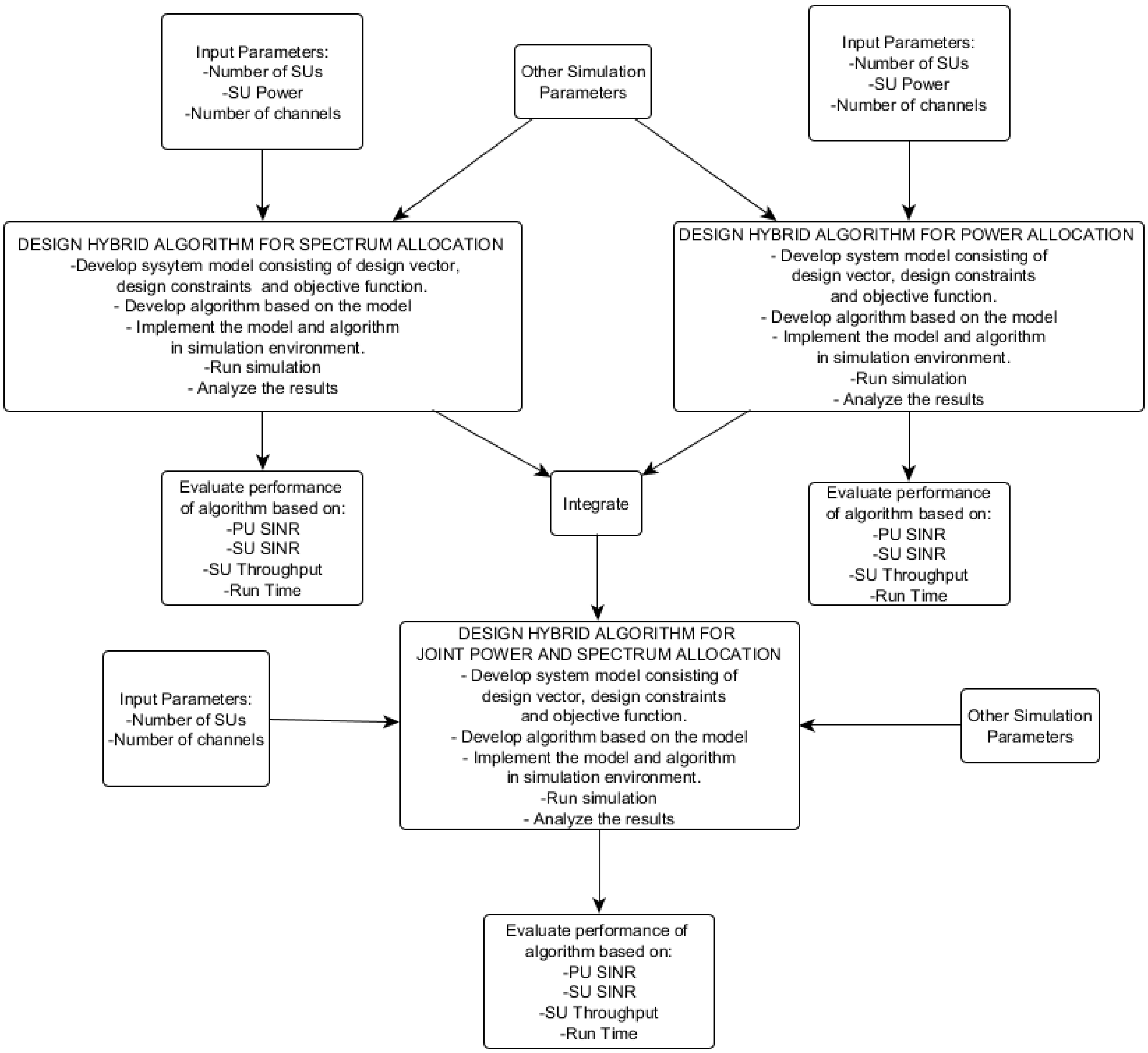

Figure 2.10: Conceptual Model

2.9 Literature Review Summary

In this chapter, existing algorithms for power allocation, spectrum allocation and joint power and spectrum allocation have been presented, evaluated and compared. It can be concluded that metaheuristic algorithms are preferred over other algorithms because of their ability to find quality solutions in reasonable amount of running time. In this thesis, a hybrid of FA, GA and PSO called FAGAPSO was designed so as to combine the benefits of the three algorithms and to overcome weaknesses of FA in exploration and exploitation.

Chapter 3: Research Methodology

This chapter describes the development of algorithms. A new algorithm based on hybrid PSO, FA and GA is presented. The chapter discusses how FA can be improved by incorporating concepts of PSO and GA. The new algorithm is applied to power allocation, spectrum allocation as well as joint power and spectrum allocation. The chapter also discusses how FA is modified to solve a binary-continuous problem. In this chapter how simulation was setup and simulation parameters used are also discussed. The various simulators available for simulating a TVWS network are also discussed in this chapter and why Matlab was chosen.

3.1 Algorithms Design

This section presents design of FAGAPSO algorithm for power allocation, spectrum allocation and joint power and spectrum allocation. This section also presents a detailed description of FA, GA and PSO.

3.1.1 Network Scenario

Network illustrated by Figure 2.4 is considered for the design of algorithms. In the figure there is a single TV receiver placed at the edge of the protection region. Among all the TV receivers in the protection region, a TV receiver at this location is the one which is most vulnerable to interference since it is very close to the secondary network. GLDB regulations require that the D/U ratio or protection ratio be measured at the edge of protection region (Gurney et al., 2008). Aggregate interference at the TV receiver, both co-channel and adjacent channel should not make the protection ratio fall below the required protection ratio threshold. It was assumed that the network consist of N SUs. An infrastructure based secondary network was considered since all the SUs in the network are under an AP.

3.1.2 Overview of Relevant Algorithms

In this section, detailed explanation of FA, GA, PSO and relevant hybrid FA algorithms has been presented.

3.1.2.1 Firefly Algorithm

As mentioned in Chapter 2, FA mimics the behavior of fireflies. Firefly is an insect that flash to either attract a mate or potential prey (Fister et al., 2013). Flashing may also serve as a warning mechanism. The flashing of a firefly is rhythmic. For female fireflies the attractiveness of male fireflies depends on its brightness. The light intensity has an inverse relationship with distance. Light intensity (I) reduces as distance (r) increases according to this formula: $I \propto \frac{1}{r^2}$. Fireflies, therefore, are visible within a limited distance. The objective function of an optimization problem can be associated with the flashing. The light intensity is determined by brightness I which is associated with objective function value. In an optimization problem, each firefly represents a possible solution to the optimization problem. Binary has been found to outperform GA and PSO (Liu et al., 2014; Anumandla et al., 2013). Binary gives a better quality solution and converges much more quickly compared to genetic algorithm and particle swarm optimization.

Pseudocode for the is presented in Algorithm 3.1. Flash flies produce short and rhythmic light to attract a female partner and potential prey. Each firefly's attractiveness is proportional to the light intensity and decreases as distance increases (Liu et al., 2014; Anumandla et al., 2013). Variation of attractiveness with distance is given by:

$$\beta = \beta_o e^{-\gamma r^2}, \tag{3.1}$$

where the term β refers to light intensity of the firefly, β_o denotes the light intensity of the source, r is the distance between two fireflies and γ is the light absorption co-efficient. For any two flashing fireflies, the less bright one will move towards the brighter one according to equation (3.2).

$$x_i^{t+1} = x_i^t + \beta_o e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha_t \epsilon_t^i. \tag{3.2}$$

The terms x_i and x_j are the locations of firefly i and firefly j, the symbol α is randomization parameter and the term ϵ_t^i is a vector of random numbers with uniform distribution. The second term represents attractiveness while the third term represents randomization. The symbol t is the iteration number. The distance between fireflies i and j, r_{ij}, is computed according to equation (3.3):

$$r_{ij} = \sqrt{\sum_{k=1}^{D}(x_{i,k} - x_{j,k})^2}, \tag{3.3}$$

where D is the number of dimensions of the problem.

Algorithm 3.1: Firefly Algorithm

Step 1: Initialize the control parameter values for the FA: light absorption coefficient γ, attractiveness β, randomization parameter α, maximum number of iterations t_{max}, number of fireflies NP, domain space D.

Step 2: Define objective function $f \underset{x}{\rightarrow}, \underset{x}{\rightarrow} = x_1, x_2, x_3, \dots, x_n$. Generate the initial location of fireflies x_i ($i = 1,2, \dots, NP$) and set the iteration number $t = 0$.

Step 3:

while $t \leq t_{max}$ **do**

  for $i = 1$ to NP (do for each individual sequentially) **do**

    for $j = 1$ to NP (do for each individual sequentially) **do**

      Compute light intensity β_i as x_i is determined by objective function $f(x_i)$

      If $\beta_i < \beta_j$, **then**

        Move firefly i towards j as described by equation (3.2)

      End if

      Attractiveness varies with distance r via $e^{-\gamma r}$

      Evaluate new solutions and update light intensity

      Check updated solutions are within limits

    end for

  end for

  Step 3.1

  Rank the fireflies and find the current best

  Increase the iteration count

end while

3.1.2.2 Genetic Algorithm

As mentioned in Chapter 2, genetic algorithm (GA) mimics evolution of biological systems (Elbeltagi et al., 2005). Algorithm steps for GA are listed in Algorithm 3.2. Each candidate solution to an optimization problem is represented by a string called a chromosome. Pseudocode for genetic algorithm is shown in the diagram below. Random solutions that represent initial chromosomes are first generated. The fitness of each of chromosome is then measured by using the objective function. In order to imitate survival of the fittest in a biological system, chromosomes will exchange information amongst each other in a random manner. The process of exchange of information is referred to as crossover. Two parents exchange information in the crossover process to create new offsprings. Just like the evolution of biological systems, the new offsprings are then mutated. The new offsprings and previous parents are then evaluated using the objective function and ranked. Only a percentage of the best chromosomes form the next generation of parents. The process of crossover and mutation is then repeated again.

Algorithm 3.2: Genetic Algorithm

Step 1: Generate the initial population of chromosomes
Step 2: Compute fitness of each chromosome
Step 3: For i = 1 to N(number of iterations)
    3.1 Perform selection of parents to be crossed over
    3.2 Perform crossover
    3.3 Perform mutation
    3.4 Compute fitness of each chromosome
  End For

3.1.2.3 Particle Swarm Optimization

As described in Chapter 2, PSO is inspired by a flock of birds flying towards a destination. Each candidate solution is referred to as a particle. Each particle represents a bird in the flock. Unlike genetic algorithm, no new birds/particles are generated. The existing particles are simply improved iteratively. The birds adjust their social behavior as they move towards the destination. Birds communicate as they fly. As they communicate they identify the bird which is in the best position and then they move towards it at a certain velocity. PSO combines both local search and global search. Local search is represented by each bird learning from their own experience. Global search is represented by each bird learning from the experience of others.

Algorithm steps for PSO are listed in algorithm 3.3. PSO starts by generating particles with random solutions to the optimization problem. The fitness of each particle is then evaluated. Each particle looks at three parameters: its current position (X_i), best position (P_i), and its flying velocity (V_i). For every iteration, the best particle and its position P_g are determined. Each particle then flies towards the best particle with its current velocity. Each particle updates its current velocity according to the equation (3.4).

$$New\ V_i = \omega \times current\ V_i + c_1 \times rand() \times (P_i - X_i) + c_2 \times rand() \times (P_g - X_i). \qquad (3.4)$$

Algorithm 3.3: Particle Swarm Optimization

```
Begin
Generate random population of N solutions (particles)
For each individual i ∈ N, calculate fitness
While termination condition is not true
        For each particle
                Set p_best as the best position of particle i
                If fitness i is better than p_best
                p_best = fitness (i)
        End
        Set g_best as the best fitness of all particles
        For each particle
                Calculate particle velocity according to equation (3.4)
                Update particle position according to equation (3.5)
        End
Check if termination is true
```

With the new current velocity, the position of the particle is then updated according to the equation (3.5).

$$New\ position\ X_i = current\ position\ X_i + New\ V_i, \qquad (3.5)$$

where c_1 and c_1 are two positive constants named, Rand() is a random function, V_{max} is the maximum particle velocity and V_{min} is the minimum particle velocity. w plays the role of balancing local search and global search.

3.1.2.4 Hybrid Firefly and Particle Swarm Optimization Algorithm

Arunachalam et al. (2015) proposed a hybrid FA and PSO for problem of combined economic and emission dispatch including valve point effect. In the proposed algorithm, there is no modification to but the initial solution is obtained from PSO. The authors argue that quality of the final solution of FA depends on the initial solution. Simulation results show that the hybrid algorithm outperforms both PSO and FA. The authors did not consider the effect on the number of iterations due to the use of PSO to generate the initial solution on the running time of the algorithm. The number of iterations of both PSO and FA can be reduced so as to reduce running time without affecting the solution quality.

Kora and Rama Krishna (2016) also proposed a hybrid FA and PSO algorithm for detection of bundle branch block. The hybrid algorithm makes use of PSO concepts and parameters. The concepts of personal best and global best which are absent in FA are introduced. All the steps in FA remain the same with that of the proposed algorithm except that equation (3.2) of the FA that represents firefly movement is changed to incorporate the idea of personal best and global best. In the proposed algorithm, each firefly movement involves a move towards the local best (P_{best}) and global best (g_{best}). In order to further improve solution quality, initial solution generated by PSO can be applied in addition to using the concept of local best (P_{best}) and global best (g_{best}) during firefly movement.

Performance of these two proposed algorithms in terms of solution quality can be further improved by hybridizing with GA operators as discussed in the next sub-section.

3.1.2.5 Hybrid Firefly and Genetic Algorithm

Rahmani and MirHassani (2014) proposed a hybrid FA and GA. All the steps in the FA remain the same except that for every iteration, the two current best solutions of FA at every iteration are crossed over. Four offsprings will be generated after crossover. The two best solutions of FA during current iteration used for crossover are then replaced by the best two (in terms of solution quality) offsprings of the four offsprings. For mutation, one of the two offsprings is randomly selected. If the selected offspring has a better solution compared to the current best solution, it replaces the current best solution in step 3.1 of Algorithm 3.1.

Luthra and Pal (2011) also proposed a hybrid FA and GA for the solution of the monoalphabetic substitution cipher. In the proposed algorithm, movement of fireflies in space is done using genetic operators (crossover and mutation) and the concept of dominant gene crossover. With dominant gene crossover, an offspring takes more from one parent than the other during crossover.

Performance of these two proposed algorithms in terms of solution quality can be further improved by hybridizing with PSO as discussed in the previous section.

3.1.3 Improving Performance of Firefly Algorithm through Hybridizing with Particle Swarm Optimization and Genetic Algorithm

In order to improve performance of FA, it is hybridized with both GA and PSO in this thesis so as to improve its exploration and exploitation ability (Gaidhane and Nigam, 2018; Singh and Singh, 2017). Algorithm steps for FAGAPSO are shown in Algorithm 3.4. In the hybrid algorithm, instead of FA starting with a random solution, it uses an initial solution as the solution found by PSO as proposed by Arunachalam et al. (2015) in step 1. In step 2, In addition to making use of initial solution of PSO, the algorithm also makes use of PSO concepts of personal best and global best during firefly movement as proposed by Kora and Rama Krishna (2016) and crossover feature of GA as proposed by Luthra and Pal (2011) and Luthra and Pal (2011).

As discussed in section 3.1.2.4, Arunachalam et al. (2015) argues that the final solution of FA depends on quality of its initial solution. This is also useful because FA and PSO have different search characteristics. By using different search characteristics, there is an improved possibility of more exploration and exploitation ability, and hence a better solution quality. PSO has a strong exploration ability because of the computation of velocity using g_{best} according to equation (3.4) that guide the particle to areas outside the neighbourhood of a particle before application in equation (3.5). However, the weakness of Arunachalam's algorithm is that FA that, runs after PSO, has stronger exploitation ability than exploration due to the nature of firefly movement that moves fireflies to areas only around the neighbourhood to a particular firefly. Exploration therefore cannot get sustained and FA can result in premature convergence because of getting trapped in a local optimum. This arises because fireflies get attracted to nearby ones according to the second term of equation (3.2). In the original FA, exploration ability is only through randomization provided by the last term of equation (3.2) and exploitation ability is through the second last term of the same equation. Original FA also has a weakness of not keeping track of the best solution obtained so far for each firefly and hence also cannot keep track of the overall global best solution.

In FAGAPSO, firefly movement will involve movement towards the global best solution and personal best solution as proposed by Kora and Rama Krishna (2016) (step 2.2.3 of Algorithm 3.4). By incorporating PSO's concept of global best solution and personal best solution, the weakness of FA of not being able to keep track of best solution found for each firefly and global best solution will be overcome. The use of PSO concepts of personal best and global best during firefly movement will also improve FA's exploration and exploitation ability. Whereas flying towards global best solution improves FA's exploration ability by directing the firefly to areas outside the neighbourhood, flying towards personal best repeatedly will improve FA's exploitation ability by directing the firefly to areas around the neighbourhood. This will also address the exploration weakness of FA in the algorithm proposed by Arunachalam et al. (2015). The hybrid algorithm proposed by Kora and Rama Krishna (2016) that is incorporated into step 2 of FAGAPSO will benefit from strong exploration ability of PSO by running PSO first before running FA as proposed by Arunachalam et al. (2015).

FAGAPSO algorithm will also make use of GA concept of crossover (step 2.2.3 of Algorithm 3.4) that helps to improve solutions of top fireflies iteratively through mixing of solutions in different chromosomes as proposed by Luthra and Pal (2011).The use of GA's crossover will further improve FA's exploration ability because new solutions in different points in the solution space will be generated. This will further address the exploration weakness of the hybrid FA and PSO algorithm proposed by Arunachalam et al. (2015). Although addition of crossover feature in FA enables it to improve its exploration ability, it does not solve the problem of FA not keeping track of the best solutions obtained so far. Through incorporating PSO concepts of personal best and global best into FA as proposed by Kora and Rama Krishna (2016) that weakness is overcome.

Algorithm 3.4: High Level Hybrid FAGAPSO

Step 1: PSO
• 1.1 Initialize PSO parameters
• 1.2 Initialize power vector and/or channel allocation matrix values with random values
• 1.3 For each iteration:
    o Update each particle velocity and position
    o Update p_{best} and g_{best}
  End
Step 2: FA (with PSO Operators) and GA
• 2.1 Initialize FA parameters and FA power vectors and/or channel allocation matrix values to those in the final value of g_{best} in Step 1.3
• 2.2 For each iteration:
    o 2.2.1 Rank fireflies and find current best
    o 2.2.3 Apply single point crossover
    o 2.2.4 For every firefly, move it towards the better solution.
      (Use p_{best} and g_{best} in firefly movement)
  End
• 2.3 Take best firefly (with power allocation matrix and/or channel allocation matrix) as final solution
Step 3: End Algorithm

Arunachalam et al. (2015) and Kora and Rama Krishna (2016) found that the hybrid FA and PSO algorithm that they proposed performs better for a continuous optimization problem compared to the original FA and PSO. These hybrid algorithms have not been tested for a binary or discrete optimization problem, especially a binary optimization problem with design variables in matrix that this thesis considers. In this thesis spectrum allocation in defined in a matrix. On the other hand Luthra and Pal (2011) found that the algorithm they proposed performed better for a binary optimization problem. This hybrid algorithm has not been tested for a continuous optimization problem. As noted in section 2.8, hybrid algorithms can behave differently for different optimization problems.

As discussed in section 2.8, this thesis investigates an FA, GA and PSO hybrid algorithm for a unique continuous-binary optimization problem. The hybrid algorithm designed for power allocation is a continuous version i.e a continuous optimization problem because the design variables are continuous. The hybrid algorithm designed for channel allocation is a binary version i.e a combinatorial/discrete optimization problem because the design variables are binary. The performance of different power allocation and spectrum allocation hybrid algorithms are then compared with other FAPSO (FA and PSO) and FAGA (FA and GA) hybrid algorithms in order to come up with the final algorithm joint power and spectrum allocation algorithm. The hybrid algorithm designed for joint power and spectrum allocation is a continuous-binary version or a discrete-continuous optimization problem. The algorithm is designed after determining the best hybrid algorithms for spectrum allocation and power allocation.

This thesis presents a new hybrid algorithm based on FA that has never been proposed and evaluated before. In subsequent sections of this Chapter, design and application of the new algorithm, FAGAPSO, for power allocation in a TVWS network, spectrum allocation in a TVWS network and joint power and spectrum allocation are discussed. In Chapter 4, the final justification for hybridization and design of joint power and spectrum allocation is presented after separately analyzing the performance of the different hybrid FA/GA/PSO algorithms for power allocation and spectrum allocation.

3.1.4 Formulation of Aggregate Interference and SINR at TV Receiver and SU

In the design of TVWS network resource allocation algorithm, the PU has to be fully protected from harmful interference. Harmful interference occurs when the PU SINR falls below the required protection ratio. Interference between SUs has to be also considered because high interference will lead to reduction in throughput according to Shannon channel capacity theorem (Jäntti et al., 2011). In this section formulation of aggregate interference at TV receiver and SU is presented.

Let the number of SUs be N and the number of channels be M. Let the potential channel allocation matrix be represented as $A = \{ a_{n,m} || a_{n,m} \in \{0,1\}$. A is of dimension N×M. $a_{n,m} = 1$ if channel m is assigned to user n. $a_{n,m} = 0$ if channel m is not assigned to user n. Let the potential power allocation vector be $P = \{P_m^1, P_m^2, .. P_m^n \dots P_m^N\}$ where P_m^n is the transmit power of SU n on channel m. Assuming that the TV receiver operates using channel c_{TV} at frequency $f_{c_{TV}}$, the interference by a single SU n to the TV receiver can be written as (Xue, 2015; Xue et al., 2014):

$$I_{TV,n} = \mu(c_{TV}, c_n) P_n^{c_n} G_n^{SU \rightarrow PU} G_{SU} G_{PU}, \tag{3.6}$$

where $P_n^{c_n}$ is the transmit power of SU n operating on channel c_n, $G_n^{SU \rightarrow PU}$ is the path loss from SU n to the victim TV receiver, G_{SU} is the antenna gain of SU and G_{PU} is the antenna gain of the PU (TV receiver). The term $\mu(c_{TV}, c_n)$ refers to adjacent channel interference co-efficient. Adjacent channel interference co-efficient is defined as (Xue, 2015; Xue et al., 2014):

$$\mu(c_{TV}, c_n) = \begin{cases} 1 & c_{TV} = c_n \\ \dfrac{\gamma(\Delta f)}{\gamma(0)} & c_{TV} \neq c_n \end{cases}, \tag{3.7}$$

where $\Delta f = |f_c - f_y|$ is the frequency difference between two channels c and y. When $\Delta f = 0$, it implies co-channel interference. The term $\gamma(\Delta f)$ denotes the minimum required SINR with frequency offset Δf at the receiver. If adjacent channel interference is modeled as equivalent co-channel interference, the total interference to the PU can then be expressed as:

$$I_{TV} = \sum_{n=1}^{N} I_{TV,n}. \tag{3.8}$$

Equation (3.9) below represents the SINR at the TV receiver. In equation (3.9), ω is the SINR at the TV receiver, the term ω_o is the minimum required SINR at the TV receiver, P_{DTV} is the received power from the TV transmitter at the TV receiver and δ_p^2 is noise power.

$$\omega = \frac{P_{DTV}}{I_{TV} + \delta_p^2} \geq \omega_o. \tag{3.9}$$

Every single SU will receive interference from other SUs. The interference at SU n using channel c_n from all other SUs in the network using channel c_j is denoted as:

$$I_{SU_n} = \sum_{\substack{j=1 \\ j\neq n,}}^{N} I_{n,j} = \sum_{\substack{j=1 \\ j\neq n}}^{N} P_j^{c_j} G_j^n G_{SU,} \tag{3.10}$$

where $I_{n,j}$ is the interference caused by SU j to SU n, G_j^n is the distance based path loss from SU j to SU n . SINR at each SU can then be written as:

$$\rho_n = \frac{P^{BS} G_{SU} G_{BS}}{I_{SU_n} + \delta_n^2} \geq \rho_o, \tag{3.11}$$

where P^{BS} is the transmit power of the access point (TVWS base station) and G_{BS} is the antenna gain of the base station. The term ρ_o is the minimum required SINR at SUs.

3.1.5 Optimization of Power Allocation Using Firefly Algorithm

Power allocation only using FA is first considered. In order to reduce interference to the PU and among SUs, optimization of power allocation is necessary. The optimization goal is to find a power vector $P = \{P_m^1, P_m^2, .. P_m^n \dots P_m^N\}$ (where P_m^n is the power of SU n on the allocated channel m) to minimize the sum power, $\varphi(P) = \sum_{n=1}^{N} P_m^n$, used by all SUs while ensuring that interference constraints at the PU and all SUs are met. The power of each SU is adjusted between the range $[P_{min}, P_{max}]$. Optimal power vector can be found by solving the optimization problem 3.1.

Problem 3.1

$$P^* = \arg min\, \varphi(P) \tag{3.12}$$

subject to:

$$C_1: \omega \geq \omega_o \tag{3.13}$$

$$C_2: \rho_n > \rho_o, n = 1,2 \ldots\ldots N \tag{3.14}$$

$$C_3: p_{min} \leq p_n \leq p_{max}. \tag{3.15}$$

where $\varphi(P)$ is the objective function (sum power) value to be minimized, ω is the TV receiver SINR, ω_o is the minimum TV receiver SINR threshold, ρ_n is SU SINR for SU n and ρ_o is the minimum SU SINR threshold.

Optimization problem 3.1 is solved using FA. The optimization of power allocation problem defined in Problem 3.1 is a constrained optimization problem. The most common way to deal with constraints when using evolutionary algorithms to solve optimization problems is to use an exterior penalty function(Vardhan and Vasan, 2013). Exterior penalty functions are preferred over interior penalty functions because they do not require an initial feasible solution (Vardhan and Vasan, 2013). Penalty functions changes a constrained optimization problem into an unconstrained optimization problem. This is achieved by adding to the objective function, a penalty term that prescribes a high cost for violation of constraints. The objective function of optimization problem 3.1 will change to:

$$\emptyset(P) = \varphi(P) + c_s \sum_{n=1}^{N} \max[0, g_n^s]^2 + c_p \max\left[0, g_n^p\right]^2, \tag{3.16}$$

where $g_n^s = \rho_o - \rho_n$ and $g_n^p = \omega_o - \omega_n$. The terms c_s and c_p are penalty factors for SU SINR threshold violation and PU SINR threshold violation, respectively. The optimization Problem 3.1 can then be re-written as:

Problem 3.2

$$P^* = \arg min\, \emptyset(P) \tag{3.17}$$

subject to $C1: p_{min} \leq p_n \leq p_{max}$.

Problem 3.2 is then solved using Algorithm 3.5.

Algorithm 3.5 shows the steps for solving Problem 3.2 using FA. The algorithms starts with specifying the number of fireflies as NP and dimension of each firefly as $D = N$. Initially, each firefly will have random power values for each position assigned. All fireflies will have the same channel assignment for SUs. Channel assignment is done randomly in Step 1. In all the steps channel allocation will not change. Each firefly represents a potential solution to the problem of finding optimal power allocation to all SUs in the TVWS network. At every iteration, the best firefly is determined and firefly movement is done according to step 5. After a fixed number of iterations, the best firefly is selected as the solution to the power allocation problem.

Algorithm 3.5: Optimization of Power Allocation using Firefly Algorithm

Step 1:

- Specify the number of SUs, N
- Set the dimension of fireflies D as N
- Specify the number of fireflies as NP

Step 2:

- Allocate a single channel to each SU randomly
- Initialize the control parameters of the algorithm α, β, γ firefly number NP and maximum number of iterations t_{max}.
- Generate initial position of fireflies randomly $x_i = [x_{1,i}, x_{2,i}, , \dots x_{d,i} \dots \dots , , x_{D,i}]$ where $P_{min} \leq x_{d,i} \leq P_{max}$ and $i \in (1 \dots \dots NP)$ by assigning random power values for each SU and for each firefly.

Step 3:

- Check firefly x_i to see if the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.

Step 4

- Calculate the fitness value of each firefly using equation (3.17) and rank the fireflies according to their fitness values

- Find the current best solution

Step 5

- For every firefly, move it to the better solution according to equation (3.2).

Step 6

- If it reaches the predefined maximum number of iterations, then the power vector of the current best solution mentioned in step 4 is derived and stop the progress else go to step 3 and continue.

3.1.6 Optimization of Power Allocation Using FAGAPSO

The algorithm steps are outlined in Algorithm 3.6. In step 1 of Algorithm 3.6, optimization power allocation is first done using PSO. When PSO is used for optimization of power allocation, each particle (X_i) represents a possible solution to the problem of finding optimal power allocation to all SUs. Initially each particle will have random power assignment for each SU. At each iteration the best power vector for each particle (P_i) and global best power vector (P_g) are updated if there is an improvement. At every iteration, X_i will then move towards (P_i) and (P_g) at a certain velocity. After a fixed number of iterations, P_g will be selected as the optimal solution to the problem of power assignment.

In step 2, FA starts with initial solution of PSO generated in Step 1. All fireflies will be initiated with solutions found in PSO particles at the end of PSO in Step 1. In step 3, after ranking fireflies according to their fitness as measured by equation (3.17), the best two fireflies are crossed over to generate four new offsprings. The four new offsprings are then ranked according to their fitness. The top four fireflies will then be replaced by the chromosomes generated through crossover if their fitness values are lower (better).

Single point crossover with mixing parameter was used. This is illustrated in figure 3.1. In the figure, $0 < r < 1$ is the mixing parameter. r is generated randomly during the execution of the algorithm. Mixing parameter is necessary for an optimization problem with continuous values in order to have the crossover process to generate new values that are to be passed into the offsprings. The consequence of this is that crossover process will push the fireflies more diverse and different solution areas that may have better solutions.

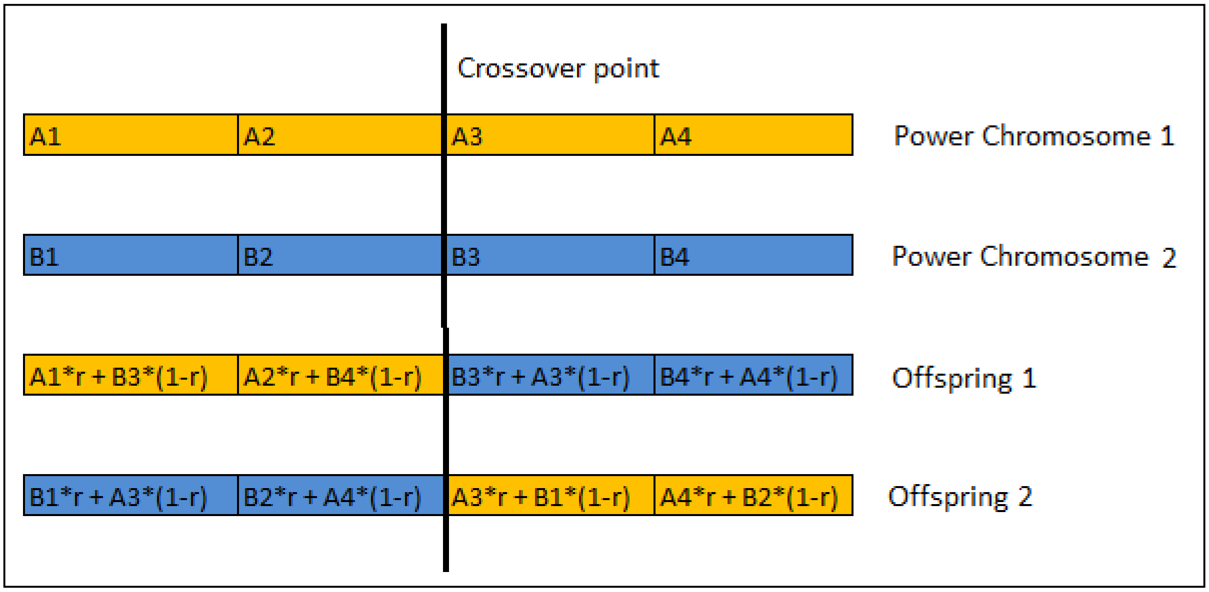

Figure 3.1: Illustration of single point crossover with mixing parameter

Instead of firefly movement being that described by equation (3.2), firefly movement will involve local search towards local personal best and global search towards global best according to equation (3.18). The algorithm makes use some PSO operators including ω, P_{best}, g_{best}, c_1 and c_2.

$$x_i^{t+1} = \omega x_i^t + c_1 e^{-\gamma r_{ij}^2}(p_i - x_i^t) + c_2 e^{-\gamma r_{ij}^2}(p_g - x_i^t) + \alpha_t \epsilon_t^i. \quad (3.18)$$

Algorithm 3.6: Optimization of Power Allocation using FAGAPSO

Step 1:

- Initialize number of particles, c_1, c_2, ω, v_{min}, v_{max}
- For each SU, assign a single channel from the set of available channels.
- For each particle

    Initialize particle with random power values that are within allowed range.

End

- Do

For each particle

Compute fitness value using equation (3.17)

If the value of fitness can outmatch the best fitness value (p_{i}) in history

set current value as the new p_i

End

Select the particle with the best fitness value among all the particles as the p_{best}

If current p_{best} and its associated x_{best} is better than g_{best}set current p_{best} as g_{best}

For each particle

Compute particle velocity according equation (3.4)

Update position of particle according equation (3.5). If any position of the particle has power values that are out of range, replace random power value that is within range.

End

While maximum iterations has not been reached.

- g_{best} set as the final solution of PSO.

Step 2

- Initialize the control parameters of the algorithm α, β, γ firefly number NP and highest number of iterations t_{max}.
- Set the dimension of fireflies D.
- Set initial position of fireflies as those of the solution for Problem 3.2 generated by PSO in Step 1.

Step 3

- Compute the value of fitness of each firefly using equation (3.17) and rank the fireflies according to their fitness values.
- Determine the current best solution.
- Apply single point crossover with mixing parameter mechanism on the top two best solutions.
- Select the best offspring out of the four offsprings created through crossover and use it as the current best solution of FA if its fitness is better than that of the current best.

Step 4

- For every firefly, move it to the better solution according to equation (3.18).
- Check firefly x_i to see if the all the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.

Step 5

- If it reaches the predefined maximum number of iterations, then the power vector of the current best solution mentioned in step 3 is derived and stop the progress else go to step 3 and continue.

3.1.7 Optimization of Spectrum Allocation Using Firefly Algorithm

Optimization of spectrum allocation only using FA is now considered. In order to reduce interference to the PU and among SUs, optimization of spectrum allocation is necessary. Let the potential channel allocation matrix be represented as $A = \{a_{n,m} || a_{n,m} \in \{0,1\}$. A is of dimension N×M. $a_{n,m}$ = 1 if channel m assigned to user n. $a_{n,m}$ = 0 if channel m is not assigned to user n. Spectrum allocation deals with binary values unlike for the case of power allocation where the values are continuous. The optimization goal is to find a channel allocation matrix A^* to maximize sum throughput, U, of all SUs as defined in equation (3.19).

$$U = \sum_{n=1}^{N} \sum_{m=1}^{M} r_{n,m}. \tag{3.19}$$

where b_m is the bandwidth of channel m and $r_{n,m}$ is the throughput of single SU transmitter n on channel m computed as follows:

$$r_{n,m} = {}^{1}/_{2}\, a_{n,m} b_m log_2(1 + \rho_n). \tag{3.20}$$

Optimal channel allocation matrix can be found by solving the optimization Problem 3.3.

Problem 3.3

$$A^* = \arg max\, U \tag{3.21}$$

subject to:

$$C_1: \omega > \omega_o, \tag{3.22}$$

$$C_2: \rho_n > \rho_o, n = 1,2 \ldots\ldots N, \tag{3.23}$$

$$C_4: a_{n,m} \in \{0,1\}, \tag{3.24}$$

$$C_5: a_{n,m} = 1, c_n = m, \tag{3.25}$$

$$C_6: a_{n,m} = 0, c_n \neq m. \tag{3.26}$$

Just like in optimization of power allocation, penalty functions are used to change the constrained optimization problem into an unconstrained optimization problem. By applying penalty functions, the objective function of optimization Problem 3.3 will change to:

$$\emptyset(A) = U - c_s \sum_{n=1}^{N} \max[0, g_n^s]^2 - c_p \max\left[0, g_n^p\right]^2, \tag{3.27}$$

where $g_n^s = \rho_o - \rho_n$ and $g_n^p = \omega_o - \omega_n$. The terms c_s and c_p are penalty factors for SU SINR threshold violation and PU SINR threshold violation respectively. Problem 3.3 can then be re-written as:

Problem 3.4

$$A^* = \arg max\, \emptyset(A) \tag{3.28}$$

subject to:

$$C_1: \omega > \omega_o, \tag{3.29}$$

$$C_2: \rho_n > \rho_o, n = 1,2 \ldots\ldots N, \tag{3.30}$$

$$C_3: a_{n,m} \in \{0,1\}, \tag{3.31}$$

$$C_4: a_{n,m} = 1, c_n = m, \tag{3.32}$$

$$C_5: a_{n,m} = 0, c_n \neq m. \tag{3.33}$$

Algorithm 3.7 shows the steps for solving Problem 3.4 using FA. The algorithms starts with specifying the number of fireflies as NP and dimension of each firefly as $D = N$. For spectrum allocation, each firefly represents a possible solution to the problem of finding optimal spectrum allocation to all SUs in the TVWS network. Each firefly is in form of channel allocation matrix. Each firefly will have the same power allocation assigned to SUs that is randomly generated. In all the steps, power assignment will not change. At every iteration, the best firefly is determined and each firefly movement is done according to Step 3 in Algorithm 3.1. Equation (3.3) applies when the values being considered are continuous. It will not apply to the spectrum allocation matrix because the values in the matrix are binary (0 or 1). The following equation will be used for computing distance (r_{ij}) between two channel allocation matrices:

$$r_{ij} = \sum_{d=1}^{D} \sum_{m=1}^{M} x_{m,d,i} \otimes x_{m,d,j}, \tag{3.34}$$

where $x_{m,d,i}$ and $x_{m,d,j}$ are the channel allocation values in fireflies i and j, respectively at position m, d in the channel allocation matrix. Since the channel allocation matrix is made up of binary values, equation (3.4) will not apply for the channel allocation matrix since firefly movement results in values that are not binary. In order to determine whether $x_{m,d,i}$ will be a 0 or 1, Sigmoid function is first used to change the value after the firefly mobility using the following equation:

$$sig(x_{m,d,i}) = \frac{1}{1+\mathrm{e}^{-x_{m,d,i}}}. \tag{3.35}$$

The value for each position in the channel allocation matrix is then computed as follows:

$$x_{m,d,i}^{t+1} = \begin{cases} 1 & rand() < sig(f) \\ 0 & else \end{cases}$$
$$\text{where } f = x_{m,d,i}^{t}. \tag{3.36}$$

After a fixed number of iterations, the firefly with the best objective function is selected as the solution to the spectrum allocation problem.

Algorithm 3.7: Optimization of Spectrum Allocation using Firefly Algorithm

Step 1:

- Specify the number of SUs, N
- Set the dimension of fireflies as D
- Specify the number of fireflies as NP

Step 2:

- Initialize the control parameters of the algorithm α, β, γ firefly number NP and maximum number of iterations t_{max}.
- Randomly assign each SU power values between p_{min} and p_{max}
- Generate initial position of fireflies randomly for each firefly x_i:

$$x_i = \begin{matrix} x_{1,1,i} & x_{1,2,i} & \cdot\cdot & x_{m,d,i} & \cdot\cdot & x_{1,D,i} \\ x_{2,1,i} & x_{2,2,i} & \cdot\cdot & x_{m,d,i} & \cdot\cdot & x_{2,D,i} \\ \cdot\cdot & x_{3,2,i} & \cdot\cdot & x_{m,d,i} & \cdot\cdot & \\ x_{m,d,i} & x_{4,2,i} & \cdot\cdot & x_{m,d,i} & \cdot\cdot & x_{m,D,i} \\ \cdot\cdot & & \cdot\cdot & & \cdot\cdot & \cdot\cdot \\ x_{M,d,i} & x_{M,2,i} & \cdot\cdot & x_{m,d,i} & \cdot\cdot & x_{M,D,i} \end{matrix}$$

where $x_{m,d,i} \in \{0,1\}$ and $i \in (1 \ldots\ldots NP)$

Step 3:

- Check firefly x_i to find if only one channel is assigned to each SU. If more one than channel is assigned to SU, randomly pick one of the channels and assign to SU.

Step 4

- Calculate the fitness value of each firefly using equation (3.27) and rank the fireflies according to their fitness values
- Find the current best solution

Step 5

- For every firefly, move it to the better solution according to equation (3.2) and with application of equations (3.34), (3.35) and (3.36).

Step 6

- If it reaches the predefined maximum number of iterations, then the power vector of the current best solution mentioned in step 4 is derived and stop the progress else go to step 3 and continue.

3.1.8 Optimization of Spectrum Allocation Using FAGAPSO

In this section, optimization of spectrum allocation using hybrid firefly and particle swarm optimization with genetic operators is discussed. The algorithm steps are outlined in Algorithm 3.8. In step 1 of Algorithm 3.8, optimization spectrum allocation is first done using PSO. Each PSO particle is made up channel allocation matrix of dimension N×M. Position update in step 1.4.3 may result in values that are not binary. Just like FA, equations (3.35) and (3.36) will be used to convert the values obtained during particle position update to binary values. If particle position update result in allocation of more than one channel to SU, one channel will be randomly chosen.

In step 2, FA starts with initial solution of PSO generated in Step 1. All fireflies will be initiated with solutions found in PSO particles at the end of PSO in Step 1. Each firefly is made up of a channel allocation matrix of dimension N×M. In step 3, after ranking fireflies according to their fitness, the best two fireflies are crossed over to generate four new offsprings. The four new offsprings are then ranked according to their fitness. The top four fireflies will then be replaced by the chromosomes generated through crossover if their fitness values are higher (better). Single point crossover is used. Both horizontal and vertical crossover is used interchangeably in a random manner. Horizontal and vertical crossover applied are illustrated in figures 3.2 and 3.3. Instead of firefly movement being that described by equation (3.3), firefly movement will involve local search towards local personal best and global best according to equation 3.18. The algorithm therefore makes of use PSO operators including ω, P_{best}, g_{best}, c_1 and c_2.

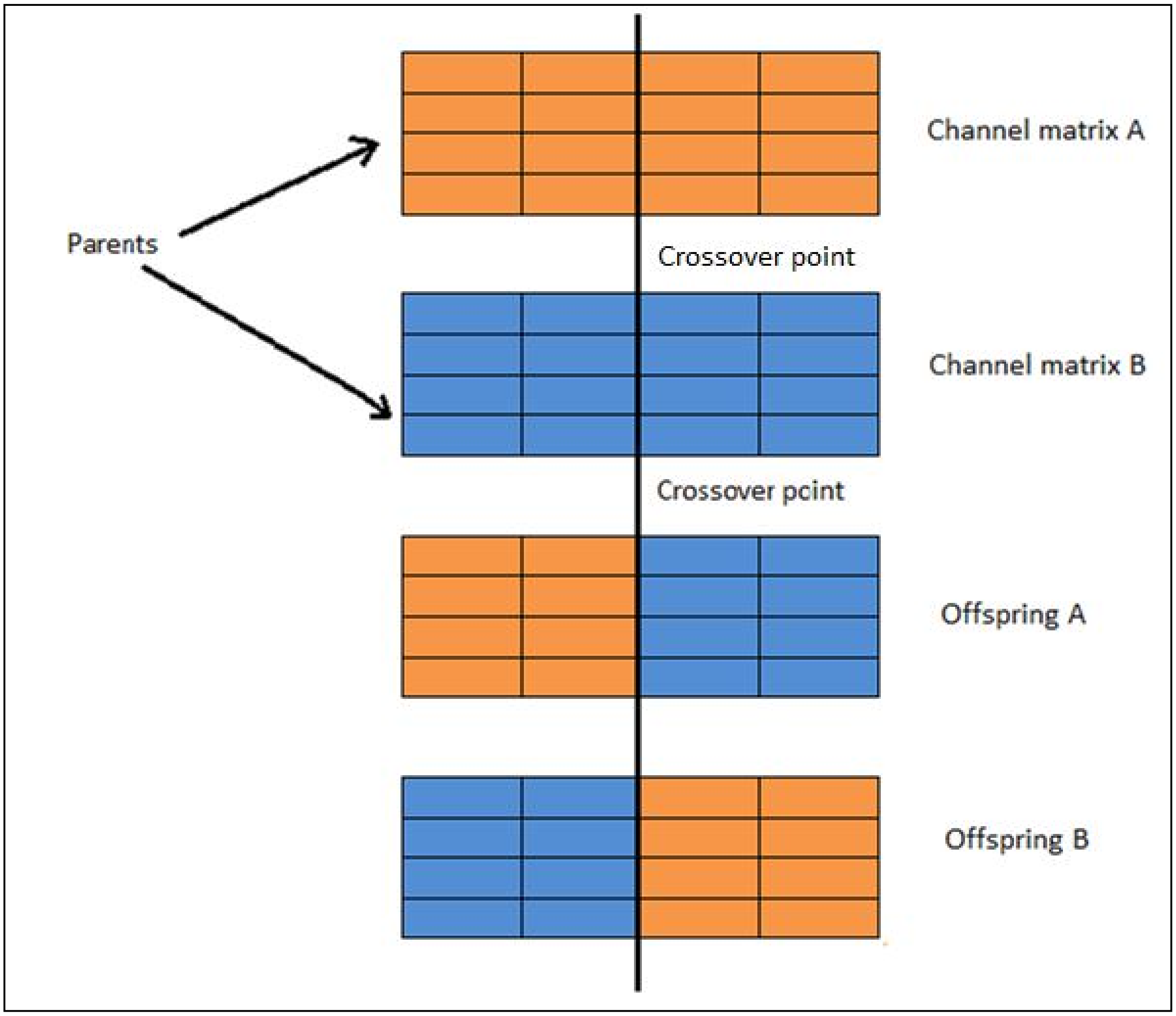

Figure 3.2: Illustration of single point vertical crossover for channel allocation matrix

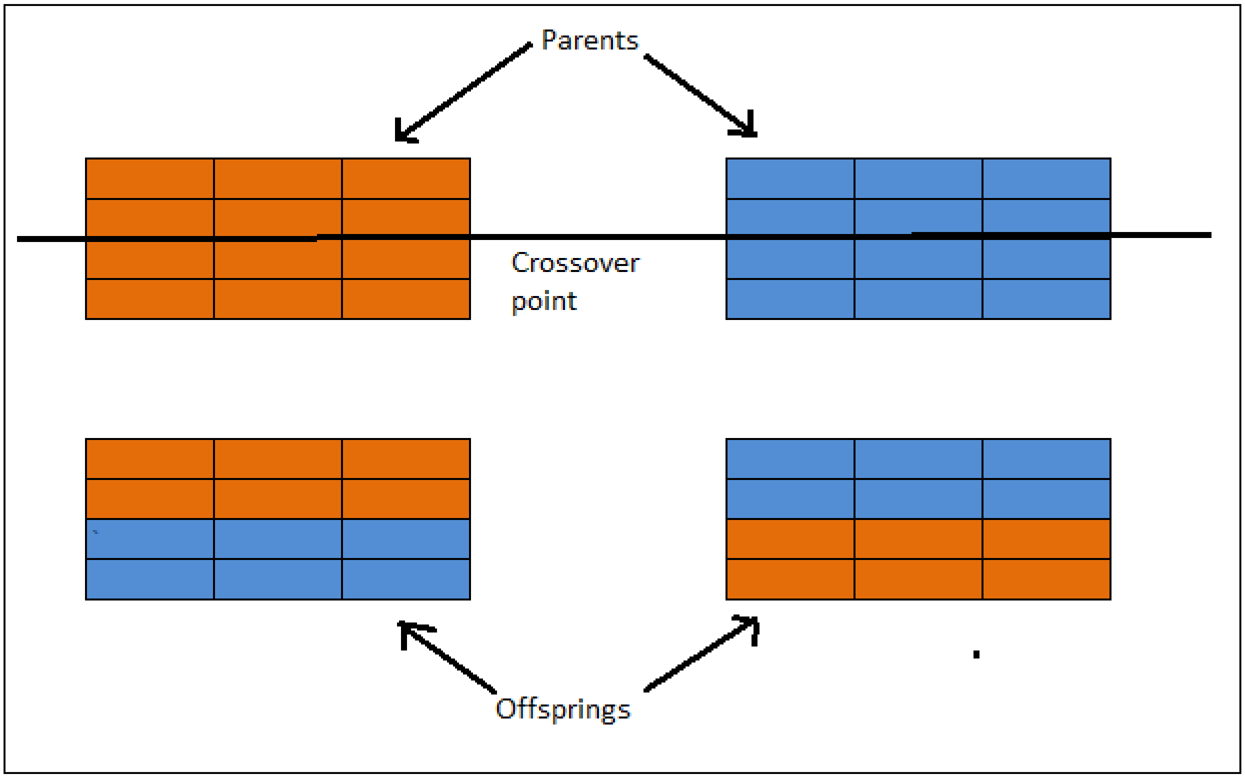

Figure 3.3: Illustration of single point vertical crossover for channel allocation matrix

Algorithm 3.8: Optimization of Spectrum Allocation using FAGAPSO
Step 1: • 1.1 Initialize number of particles, c_1, c_2, ω, v_{min}, v_{max} • 1.2 Assign each SU randomly power values within range. • 1.3 For each particle Initialize particle with random channel assignment End • 1.4 Do 1.4.1 For each particle Compute fitness value using equation (3.27) If the value of fitness can outmatch the best fitness value (p_i) in history set current value as the new p_i End 1.4.2 Select the particle with the best fitness value of all the particles as the p_{best}

If current p_{best} and its associated x_{best} is better than g_{best}set current p_{best} as g_{best}

1.4.3 For each particle

Compute particle velocity according equation (3.4)

Update position of particle according equation (3.5) and with application of equations (3.35) and (3.36)

If particle position update result in allocation of more than one channel, randomly select only one channel

End

While maximum iterations has not been reached.

- 1.5 g_{best} set as the final solution of PSO.

Step 2

- 2.1 Initialize the control parameters of the algorithm α, β, γ firefly number NP and maximum number of iterations t_{max}.
- 2.2 Set the dimension of fireflies D.
- 2.3 Set initial position of fireflies as those of the solution for Problem 3.4 generated by PSO in Step 1.

Step 3

- 3.1 Compute the fitness value of each firefly using equation (3.27) and rank the fireflies according to their fitness values.
- 3.2 Determine the current best solution.
- 3.3 Apply horizontal and vertical crossover interchangeably in a random manner on the top two best solutions.
- 3.4 Choose the best offspring out of the four offsprings created through crossover and use it as the current best solution of FA if its fitness is better than that of the current best.

Step 4

- 4.1 For every firefly, move it to the better solution according to equation (3.2) and with application of equations (3.34), (3.35) and (3.36).
- 4.2 Check firefly x_i to see if each firefly has only one channel assignment to SU. If there is an SU that has been assigned more than one channel, randomly select one channel only.

Step 5

- If it reaches the predefined maximum number of iterations, then the power vector of the current best solution mentioned in step 3 is derived and stop the progress else go to step 3 and continue.

3.1.9 Joint Power and Spectrum Allocation Optimization using Modified Firefly Algorithm

Joint power and spectrum allocation is now considered. This section presents modified FA for joint optimization of spectrum and power allocation. The optimization goal is to find a power vector P^* and channel allocation matrix A^* that maximizes sum downlink throughput while ensuring that interference constraints at the PU and all SUs are met. The power of each SU is adjusted between the range $[P_{min}, P_{max}]$. Optimal power vector and spectrum allocation matrix can be found by solving optimization Problem 3.5 below.

Problem 3.5

$$P^*, A^* = \arg\max(U), \tag{3.37}$$

subject to:

$$C_1: \omega > \omega_o, \tag{3.38}$$

$$C_2: \rho_n > \rho_o, n = 1,2 \ldots\ldots N, \tag{3.39}$$

$$C_3: p_{min} \leq p_n \leq p_{max}, \tag{3.40}$$

$$C_4: a_{n,m} \in \{0,1\}, \tag{3.41}$$

$$C_5: a_{n,m} = 1, c_n = m, \tag{3.42}$$

$$C_6: a_{n,m} = 0, c_n \neq m, \tag{3.43}$$

where ω is SINR at the TV receiver and U is the sum throughput given by equation (3.14). Constraints C_5 and C_6 imply that one channel ($c_n = m$) only in SU_n channel allocation row will have a value 1, the rest will be 0.

Since optimization problem is about joint optimization of power and spectrum allocation, each firefly, x_i, will be made up of a power vector ($x_{P,i}$) and a spectrum allocation matrix ($x_{C,i}$) unlike in a original FA where there is only one vector which could be made up of either binary or continuous values. Firefly movement will be done separately for the power vector and channel allocation matrix since each firefly is made of power vector and channel allocation matrix. This implies that distance between the channel allocation matrices and power allocation vector will be done separately. The following equation will be used for computing distance ($r_{ij,C}$) between two channel allocation matrices x_i and x_j :

$$r_{ij,C} = \sum_{d=1}^{D} \sum_{m=1}^{M} x_{Cm,d,i} \otimes x_{Cm,d,j}, \tag{3.44}$$

where $x_{Cm,d,i}$ and $x_{Cm,d,j}$ are the channel allocation values in fireflies i and j, respectively at position m, d. The following equation will be used for computing distance between two power vectors:

$$r_{i,j,P} = \sqrt{\sum_{d=1}^{D} (x_{Pd,i} - x_{Pd,j})^2}\ , \tag{3.45}$$

where $x_{Pd,i}$ and $x_{Pd,j}$ are the power vectors in fireflies i and j, respectively.

New power vector and channel matrix for each firefly, x_i, will be computed according to equation (3.46) and (3.47), respectively.

$$x_{P_{d,i}^{t+1}} = x_{P_{d,i}^{t}} + \beta_o e^{-\gamma r_{ij,P}^2} \left(x_{P_{d,j}^{t}} - x_{P_{d,i}^{t}} \right) + \alpha_t \epsilon_t^i. \tag{3.46}$$

$$x_{C_{m,d,i}^{t+1}} = x_{C_{m,d,i}^{t}} + \beta_o e^{-\gamma r_{ij,C}^2} \left(x_{C_{m,d,j}^{t}} - x_{C_{m,d,i}^{t}} \right) + \alpha_t \epsilon_t^i. \tag{3.47}$$

Algorithm 3.9: Joint Power and Spectrum Allocation using Modified Firefly Algorithm
Step 1: • Specify M, N • Set the dimension of fireflies D **Step 2**: • Initialize the control parameters of the algorithm α, β, γ, number of fireflies NP and maximum number of iterations t_{max}. • Generate initial position of each firefly (x_i) randomly with each firefly consisting

of power vector and channel vector:

- Set of power vectors in the fireflies:

$$x_P = [x_{P1}, x_{P2}, \ldots x_{Pi}.\,.\,,\,, x_{P,NP}] \text{ and } i \in (1 \ldots\ldots NP)$$

- Set of channel vectors in the fireflies:

$$x_C = [x_{C1}, x_{C2}, \ldots x_{Ci}.\,.\,,\,, x_{C,NP}] \text{ and } i \in (1 \ldots\ldots NP)$$

Step 3:

- Check firefly x_i to see if the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.
- Randomly select a single channel for each SU, if there is assignment of more than one channel to a SU.

Step 4:

- Calculate the brightness/fitness value of each firefly using equation (3.48) and rank the fireflies according to their fitness values.
- Find the current best solution.

Step 5:

- For every firefly, move it to the better solution according to equation (3.2) through application of equations (3.46) for power mobility and (3.47) for channel matrix mobility.

Step 6:

- If it reaches the predefined maximum number of iterations then derive the spectrum allocation matrix and power allocation vector of the current best solution mentioned in step 4 and stop the progress else go to step 3 and continue.

As discussed in section 3.1.7, since the channel allocation matrix is made up of binary values, equation (3.3) will not apply for the channel allocation matrix because firefly movement results in values that are not binary. Equations (3.35) and (3.36) will be used to change the values to binary values.

The power and channel allocation problem defined in Problem 3.3 is a constrained optimization problem. After applying penalty functions so that the optimization problem in Problem 3.5 is converted to a non-constrained optimization problem, the objective function of optimization problem will change to:

$$\emptyset = U - c_s \sum_{i=1}^{N} \max[0, g_i^s]^2 - c_p \max[0, g_i^p]^2, \qquad (3.48)$$

where c_p and c_s are co-efficients for the two penalty terms, $g_i^s = \rho_o - \rho_i$ and $g_i^p = \omega_o - \omega_i$, respectively. The optimization Problem 3.5 can then be re-written as that in Problem 3.6.

Problem 3.6

$$P^*, A^* = \arg max\, \emptyset \qquad (3.49)$$

subject to

$$C_1: p_{min} \le p_n \le p_{max} \qquad (3.50)$$

$$C_2: a_{n,m} \in \{0,1\} \qquad (3.51)$$

$$C_3: a_{n,m} = 1, c_n = m \qquad (3.52)$$

$$C_4: a_{n,m} = 0, c_n \neq m \qquad (3.53)$$

Problem 3.6 is then solved using Algorithm 3.9.

3.1.10 Joint Power and Spectrum Allocation Optimization Using FAGAPSO

This section presents joint power and spectrum allocation optimization using hybrid firefly and particle swarm optimization with genetic operators. The algorithm steps are outlined in Algorithm 3.10. In step 1 of Algorithm 3.10, optimization of resource allocation is first done using PSO. Each particle will consist of power vector and channel allocation matrix. All particles will be initialized with random valid power and channel assignment for all SUs. In step 1.3.4, computation of velocity (equation (3.4)) and position update (equation (3.5)) will be done separately for channel allocation matrix and power allocation vector.

In step 2, FA starts with initial solution of PSO generated in Step 1. All fireflies will be initiated with solutions found in PSO particles at the end of PSO in Step 1. In step 3, after ranking fireflies according to their fitness, the best two fireflies are crossed over to generate four new offsprings. The four new offsprings are then ranked according to their fitness.

The top four fireflies will then be replaced by the chromosomes generated through crossover of top two fireflies if their fitness values are higher (better). Crossover with mixing parameter illustrated by figure 3.1 is applied for power allocation vectors and crossover illustrated by figure 3.2 and 3.3 are applied interchangeably and in a random manner for channel allocation matrices. Instead of firefly movement being that described by equation (3.3), firefly movement will involve local search towards local personal best and global best according to equation (3.54). The proposed algorithm therefore makes use of some PSO operators including ω, g P_{best}, g_{best}, c_1 and c_2.

$$x_i^{t+1} = \omega x_i^t + c_1 e^{-\gamma r_{ij}^2}(p_i - x_i^t) + c_2 e^{-\gamma r_{ij}^2}\left(p_g - x_i^t\right) + \alpha_{t}., \tag{3.54}$$

Algorithm 3.10: Joint Power and Spectrum Allocation Optimization Using FAGAPSO
Step 1: • 1.1 Initialize number of particles, c_1, $c_{2,}$ ω, v_{min}, v_{max} • 1.2 For each particle Initialize power vector with random power values that are within allowed range. Initialize channel allocation matrix, with one channel assigned to each SU. End • 1.3 Do 1.3.1 For each particle Calculate fitness value If the fitness value is better than the best fitness value (p_{i}) in history set current value as the new p_i End 1.3.2 Choose the particle with the best fitness value of all the particles as the p_{best} 1.3.3 If current p_{best} and its associated x_{best} is better than g_{best} set current p_{best} as g_{best}

1.3.4 For each particle

- Calculate particle velocity according equation (3.4)
- Update particle position for both the power vector and channel matrix according to equation (3.5)
- Check power vector to see if the all the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.
- Randomly select a single channel for each SU, if there is assignment of more than one channel to a SU.

End

While maximum iterations has not been reached.

- 1.4 g_{best} set as the final solution of PSO.

Step 2

- 2.1 Initialize the control parameters of the algorithm α, β, γ firefly number NP and maximum number of iterations t_{max}.
- 2.2 Set the dimension of fireflies D.
- 2.3 Set initial position of fireflies as those of the solution for Problem 1 generated by PSO in Step 1.

Step 3

- 3.1 Calculate the fitness value of each firefly using equation (3.48) and rank the fireflies according to their fitness values.
- 3.2 Find the current best solution.
- 3.3 Apply crossover mechanism separately for both the channel matrix (horizontal and vertical crossover interchangeably in a random manner) and power vector (single point crossover with mixing parameter) on the top two best solutions.
- 3.4 Select the best offspring out of the four offsprings created through crossover and use it as the current best solution of FA if its fitness is better than that of the current best.

Step 4

- 4.1 For every firefly, move it to the better solution according to equation (3.54).

- 4.2 Check firefly x_i to see if the all the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.
- 4.3 Check firefly x_i to if only one channel is assigned to each SU. If more than channel is assigned to SU, randomly pick one of the channels and assign to SU.

Step 5

- If it reaches the predefined maximum number of iterations, then the power vector and channel allocation matrix of the current best solution mentioned in step 3 is derived and stop the progress else go to step 3 and continue.

3.2 Algorithms Compared

In order to analyze the performance of FAGAPSO, it was compared to PSO, GA, FA, other hybrid algorithms and a few other algorithms. Table 3.1 shows a list of algorithm that were compared for power allocation, spectrum allocation and joint power and spectrum allocation.

Table 3.1: Algorithms Compared

	Power Allocation	Spectrum Allocation	Joint Power and Spectrum Allocation
FA	✓	✓	✓
PSO	✓	✓	✓
GA	✓	✓	✓
Hybrid FA and PSO	✓	✓	✗
Hybrid FA, PSO and GA	✓	✓	✓
Hybrid FA and GA	✓	✓	✗
Heuristic Algorithm (Xue et al., 2014)	✗	✗	✓
Spatial adaptive play (SAP) (Xue and Wang, 2015)	✗	✗	✓

3.3 Performance Metrics

For each change in configuration, the following parameters were analyzed:

- SU SINR
- PU SINR
- Throughput
- Objective function value
- Percentage of SUs below the desired threshold.

3.4 Research Approach and Context

Simulation was chosen over real world implementation using CR equipment. The reasons are as follows. Firstly, a well designed model is able to represent reality. In this study, the model was thoroughly verified. Secondly, simulation allows simpler change of configuration in order to be able to study different scenarios. Thirdly, the equipment for simulation of TVWS network is costly. One customer white space device costs approximately US$ 500.

Cellular network offload to TVWS was considered because it represents a scenario where there is high density of users. Cellular offload to TV White Spaces, as discussed in section 2.1.4, means cellular network such as 3G, 4G or 5G can make use of TV white spaces. This will imply that the end user devices will be armed with cognitive radio that can allow it to change frequencies of operation from the normal cellular network frequencies (such as 900MHz, 2.1GHz or 700MHz) to the available TV white space channels. Packet switched network was considered instead of a circuit switched network. This means mobile data is offloaded to TV white spaces and not calls.

A scenario in Kenya was considered. More specifically a hotspot in Nairobi CBD was considered because of dense population.

3.5 Options Available for TVWS Network Simulation

A TVWS network is a cognitive radio network. A number of network simulators can be used for cognitive radio simulation. They include NS-2, NS-3, OMNET and Matlab.

3.5.1 NS-2

NS-2 is a discrete event and open source network simulator (Köksal, 2008). It can be used to simulate TCP, routing and multicast protocols over wired and wireless networks. It has many features and already has many protocols implemented. NS-2 is based on C++ and OTcl. OTcl is used for scenario configuration and manipulation of existing C++ objects. A number of cognitive radio simulators based on NS-2 have been proposed. They include Cog-NS, CRCN and CRAHN. Over the years NS-2 has lost favor. The main reason for this is its inherent complexity due to its reliance on OTcl scripts to create simulation scenarios(Khan et al., 2013). The following are CR simulators based on NS-2.

a. Cognitive Radio Cognitive Network (CRCN)

CRCN allows simulation of the following: spectrum allocation, power control algorithms, CR MAC algorithms and CR routing protocols. In the simulator, a reconfigurable multi-radio multi-channel PHY layer is available for each node. In the PHY layer, the following parameters can be customized: transmission power or propagation model.

b. *Cognitive Radio Ad Hoc Network (CRAHN)*

The CR module is based on spectrum sensing. The CR module can sense PU activity and pause transmission when the PU claims the spectrum.

3.5.2 NS-3

NS-3 is an open source, discrete event network simulator (Köksal, 2008). NS-3 is an replacement of NS-2. NS-3 is written in C++ and Python. NS-3 simulations can be implemented using either C++ or Python. Traffic can be analyzed using Wireshark through reading of Trace files. Unlike NS-2, NS-3 does not use oTcl scripts to control simulation(Weingartner et al., 2009). Therefore, problems that were there as a result of combination of C++ and oTcl scripts are not there in NS-3.

3.5.3 OPNET

OPNET (Optimized Network Engineering Tools) is a commercial discrete event simulator (Köksal, 2008). OPNET allows for protocols design and testing in realistic scenarios in hierarchical manner. It consists of a number of sub-modules that represent sub-networks or nodes. With OPNET the topology can be created manually or imported. Inbuilt samples can also be used. The simulator consists of OPNET Modeler Wireless Suite that can be used for modeling, simulation and analysis of wireless networks. The main disadvantage of OPNET is that it is not an open source simulator. Since TVWS network is different from other wireless networks due to secondary use of spectrum, OPNET cannot be used for TVWS network simulation.

3.5.4 OMNET++

OMNET is an acronym for Objective Modular Network. OMNET++ is a discrete event simulator based on C++. The primary use of OMNET++ is simulation of communication and computer networks (Köksal, 2008). It can also be used to simulate complex IT systems, queuing networks, and hardware architectures. OMNET++ has become a popular network simulator because of its hierarchical, well organized component based, good documentation, modular and extensible architecture (Marinho and Monteiro, 2011). Several models have been developed to allow simulation of wireless networks in OMNET++. They include INET framework, Mixim (Mixed Simulator) and Veins (Khan et al., 2013). Among the three, Mixim is the most widely used for wireless and ad hoc networks in OMNET++. Mixim provides models for mobility, localization, signal propagation and MAC. INET, Mixim and Veins are not specifically designed for cognitive radio simulation.

Marinho and Monteiro (2011) extended Mixim to allow for simulation of cognitive radio. They extended Mixim by developing a cognitive radio node with two radios and MAC modules. One radio is dedicated to common control channel while the other one is a reconfigurable radio. The cognitive radio node also has cognitive engine which is responsible for learning and decision making. The disadvantage of this implementation is that it does not suit SDR and TVWS operation because, a cognitive radio node should have only one transceiver radio capable of operating in multiple channels.

3.5.5 Matlab Based CR Simulators

Tabassam et al. (2011) designed a SDR prototype based on Matlab and Simulink for sensing PUs. Matlab/Simulink is interfaced with USRP-2 main board and RFX-400 daughter board. The system is able to sense, predict and adjust operating paramaters so as to achieve desired objectives. Spectrum sensing is performed using statistical spectrum sensing techniques. Ghosh et al. (2014) designed a simulator based on Matlab for spectrum sensing based on power spectral density. These simulators are mainly designed for spectrum sensing. In this research, spectrum sensing is not considered.

3.6 Choice of Simulator

The simulator used for the study was developed from scratch using Matlab. Matlab was chosen as the programming language for this study because the main interest of this study is analysis of performance of algorithm. This research work involves a lot of equations. Matlab has so many inbuilt functions. Matlab also allows easy change of configuration. Existing simulators based on Matlab discussed in section 3.5 are not suitable for this study because they are not designed for GLDB based TVWS network. Existing CR simulators based on NS-2 or OPNET are not suitable because they will require extensive changes to fit the simulation scenarios considered in this research.

3.7 Simulation Environment and SetUp in Matlab

This section describes how simulation was conducted. It presents how simulation was setup in Matlab, simulation parameters and the simulation steps.

3.7.1 Frequencies and Channels to be Considered

The frequencies and channels considered for simulation are those for Kenya. As discussed in section 2.2, TVWS channels in Kenya range from 470 MHz and 690 MHz. Fig. 3.4 shows TV frequencies and associated channel numbers. There are 28 channels with a bandwidth of 8 MHz in the TV spectrum (470 MHz and 690 MHz).

Fig. 3.5 shows coverage map for channel 46 (674 MHz) used in central Kenya but not used in Nairobi CBD. Fig. 3.3 provides the legend for TV coverage. Channel 46 has its boundary of protection region around Nairobi CBD. Fig. 3.7 shows available TVWS channels found in Nairobi CBD. The maps are generated by ICS Telecom, software used for frequency planning by Communication Authority of Kenya. The white space channels to be considered in the simulation are the ones found in Nairobi CBD.

Channel Number	Centre Frequency (MHz)
21	474
22	482
23	490
24	498
25	506
26	514
27	522
28	530
29	538
30	546
31	554
32	562
33	570
34	578
35	586
36	594
37	602
38	610
39	618
40	626
41	634
42	642
43	650
44	658
45	666
46	674
47	682
48	690

Figure 3.4 TV Channel Numbers and Associated Frequencies in Kenya according to Communication Authority of Kenya

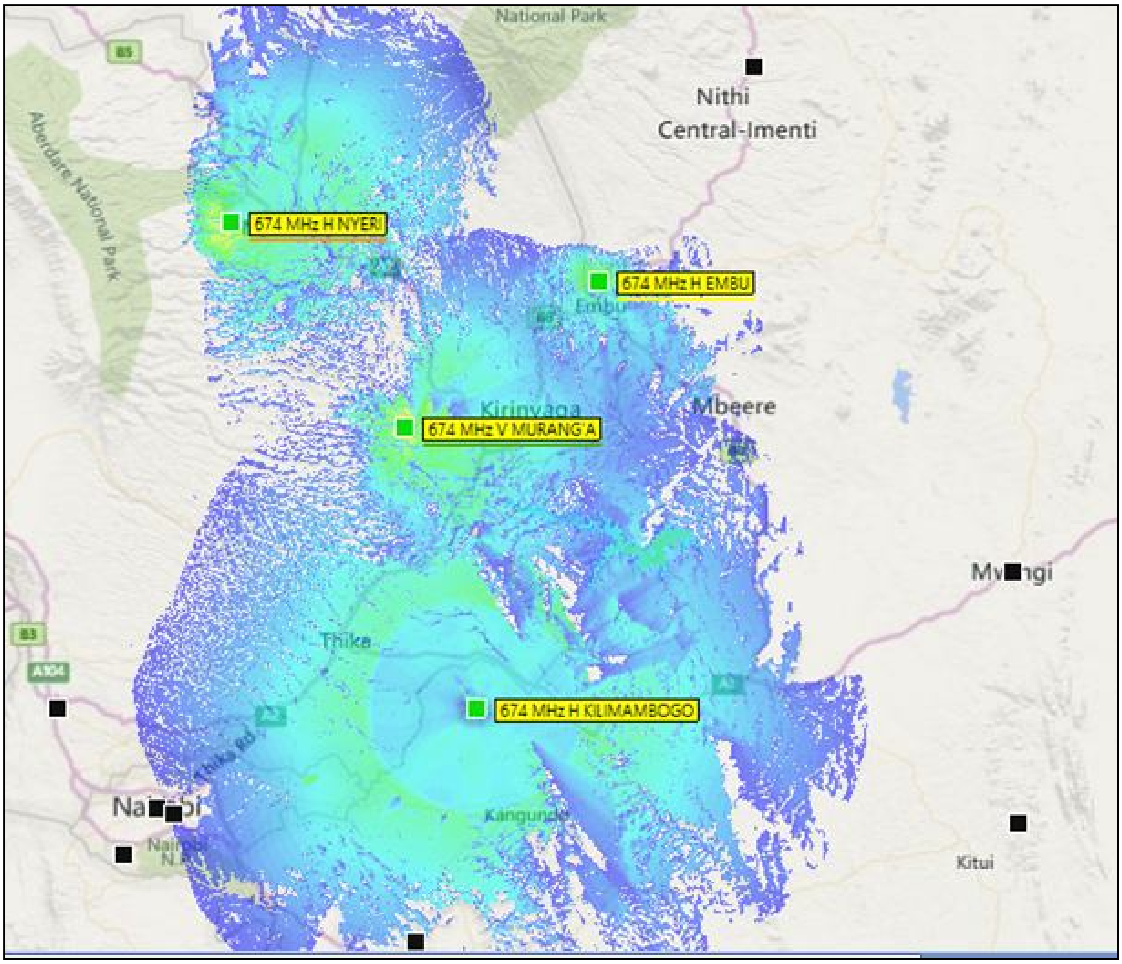

Figure 3.5: Coverage Maps for Channel 46 used in Central Kenya

Figure 3.6: TV Signal Received Power legend

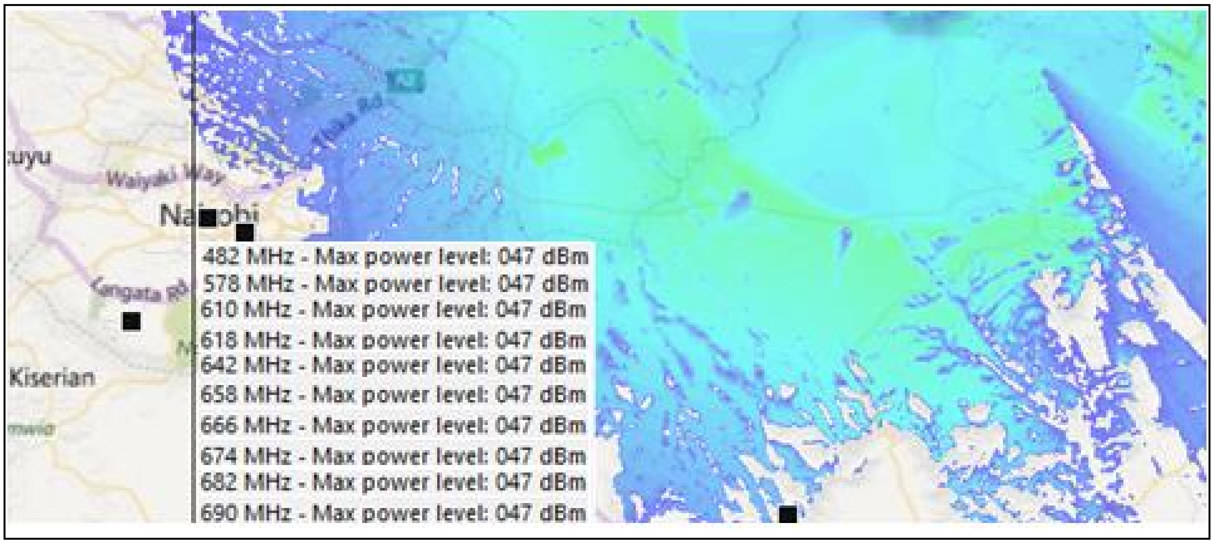

Figure 3.7: White Space Channels in Nairobi CBD.

3.7.2 Simulation SetUp and Steps

Fig. 3.8 shows the scenario considered for simulation. This research considered a TVWS network with one PT, one PU at the edge of protection region and one secondary cell under the control of one base station.

Aggregate interference, both co-channel and adjacent channel, from all the users in the secondary cell should not make the PU's SINR fall below the required protection ratio (Kusaladharma and Tellambura, 2012; Obregon et al., 2011). Fig. 3.8 shows the simulation setup in Matlab. SUs were distributed randomly over a given area of interest.

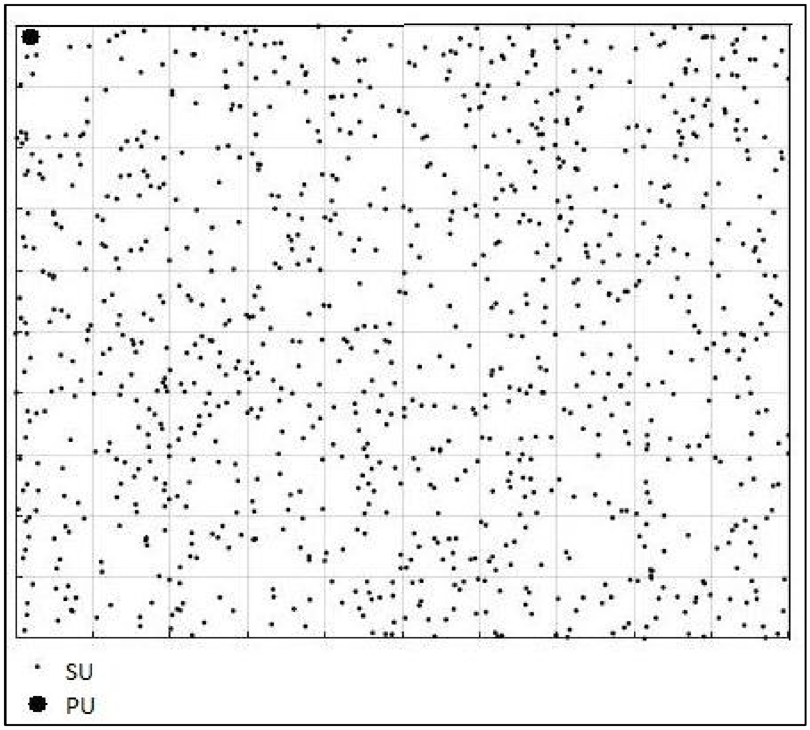

Figure 3.8: Simulation Setup in Matlab

Fig. 3.9 shows simulation steps. The first step was to randomly distribute SUs in the area of interest. The size of the area to be considered was 1km^2 because a typical cellular small cell has a size of between 200m to 3km ("3GPP TR 43.030," 2016). The second step was to place a PU at the edge of protection region. The third step was to randomly assign power and channels to SUs. A total of 10 channels was were used because these are the number of white space channels in Narobi CBD as shown in Fig. 3.7. One channel will be used by the PU (Channel 46). The fourth step was to run the resource allocation algorithm. The fifth step was to process simulation results. The sixth step was to output simulation results.

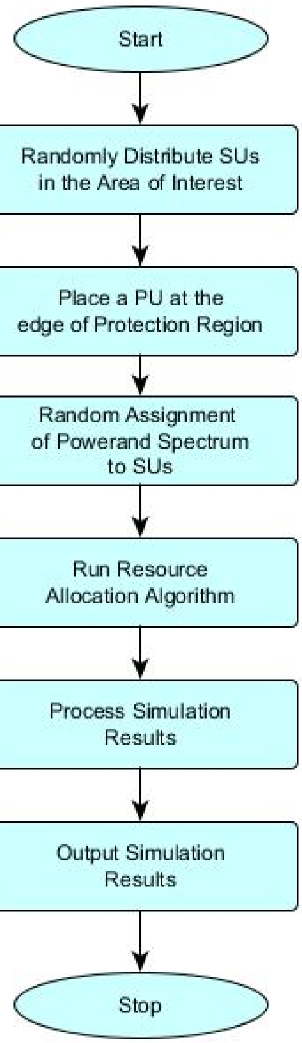

Figure 3.9: Simulation Steps

10 simulation runs were performed. For each simulation run different seeds were used for random distribution of SUs across channels so that different configurations can be analyzed. For each configuration, different algorithm was applied for resource allocation.

3.7.3 Path Loss Model

Okomura-Hata path loss model was used to model path loss because it can accurately compute path loss in an urban area. The model is as follows:

$$l_p(dB) = \begin{cases} A+B\log_{10}(d) & \text{for urban areas} \\ A+B\log_{10}(d) - C & \text{for suburban areas} \\ A+B\log_{10}(d) - D & \text{for open areas} \end{cases} \qquad (3.55)$$

where: $A = 69.55 + 26.16\log_{10}(f) - 13.82\log_{10}(h_{bs}) - x$

$B = 44.9 - 6.55\log_{10}(h_{bs})$

$C = 5.4 + 2\left[\log_{10}\left(\frac{f}{28}\right)\right]^2$

$D = 40.94 + 4.78[\log_{10}(f)]^2 - 18.33\log_{10}(f)$

d is the distance from transmitter to receiver.

and,

$$x = \begin{cases} [1.1\log(f)-0.7]h_{ms} - [1.56\log_{10}(f) - 0.8] & \text{for medium / small city} \\ 8.29[\log(1.54\,h_{ms})]^2 - 1.1 & \text{for large city and } f < 300\text{MHz} \\ 3.2[\log(11.75h_{ms})]^2 - 4.97 & \text{for large city and } f >= 300\text{ MHz} \end{cases}$$

where the range of validity for each component is given as:

150MHz <= f <= 1000MHz

30m <= h_{bs} <= 200m h_{bs} is the height of base station

1m <= h_{ms} <= 10m, h_{ms} is the height of mobile station

1 km <= d <= 20km

3.7.4 Simulation Parameters

Simulation parameters that were used are presented in Table 3.2. Bandwidth of 8 MHz was chosen because in Kenya TV channels have a bandwidth of 8 MHz. TV receiver was assumed to be operating at 674 MHz which is one of the white space channels in Nairobi CBD as can be seen from Fig. 3.7. Maximum transit power of base station was set to 4W (36 dBm) as required by FCC regulations (Nekovee et al., 2012). Maximum SU power was set to 1W (30 dBm) as required by FCC (Nekovee et al., 2012). Antenna gain should not exceed 12 dB according IEEE 802.11 af (Flores et al., 2013).

Table 3.2: Simulation Parameters

Parameter	***Value***	***Description***
B	8 MHz	Bandwidth of TV channel
f_a	674 MHz	Centre frequency of DTV signal
δ_n^2	-102 dBm	Noise power
ω_o	23 dB	TV receiver SINR threshold (Karimi, 2011)
ρ_o	7 dB	SU SINR threshold(Karimi, 2011)
P^{BS}	36 dBm (4W)	Transmit power of base station
p_{max}	30 dBm	Maximum SU transmit power
$\mu(x_i, a)$	0, -33 dB	Adjacent channel interference co-efficient(Karimi, 2011)
G_{SU}	10 dB	SU antenna gain
G_{PU}	10 dB	PU antenna gain
G_{BS}	10 dB	Access point antenna gain
N	200, 400, 600,800,1000	Number of secondary users considered for a hotspot area.
M	2, 4,6,8,10	Number of channels set to a maximum of 10. As discussed in section 3.7.1, this is the number of TVWS channels in Nairobi CBD.

Parameters used for FA were as follows: $\beta_o = 1$, $\alpha = 30$, $\gamma = 10$, number of fireflies NP = 20. Parameters used for PSO were as follows: number of particles = 20, inertia weights: $w_{max} = 4$, $w_{min} = 2$, social parameter $c_1 = 2$ and cognitive parameter $c_2 = 2$. Parameters used for GA were as follows: number of chromosomes=20, mutation rate = 0.8 and selection rate = 0.5. The parameters were set using trial and error and also consideration of values used in a number of peer reviewed journals. Different parameter values were tried before settling on the stated parameters that provided good performance.

The number of SUs considered in analyzing the performance of the algorithm was 200, 400, 600, 800 and 1000. This is because these are the typical number of users in a hotspot. Number of channels, M, was set to maximum of 10. As discussed in section 3.7.1, this is the number of TVWS channels in Nairobi CBD. The number of channels studied to see the effect on the performance of the algorithms was 2,4,6,8 and 10.

3.8 Chapter Summary

In this chapter, design of a novel algorithm based on hybrid FA, GA and PSO (FAGAPSO) has been presented. FAGAPSO was designed separately for power allocation, spectrum allocation and joint power and spectrum. This chapter has also discussed how simulation environment was developed and how simulation was set up and executed. The simulation environment was developed from scratch using Matlab. Simulation software options available have been discussed and an explanation why Matlab was chosen has been provided.

Chapter 4: Results and Discussion

This chapter presents simulation results and analysis of simulation results. Performance of FAGAPSO in comparison other hybrid algorithms as applied to power allocation, spectrum allocation and joint power and spectrum allocation has been discussed in this chapter. Performance of FAGAPSO has also been compared with existing joint power and spectrum allocation algorithms. This chapter also presents the final design for joint power and spectrum allocation algorithm.

4.1 Power Allocation

In this section, simulation results for optimization of power allocation using a variety of hybrid FA, PSO and GA algorithms are presented and discussed. FAGAPSO is compared with:

- FA, GA, PSO
- FA with initial solution of PSO (FAPSO1).
- FA with PSO operators (FAPSO2)
- FA with PSO operators (i.e firefly movement using P_{best}, g_{best}, c_1 and c_2 as expressed in equation (3.18)) as well as initial solution of PSO (FAPSO3).
- FA with GA's crossover feature – FAGA

Simulation results were generated for 10 simulation runs and an average was done. 100 iterations were used for GA, FA, PSO, FAGA and FAPSO2. In FAPSO1, FAPSO3 and FAGAPSO, 50 iterations were used for both FA and PSO so that the total number of iterations will be also 100. The performance of the algorithms was compared using the following metrics: running time of algorithm, objective function value, sum throughput, sum power and SU SINR.

4.1.1 Sum Power

Figure 4.1 shows performance comparison of FAGAPSO with the rest of the algorithms in terms of sum power in the network for different number of SUs, N and with M set to 10. The figure shows that FAGAPSO achieves the lowest sum power for all the values of N under consideration. The algorithm also achieves lower sum power compared to FAGA, FAPSO1, FAPSO2 and FAPSO3. This is because FAGAPSO is able to achieve the most optimal power allocation to SUs that minimizes sum power to all SUs according to equation (3.16). The sum power increases for all the algorithms as N increases because of more active SUs in the network.

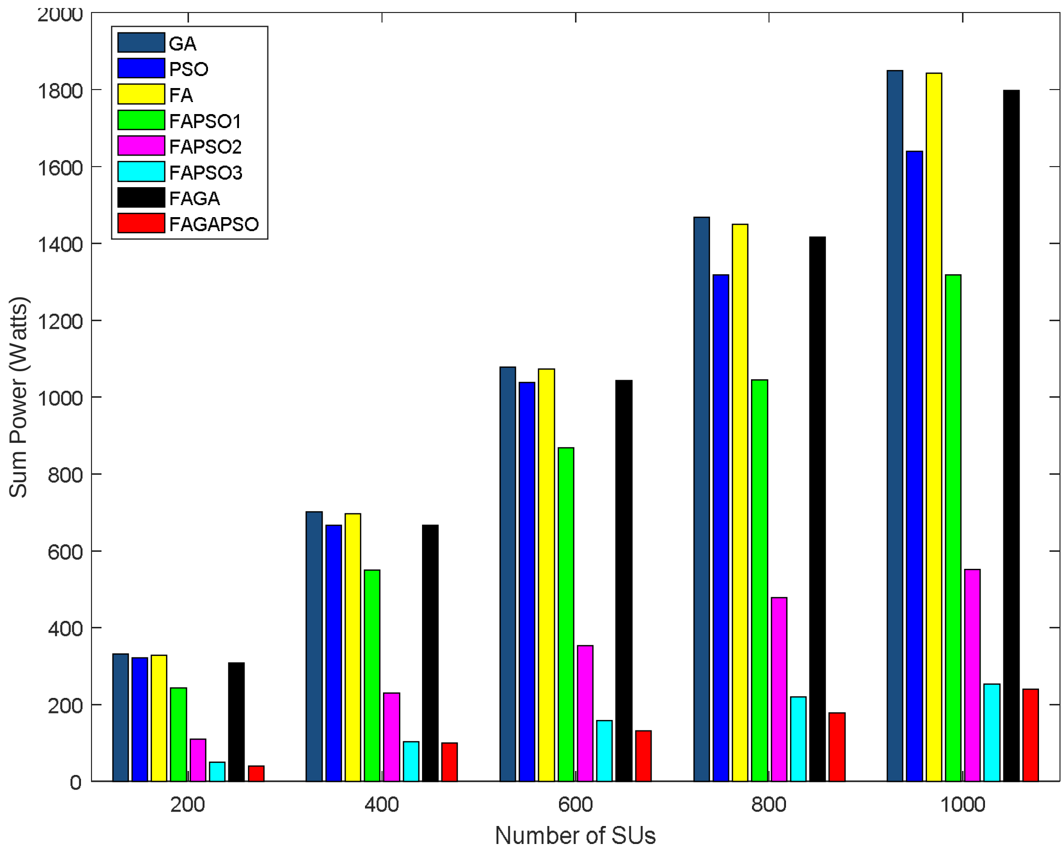

Figure 4.1: Sum Power for Different Algorithms and Values of N

4.1.2 Objective Function Value

Figure 4.2 shows comparison of FAGAPSO with the rest of the algorithms in terms of objective function (equation (3.16)) value for different number of SUs, N, with M set to 10. The figure shows that FAGAPSO achieves the best (lowest) objective function value represented by equation (3.12) for all the values of N under consideration. The objective function value increases as N is increased because as N increases the values of both sum power and penalty function terms in equation (3.16) increases. The sum power increases as N is increases because there are more active SUs in the network. The SU and PU penalty function terms in equation (3.16) increase because there is more interference among SUs and to the PU. Interference among SUs increases because there will be more SUs sharing the same number of channels.

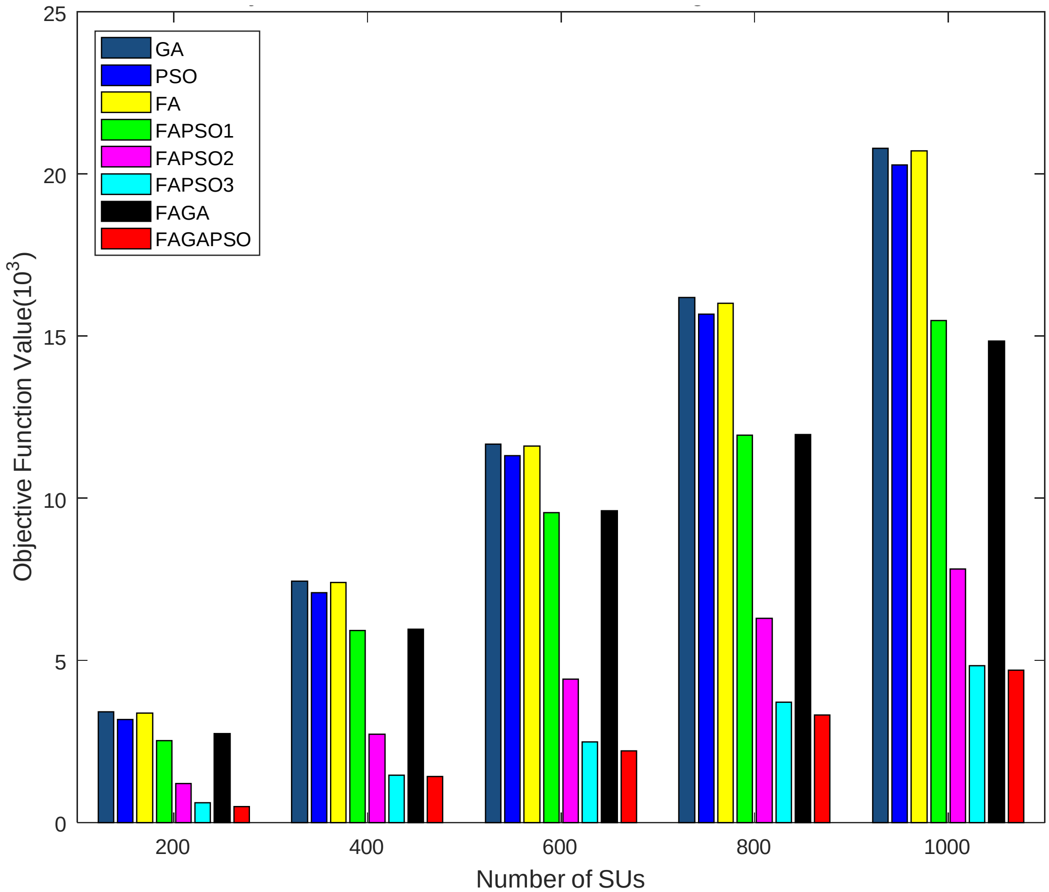

Figure 4.2: Objective Function Values for Different Algorithms and Values of N

4.1.3 Sum Throughput

Figure 4.3 shows comparison of FAGAPSO with the rest of the algorithms in terms of sum throughput in the network, for different values of N with M set to 10. The figure shows that FAGAPSO achieves the highest sum throughput compared to all the other algorithms. This is because of the improved power allocation that minimizes interference in the network. According to Shannon channel capacity theorem, reduction in interference improves throughput. As N is increased from 200 to 800, there is a steady increase in sum throughput because the effect of interference is not significant. There is no significant difference in throughput as N is varied from 800 to 1000 because the effect of interference term in the Shannon channel capacity formula becomes more significant such that throughput can longer increase.

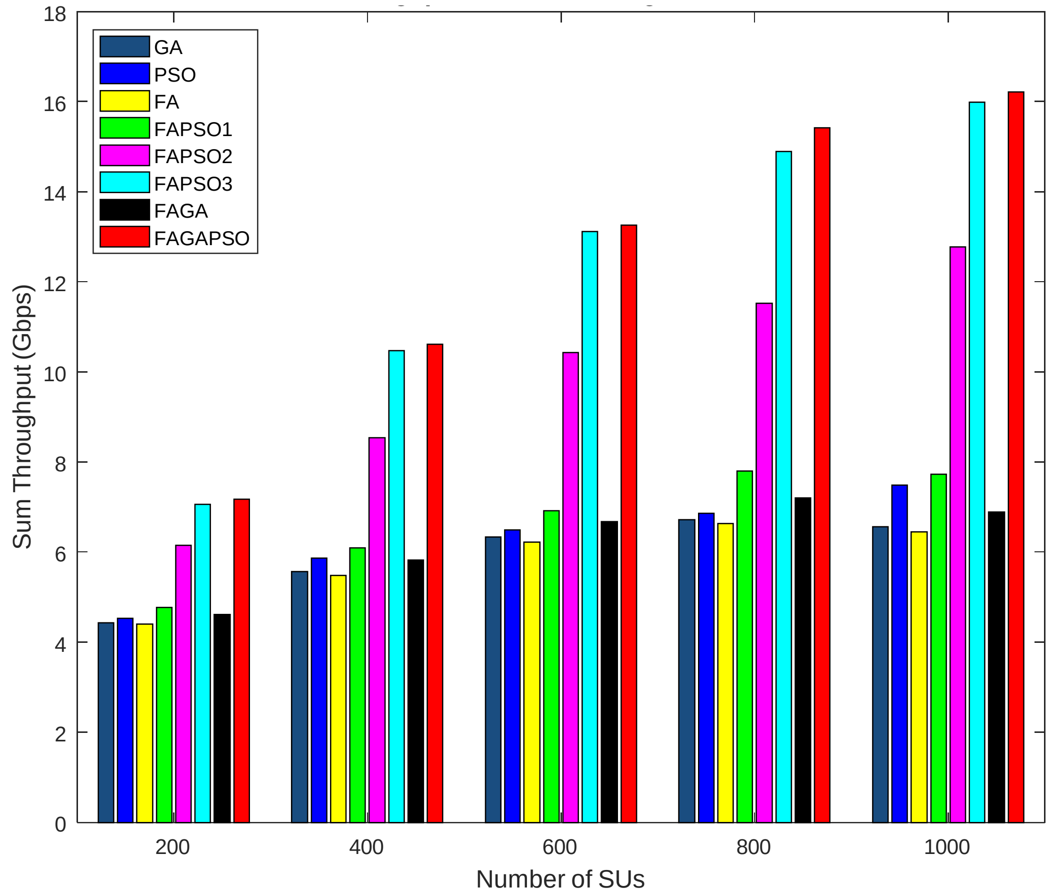

Figure 4.3: Sum Throughput for Different Algorithms and Values of N

4.1.4 Percentage of SUs less than SU SINR Threshold

Figure 4.4 show comparison of FAGAPSO with the rest of the algorithms in terms of percentage of SUs with SU SINR less than required threshold of 13dB in the network for different values of N with M set to 10. The results show that FAGAPSO achieves the lowest percentage of SUs with SU SINR below threshold compared to other algorithms except FAPSO3 where its value almost equal for FAGAPSO and FAPSO3 in some instances. This is because of the improved power allocation that minimizes interference in the network. As N is increased, the percentage of SUs less than SINR threshold for all algorithms increases because of the increased interference in the network.

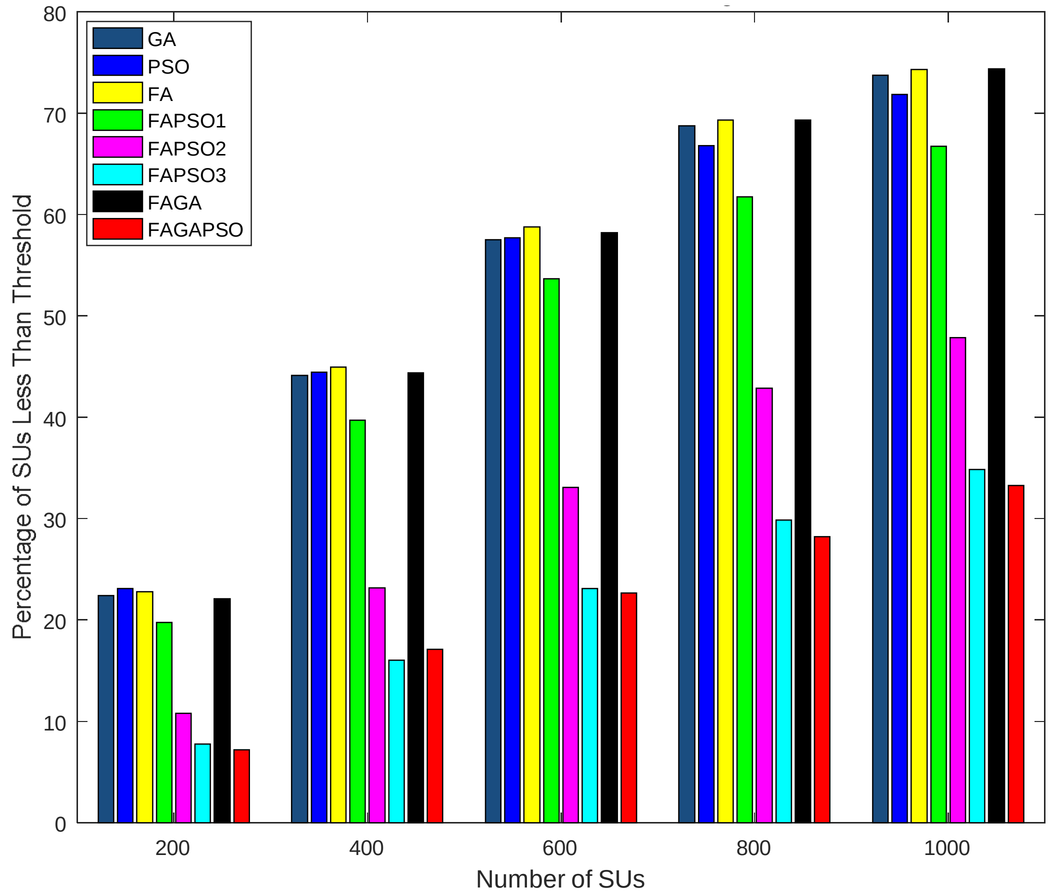

Figure 4.4: Percentage of SUs Less Than SINR Threshold for Different Algorithms and Values of N

4.1.5 Effect of Varying the Number of SUs (N)

Overall, changing the number of SUs does not significantly change the comparative performance of all the algorithms under consideration. FAGAPSO is still able to outperform other algorithms in terms of objective function value and sum throughput when N is increased. This implies that for a continuous optimization problem, the performance of population based metaheuristic algorithm does not change when the dimension of the problem changes.

4.1.6 Effect of Varying Number of Channels (M)

In order to study the effect of M on the performance of the algorithms, M was changed from 2 to 10 in steps of 2. N values of 200 and 800 were considered. Results for N=200 an N=800 are shown in Figures 4.5 and 4.6, respectively. It can be seen for the figures that as number of channels, M, is increased, the throughput increases for both cases of N=200 and N=800. This is because as the number of channels increase, there will be less interference among SUs because there will be fewer SUs sharing a channel. The results show that comparative performance of other algorithms does not also change when M is varied. FAGAPSO still outperform all other algorithms even when M is varied.

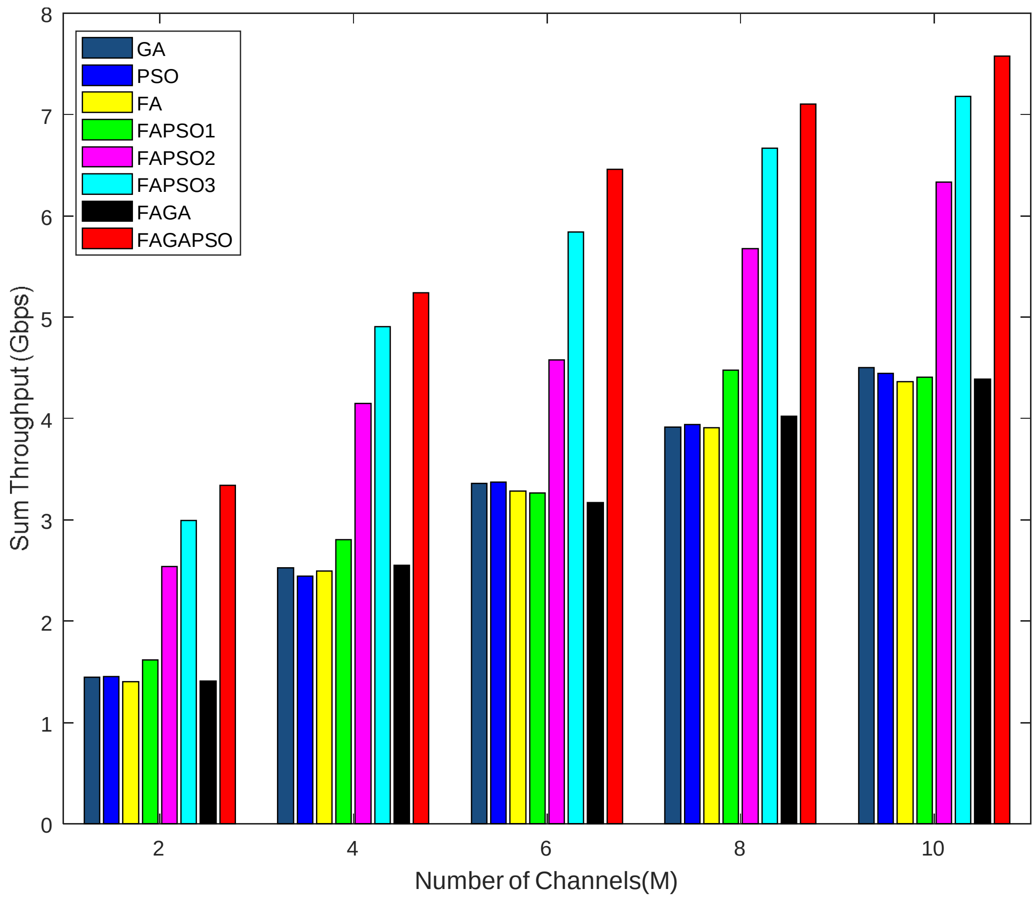

Figure 4.5: Sum Throughput for Different Algorithms and Values of M for N=200.

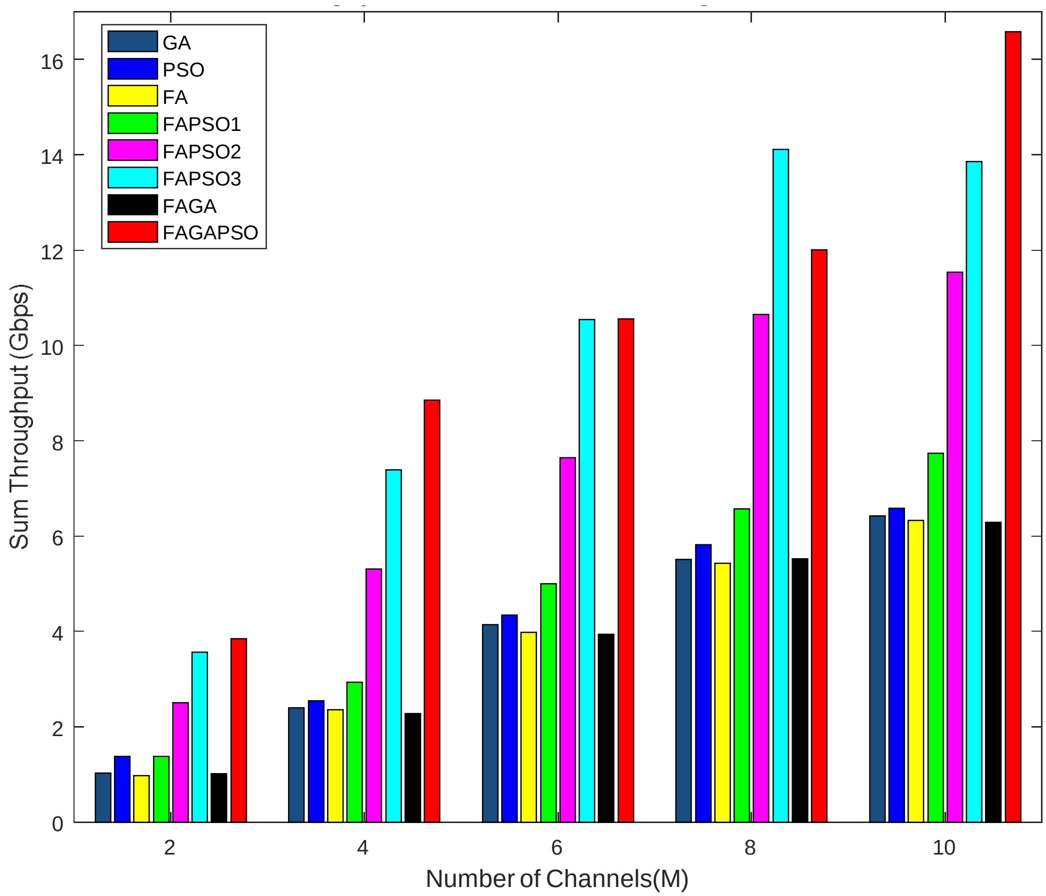

Figure 4.6: Sum Throughput for Different Algorithms and Values of M for N=800.

4.1.7 Running Time Comparison

In order to compare the running time of the algorithms, Matlab timeit() function was used. Each of the algorithm's function handle was passed to the function. The specifications for the computer that was used to run the simulations are as follows: 64 bit Windows 7 operating system, 4GB RAM and 2.5 GHz dual-core processor. The function timeit() calls a function several times and then returns a median of the computed running time of a function

Figure 4.6 shows comparison of running time of FAGAPSO with other algorithms. The run time in the table is for different values of N in a network. 100 iterations were used for FA, GA and PSO. The number of iterations used for FAGAPSO was 100 which was split as follows: for FA it was set to 50 (half of iterations used by pure FA) and for PSO it was set to 50 (half of iterations used for pure PSO). The same number of iterations was also applied to FAPSO and FAPSO2. For FAPSO1 (FA with PSO parameters), the number of iterations for FA was set to 100.

FAGAPSO requires less time to run compared to all other algorithms except FAPSO3, PSO and GA for all values of N under consideration. Although FAGAPSO requires slightly more time to run compared to GA, PSO, FAPSO1 and FAPSO3, the higher running time can be tolerated for improved optimization of power allocation. As the number of SUs increase, the running time also increases for all the algorithms under consideration.

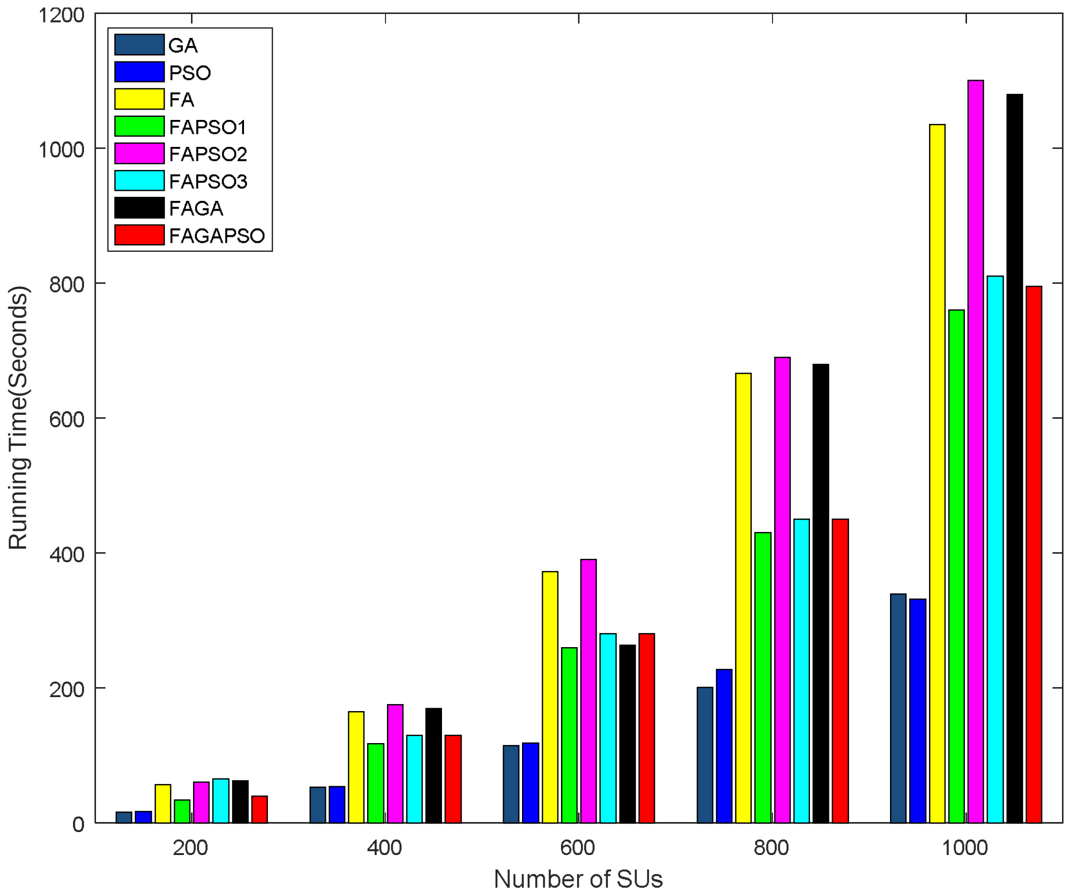

Figure 4.7: Running Time Comparison

4.1.8 Analysis and Comparison of Performance of FAGAPSO for Power Allocation as a Continuous Optimization Problem

In this section further analysis and comparison of the algorithms for power allocation, a continuous optimization problem, is presented.

4.1.8.1 Comparison of FA, GA and PSO

PSO outperforms FA and GA in terms of objective function value, sum power, sum throughput and percentage of SUs less than SU SINR threshold. The performance of FA is better than that of GA. Results are in agreement with the findings of Łukasik and Żak (2009) that PSO can outperform FA for continuous optimization problems. It has also been reported that PSO closely matches the performance of FA for a continuous optimization problem (Pal et al., 2012). The results are not in agreement with the findings of Yang (2009) that FA always outperforms PSO and GA. This implies that performance of population based metaheuristic algorithms depends on the nature of the optimization problem.

4.1.8.2 Comparison of FAGA with FA and GA

FAGA outperforms FA and GA in terms of objective function value, sum power, sum throughput and percentage of SUs less than SU SINR threshold. Results agree with findings by Rahmani and MirHassani (2014) as well as Luthra and Pal (2011) that the use of crossover feature in FA makes it be able to search the solution space better through improved exploration. This is because in the FAGA algorithm the best two solutions are crossed over before firefly movement so that four new chromosomes are generated. The new chromosomes have potentially better solutions. At every iteration, if the four new chromosomes have better solutions, they will replace the top four fireflies. The use of GA's crossover feature improves FA's exploration ability.

4.1.8.3 Comparison of FAPSO1 with FA and PSO

FAPSO1 (FA with initial solution of PSO) outperforms PSO and FA in terms of objective function value, sum power, sum throughput and percentage of SUs less than SU SINR threshold. Results agree with findings by Arunachalam et al. (2015) that the use of initial solution generated by PSO in FA enables it to generate a better solution. This is because performance of FA depends on quality of initial solution used.

4.1.8.4 Comparison of FAPSO2 with FA and PSO

FAPSO2 (FA with PSO operators) outperforms PSO and FA in terms of objective function value, sum power, sum throughput and percentage of SUs less than SU SINR threshold. Results agree with findings by Kora and Rama Krishna (2016) that the use of PSO operators in FA during firefly movement enables it to generate a better solution. This is because at every iteration fireflies fly towards the current global best and personal best. FA is able to search the solution space better when PSO operators are used in firefly movement than when each firefly flies towards every other firefly that has a better solution. The use of PSO operators improves FA's exploration and exploitation ability. Exploration ability is improved by fireflies flying toward global best. Exploitation ability is improved by fireflies flying towards personal best.

4.1.8.5 Comparison of FAPSO3 with FAPSO1 and FAPSO2

FAPSO3 (FA with PSO operators as well as initial solution of PSO) outperforms FAPSO1 and FAPSO2. This is because a hybrid FA with the use of initial solution of PSO as well the use PSO operators (P_{best}, g_{best}, c_1 and c_2 as expressed in equation (3.18)) enables FA to search the solution space better compared with FA, FAPSO1 and FAPSO2 through improved exploration and exploitation ability. The use of PSO's initial solution also enables FAPSO3 to get better solutions because the quality of FA's final solution depend on the initial solution.

4.1.8.6 Comparison of FAGAPSO with All other Algorithms

Simulation results have shown that FAGAPSO improves all the performance metrics of power allocation except percentage of SUs with SU SINR less than required threshold where it closely matches that of FAPSO3. Optimization of power allocation is a continuous optimization problem. The results therefore show that FAGAPSO is better than FA as well as GA and PSO. FAGAPSO is also better than the three versions of FAPSO as well as FAGA. This is because the use of crossover feature of GA to mix top ranked fireflies in addition to the use PSO's final solution as FA's initial solution as well as the use of PSO operators during firefly movement in FA allows it to have more exploration and exploitation ability compared to the rest of the algorithms. This enables FAGAPSO to generate highest sum throughput as well as the lowest sum power and objective function value. FAPSO3 at times outperforms FAGAPSO in some iterations. However, averaging the results of iterations shows that FAGAPSO has better performance.

The only disadvantage of FAGAPSO is the slightly higher running time compared to GA and PSO. However the slightly higher running time can be tolerated for improved power allocation that improves SU throughput and SU SINR.

4.1.9 Summary

FAGAPSO is superior compared to FA, GA, PSO as well as all other hybrid algorithms for power allocation as a continuous optimization problem even when N and M is varied. This is because for a continuous optimization problem, hybridizing FA with PSO and GA improves its exploration and exploitation ability. It can also be concluded that performance of population based metaheuristic algorithms does not depend on the dimension of the problem.

4.2 Spectrum Allocation

In this section, simulation results for optimization of spectrum allocation using a variety of hybrid FA, PSO and GA algorithms are presented and discussed. FAGAPSO is compared with:

- FA, GA and PSO.
- FA with initial solution of PSO (FAPSO1)
- FA with PSO operators (FAPSO2)
- FA with PSO operators (i.e firefly movement using P_{best}, g_{best}, c_1 and c_2 as expressed in equation (3.18)) as well as initial solution of PSO (FAPSO3).
- FA with GA's crossover feature - FAGA

Simulation results were generated for 10 simulation runs and an average was done. 100 iterations were used for GA, FA, PSO, FAGA and FAPSO2. In FAPSO1, FAPSO3 and FAGAPSO, 50 iterations were used for both FA and PSO so that the total number of iterations will be also 100. The number of channels, M, was set to a maximum of 10 because this is the number of channels in Nairobi CBD as discussed in section 3.7.4. The number of SUs, N, considered was 200, 400, 600, 800 and 1000. These values are sample number of SUs in a hotspot as discussed in sections 3.7.4 and 3.4. The performance of the algorithms was compared using the following metrics: objective function value, sum throughput, PU SINR and SU SINR.

4.2.1 Objective Function Value

Figure 4.8 shows comparison of FAGAPSO with the rest of the algorithms in terms of achieved objective function value (Equation (3.27)) for different values of N and M set to 10. The results show that FAGA achieves the best (highest) objective function (Equation (3.27)) value compared to all other algorithms for all values of N. The objective function value increases as N is increased from 200 to 400 for all the algorithms. However, after a value of N=400, the objective function value generally flattens. The flattening is because the increase in objective function value is offset by the penalty function terms in equation (3.19). At N=1000, the objective function value starts to reduce because the penalty function terms value starts becoming more significant such that it reduces the sum throughput in equation (3.27).

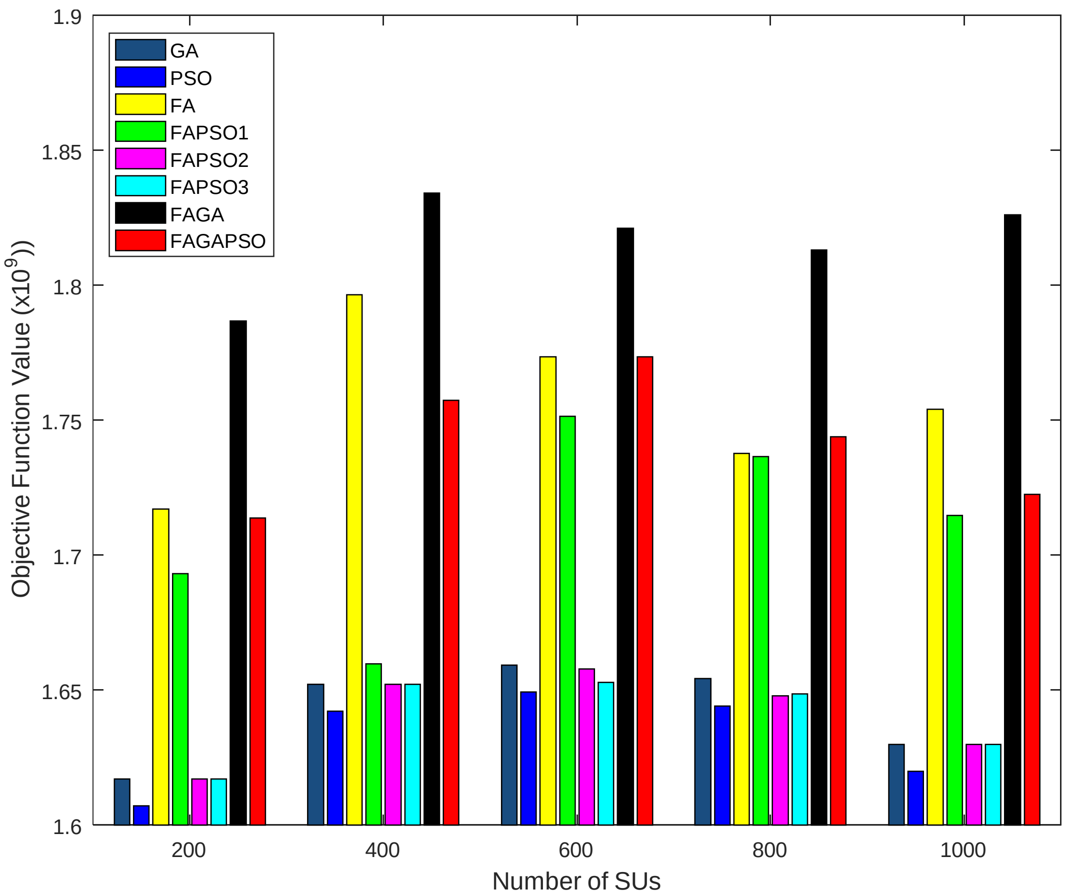

Figure 4.8: Objective Function Values for Different Algorithms and Values of N

4.2.2 Sum Throughput

Figure 4.9 shows comparison of FAGAPSO with the rest of the algorithms in terms of sum throughput in the network for different values of N and M set to 10. The results show that FAGA achieves the highest sum throughput compared to the rest of algorithms. This is because of the better spectrum allocation by FAGA that minimizes interference in the network. According to Shannon channel capacity theorem, reduction in interference improves throughput. As the number of SUs increase, the sum throughput increases for all the algorithms under consideration up to N=800. There is no significant difference between throughput values for N=800 and N=1000. This is because the effect of interference term in the Shannon channel capacity formula (equation (3.20)) starts becoming significant such that throughput can no longer increase.

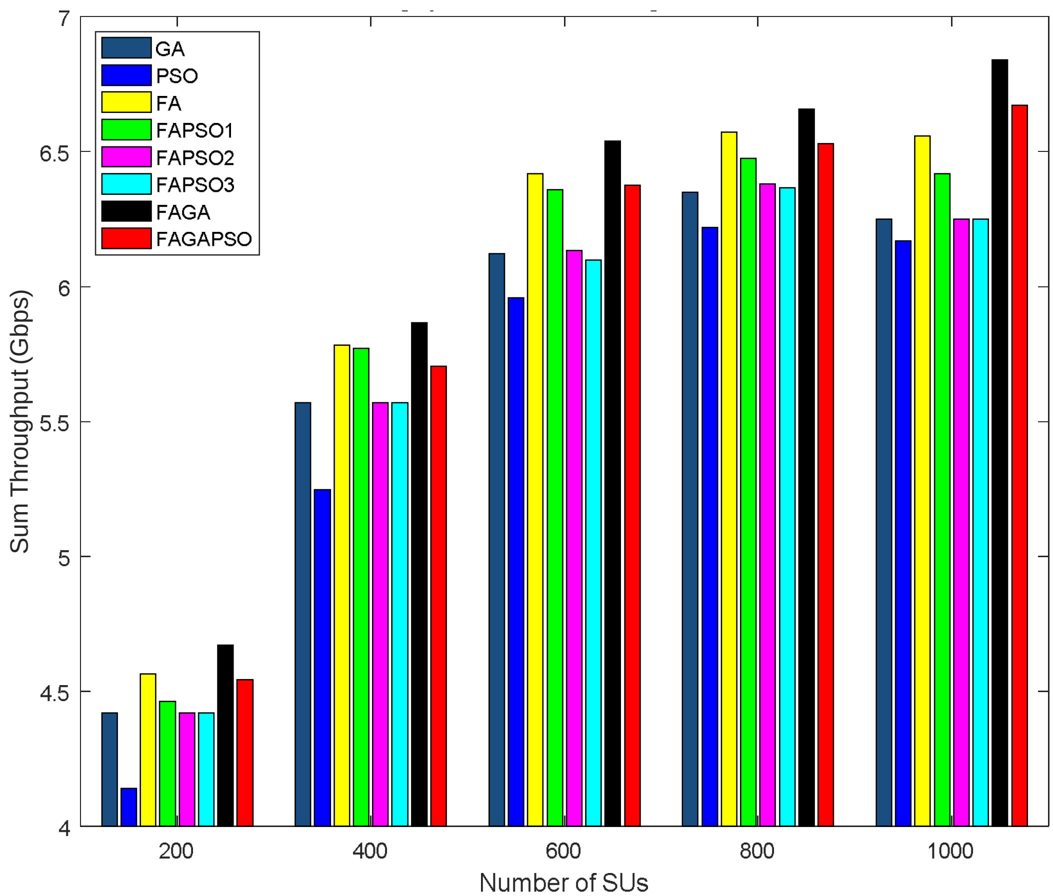

Figure 4.9: Sum Throughput for Different Algorithms and Values of N

4.2.3 Percentage of SUs less than SU SINR Threshold

Figure 4.10 show comparison of FAGAPSO with the rest of the algorithms in terms of percentage of SUs with SU SINR less than required threshold of 13dB in the network for different values of N and with M=10. Results show that optimization of spectrum allocation alone does not improve percentage of SUs less than SU SINR threshold. The figure also shows that as N is increased, the number of SUs falling below the required SU SINR threshold reduces. This is because of increased interference that arises because of the increasing number of SUs.

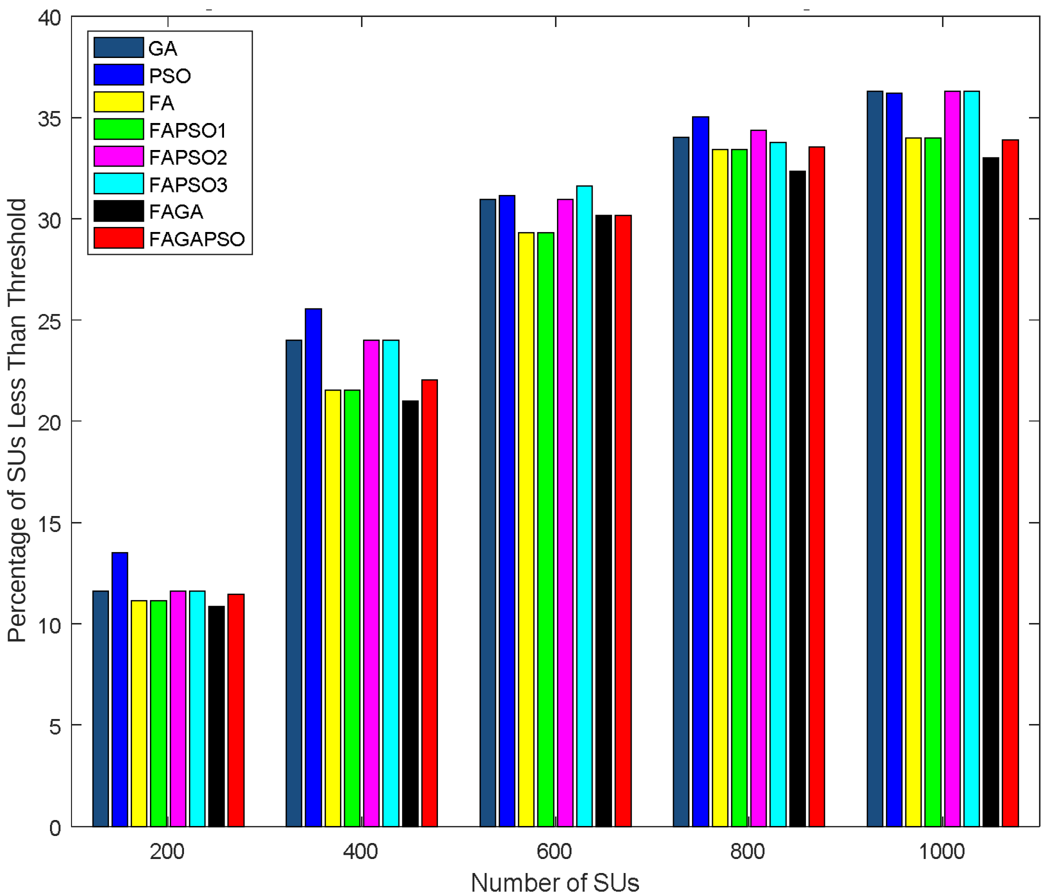

Figure 4.10: Percentage of SUs Less Than SINR Threshold for Different Algorithms and Values of N

4.2.4 PU SINR

Figure 4.11 show comparison of FAGAPSO with the rest of the algorithms in terms of PU SINR for different values of N. PU SINR generally worsens (becomes lower) as N is increased because of the increasing interference. PU SINR values for all the algorithms and N values are generally low. Results show that optimization of spectrum allocation alone does not improve PU SINR. There is need to have both power and spectrum allocation.

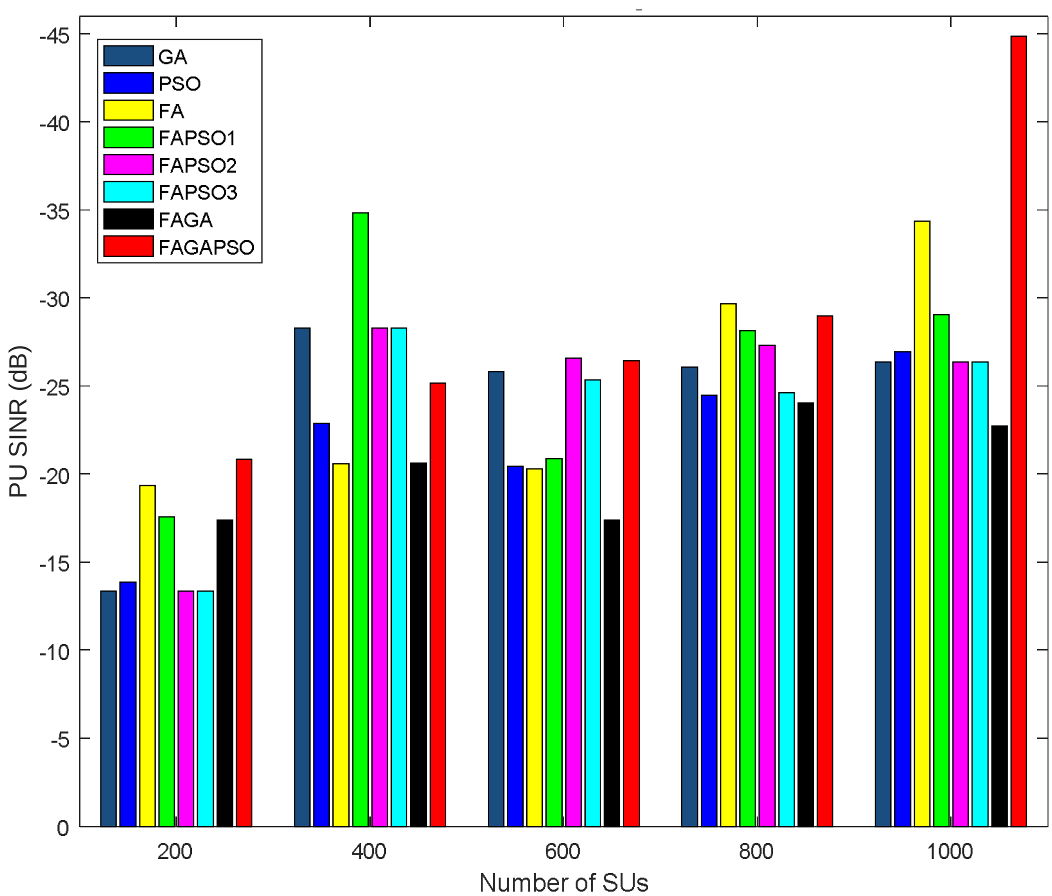

Figure 4.11: PU SINR for Different Algorithms and Values of N

4.2.5 Effect of Varying the Number of SUs (N)

Changing the number of SUs, N, does not significantly change the comparative performance of the algorithms. FAGA is still able to outperform other algorithms, including FAGAPSO, in terms of objective function value and sum throughput when N is increased. This implies that for a binary optimization problem, the performance hybrid algorithm does not change when the dimension of the problem changes.

4.2.6 Effect of Varying Number of Channels (M)

Figures 4.12 and 4.13 show comparison of sum throughput for different values of the number of channels, M for N=800 and 200, respectively. The two figures show that as M is increased, the sum throughput increases for all the algorithms. This is because there will be fewer SUs occupying a single channel as M is increased. When M is varied, comparative performance of the algorithms do not change. In all cases FAGA still outperforms all other algorithms, including FAGAPSO. Sum throughput for N=800 is generally higher than that for N=200 because of more SUs in the network.

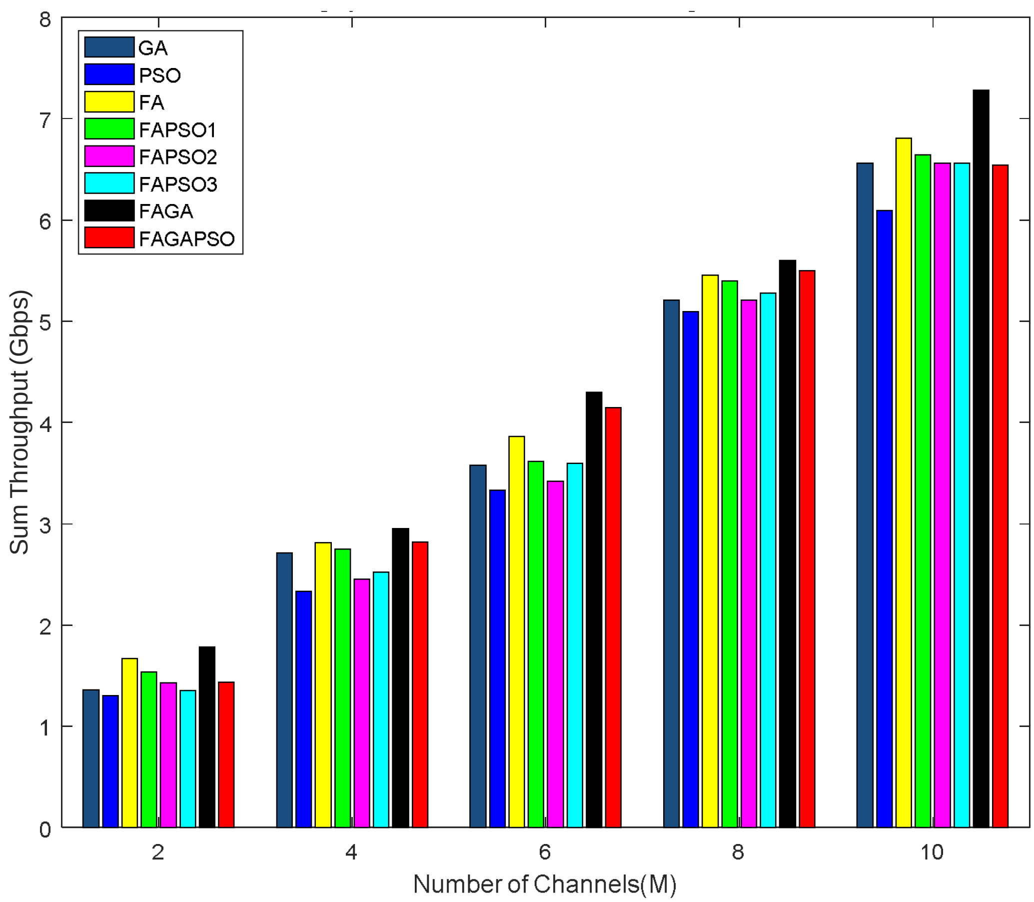

Figure 4.12: Sum Throughput for Different Algorithms and Values of M for N=800.

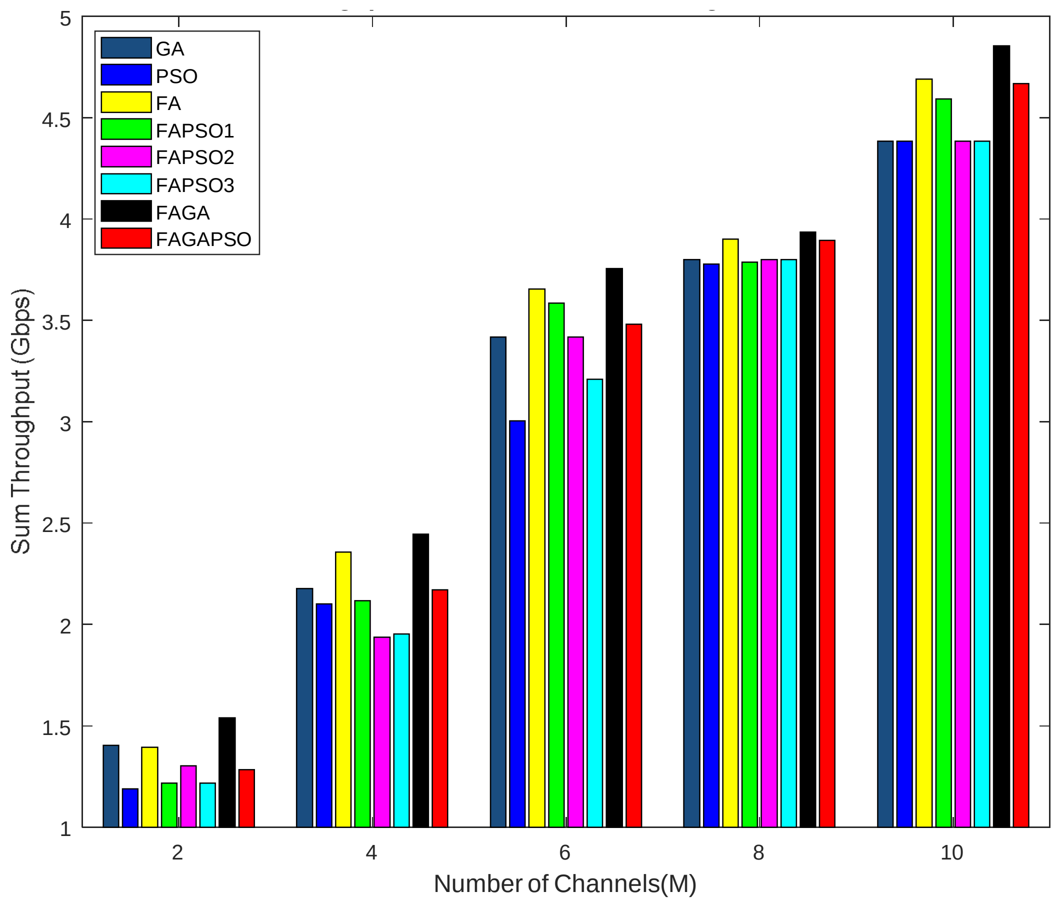

Figure 4.13: Sum Throughput for Different Algorithms and Values of M for N=200.

4.2.7 Analysis and Comparison of Performance of FAGAPSO for Spectrum Allocation as a Binary Optimization Problem

4.2.7.1 Comparison of FA, GA and PSO

FA outperforms PSO and GA in terms of objective function value and sum throughput for a binary optimization problem. GA outperforms PSO. Firefly movement in FA works better for a binary optimization problem compared to the use P_{best} and g_{best} in PSO as well as mutation and crossover of GA. The results are in agreement with the findings of Liu et al. (2014) and Anumandla et al. (2013).

4.2.7.2 Comparison of FAGA with FA and GA

FAGA outperforms FA and GA in terms of objective function value and sum throughput. Results agree with findings by Rahmani and MirHassani (2014) and Luthra and Pal (2011) that the use crossover feature in FA makes it be able to search the solution space better. This is because, in the FAGA algorithm, the best two algorithms are crossed over before firefly movement so that new chromosomes are generated. The new chromosomes are potentially better solutions that can replace the top four fireflies. At every iteration, if the four new chromosomes have better solutions, they will replace the top four fireflies. The use of GA's crossover feature enables FA to have better exploration ability.

4.2.7.3 Comparison of FAPSO1 with FA and PSO

FAPSO1 (FA with initial solution of PSO) performs better in terms of objective function value and sum throughput compared to PSO but FA has better performance compared to FAPSO1. Results do not agree with findings by Arunachalam et al. (2015) that the use of initial solution generated by PSO in FA enables it to generate a better solution. This is because the problem considered by Arunachalam et al. (2015) was continuous optimization problem. FA is able to generate better solution over 100 iterations than when 50 iterations are used for FA and 50 for PSO. This is because FA outperforms PSO for a binary optimization problem as discussed in section 4.2.5.1. FA has better exploration and exploitation ability compared to PSO for a binary optimization problem.

4.2.7.4 Comparison of FAPSO2 and FA

FA performs better FAPSO2 (FA with PSO operators) terms of better objective function value and sum throughput. Results do not agree with findings by Kora and Rama Krishna (2016) that the use of PSO operators in FA during firefly enables it to generate a better solution. This is because the problem considered by Arunachalam et al. (2015) was continuous optimization problem. FA is able to generate better solutions with its normal firefly movement than with firefly movement towards P_{best} and g_{best}. This implies that for a binary optimization problem, the use of PSO operators during firefly movement in FA degrades the performance of FA. Pure FA has better exploration and exploitation capability compared to the use of PSO operators during firefly movement.

4.2.7.5 Comparison of FAPSO3 with FA, FAPSO1 and FAPSO2

FAPSO3 matches the performance of FAPSO2 but FAPSO1 outperforms both FAPSO2 and FAPSO3. Compared to FAPSO3, FA outperforms FAPSO3. This implies that the use of PSO operators degrades the performance of FA. As discussed in section 4.2.5.1, FA outperforms PSO for a binary optimization problem. The use initial solution generated by PSO degrades the performance of FA. This is because FA is able to generate better solution over more (100 for the study) iterations than when 50 iterations are used for both FA and PSO. The use of PSO operators during firefly movement also further degrades the performance of FAPSO3.

4.2.7.6 Comparison of FAGAPSO with All other Algorithms

FAGAPSO matches the performance of FA and FAPSO1 but outperforms FAPSO2 and FAPSO3. This can be explained as follows. Although the use of PSO operators and initial solution in FA degrades its performance (as discussed in section 4.2.5.6), its performance is improved by crossover feature of GA.

FAGA outperforms FAGAPSO. This is because the use of GA's crossover feature only in FA is more effective for a binary optimization compared to the use of initial solution of PSO and the use of PSO's P_{best} and g_{best} during firefly movement. This can be attributed to the structure of the spectrum allocation matrix. In the spectrum allocation matrix, only one position has a value of 1 in the spectrum allocation vector of an SU.

4.2.7.7 Summary

FAGA is superior to all other algorithms including FAGAPSO for a binary optimization problem even when N and M is varied. It can be concluded that for a binary optimization problem, FA has better exploitation and exploration ability when it hybridized with GA compared to when it is hybridized with GA and PSO. Hybridizing FA with PSO degrades it performance for a binary optimization problem.

4.3 Comparison of Performance of Hybrid FA Algorithms for Power and Spectrum Allocation

The use of initial solution generated PSO in FA as well as PSO operators in FA is able to improve the final solution power allocation problem but not for spectrum allocation. This can be explained as follows:

As discussed in section 4.2.5, FA is superior compared to PSO for a binary optimization problem. Performance of FA degrades when initial solution of PSO is used in FA because iterations are shared between FA and PSO. This is because FA's firefly movement is more effective for a binary optimization problem than a continuous optimization problem. However, for a continuous optimization problem, the use of initial solution generated by PSO in FA improves FA's performance because PSO performs better compared to FA for a continuous optimization problem.

The use of PSO's P_{best} and g_{best} in FA during firefly movement degrades its performance for a binary optimization problem. FA is able to search the solution space better for a binary optimization problem with its normal firefly movement than with the use of PSO's P_{best} and g_{best} during firefly movement.

FAGAPSO outperforms all other algorithms under consideration for power allocation but for spectrum allocation FAGA outperforms all other algorithms. This is because for power allocation the use of GA's crossover feature in addition to the use of PSO's initial solution in FA as well as the use of PSO's P_{best} and g_{best}during firefly movement is able to generate a better solution compared to FA only for a continuous optimization problem through better exploration and exploitation ability. However, for a binary optimization problem, the use of GA's crossover feature only in FA, improves its performance compared to the use PSO's initial solution in FA as well as PSO's P_{best} and g_{best}during firefly movement. This is mainly because of the structure of the spectrum allocation matrix whereby only one position has a value of 1 in the spectrum allocation vector of an SU.

4.4 Final Algorithm for Joint Power and Spectrum Allocation Based on Hybrid FA, PSO and GA

This section presents joint power and spectrum allocation optimization using hybrid firefly and particle swarm optimization with genetic operators. Foregoing discussions in sections 4.1, 4.2 and 4.3 have shown that FAGAPSO outperforms other hybrid algorithms for power allocation while for spectrum allocation FAGA outperforms other algorithms including FAGAPSO. This will guide the design of the hybrid algorithm.

The algorithm steps are outlined in Algorithm 4.1. In step 1 of Algorithm 4.1, optimization of resource allocation is first done using PSO. Each particle will consist of power vector only. All particles will be initialized with random valid power values for all SUs. Initial channel allocation will also be random. Only optimization of power allocation is done using PSO in step 1. The channel allocation will not be altered by PSO. This is because the use of hybrid FA and PSO degrades spectrum allocation but improves power allocation.

In step 2, FA starts with final solution of power allocation generated by PSO in Step 1 and the same random allocation of channels like that in Step 1. Therefore, the power vectors of all fireflies will be initiated with solutions found in PSO particles at the end of PSO in Step 1 and initial channel allocation matrices of all fireflies will be the same as that used in step 1. In step 3, after ranking fireflies according to their fitness, the best two fireflies are crossed over to generate four new offsprings. Crossover will be done separately for power vectors and channel allocation matrices. The four new offsprings are then ranked according to their fitness.

The current best firefly will then be replaced by the best offspring if its fitness is higher (better) than that of the best offspring. For the channel allocation vector, firefly movement will be done according to equation (3.3). For the power allocation vector, instead of firefly movement being that described by equation (3.3), firefly movement will involve local search towards local personal best and global best according to equation (3.54). For the channel allocation matrix, the firefly movement will be according to equation (3.3). Normal firefly movement will be applied to the channel allocation matrix.

Algorithm 4.1: Final Joint Power and Spectrum Allocation Optimization Using FAGAPSO
Step 1: • 1.1 Initialize number of particles, $c_1, c_{2,}\ \omega, v_{min}, v_{max}$ • 1.2 For each particle Initialize power vector with random power values that are within allowed range. Initialize channel allocation matrix randomly, with one channel assigned to each SU. End • 1.3 Do 1.3.1 For each particle Compute fitness value If the value of fitness can outmatch the best fitness value (p_{i}) in history

set current value as the new p_i

End

1.3.2 Select the particle with the best fitness value of all the particles as the p_{best}

1.3.3 If current p_{best} and its associated x_{best} is better than g_{best}set current p_{best} as g_{best}

1.3.4 For each particle

- Compute particle velocity according equation (3.4)
- Update position of particle for the power vector according o equation (3.5)
- Check power vector to see if the all the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.

End

While maximum iterations has not been reached.

- 1.4 Set g_{best} set as the final solution of PSO.

Step 2

- 2.1 Initialize the control parameters of the algorithm α, β, γ firefly number NP and maximum number of iterations t_{max}.
- 2.2 Set the dimension of fireflies D.
- 2.3 Set initial position of fireflies as follows:
    - For the power vector set to values generated by PSO in Step 1.
    - For channel allocation matrix, set the values to those generated in Step 1.

Step 3

- 3.1 Calculate the fitness value of each firefly using equation (3.48) and rank the fireflies according to their fitness values.
- 3.2 Find the current best solution.
- 3.3 Apply crossover mechanism separately for both the channel matrix and power vector on the top two best solutions.
- 3.4 Select the best offspring out of the four offsprings created through crossover and use it as the current best solution of FA if its fitness is better than that of the current best.

Step 4

- 4.1 For power allocation vector of every firefly, move it to the better solution according to equation (3.54).
- 4.1 For channel allocation vector of every firefly, move it to the better solution according to equation (3.3).
- 4.2 -Check firefly x_i to see if the all the power values in the power vector are within range. If any values are out of range then create random values that are within range to replace them.

  - Check firefly x_i to if only one channel is assigned to each SU. If more than channel is assigned to SU, randomly pick one of the channels and assign to SU.

Step 5

- If it reaches the predefined maximum number of iterations, then the power vector and channel allocation matrix of the current best solution mentioned in step 3 is derived and stop the progress else go to step 3 and continue.

4.5 Joint Power and Spectrum Allocation

In this section, simulation results for joint optimization of spectrum allocation using hybrid PSO and FA with genetic operators (FAGAPSO) are presented. FAGAPSO is compared with FA, PSO, GA, heuristic algorithm (HA) and spatial adaptive play (SAP). FAGAPSO is compared with two algorithms: SAP (Xue and Wang, 2015) and HA (Xue et al., 2014) because they are two existing joint power and spectrum allocation algorithms for a TV white space network in literature. They are discussed in Chapter 2, section 2.6.3. Simulation results were generated for 10 simulation runs and an average was done.

The performance of the algorithm was evaluated using the following metrics: running time of algorithm, objective function value, sum throughput, PU SINR and SU SINR. The maximum number of channels, M, was kept constant at 10 because this is the number of channels in Nairobi CBD as discussed in section 3.7.4. The number of SUs considered were 200, 400, 600, 800 and 1000. These values are sample number of SUs in a hotspot as discussed in sections

3.7.4 and 3.4. 100 iterations were used for FA, GA and PSO. In FAGAPSO, 50 iterations were used for both FA and PSO so that the total number of iterations will be also 100.

4.5.1 Objective Function Value

Figure 4.14 shows comparison of FAGAPSO with the rest of the algorithms in terms of achieved objective function value for different values of N. The results show that the FAGAPSO achieves the best (highest) objective function value represented by equation (3.49) for all values of N values except for SAP. As N increases, the objective function value increases up to N=800 where it starts to drop. The objective function value reduces at N=1000 because interference effects become significant such that the throughput starts reducing as per Shannon channel capacity theorem. The reduction in objective function value can also be attributed to increase in penalty terms value in equation (3.48) that are subtracted from the overall throughput.

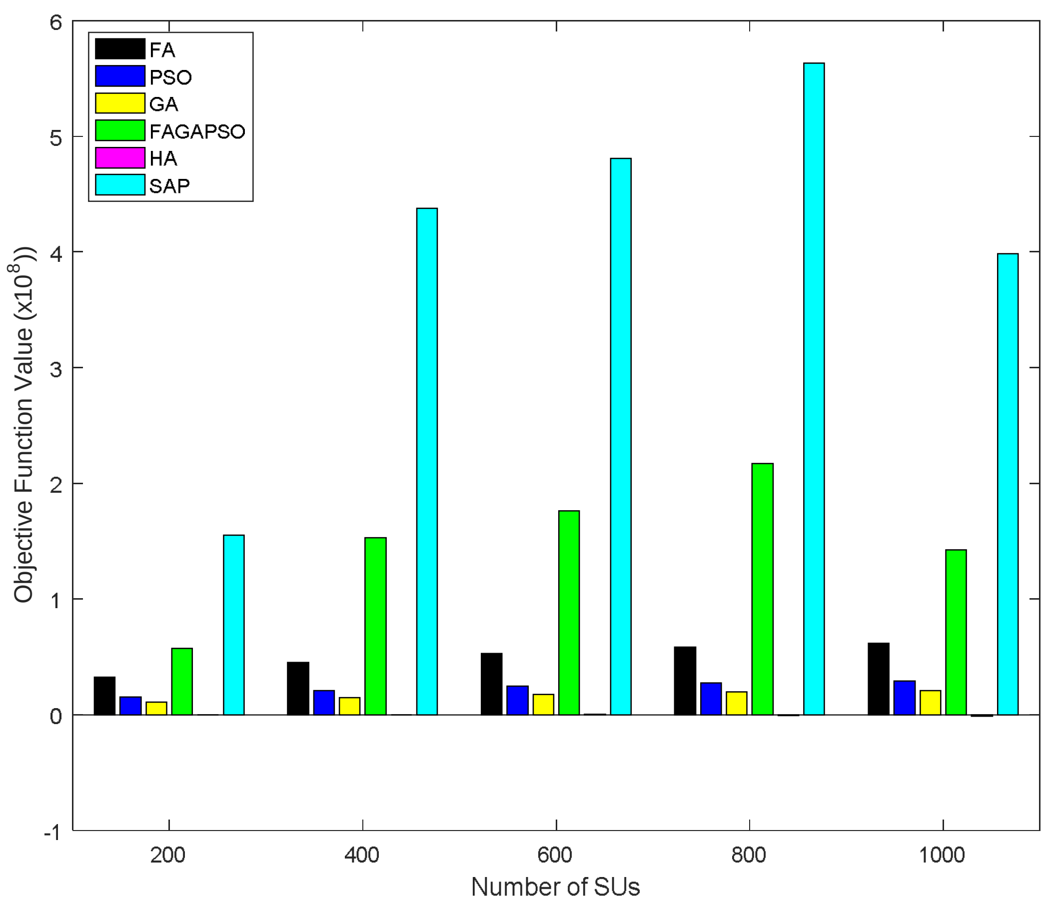

Figure 4.14: Objective Function Value for Different Algorithms and Values of N

4.5.2 Sum Throughput

Figure 4.15 shows a comparison FAGAPSO with the rest of the algorithms in terms of sum throughput in the network for different values of N. The results show that FAGAPSO achieves the highest sum throughput for all values of N except for SAP. This is because of the improved power and spectrum allocation that minimizes interference in the network. According to Shannon channel capacity theorem, reduction in interference improves throughput. As N increases, the sum throughput increases because of increased active SUs in the network. However at N=800, the sum throughput for all the algorithms flatten. This is because of increased interference.

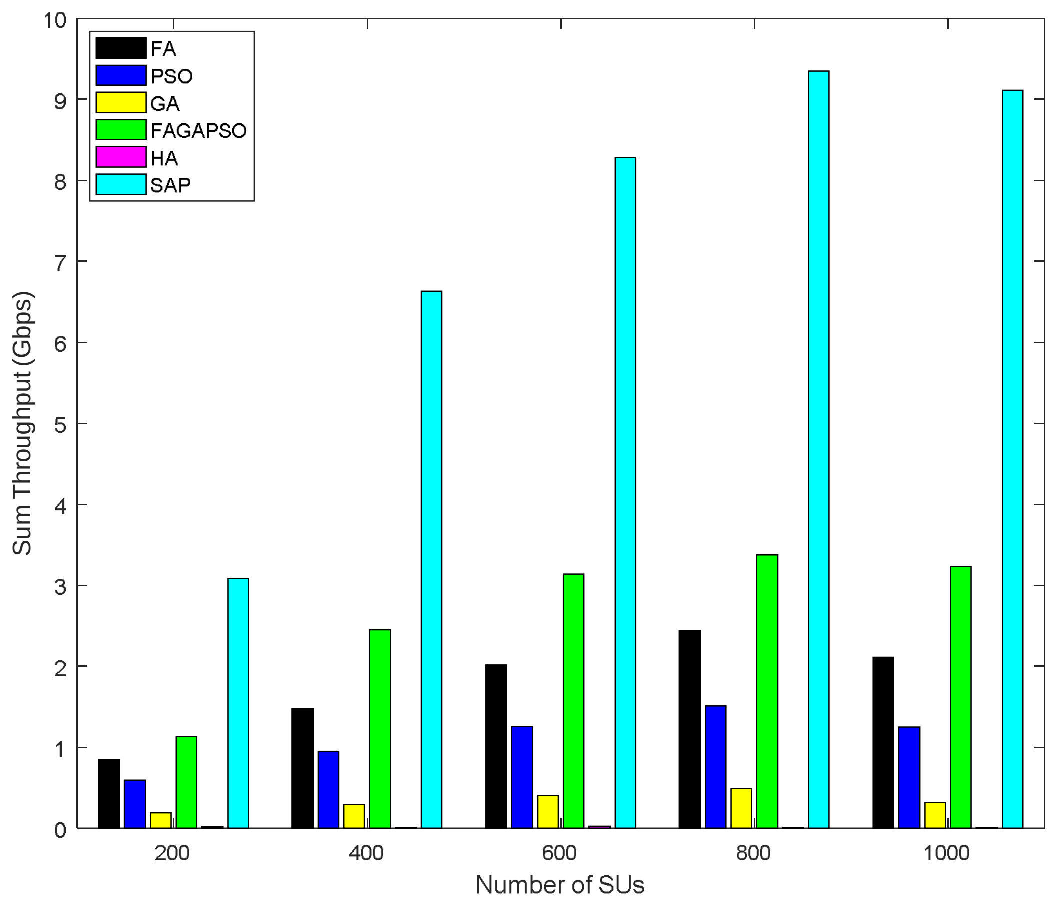

Figure 4.15: Sum Throughput for Different Algorithms and Values of M for N=200.

4.5.3 Percentage of SUs less than SU SINR Threshold

Figure 4.16 shows a comparison of FAGAPSO with the rest of the algorithms in terms of percentage of SUs with SU SINR less than required threshold of 13dB in the network. The results show that FAGAPSO achieves the lowest percentage of SUs with SU SINR below threshold for values of N except for SAP. This is because of the improved power and spectrum allocation that minimizes interference in the network.

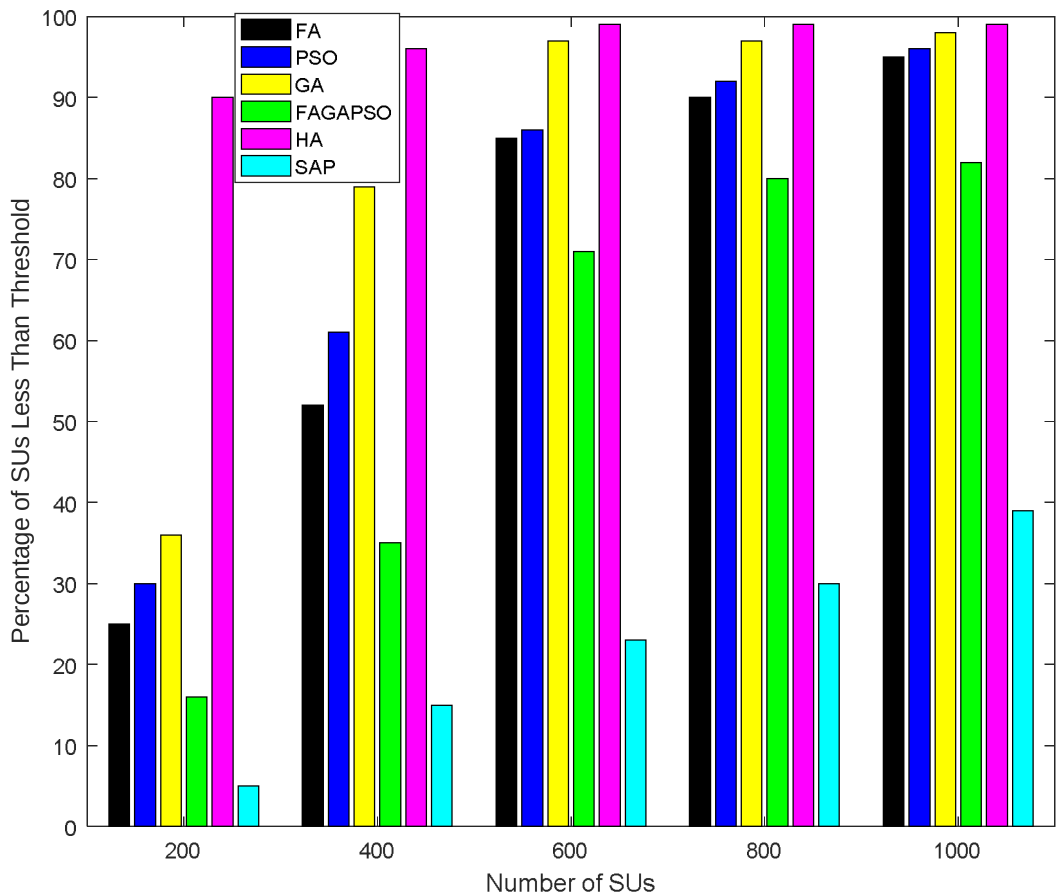

Figure 4.16: Percentage of SUs Less Than SINR Threshold for Different Algorithms and Values of N

4.5.4 SU SINR Distribution and Average SU SINR

Figure 4.17 show comparison of FAGAPSO with the rest of the algorithms in terms of average SU SINR in the network for different values of N. The results show that FAGAPSO achieves the highest average SU SINR for all values of N except for SAP. This is because of the improved power and spectrum allocation that minimizes interference in the network. SAP outperforms other algorithms in terms of SU SINR because of the iterative power allocation described in section 2.6.3.5 that reduces power allocation to SUs. Fig. 4.18 shows SINR distribution for the different algorithms for N=1000. In comparison, only SAP has better SINR distribution. Average SU SINR will improve if an admission control algorithm is applied.

SU SINR is calculated as a ratio of received power from the base station to the total sum interference power to an SU (Equation (3.11)). As N increases, the sum interference power to an SU increases, hence average SU SINR decreases as N increases. The negative SINR values in dB indicate that the received power from the base station to the SU is less than the sum interference received from all SUs. Applying other MAC protocols such TDMA, CDMA CSMA/CA or CSMA/CD will improve the average SU SINR. Only FDMA was applied in this research.

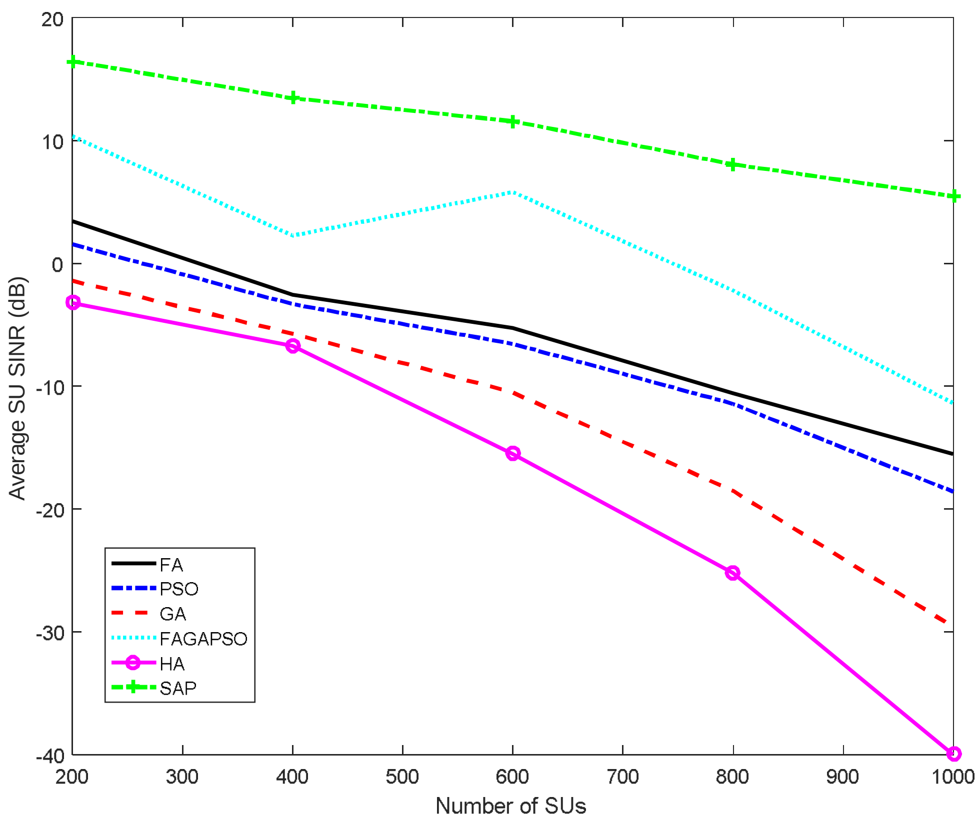

Figure 4.17: Average SU SINR for Different Algorithms and Values of N

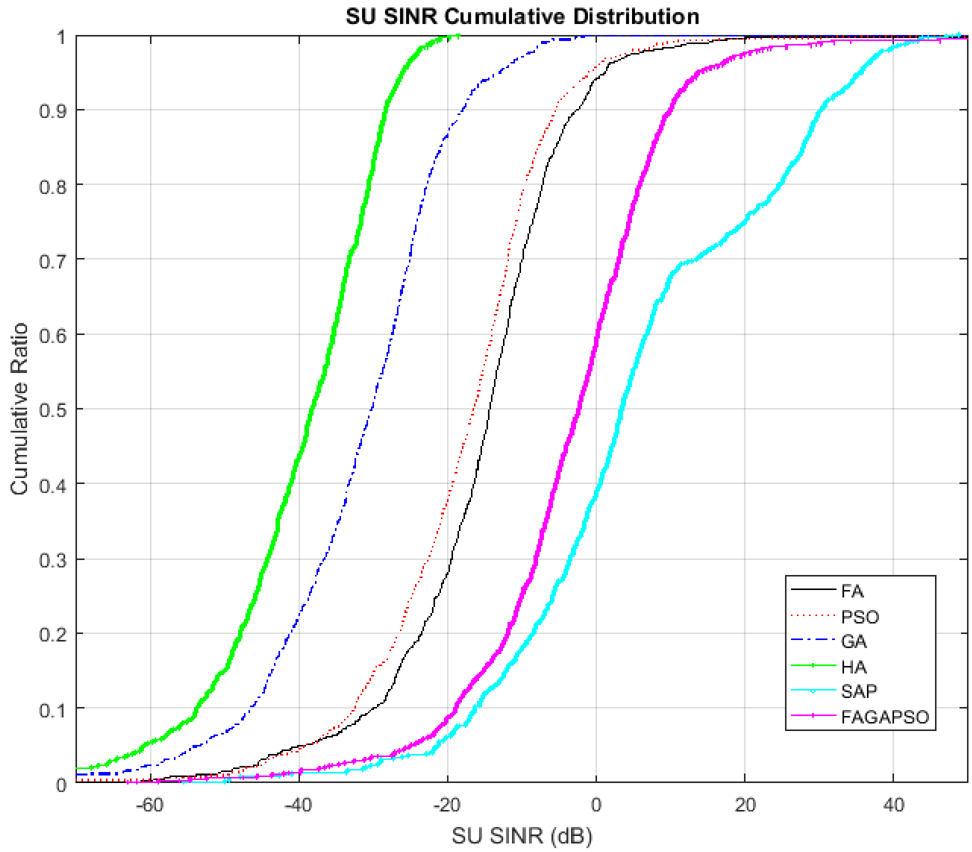

Figure 4.18 SU SINR Distribution for N=1000

4.5.5 PU SINR

Figure 4.19 show comparison of FAGAPSO with the rest of the algorithms in terms of PU SINR in the network for different values of N. As N increases, the PU SINR generally reduces because there is increased interference from higher number of SUs in the network according equation (3.9). The results show that the FAGAPSO achieves the highest PU SINR for all values of N except for SAP. This is because of the improved power and spectrum allocation that minimizes interference in the network including to the PU. The results demonstrate the need to have a protection distance between a PU and a secondary network cell.

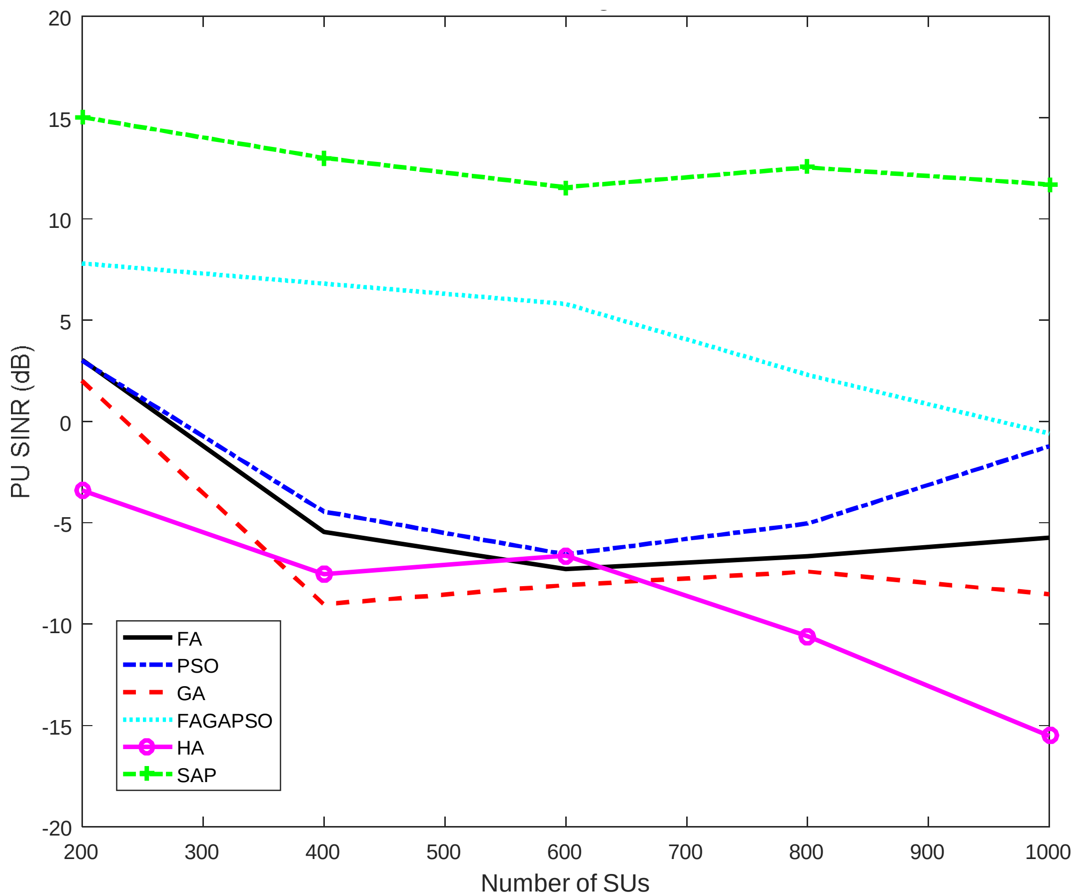

Figure 4.19: PU SINR for Different Algorithms and Values of N

4.5.6 Running time

In order to compare the run time of algorithms, Matlab timeit() function was again used. Figure 4.20 show comparison of running time of FAGAPSO with other algorithms for different values of N. 100 iterations were used for FA, GA and PSO. In FAGAPSO, 50 iterations were used for both FA and PSO so that the total number of iterations will be also 100.The results show that SAP has the worst running time and PSO show the lowest running time. The running time for FAGAPSO is higher than that of GA, HA and PSO but lower than that of FA and SAP. As N increases, the running time increases for all the algorithms. The increases is much more SAP. SAP has the worst running time because of iterative power allocation algorithm within the algorithm.

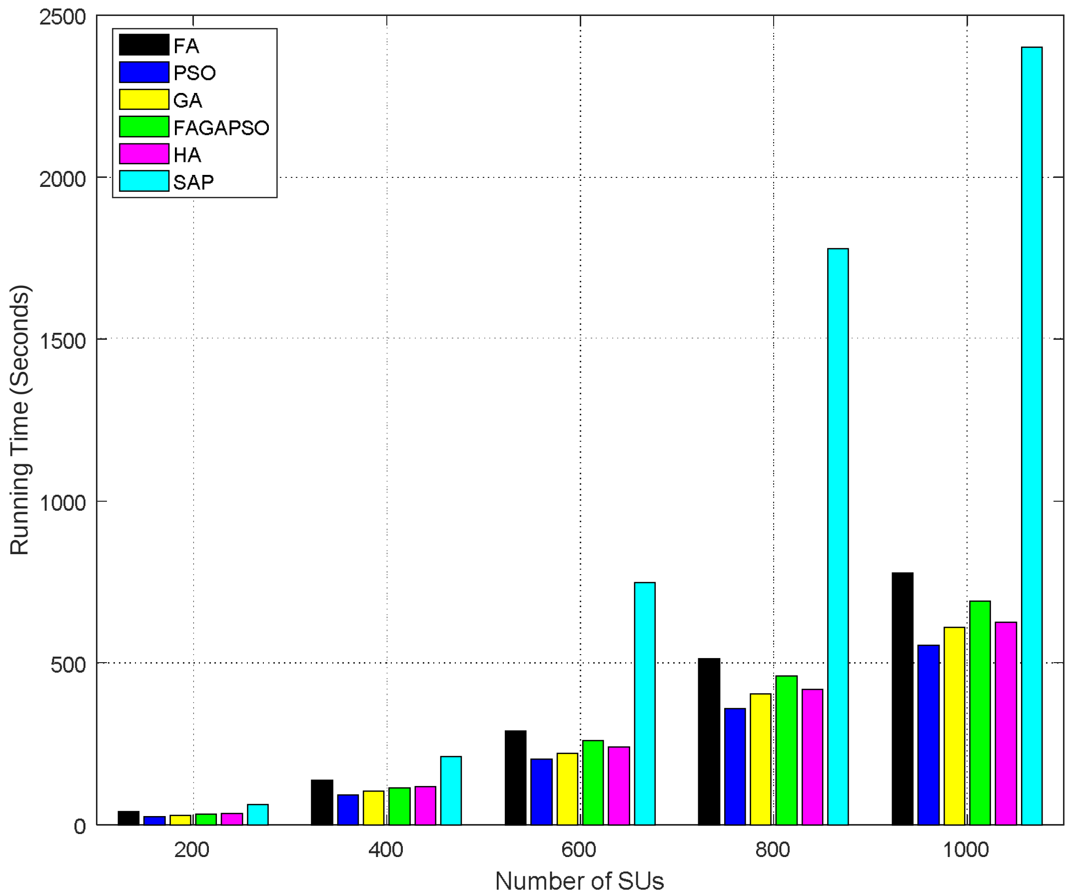

Figure 4.20: Running Time Comparison

4.5.7 Effect of Increasing the Number of SUs

Changing the number of SUs does not significantly change the performance of the algorithms. Performance of FAGAPSO compared to all the algorithms under consideration with respect to sum power and objective function value does not change significantly when N is increased. FAGAPSO is still able to outperform all the algorithms under consideration except SAP. This implies that the FA and PSO perform well even when N is increased to 1000. This implies that the performance of hybrid population based metaheuristic algorithms do not depend on the dimension of the problem for a continuous-binary optimization problem.

4.5.8 Effect of Varying Number of Channels (M)

In order to study the effect of M on the performance of the algorithms, M was changed from 2 to 10 in steps of 2. N values of 200 and 800 were considered. Results for N=200 an N=800 are shown in Figures 4.19 and 4.20, respectively. It can be seen for the figures that as number of channels, M, is increased, the throughput increases for both cases of N=200 and N=800. This is because as the number of channels increase, the less interference among SUs because there will be fewer SUs sharing a channel. The results show that comparative performance of other algorithms does not also change when M is varied. FAGAPSO still outperform all other algorithms even when M is varied. The results further demonstrate that the performance of the algorithms is not affected by the dimension of the problem.

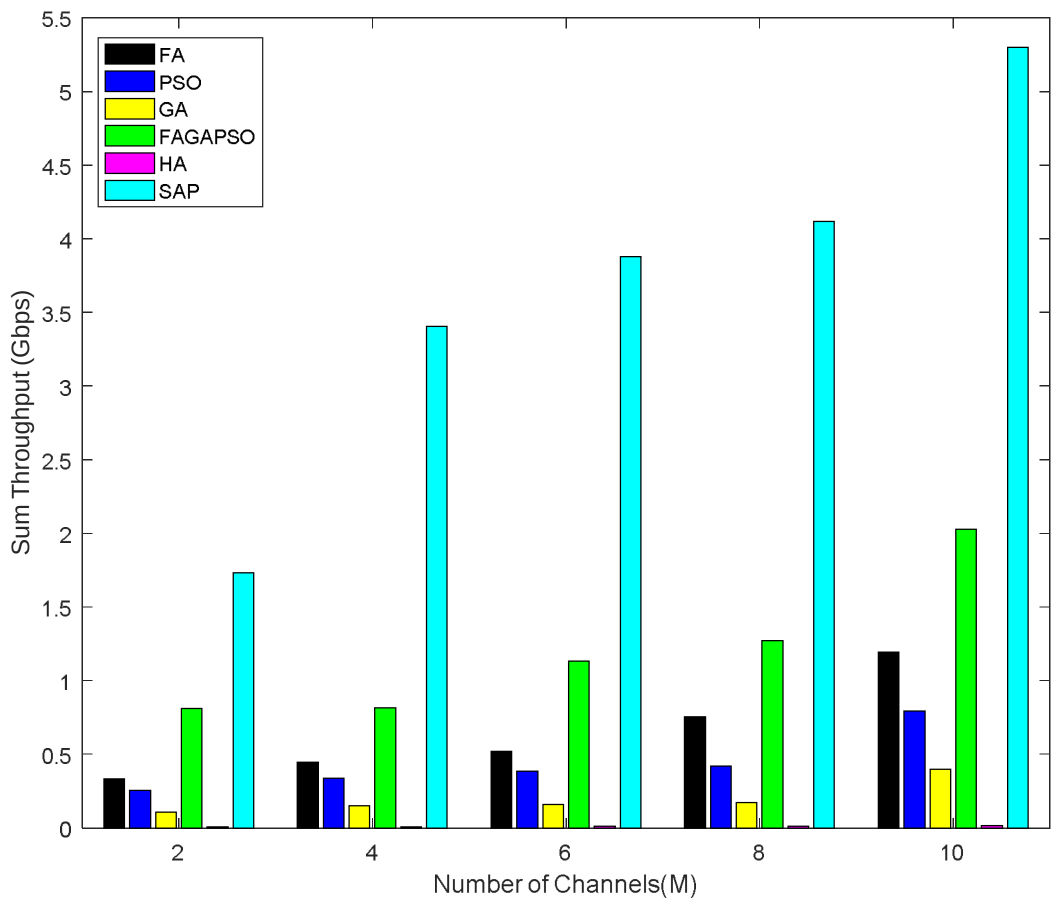

Figure 4.21: Sum Throughput for Different Algorithms and Values of M for N=200.

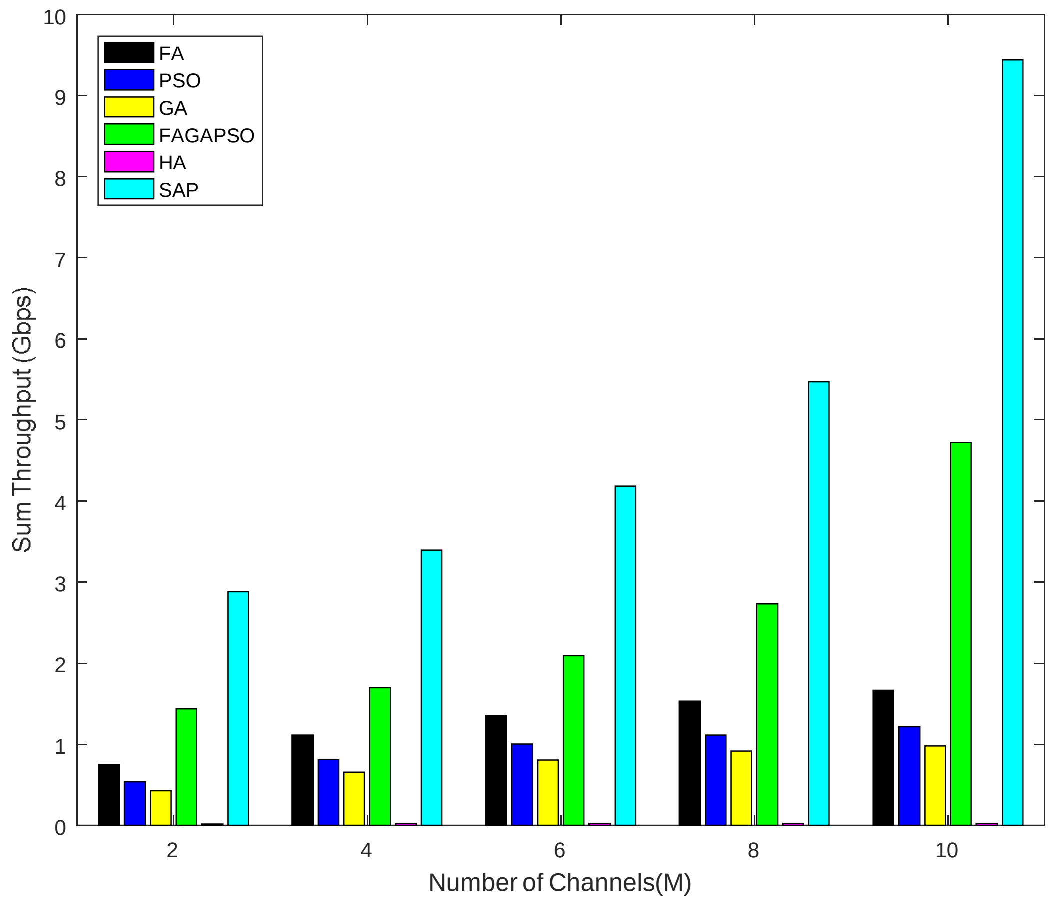

Figure 4.22: Sum Throughput for Different Algorithms and Values of M for N=800.

4.5.9 Analysis and Comparison of Performance of FAGAPSO for Joint Power and Spectrum Allocation

In this subsection, analysis of performance of various algorithms for joint power and spectrum allocation is presented.

4.5.7.1 Comparison of FAGAPSO with FA, GA and PSO

Simulation results show that the use of FAGAPSO outperforms FA, GA and PSO. The use of crossover feature of GA for both power and spectrum allocation in FA as well as initial solution from PSO and PSO operators allows FA to search the solution better. FAGAPSO results in better SU and PU SINR, SU throughput and objective function value compared to FA, GA and PSO. This is because of improved exploration and exploitation ability compared to FA, GA and PSO.

4.5.7.2 Comparison of FAGAPSO with HA

HA is the worst performing algorithm. This is mainly because it is a greedy algorithm. A greedy algorithm will result in sub optimal spectrum allocation.

4.5.7.3 Comparison of FAGAPSO with SAP

Although SAP achieves better performance metrics compared to FAGAPSO, it has poor running time. This is mainly because of the iterative power allocation algorithm. The iterative algorithm enables SAP to achieve the best power allocation to SUs. Due to reduced allocated power to SUs, interference reduces and this results in improved throughput as well as SINR and objective function value.

4.5.7.4 Analysis of Efficiency FAGAPSO

Power and spectrum allocation in a TVWS network is a NP hard optimization problem. As discussed in sections 2.5.2.2, such an optimization problem cannot use exact algorithms such as exhaustive search because they have poor time complexity. Metaheuristics instead are preferred because they are able to give good solutions in reasonable time complexity. In this thesis, FAGAPSO, a metaheuristic algorithm has been applied.

Algorithm 4.2 shows the pseudo code for FAGAPSO. In the FAGAPSO algorithm PSO runs first and then FA runs. In terms of complexity, both FA and PSO are of low complexity because both of them have a linear relationship O(n) with the respective main input N (number of users). Although FA has a nest loop with a quadratic operation $O(n^2)$, the quadratic relationship is with respect to the number of fireflies. The combination of FA and PSO, therefore, do not increase the complexity. The complexity still remain O(n) and it is, therefore, an efficient algorithm.

Algorithm 4.2: FAGAPSO Pseudocode for Joint Power and Spectrum Allocation

Step 1: PSO

- Initialize PSO parameters
- Initialize each particle – power vector with random power values
- Do
  - Update each particle velocity and position
  - Update p_{best} and g_{best}

  While maximum number of iterations has not been reached
- Set g_{best} as the final solution

Step 2: FA and GA

- Initialize FA parameters
- Initialize FA power vector fireflies to those in p_{best}
- Initialize each particle - channel matrix values (with random channel allocation)
- For each iteration
  - Rank fireflies and find current best
  - Apply single point crossover for top fireflies – separately for power vector and channel matrix
  - For every firefly, move it towards the better solution

    Use p_{best} and g_{best} in firefly movement

    Firefly movement done separately for power vector and channel matrix

  End
- Take best firefly as final solution

Step 3: End Algorithm

4.5.7.5 Summary

The results show that FAGAPSO provides good tradeoff between improving resource allocation and run time. Although SAP has the best resource allocation as measured by SU SINR, PU SINR and throughput, it has the worst running time. In a big network, this may not be tolerable. Results also show that hybrid FA, GA and PSO performs better compared to HA, FA, PSO and GA for all values of N and M considered. Changing the dimension of the problem by varying N and M does not affect the comparative performance of the algorithms. The results also show that FA can be modified to solve a continuous-binary problem that consists of both continuous and binary values.

4.6 Chapter Summary

In this chapter, simulation results for power allocation, spectrum allocation and joint power and spectrum allocation have been presented. Simulation results have shown that FAGAPSO performs better compared to FA, GA, PSO as well as other hybrid FA, GA and PSO algorithms. Simulation results have shown that FAGA performs better compared to FA, GA, PSO as well as other hybrid FA, GA and PSO algorithms including FAGAPSO for spectrum allocation. In the final joint power and spectrum allocation algorithm FAGA is applied for spectrum allocation while the entire FAGAPSO is applied for power allocation. For joint power and spectrum allocation, FAGAPSO is found to perform better than other algorithms except SAP but which has poor running time. The only disadvantage is the slightly higher running time compared to GA and PSO. This can be tolerated for improved resource allocation. The results in this chapter have also shown that changing the dimension of the optimization problem does not affect the comparative performance of the algorithms. However when the problem changes for continuous to binary/discrete, the performance population based metaheuristic algorithm is affected, even for hybrid ones.

Chapter 5: Contributions, Conclusion and Recommendation

In this study, an improved version of FA based on hybrid FA, PSO and GA has been developed. The algorithm has been applied for optimization of power allocation, optimization of spectrum allocation and joint optimization of power and spectrum allocation.

5.1 Review of Research Objectives

The research was broken down into three objectives. In this section, how each research objective was achieved is discussed.

Objective 1: To demonstrate the inefficiency of existing joint power and spectrum allocation algorithms.

The objective was achieved by conducting extensive comparison of existing algorithms for power allocation in TVWS network, spectrum allocation in TVWS network and joint power and spectrum allocation in a TVWS network.

The following algorithms for joint power and spectrum allocation for a TVWS network that exists in literature have been discussed and compared in Chapter 2: heuristics in addition to game theory (Xue and Wang, 2015) and heuristics in addition to greedy algorithms (Xue et al., 2014). IEEE 802.11af and IEEE 802.22 do not provide algorithms for resource allocation. SUs are assigned resources one by one as they make requests to the GLDB. This will result in sub optimal spectrum allocation. Since the objective of this thesis was to design an improved joint power and spectrum resource allocation algorithm, a detailed analysis of these proposed resource allocation techniques or algorithms was done and their inefficiencies shown.

The use of heuristics and game theory proposed by Xue and Wang, 2015 have the following weaknesses. First, the algorithm ignores adjacent channel interference. Secondly, the use of iterative power allocation technique makes the algorithm have high running time. The use of heuristics in addition to greedy algorithm proposed by Xue et al., 2014 have the following weaknesses. Firstly, resource allocation is done without use of any objective function value and in greedy manner. Secondly, each SU is assigned a channel one by one. These two features make the proposed algorithm result in sub optimal resource allocation.

Objective 2: On the basis of the outcome of objective 1, develop a potentially improved and efficient algorithm for optimization of power and spectrum allocation in a geo-location database based TV White Space network.

Due to the inefficiencies of the existing joint power and spectrum allocation algorithms, literature was studied to find out suitable and better algorithms. It was found out that metaheuristic algorithms are preferred over other algorithms for resource allocation because they are able to give a good solution in a reasonably good time. FA and PSO were chosen because it has been found that they are able to converge to a good solution much faster compared to other evolutionary algorithms. GA's concept of crossover was added into the hybrid of FA and PSO so as to diversify the search of solution space through improved exploration.

Literature was studied to find out the concepts of GA and PSO that can be incorporated into FA. Existing Hybrid FA and GA and hybrid FA and PSO in literature are as follows:

- Cross-over of two current best fireflies
- Application of PSO final solution as initial solution of FA.
- In firefly movement, PSO concept of p_{best} and g_{best} is applied.

In the new hybrid algorithm designed, the above three concepts are combined, FA starts with an initial solution of PSO. The hybrid algorithm also applies the concept of p_{best} and g_{best} in firefly movement as well as the GA's concept of crossover.

Having discovered how to come up with a hybrid FA, GA and PSO algorithm (FAGAPSO), the algorithm is then applied to power allocation, spectrum allocation and joint power and spectrum allocation. For power allocation, the algorithm solves a continuous optimization problem. For spectrum allocation, the algorithm solves a binary optimization problem. For joint power and spectrum allocation, the algorithm solves a continuous-binary problem. This is a modified version of FA because FA usually is applied for either continuous optimization problem or binary optimization problem. In order to achieve this objective, simulation of the algorithms was done using Matlab. Before implementing the algorithms, a simulation environment was first developed.

In order to evaluate the effectiveness of the FAGAPSO algorithm for power allocation and spectrum in a TVWS network, the following algorithms were implemented in the developed Matlab simulation environment and compared:

- FAGAPSO
- GA
- FA
- PSO
- Hybrid FA and PSO algorithms:
- FA with initial solution of PSO
- FA with PSO operators
- FA with PSO operators and initial solution of PSO.

The following performance metrics were used to evaluate of the listed power allocation algorithms: objective function value, sum throughput, SU SINR and sum power.

For power allocation, it is found out that FAGAPSO outperforms the rest of the algorithms. For spectrum allocation it is found out that FAGA outperforms the rest of the algorithms including FAGAPSO.

Having found out the performance of FAGAPSO for power allocation and spectrum allocation, hybrid algorithm for joint power and spectrum allocation is then designed. The final algorithm is presented in section 4.4.

Objective 3: To evaluate performance of the algorithms developed in 2 above.

In order to evaluate the performance of the FAGAPSO algorithm for joint power and spectrum allocation in a TVWS network, the following algorithms were implemented in a Matlab simulation environment and compared:

- FAGAPSO
- GA
- FA
- PSO
- SAP
- HA

The performance metrics used are objective function value, sum power, sum throughput, percentage of SUs less than SU SINR threshold, PU SINR and algorithm running time. Simulation results show that FAGAPSO has superior performance compared to other algorithms except SAP. However, SAP has a poor running time.

5.2 Research Contributions

In this section, theoretical contributions, technical contributions and implications of research on TVWS standards, regulations and research are discussed.

5.2.1 Theoretical contributions

The study resulted in the following theoretical contributions:

- FAGAPSO for joint power spectrum allocation in a TVWS network in the presence of both co-channel and adjacent channel interference. This is a novel and improved algorithm for joint power spectrum allocation in a TVWS network. This new hybrid FA, PSO and GA can also be applied in other optimization problems with both continuous and binary decision variables. Examples of such optimization problems are multi-target tracking (Andriyenko et al., 2012) or optimization of large scale structure from motion (Crandall et al., 2011).
- Comparison of hybrid firefly, particle swarm optimization and genetic algorithm for continuous optimization and discrete or binary optimization. Among other hybrid algorithms, FAGAPSO is found to be the best for a continuous optimization problem.

However, for binary optimization, FAGA is found to be the best compared to other hybrid algorithms.

- FAGAPSO for power allocation in a TVWS network. This is a new algorithm for power allocation in a TVWS network. This new hybrid FA, PSO and GA can also be applied in other optimization problems with continuous decision variables. This is a new hybrid FA for optimization of continuous decision variables such as linear programming or quadratic programming.
- FA for joint power and spectrum allocation. This is a new and modified FA that can be used to solve a binary continuous problem. Usually FA has been applied either to optimization problems with continuous decision variables only or optimization problems with binary decision variables only. Examples of such optimization problems are multi-target tracking (Andriyenko et al., 2012) or optimization of large scale structure from motion (Crandall et al., 2011).
- Crossover mechanism for a binary-continuous problem. GA's crossover mechanism usually involved either continuous decision variables or binary decision variables. In this thesis, a crossover mechanism for an optimization problem with both continuous and discrete values.

5.2.2 Technical Contributions

The study resulted in development of a simulation environment based on Matlab for a TVWS network. The simulation scripts used in this thesis were developed from scratch using Matlab. For a TVWS the following were Matlab scripts developed:

- FA Matlab script for optimization of spectrum allocation, power allocation and joint power and spectrum allocation.
- PSO Matlab script for optimization of spectrum allocation, power allocation and joint power and spectrum allocation.

- GA Matlab script for optimization of spectrum allocation, power allocation and joint power and spectrum allocation.
- Hybrid PSO and FA Matlab script for optimization of spectrum allocation, power allocation and joint power and spectrum allocation.
- Hybrid GA and FA Matlab script for optimization of spectrum allocation, power allocation and joint power and spectrum allocation.
- Hybrid PSO, GA and FA Matlab script for optimization of spectrum allocation, power allocation and joint power and spectrum allocation.

5.2.3 Implications of Study Findings on Population Based Metaheuristics Research

This study has presented a new hybrid population based metaheuristic algorithm, FAGAPSO, based on FA, GA and PSO that has never been presented before. Performance of FAGAPSO has been compared with FA, GA and PSO and other hybrid FA, GA and PSO algorithms. The study has shown that FAGAPSO outperforms FA, GA and PSO and other hybrid FA, GA and PSO algorithms for a continuous optimization problem. On the other hand, for a binary optimization problem, FAGA outperforms other hybrid algorithms including FAGAPSO. Based on the analysis of performance of the hybrid algorithms, FAGAPSO for solving a binary-continuous optimization problem was designed. FAGAPSO designed for power allocation can be applied to other continuous optimization problems discussed in Section 5.2.1. FAGAPSO designed for joint power and spectrum allocation can be applied to other discrete-continuous optimization problems discussed in Section 5.2.1.

The study has also shown that hybrid population based metaheuristic algorithms may perform differently for continuous optimization problems and binary optimization problems. Therefore, when designing hybrid algorithms for binary-continuous problem, it is important to analyze the performance of hybrid algorithms in the binary domain as well as the continuous domain.

5.2.4 Implications of Study Findings on TVWS Standards, Regulations and Research

The focus of research on resource allocation in TVWS has been on power allocation only or spectrum allocation only. In this study, FAGAPSO, a metaheuristic algorithm for joint power and spectrum allocation has been developed. This algorithm can be incorporated into IEEE 802.22 or IEEE 802.11af standards. Both standards do not have an algorithm for joint power and spectrum allocation. The algorithm is especially useful because there is an increased demand for spectrum. TVWS use cases with high number of users such as cellular access to TVWS can apply this algorithm so to prevent harmful interference to PU and reduce interference among SUs.

FAGAPSO for power allocation and FAGA for spectrum allocation can also be incorporated into IEEE 802.22 or IEEE 802.11af standards as well as TVWS regulations such as those of FCC, OFCOM, ECC and other regulations developed by other NRAs.

5.3 Conclusions

There is continued increased demand for DSA to TVWS from vehicle to vehicle communications, 5G, 4G and IoT. This will result in secondary networks with a high density of users that will result in a problem of interference. In a network where there is high number of devices seeking access to a secondary network, allocation of power and spectrum needs to be optimized to minimize interference to PU and among SUs. Existing algorithms can get trapped in local optimum or allocate spectrum and power in a one by one, greedy, heuristic manner as SUs make request to the GLDB. This results in sub-optimal resource allocation.

This study has presented a novel hybrid FA, GA and PSO (FAGAPSO) algorithm that improves joint power and spectrum allocation in a TVWS network that is efficient. The novel hybrid algorithm, FAGAPSO, result in better joint power and spectrum allocation in a TVWS network since it improves SU throughput, SU SINR and PU SINR when compared to all other algorithms except for SAP. However, SAP based resource allocation has poor running time. FAGAPSO, therefore, has a good trade-off between optimization of resource allocation and running time. FAGAPSO is efficient to resource allocation because it is a metaheuristic algorithm and not an exact algorithm. Metaheuristic algorithms are known to give good solutions with reasonable time complexity unlike exact algorithms.

The new hybrid FA, GA and PSO (FAGAPSO) algorithm can also be used for solving continuous optimization problems, binary optimization problems and continuous-binary problems. The study has shown that incorporating PSO and GA concepts into FA improves performance of FA for all the three different optimization problems.

The study has also shown that FA can be modified to solve a binary-continuous problem and that hybrid metaheuristic algorithm may perform differently for continuous and binary optimization problems.

5.4 Limitations and Recommendations for Future Work

The current study was carried out in a simulated environment. In future, performance of FAGAPSO will be validated in a real world TVWS network. The work in this thesis can be extended as follows:

- The algorithm can be extended to a TVWS network consisting of more than one cell i.e more than one AP and also more than one PU.
- As currently implemented, firefly movement may result in allocation of more than one channel to SU. There is need to develop a technique to select one of the channels when firefly movement results in allocation of more than one channel.
- FAGAPSO can be compared with other evolutionary algorithms in addition to PSO and GA. An example is the hybrid FA developed by Farshi (2019).
- The model developed in this thesis does not consider fading. The model developed in this thesis can be extended to incorporating fading.
- An admission control algorithm can be added to the algorithm presented so that it is possible to remove some SUs in the network whenever SINR thresholds for SUs or PU are not met. This will ensure all SUs in the network meet the minimum required SINR threshold.
- In the simulation environment, FDMA was used as the only MAC protocol. Other MAC protocols can be added to the simulation environment.

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Appendix

A1. Publications

A1.1. Journal Papers

1. K. Ronoh, G. Kamucha, T. Olwal, and T. Omwansa, “Improved Resource Allocation for TV White Space Network Based on Modified Firefly Algorithm,” Journal of Computing and Information Technology, vol. 26, no. 3, pp. 167–177, Sep. 2018.
2. K. Ronoh, T. Omwansa and G. Kamucha, “Novel Resource Allocation Algorithm for TV White Space Networks Using Hybrid Firefly Algorithm,” International Journal of Computer, vol. 32, no. 1, pp. 34–53, Mar. 2019
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