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Spectrum and Power Optimisation in Wireless Multiple Access Networks

by

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Declaration of Authorship

I, JIA YUAN CHEN, declare that the work presented in this thesis and the thesis itself was composed and originated by myself in the Department of Electronic and Electrical Engineering, University College London. The work of other persons is appropriately acknowledged

Signed: ______________________________

Date: 10/12/2008. ______________________________

Abstract

Emerging high-density wireless networks in urban area and enterprises offer great potential to accommodate the anticipated explosion of demand for wireless data services. To make it successful, it is critical to ensure the efficient utilisation of limited radio resources while satisfying predefined quality of service. The objective of this dissertation is to investigate the spectrum and power optimisation problem for densely deployed access points (APs) and demonstrate the potential to improve network performance in terms of throughput and interference.

Searching the optimal channel assignment with minimum interference is known as an $\mathcal{NP}$-hard problem. The increased density of APs in contrary to the limited usable frequencies has aggravated the difficulty of the problem. We adopt heuristic based algorithms to tackle both centralised and distributed dynamic channel allocation (DCA) problem. Based on a comparison between Genetic Algorithm and Simulated Annealing, a hybrid form that combines the two algorithms achieves good trade-off between fast convergence speed and near optimality in centralised scenario. For distributed DCA, a Simulated Annealing based algorithm demonstrates its superiority in terms of good scalability and close approximation to the exact optimal solution with low algorithm complexity.

The high complexity of interactions between transmit power control (TPC) and DCA renders analytical solutions to the joint optimisation problems intractable. A detailed convergence analysis revealed that optimal channel assignment can strengthen the stability condition of TPC. Three distributed algorithms are proposed to interactively perform the DCA and TPC in a real time and open ended manner, with the ability to appropriately adjust power and channel configurations according to the network dynamics. A real network with practical measurements is employed to quantify and verify the theoretical throughput gain of their integration. It shows that the integrated design leads to a substantial throughput improvement and power saving compared with conventional fixed-power random channel allocation system.

Acknowledgements

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Getting this far has only been possible thanks to my parents and grandmother, who have provided so much warmth and support through the years.

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Abbreviations

AP	Access Point
ATC	Air Traffic Control
AWGN	Additive White Gaussian Noise
BCA	Borrowing Channel Allocation
BSS	Basic Service Set
CSMA/CA	Carrier Sense Multiple Access with Collision Avoidance
DCA	Dynamic Channel Allocation
DCF	Distributed Coordination Function
DFS	Dynamic Frequency Selection
DS	Distribution System
DSSS	Direct Sequence Spread Spectrum
EIRP	Effective Isotropic Regulatory Power
ES	Evolutionary Strategy
ESS	Extended Service Set
ETSI	European Telecommunications Standards Institute
FCA	Fixed Channel Allocation
FCC	Federal Communication Commission
FHSS	Frequency Hopping Spread Spectrum
GA	Genetic Algorithm
HCA	Hybrid Channel Allocation
HD-WLAN	High Density-Wireless Local Area Network
IEEE	Institute of Electrical and Electronics Engineers
ILP	Integer Linear Programming
IP	Integer Program

ISM	Industrial, Scientific and Medical
ITU	International Telecommunication Union
LCCS	Least Congested Channel Search
LOS	Line-of-Sight
LP	Linear Programming
MAC	Media Access Control
MILP	Mixed Integer Linear Programming
MIMO	Multiple-Input Multiple-Output
MIP	Mixed Integer Program
NLOS	Non Line-of-Sight
NLP	Non-linear Programming
OFDM	Orthogonal Frequency Division Multiplexing
PC	Personal Computer
PDA	Personal Digital Assistant
PDF	Probability Density Funcation
QoS	Quality of Service
RF	Radio Frequency
RSC	Receiver Sensitivity Control
SA	Simulated Annealing
SACA	Simulated Annealing Channel Allocation
SINR	Signal to Interference plus Noise Ratio
TPC	Transmit Power Control
TC	Tabu Search
UWB	Ultra-Wideband
WLAN	Wireless Local Area Network
WMN	Wireless Mesh Network

Chapter 1

Introduction

1.1 Introduction

The first generation of wireless local area network (WLAN) system was designed based on the Ethernet hub-like media access control (MAC) model. It assumes that the typical WLAN deployment is one, stand-alone access point (AP) for wireless data traffic, either in a small business or in a corporate hot spot such as a conference room. In fact, such a system does provide a fairly high-quality user experience, as long as there is only one AP and there are only one to three users (clients) connected to it [1]. However, since the ratification of the first IEEE802.11 standard in 1997, the landscape for WLANs has undergone dramatic changes. The initial design for the non-bandwidth-intensive applications but coverage oriented WLANs, now has to provide far greater performance due to the multi-cell deployment and high user densities, which are typically found in larger scale environment such as enterprises and public areas. Thanks to the high-density deployment, not only the coverage problem of traditional WLANs can be automatically eliminated, but also the higher throughput requirement can be achieved with low transmission power.

However, the high density deployment also poses several non-trivial disadvantages. If the devices are being increasingly added into the network in a chaotic way ("devices" here refer to both APs and wireless communication equipments, such as laptops, personal digital assistants (PDAs) and mobile phones), it will pose many technical challenges to the network deployment and operation. First of all, in a typical high-density WLAN (HD-WLAN), a large number (in the order of hundreds and thousands) of clients are served by several APs. Consider the IEEE standard that only defines a limited number of channels for communication, there will be a high probability for each device to suffer co-channel interference from close neighbours. Besides, the contention based MAC protocol also results in suboptimal overall user throughput, as congestions force devices to wait in the back off state. Therefore, it is essential to coordinate the channel access among APs and clients. Secondly, in traditional WLANs with isolated APs, the minimum link rate can be provisioned over a careful radio frequency (RF) site-survey [2]. However, in HD-WLANs, this static site-survey planning is not adequate. This is due to the fact that, these APs belong to different administrative domains and the network dynamics resulting from newly added APs or traffic variations are unpredictable in the system. It is impossible to ensure that the perfect configuration valid at the time the network was initially designed will continue to be valid and deliver good service in future. Consequently, a single static and centralised processing unit could easily become a vulnerable performance bottleneck and a main obstacle towards scalability of the HD-WLANs.

1.2 Motivations and Objectives

Generally, there is a range of different techniques available to improve the system throughput, including dynamic channel allocation (DCA), adaptive transmit power control (TPC), spatial diversity, multiple antennas system, etc. In this thesis, we focus on the distributed design of the first two techniques to deal with the interference problem in HD-WLANs. They have been extensively studied in the centralised cellular systems, both in a separate and integrated way, where a centralised based station is dedicated to perform the resource allocation. For 802.11 WLANs, channel selection is currently performed in a static way, where each AP selects a channel with the least interference when it was initially deployed and then stays in that channel until it is powered off and on again next time. In addition, transmit power is usually configured at the default maximum level regardless of the interference environment. These configurations cannot account for varying traffic conditions and thus have been proved with limited performance gain. In this work, we are more interested in investigating dynamic schemes, regarding DCA and TPC, which can quickly respond to the changing propagation environment and multiple access interference. From the reported research literature, the resource allocation problem is usually solved by traditional constraints based optimisation techniques, which eventually falls into an $\mathcal{NP}$-hard problem. The complexity of the problem grows exponentially against the size of the input. Therefore, instead of finding the exact optimal allocation, we introduce heuristic-based algorithms which are believed to deliver suboptimal solutions.

The aims of this research program are to identify the constraints and limitations of the current licence-exempt wireless networks and to advance the state of the art in such systems. Efforts have been devoted to establishing a framework of using optimisation heuristics to solve the spectrum and power optimisation problems in single-hop multiple-AP HD-WLANs. This task is accomplished through following steps:

1. We first proposed biologically inspired approaches to solve the centralised DCA problem.
2. And then considering that the real systems are deployed by different network vendors, distributed algorithm is employed with the aim to search for sup-optimal channel assignment with a sensible time scale.
3. In order to further improve the system throughput and minimise power usage, a joint design between DCA and TPC is then proposed in a distributed manner.

4. In the end, all the distributed algorithms proposed in this work are validated through a set of real data, in order to provide useful guidelines to further network deployment.

The reason of employing biologically inspired approaches, such as Genetic Algorithm (GA) and Simulated Annealing (SA), is that traditional optimisation algorithms are not capable of obtaining the optimal solutions within a sensible time scale. The work is started by defining the feasibility of applying these heuristics to the practical DCA problem and proposing centralised algorithms to solve it. Simulation results are analysed carefully to evaluate the performance of each algorithm and identify the possible limitations. In the second step, we apply these heuristics in a distributed way, with the requirements to deliver acceptable results within reasonably short time and be capable of handling different networks with good scalability. Inspired from previous research, further throughput improvement can be achieved by combining the DCA and TPC together. This is because DCA scheme is susceptible to service disconnection or at least degraded service quality due to frequent channel switching. TPC can be incorporated into DCA with the potential to compensate these deficiencies, as appropriately adjusted transmit power can reduce the overlapping coverage to enhance the channel access efficiency. Therefore, in the third step, we consider joint design between DCA and TPC. Instead of using simulations to verify the benefit of the joint design, we will first theoretically prove this and then use a simulation case to support this finding. In the end, all the distributed algorithms proposed in this thesis are validated by using the measurement data from a real network of BT Wireless City project [3]. The validation results provide some useful insights and guidelines towards further network size expansion and improve the service quality delivered to the clients.

The research work is mainly focused on 802.11b networks where the spectrum restrictions are even harder because there are only three non-overlapping channels available. However, the methodologies developed using 802.11b can be easily extended to any other networks with spectrum restrictions.

1.3 Contributions

The primary goal of this research is to investigate and solve the dynamic resource allocation problem in 802.11 HD-WLANs. It has demonstrated a novelty in successfully applying biologically inspired methods to tackle the interference problem via DCA and TPC. The main contributions of this research work are summarised as follows:

- This work has established a framework of using GA and SA to solve the DCA problem in wireless communication networks. It defined the detailed analogy to apply the theory to the practical channel optimisation problem and conducted necessary modifications to fit into the specific problem structure.
- This work identified the limitations of each heuristic algorithm by statistical analysis of the simulation results and proposed a hybrid form to address the channel optimisation problem, and demonstrated a good trade-off between the fast convergence rate and optimality of the solution.
- This work also explored the possibility of using SA in a distributed manner for channel allocation to accommodate the situation that APs deployed in real networks have low coordination with each other. The implementation of the distributed algorithm is effective and simple and requires no knowledge about the wireless channels. However, it still demonstrated superior performance in terms of near optimality, low complexity and good scalability.
- In the joint design of DCA and TPC, this work theoretically proved that in the case of optimal channel allocation, stability condition of power control can be strengthened. This finding is also supported by a simulation case.
- This work proposed three real time and open ended algorithms to interactively perform DCA and TPC. The proposed algorithms can handle the dynamic network by instantaneously adjust channel and power configuration to respond to the changing environment.

- The DCA and TPC algorithms proposed in this work were validated by a real WLAN system in BT's Wireless City project. All the algorithms contributed to the minimisation of the interference in the system. The joint design between power control and channel allocation substantially increased the user throughput.

- This work provided valuable insights to the further deployment of the HD-WLANs and effective methods on how to appropriately adjust the network setting in order to achieve a specific performance target.

These contributions have led to the following publications:

1. J. Y. Chen, S. Olafsson, Y. Yang and X. Gu,"Joint optimisation of the distributed channel allocation and power control in scalable wireless LANs," submitted to *IEEE Transactions on Communications.*

2. J. Y. Chen, S. Olafsson, X. Gu and Y. Yang, "SACA: A simulated annealing based distributed channel allocation algorithm with low interference for high-density WLANs," submitted to *IEEE Transactions on Mobile Computing.*

3. J. Y. Chen, S. Olafsson, Y. Yang and X. Gu, "Joint Distributed Transmit Power Control and Dynamic Channel Allocation for Scalable WLANs, " accepted by *IEEE Wireless Communications & Networking Conference (WCNC 09)*, Budapest, Hungary, 4-8 April, 2009

4. J. Y. Chen, S. Olafsson, X. Gu and Y. Yang,"Joint optimisation of the distributed channel allocation and power control in scalable wireless LANs," accepted by the *4th IEEE International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM 08)*, Dalian, China, 12-14 October, 2008.

5. J. Y. Chen, S. Olafsson, X. Gu and Y. Yang, "A Fast Channel Allocation Scheme Using Simulated Annealing in Scalable WLANs," in the Proceedings of the *5th International Conference on Broadband Communications, Networks and Systems (Broadnets 08)*, London, 8-11 September, 2008.

6. J. Y. Chen, S. Olafsson and X. Gu, "Observations on Using Simulated Annealing for Dynamic Channel Allocation in 802.11 WLANs," in the Proceedings of *67th IEEE Vehicular Technology Conference (VTC2008Spring)*, Singapore, 11-14 May, 2008, pp.1801-1805.

7. J. Y. Chen, S. Olafsson and X. Gu, "A Biologically Inspired Dynamic Channel Allocation Technique in 802.11 WLANs with Multiple Access Points," in the Proceedings of *18th Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC07')*, Athens, Greece, 3-6 September, 2007, pp.1-5.

8. J. Y. Chen, S. Olafsson and X. Gu, "Dynamic Channel Allocation through Improved Genetic Algorithm in 802.11 WLANs with Multiple APs," in the proceedings of *Networking and Electronic Commerce Research Conference*, Lake Garda, Italy, September 2007.

9. J. Y. Chen, S. Olafsson and X. Gu, "Dynamic Channel Allocation in IEEE 802.11," Book Chapter in *4G Mobile & Wireless Communications Technologies*, River Publishers, 2007.

10. J. Y. Chen, Y. Yang and H. Wu, "Network Coverage and Routing Schemes for Wireless Sensor Networks," Book Chapter in *Modeling and Simulation of Wireless Networks*, Nova Science. 2006.

11. J. Y. Chen, X. Gu and Y. Yang, "Stable Distributed Power Control with High SIR Target for Cellular Wireless Communication Systems," in the Proceedings of *London Communications symposium*, London, 8-9 September, 2005.

12. J. Y. Chen, X. Gu and Y. Yang, "An Improved Distributed Power Control Algorithm for Wireless Systems with Reduced Constraint on SIR," in the Proceedings of *Postgraduate Research Conference in Electronics, Photonics, Communications and Networks, and Computing Science*, University of Lancaster, 30 March - 1 April, 2005.

1.4 Thesis Structure

The thesis is organised as follows:

- Chapter 2 outlines the essential background information for the research project conducted. The IEEE 802.11 standard is introduced in this section, including characteristics for each individual standard and their dedicated systems. The characteristics of HD-WLAN and its technical challenges during network deployment and operation are highlighted. Algorithmically, various classes of optimisation problems are briefly reviewed especially for the application of wireless network planning. This chapter ends by an illustration of the network model and the adopted wireless signal propagation model.

- Chapter 3 describes the centralised schemes solving the DCA problem. A detailed overview of the state-of-the-art thinking relating to this problem will be addressed from cellular networks to WLANs. The channel allocation problem is then formulated in terms of a non-linear combinatorial optimisation problem, which is believed to be an $\mathcal{NP}$-hard problem. Two centralised algorithms based on GA and SA are proposed to find sub-optimal solutions. For each algorithm, the analogy to apply the theory into this practical channel optimisation problem and the detailed implementation are discussed. After that, by revealing the limitations of each algorithm in this application, a hybrid form of GA and SA is proposed to achieve a better trade-off between high achievable signal to interference plus noise ratio (SINR) and fast convergence speed. A statistical analysis is provided to compare the solutions delivered by each of the algorithms in different systems.

- Chapter 4 deals with a fully distributed algorithm namely Simulated Annealing channel allocation (SACA) algorithm. The simulation result reveals that it is a very efficient algorithm and offers near optimal solutions to the system with a wide range of network topologies. The proposed algorithm is compared with many other existing schemes, and demonstrates the superior performance in terms of fast convergence, near optimality and good scalability.

- In Chapter 5, TPC is incorporated into DCA with the aim to further improve the user throughput. The joint optimisation is defined as a non-linear mixed continuous and discrete optimisation problem. We first theoretically prove that if performed separately, the optimal channel allocation can strengthen the stability condition of the TPC. By taking the dynamic environment of HD-WLANs into account, a family of distributed algorithms are proposed to interactively and continuously perform DCA and TPC on all APs. The proposed algorithms are all real time and open ended algorithms, which can instantaneously respond to the rapid changing environment.

- Chapter 6 validates the proposed distributed algorithms by using measurement data from a real WLAN deployed in SOHO area in London. Data inputs include APs' locations, path-loss measurements between APs and clients and quality of service (QoS) requirements. It shows that by employing the proposed distributed SACA algorithm, interference is minimised since channels are evenly distributed across the network. And by using the joint design of DCA and TPC, the user throughput is substantially improved.

- Chapter 7 concludes our work and gives recommendations for future work.

Chapter 2

Technical Background

This chapter gives essential information for the performance optimization in WLANs. The designated networks for performance optimisation are IEEE 802.11 networks, which are expected to significantly grow their service volumes in the next 5-10 years.

2.1 IEEE 802.11 WLAN System

2.1.1 Basic Architecture

Owing to the simplicity and cost efficiency, 802.11 WLANs have been widely used as a wireless extension for local area network. The basic element of a WLAN is basic service set (BSS). Each BSS is controlled by one AP. Most WLANs are formed by several BSSs where APs are connected through distribution systems (DS), typically Ethernet. A whole interconnected WLAN including different BSSs, their respective APs and the DS, is called extended service Set (ESS). A typical layout of a WLAN with two APs is illustrated in Figure 2.1.

A WLAN can be configured in two basic modes:

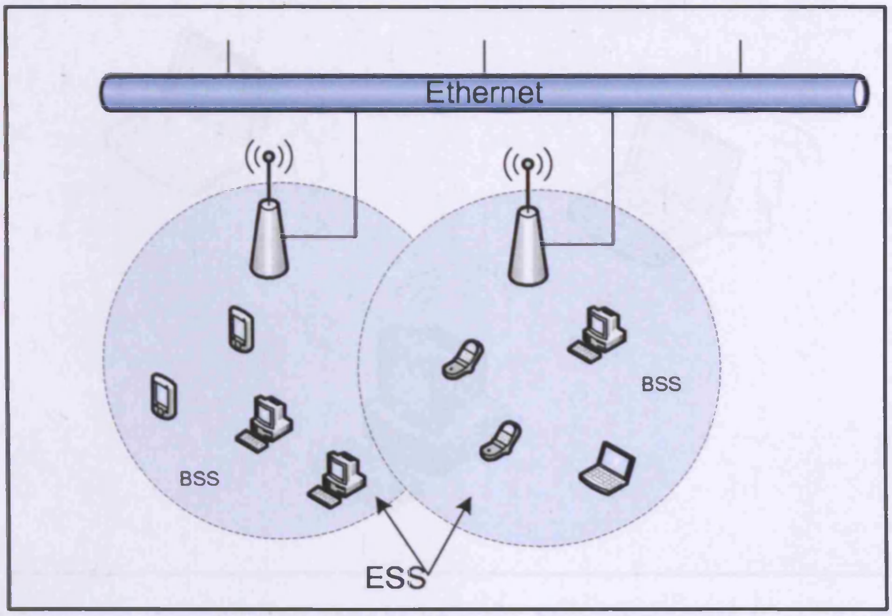

FIGURE 2.1: An 802.11 WLAN with two APs

- Peer-to-Peer (ad hoc) mode - This mode consists of two or more personal computers (PCs)/laptops equipped with wireless adapter cards, but with no connection to a wired backhaul, as shown in Figure 2.2. It is usually used to quickly and easily set up a WLAN where no infrastructure is available, such as in a convention center or off site meeting room. The channel allocation in this mode is similar to the edge colouring problem in graph theory [4], where channels are allocated on link basis. This channel allocation method requires two end nodes on a single link to use the same channel.

- Client/Server (infrastructure) mode - This mode consists of multiple stations (laptops, PDAs, PCs) linked to a central AP that acts as a bridge to the resources from the wired Ethernet, as shown in Figure 2.3, offering fully distributed data connectivity. The channel allocation in this mode is similar to the node colouring problem in graph theory [4]. It requires each AP to use different channels from their neighbours in order to avoid co-channel interference.

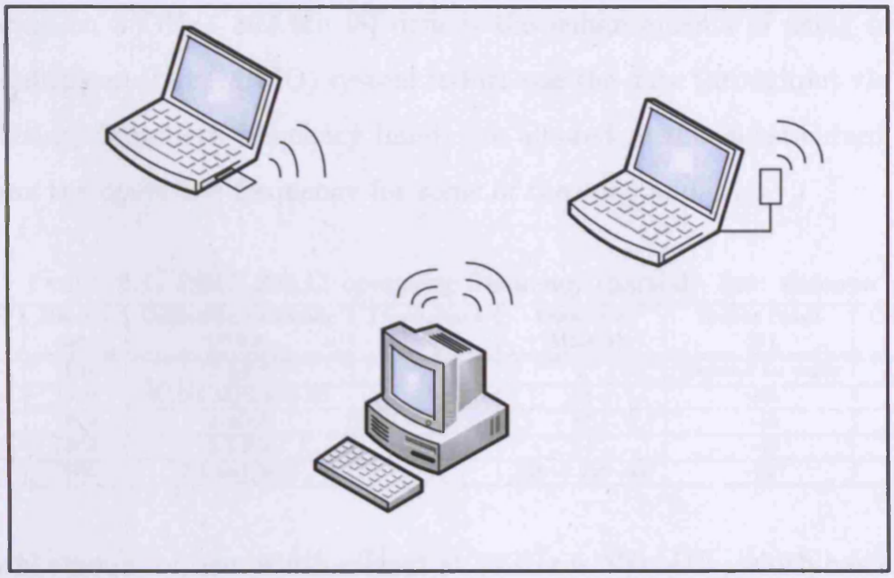

FIGURE 2.2: Peer to peer WLAN configuration

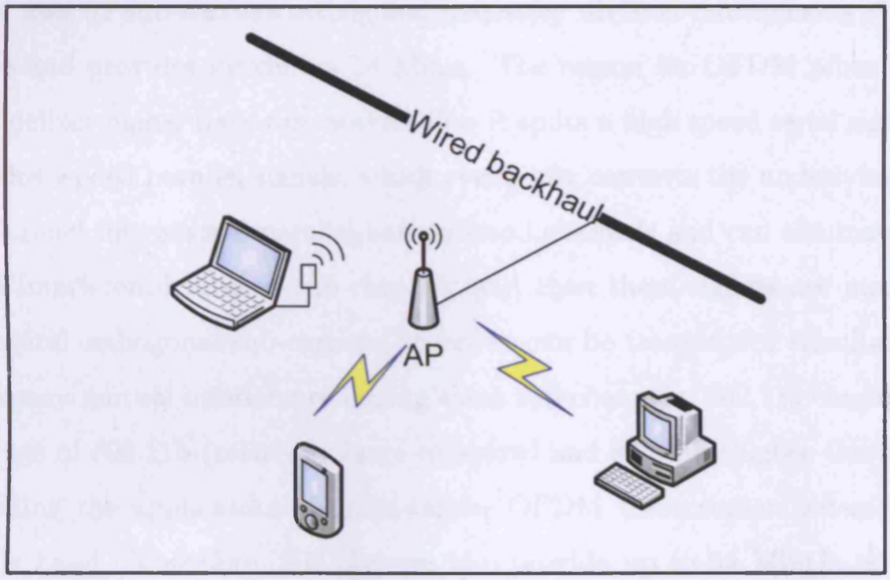

FIGURE 2.3: Client/Server WLAN configuration

2.1.2 Channel Configuration

In 1985, the Federal Communication Commission (FCC) authorised the free public use of the Industrial, Scientific and Medical (ISM) frequency bands on 2.4 GHz and 5 GHz to encourage innovation and low-cost implementations. According to the IEEE 802.11 standard, 802.11b/g [5, 6] operate on 2.4 GHz, while 802.11a

[7] operate on 5 GHz. 802.11n [8] defines the enhancements of using multiple-input multiple-output (MIMO) system to increase the data throughput via spatial multiplexing, thus both frequency bands are allowed in this substandard. Table 2.1 shows the operating frequency for some of the substandards.

TABLE 2.1: IEEE 802.11 operating frequency (partial). ant: antenna

Protocol	Release date	Operating frequency (GHz)	Throughput (Mbit/s)	Data rate (Mbit/s)	Indoor range (ft)	Outdoor range (ft)
Legacy	1997	2.4-2.5	1	2	Depend on walls	~75
802.11a	1999	5.15-5.35/5.49-5.85	25	54	~35	~75
802.11b	1999	2.4-2.5	6.5	11	~40	~150
802.11g	2003	2.4-2.5	20	54	~40	~150
802.11n	2009	2.4 and/or 5	74	248 = 2x2 ant	~220	~500

The total amount of bandwidth offered at 5 GHz is 550 MHz, which has as many as 19 non-overlapping channels compared to 3 in 802.11b/g at 2.4 GHz. Besides, 802.11a uses 52 sub-carriers orthogonal frequency division multiplexing (OFDM) schemes and provides maximum 54 Mbps. The reason for OFDM scheme to be able to deliver higher data rate is that, first it splits a high speed serial signal into several low speed parallel signals, which eventually converts the underlying broad band channel into several parallel narrow band channels and can eliminate inter-symbol interference in each sub-channel; and then these signals are modulated onto several orthogonal sub-carriers, therefore can be transmitted simultaneously without any mutual interference among these sub-channels. 802.11g combines the advantage of 802.11b (relatively large coverage) and 802.11a (higher throughput) by defining the application of multi-carrier OFDM transmission scheme in the 2.4 GHz band. Therefore, 802.11g can also provide up to 54 Mbit/s at the air interface. In contrast, 802.11b operating in the same frequency band can only offer up to 11 Mbit/s data rate. The scope of our work is to design a DCA and TPC scheme under 802.11b specification, where the spectrum restriction is severer than other type of networks.

Figure 2.4 shows the channel configuration for 802.11b. Channels are represented by their center frequency, starting from 2.412 GHz to 2.477 GHz, with up to 14 channels in total (the first 13 channels are used in Europe). Each channel is 22 MHz wide in order to accommodate a wireless signal. But since channels are

5 MHz apart from each other, there are only up to 3 non-overlapping channels, channel 1, 6 and 11 are currently used to transmit signal.

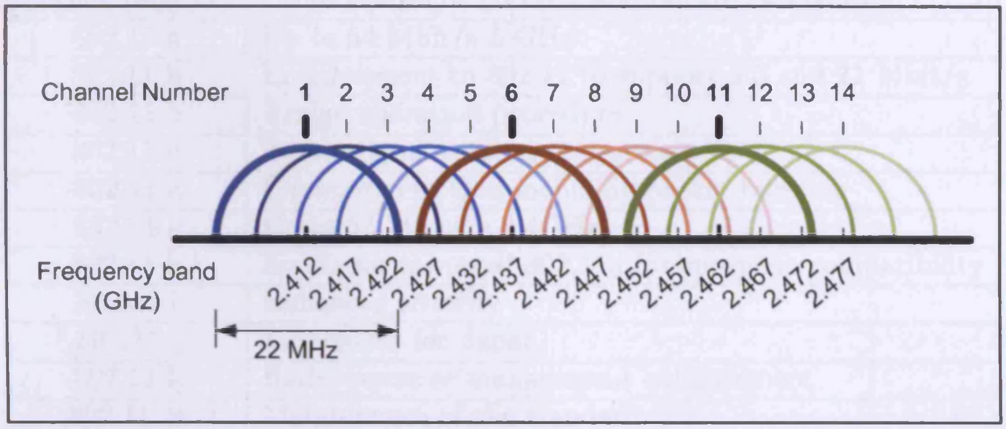

FIGURE 2.4: IEEE802.11b channel configuration

From the research point of view, overlapping channels can also be used for transmissions as long as the interference is calculated with the channel overlapping coefficient, which imposes complicated management overhead. Nevertheless, since the off-the-shelf products only support three-channel configuration, our proposed schemes are mainly based on non-overlapping channels.

Current channel assignment for most 802.11b WLANs is carried out in a static manner, using the fixed channel allocation (FCA) scheme. FCA scheme is usually run in the initial installation when an AP is initialized. Based on a careful RF site survey, there will be an optimal number of APs and their locations to provide adequate coverage and performance for their users. After the deployment, APs scan for a channel to use with the least interference level and to separate neighbouring APs that share the same channel [9]. This static scheme cannot adapt to local environment changes and traffic conditions afterwards. Therefore, it could not provide the best performance for WLANs, where traffic load in the network usually varies in time. There are some commercial vendors developing DCA techniques for their products, but the key technology is proprietary, which imposes some difficulties for academic researchers to evaluate new ideas by comparisons with current state-of-the-art.

TABLE 2.2: IEEE 802.11 standards and amendments

Protocol	Description
Legacy (802.11)	Up to 2 Mbit/s 2.4 GHz and infrared standard
802.11 a	Up to 54 Mbit/s 5 GHz
802.11 b	Enhancement to 802.11 to support 5.5 and 11 Mbit/s
802.11 c	Bridge operation procedure
802.11 d	International roaming extensions
802.11 e	Enhancement QoS including packet bursting
802.11 g	Up to 54 Mbits/s 2.4GHz
802.11 h	Spectrum managed 802.11a for european compatibility
802.11 i	Enhanced security
802.11 j	Extensions for Japan
802.11 k	Radio resource management enhancement
802.11 m	Maintenance of the standard
802.11 n	Higher throughput improvement using MIMO
802.11 r	Fast roaming
802.11 s	ESS mesh networking
802.11 t	Wireless performance prediction
802.11 u	Inter-working with non-802.11 networks
802.11 v	Wireless network management
802.11 y	3.65 - 3.7 GHz operation in US

The IEEE 802.11 working group defined mechanisms for 802.11a devices to operate dynamic frequency selection (DFS) and TPC in 802.11h [10] in order to avoid interference from military radar or other WLANs. It regulates the operation of an AP or a client initiating the channel selection request or adjustment of transmission power. It also defines the standard method to exchange such information between each other. The decision of choosing which channel and power level depends on the measurements made by each device. However, as for what algorithms should be used to make such decision is beyond the scope of this substandard.

In addition, IEEE 802.11 working group also defined other amendments for various purposes. Table 2.2 gives a quick reference on the main tasks for each group, their corresponding standards and specifications.

2.2 High-Density WLANs

As briefly mentioned previously, in the recent years, the density of 802.11 WLANs has been dramatically increased. On one hand, this phenomenon is due to the low cost and eases of deployment of WLANs. On the other hand, the capability of current 802.11 standards to support high data rate applications has allowed bandwidth-intensive applications to be tapped into the given network. From a commercial perspective, in May 2005, laptops outsold desktops in the United States for the first time in sales history[1]. The convenience and flexibility to work nearly anywhere and anytime offered by WLANs has led to the emergence of large scale WLANs in urban areas and enterprises. In such environments, densities of both users and APs are relatively high, which can be as close as only a few meters away from each other [11]. This multi-AP network to serve an even larger number of clients is defined as a high-density WLAN (HD-WLAN). With the rise of HD-WLANs, mobile users are rarely out of signal range [12], hence coverage is often less of a concern due to the ubiquitous deployment of APs. Instead, scalable network capacity becomes a primary design challenge.

In principle, HD-WLAN is a deliberate design choice for the enterprise or public network scenarios. As distances from clients to APs have been shortened, lower transmit power is preferable to achieve high throughput. In [13], a picocell structure (a substantially small RF coverage area) is introduced to build high-throughput 802.11 networks. In the creation of picocell, TPC and receiver sensitivity control (RSC) is required to minimise cell overlap and avoid co-channel/adjacent-channel interference. However, surveys of typical deployments [14], such as in a sporting arena or the trading floor of a stock exchange, have shown that the default power level is often set to the maximum without consideration of the distance from clients to APs. Therefore, HD-WLANs deployments face significant challenges from the increased interference in close proximity among APs and clients. It is widely understood that 802.11 adopts a distributed, contention based carrier sense multiple access/colission avoidance (CSMA/CA) approach for access control

[1] Michael Singer, "PC milestone-notebooks outsell desktops," CNET News.com (June 3, 2005) http://news.com.com/PC+milestone–notebooks+outsell+desktops/2100-1047_3-5731417.html.

and interference mitigation between devices [7]. It can achieve a peak capacity of about 50% efficiency with 3 or 4 contending stations (clients). However, as the number of contending stations increases, aggregated capacity drops dramatically. As more and more stations try to gain access to the medium and transmit packets, more and more collisions occur. Stations remain in "back off and wait" more than they actually transmit. From APs' perspective, another challenge is due to the relative large number of APs in the system compared with relatively small number of channels available. In such an environment, an AP will have high probability to experience co-channel interference from neighbouring APs. Besides, in this large and growing system, many APs belong to different administrative domains. A single centralised processing unit may easily become a vulnerable performance bottleneck. Therefore, to improve the spatial and spectrum reuse in a distributed manner is the key issue to realise the proliferation of HD-WLAN in the future.

By exploiting the potential for increasing capacity in HD-WLANs, many companies have launched their own high density networks and high density compatible products. Foundry Networks [15] has launched various APs, switches and software to help increase the capacity and security of enterprise wireless networks. The designated AP (IronPoint Mobility AP150) and switch (IronPoint Mobility Radio Switch 4000) provide multiple radio coverage in the entire WLAN, whilst location management software (IronPoint Wireless Location Manager 2.02 software) let users perform rogue AP detection and asset tracking. This combination is aimed to help run services such as VoIP and location tracking on a single 802.11 infrastructure. These products can support up to 256 WLAN connections for large public spaces or high traffic areas with 802.11 a/b/g compatibility. In 2005, MERU helped build the world's highest density WLANs in Northern Michigan University in order to enhance the learning experience for over 6000 students and faculty daily [16], [17]. Initially, this network suffers significant challenges from high density of mixed 802.11b and 802.11g clients. MERU uses a single controller, called the air traffic control (ATC), to determine a static channel access scheme and enables fair time-based access for both 802.11b and 802.11g clients to maintain high throughput performance.

From an academic perspective, many research groups have focused their study in this area and proposed a range of different techniques, including DCA [18], adaptive TPC [19], cooperative communication between APs and users by utilizing directional antenna [20] and intelligent MAC protocol design [12]. Each of these has the potential to improve the system capacity in different ways. DCA algorithms can help each AP chooses appropriate channels to transmit on, and avoid co-channel interference from neighbouring cells as much as possible. TPC schemes can be used to minimise the overlapping coverage among APs. Along with user association, these techniques help traffic load to be evenly distributed within the network, which can consequently improve data throughput in hot spot area. Besides, a cross-layered approach with joint adaptive TPC and MAC can help enhance the efficiency of channel access without any compensation on the network performance. Coverage redundancy in the HD-WLAN can also be utilised by cooperative communications.

2.3 Optimisation Theory

The DCA and TPC problems studies in this work can be viewed as optimisation problems with the aim of maximising some measure of the system performance by optimally allocating channel and power to each device.

2.3.1 Basic Terminology

An optimisation problem begins with a set of independent variables or parameters, and also includes conditions or restrictions that define acceptable values of the variables. We use the notation

$$\begin{aligned} &\underset{\mathbf{x}\in\mathbb{R}^n}{\text{minimise}}\ F(\mathbf{x}) \\ &\text{subject to } \mathbf{x} \in \boldsymbol{\Omega} \end{aligned} \tag{2.1}$$

to describe the optimisation problem of finding a vector $\mathbf{x}$ that minimises F over all possible vectors in $\mathbf{\Omega}$. The vector $\mathbf{x}$ is an n-dimensional vector of independent variables, which is often referred to as decision variable, $\mathbf{x} = [x_1, x_2, \ldots, x_n]^T \in \mathbb{R}^n$. The function $F : \mathbb{R}^n \rightarrow \mathbb{R}$ is called the objective function or cost function. It is a single measure of the "goodness" of the $\mathbf{x}$. The set $\mathbf{\Omega}$ is a subset of $\mathbb{R}^n$, called the constraint set or feasible set. It often takes the form $\mathbf{\Omega} = \{\mathbf{x} : \mathbf{h}(\mathbf{x}) = 0, \mathbf{g}(\mathbf{x}) \leq 0\}$, where the equation $\mathbf{h}(\mathbf{x}) = 0$ is called the equality constraint and the $\mathbf{g}(\mathbf{x}) \leq 0$ called the inequality constraint function. Problem (2.1) is said to be feasible if there exists at least one $\mathbf{x}$ that satisfies the conditions defined by the constraint functions, otherwise it is infeasible.

An optimal value P^* of $F(\mathbf{x})$ is defined as $P^* = \inf\{F(\mathbf{x})|\mathbf{h}(\mathbf{x}) = 0, \mathbf{g}(\mathbf{x}) \leq 0\}$[2]. P^* is allowed to take on the extended values $\pm\infty$. We define that $\mathbf{x}^*$ is an optimal (or global optimal) solution in $\mathbf{\Omega}$ such that $F(\mathbf{x}^*) = P^*$. The set of all $\mathbf{x}^*$ is denoted by $\mathbf{X_{opt}}$. If there exists at least one $\mathbf{x}^*$, we say the optimal value P^* is achievable and the problem (2.1) is solvable. If the $\mathbf{X_{opt}}$ is empty, the problem is then unsolvable. A feasible vector $\mathbf{x}$ with $F(\mathbf{x}) \leq P^* + \epsilon$ where $(\epsilon > 0)$is called a sub-optimal solution. Strictly speaking, an optimisation problem is solved only when a global optimal solution is found. However, in practice, the global optimal solution in general is difficult to find. Therefore, we often have to be satisfied with finding sub-optimal solutions.

2.3.2 Classification of Optimisation Problems

Although we can express the optimisation problem in a very general form, it does not imply that we should ignore the distinctions among problems. Indeed, it is always advantageous to determine special characteristics to allow the problem to be solved more efficiently. For example, the problem (2.1) can be viewed as a general form of a constrained optimisation problem, because the decision variables are constrained to be in the constraint set $\mathbf{\Omega}$. If $\mathbf{\Omega} = \mathbb{R}^n$, the problem is referred as an unconstrained optimisation problem.

[2] "inf" refers to "infimum", meaning greatest lower bound.

One can classify the optimisation problem by the special characteristics of the objective and constraint function. The functions $\mathbf{F}, \mathbf{h}$ and $\mathbf{g}$ may be very smooth in some cases, and discontinuous in others. If they are all linear functions, the problem (2.1) becomes a linear programming (LP) problem [21]. If some or all of the variables are constrained to integer values, the problem becomes mixed-integer or pure-integer linear programming (MILP/ILP) problem. Apart from linear functions, the rest of the problems belong to non-linear programming problems [22], where the objective function and/or the constraints contain nonlinear parts. If the problem variables are restricted to take on finite discrete numbers, it is a combinatorial optimisation problem. Combinatorial optimisation [23] has its roots in operation research. The channel allocation problem studied in this work is a typical non-linear combinatorial optimisation problem, as channels can only been taken on integers and the objective function (total interference in the system) is non-linear with respect to the channel numbers.

Additionally, optimisation problems can also be distinguished as convex programming or non-convex programming problems. Convex programming [24] studies the case when the objective function is convex and the constraints, if any, form a convex set, which means the objective and constraints functions satisfy the following condition [25] (to use function F as an example): $F(\alpha x + \beta y) \leq \alpha F(x) + \beta F(y)$, for all $x, y \in \mathbb{R}^n$ and all $\alpha, \beta \in \mathbb{R}$ with $\alpha + \beta = 1$, $\alpha \geq 0$ and $\beta \geq 0$. It can be viewed as a particular case of non-linear programming or as generalization of linear programming when $F(\alpha x + \beta y) = \alpha F(x) + \beta F(y)$.

As an alternative way, we can also classify the optimisation problems in terms of the number of objective functions. A significant portion of research and applications considers a single objective, although many real world problems may involve more than one objective [26]. The presence of multiple conflicting objectives can make the optimisation problem hard to solve. Since no solution can be an optimum solution to all multiple conflicting objectives, the resulting multi-objective optimisation problem resorts to a number of trade-off optimal solutions.

Those above mentioned optimisation problems are formally defined problems with some specific structures. Apart from that, the rest of the problems have a more generic form, referred to as non-linear mixed continuous and discrete optimisation problem. In this class of problem, both discrete and continuous variables and constraint functions are included in the problem definition, and no restrictions are imposed on the functional form of the objective function and constraints. The channel allocation problem incorporating with power control with continuous power level can be categorized into this problem. Since there are no effective methods to tackle this class of problems, usually heuristics is a sensible candidate to find sub-optimal solutions.

2.3.3 Applications and Modeling of Optimisation in Wireless Networks

The optimisation problem is an abstraction of the situation of making the best possible choice from a set of candidates. The variable $\mathbf{x}$ represents the choice made; the constraints represent the requirements or specifications that limit the possible choices. The objective function represents the value or cost of choosing $\mathbf{x}$. Therefore, from this point of view, problems in all areas of mathematics, applied science, engineering, economics and statistics can be posed in terms of optimisation.

For wireless systems, optimisation techniques [27] are quite useful to solve the network design and operation problem, such as network planning (including base stations' location and assignment problems), routing and clustering in large-scale multi-hop networks, load balancing and reliability issues in distributed networks, minimum cost optimisations and other stochastic issues in wireless communications.

In networking planning, for example, one of the major tasks is to find the best location of each AP such that the network can be fully covered. Here the variables represent the coordination for each AP. The constraints represent a variety of engineering requirements, such as a limit on the total area of the network, all the obstacles which affects the propagation of the wireless signal and propagation characteristics of specific spectrum.

In the channel allocation problem, we seek the best channel assignment for the APs to operate in the system. The variable x_i represents the channel selection by the i-th AP. Therefore, the vector $\mathbf{x}$ describes the channel assignment for all the APs across the network. The constraint is that there are only 3 non-overlapping channels available to choose in 802.11b case, and each AP can only operate in one channel at a time. The objective function of the channel allocation problem could be a minimisation of the total interference in the system, a minimisation of the maximal interference among all the APs or maximisation of the SINR value for each user. This problem is a typical example of a non-linear combinatorial optimisation problem, which will be discussed in detail later.

When combining the channel allocation and power control techniques together, we start to have multiple variables, such as channel assignment for each AP and the transmit power level on each device. The constraints of the problems, except for the limited channel number, are also to guarantee the SINR level to be above a pre-defined target during the whole process of the communication. Power level is also limited by a maximum value and can be continuous values. The objective function can also be set in a number of different ways, such as to find a proper channel and power setting to maximise the average system throughput, or to maximise the fraction of users reaching high SINR targets.

2.3.4 Solving Optimisation Problems

When faced with solving an optimisation problem, one would like to know how difficult it is to solve the problem. Usually, the difficulties are determined by the objective function or the constraints. In optimisation theory, the "difficulty" is termed as the "complexity" of a problem [28], which is used formally to classify a problem as easy or hard. The complexity of an algorithm is defined as the amount of resources required to find the optimal solution. The most common resources are time (how many steps it needs to solve a problem) and space (how much memory it needs to solve a problem).

A problem is considered to be easy if there exists an algorithm that solves the problem in time bounded by a polynomial function against the size of the input. Usually being able to solve an optimisation problem implies being able to answer the associated decision problem. The decision problem can only be answered yes or no. Take the channel allocation problem as an example, the decision problem will be "can we find an optimal channel assignment for APs such that the system interference is minimised?" To answer this question, one would give the steps to determine whether this optimal channel assignment could be found. If an optimisation problem is easy, then clearly the decision version of this problem is also easy. In the complexity theory, $\mathcal{P}$ is used to denote the class of decision problems that can be solved in polynomial time. The simplex method [29] was developed in 1947 by Dantzig to solve the LP problems. Generally, the simplex method is efficient and elegant. However, it has the undesirable property that, in the worst case, the number of the steps required to find a solution grows exponentially with the number of variables. Obviously, polynomial complexity is more desirable then exponential complexity. Therefore, from 1979, researchers started to devise algorithms to solve the LP problem in lower complexity. These algorithms are referred to interior-point methods [30], [31]. From a complexity point of view, these algorithms are superior to the simplex algorithm. But they have their own problem: the time required to solve a given LP problem increases with the required accuracy of the computations. Therefore, to solve the LP problem with a polynomial complexity bound remains a difficult open problem [32].

The notation $\mathcal{NP}$ stands for "nondeterministic polynomial time". It means that this class of problems is solvable in polynomial time by a non-deterministic Turing machine [33]. The class of $\mathcal{NP}$ contains an enormous number of problems, including all problems in $\mathcal{P}$. Many problems in $\mathcal{NP}$ are not known to be solvable in polynomial time. It is not known whether $\mathcal{P}$ equals $\mathcal{NP}$, but it is widely conjectured that this is not the case.

The optimisation problems discussed in this thesis are $\mathcal{NP}$-hard problems. This is a class of problems known informally "at least as hard as the hardest problems in $\mathcal{NP}$." It is impractical to solve these $\mathcal{NP}$-hard problems, i.e. to find the exact optimal solution, due to the nature of the problems or to their size, even with the advent of the new computer technologies and parallel processing. Besides, reaching optimal solutions is meaningless in many practical situations, since we are often dealing with rough simplifications of reality and the available data is not precise. Therefore, this leads to an interest in adopting heuristics for searching good approximation solutions, without necessarily providing any guarantee of the solution quality.

Simulated Annealing (SA) [34, 35], Genetic Algorithm (GA) [36] and Tabu Search (TS) [37] etc. are some of the well known heuristics. They are based on distinct paradigms and offer different mechanisms to escape from locally optimal solutions, contrarily to greedy algorithms or local search methods. Different from classical optimisation problems, heuristics can be formulated based on one or several optimality conditions which not only can provide a termination criterion, but also give helpful suggestions to direct system converge to the optimal or near-optimal solutions. More precisely, when a tentative solution does not satisfy the optimality conditions, the conditions often suggest how to improve it in order to get another tentative solution, closer to the optimum. The principles of some of the heuristics will be discussed in detail in the following chapter when they are applied to solve the DCA and TPC problem.

2.4 Network Model and Propagation Model

As shown in Figure 2.5, we consider a network of n APs and a large number of user-devices randomly deployed in an area. Each AP serves a group of user-devices in its coverage. The network size is determined by the number of APs. The number of user-devices may vary. The distance between these users-devices and APs are on average much shorter than their communication range, to represent a high-density basis. According to the standard, only 3 non-overlapping channels are available for use by all the pairs of AP and user links. Transmit power can be adjusted continuously within a predefined range to satisfy users' SINR requirements. Each user is associated with its closest AP with the strongest received signal. As the distributed coordination function (DCF) in WLANs is a contention-based MAC protocol, each AP can communicate with only one user at a time through its selected frequency channel.

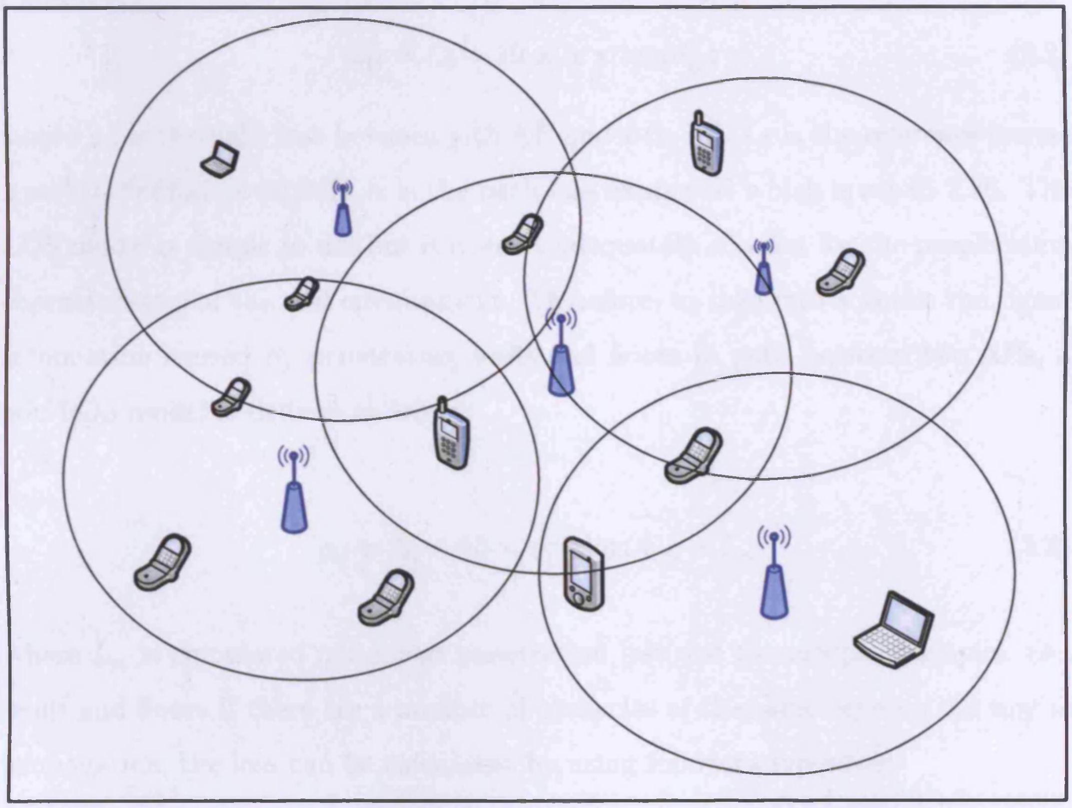

FIGURE 2.5: Network model

The model shows in Figure 2.5 represents a system with outdoor and indoor propagation environment, where both areas are equipped with APs. The coverage area of an AP is determined by the transmission power and its attenuation due to surrounding obstacles. In defining the propagation loss, we adopt the Motley and Keenan model [38] which can be used in both indoor and outdoor environment. In the Motley and Keenan model, the line of sight (LOS) model assumes a linear dependence between path loss and the logarithm of the distance d_{ij} between AP

TABLE 2.3: Penetration loss for different material types at 5GHz

Material type	Thickness	Average loss per wall
Plywood	0.4cm	0.9dB
Gypsum wall	13.5cm	3.0dB
Rough chipboard	1.5cm	1.0dB
Double glassed window	2.0cm	12dB
concrete block wall	30.2cm	10dB

i and AP j.

$$g_{ij} = L_0 + 10 \times \alpha \times \log(d_{ij}) \tag{2.2}$$

where g_{ij} is the path loss between j-th AP and i-th AP. L_0 is the reference loss at 1 meter, defined as 40.2dB. α is the path loss exponent, which is set to 2.86. The LOS model is simple to use but it doesn't adequately account for the propagation characteristics of the real environment. Therefore, to take into account the signal attenuation caused by penetrating walls and floors in path between two APs, a non-LOS model is defined as follow:

$$g_{ij} = L_0 + 10 \times \alpha \times \log(d_{ij}) + L_w \tag{2.3}$$

where L_w is cumulated non-linear penetration loss due to multiple obstacles, i.e., walls and floors.If there are a number of obstacles of the same type on the way of propagation, the loss can be calculated by using following equation:

$$L_w = L_s n_s^{\frac{n_s+5}{n_s+3} - b} \tag{2.4}$$

where L_s is path loss per obstacle in dB, depending on their thickness and material. Table 2.3 summarises the penetration loss for different material types measured at 5 GHz. n_s is the number of traversed obstacles. b is an empirical constant and estimated to be 0.5.

Chapter 3

Centralised Channel Allocation Schemes

3.1 Introduction

Channel allocation problems in general can be classified into two categories: fixed channel allocation (FCA) and dynamic channel allocation (DCA). In FCA, the set of channels are permanently allocated based on a pre-estimated traffic design [39, 40]. While in DCA, channels are allocated dynamically depending on current network conditions. Compared with FCA, DCA yields a better performance in terms of interference, throughput and delay at the expense of an added complexity in the control mechanism. The objective of DCA is to effectively allocate the available radio channels to the APs such that the overall network performance can be maximized and the co-channel interference can be minimized. We focus on DCA in this dissertation.

In this chapter, we apply heuristic based algorithms to solve the centralised DCA problem. This problem is first formulated in terms of a non-linear combinatorial optimisation problem, which is believed to be $\mathcal{NP}$-hard. A detailed overview of the related work is summarised in Section 3.3. In Section 3.4 and 3.5, two centralised algorithms based on GA and SA are proposed to find sub-optimal channel assignment. After a performance comparison between SA and GA, a hybrid algorithm is proposed in Section 3.6 to achieve a better trade-off between high achievable SINR and fast convergence speed. Section 3.7 provides the performance evaluation and statistical analysis.

3.2 Channel Allocation Problem Formulation

The channel allocation problem is formulated in the following. The set of all APs is denoted by A, (The total number of APs is represented by n). The total number of traffic channels in 802.11b is 3 (it can be easily extended to any number of channels for other systems). Channel utilization vector ρ is defined as $\rho = \{\rho_1, \rho_2, \ldots, \rho_i, \ldots, \rho_n\}$, where $\rho_i \in \{1, 2, 3\}$, $i \in \{1, 2, \ldots, n\}$. The geographic interference matrix $\Omega_{n \times n} = [\omega_{ij}]$ indicates instantaneous interference relationship among all the APs based on current channel allocation. $\omega_{ij} = g_{ij}$, if AP i and j are using the same channel and within each other's communication range, where g_{ij} captures the power loss on the path between two APs. Otherwise $\omega_{ij} = 0$. Therefore, the interference experienced by AP i, operating on channel ρ_i, from its neighbouring APs j with transmit power p_j (which is set to 100mW for all APs) is given by

$$I_i(\rho_i) = \sum_{j \in \Pi(i)} \omega_{ij} + \eta \tag{3.1}$$

where $\Pi(i)$ defines a local environment (neighbouring APs) around the AP i but not including i itself, η is the power of additive white Gaussian noise (AWGN). The objective is to find a proper channel allocation, ρ^*, such that the total interference I is minimised:

$$\rho^* = \arg \min_{\rho = \{1,2,3\}^n} I(\rho) \tag{3.2}$$

where $I(\rho) = \sum\limits_{i \in A} I_i(\rho_i) = \sum\limits_{i \in A} \sum\limits_{j \in \Pi(i)} (\omega_{ij} + \eta)$. And every AP only uses one channel at a time.

3.3 Related Work

In cellular networks, DCA schemes have been extensively studied in the past few years. Many researchers have proposed to formulate a cost function which evaluates a number of interference constraints violated by a given frequency assignment and then try to minimise this cost function. Different from WLANs, channels in cellular networks are kept in a central controller called channel pool. Each base station request channels from this global channel pool based on the traffic load it has. As the total number of channels is limited, it requires that the same channel should be reused as much as possible. While, at the same time, to avoid possible interference is also important between nearby mobile users. Therefore, DCA in cellular networks can be formulated with extra constraints as follows [41]:

$$\begin{aligned}
&\text{minimise} \quad z \\
&\text{subject to} \quad (1)\sum_{k=1}^{z} f_{ik} = d_i \qquad i \in [1,2,...,n]; k \in [1,2,...z] \\
&\qquad\qquad (2)|p-q| \geq c_{ij} \qquad p,q \in [1,2,...,z]; i,j \in [1,2,...,n] \\
&\qquad\qquad (3)f_{ik} = 0 \,\text{or}\, 1 \qquad i \in [1,2,...n]; k \in [1,2,...z]
\end{aligned} \tag{3.3}$$

where z is the total number of channels required by the system, f_{ik} is a binary matrix shows the possible channel assignment. If k-th channel is assigned to i-th cell,$f_{ik} = 1$, otherwise it equals to zero. Vector $\mathbf{D} = [d_i]$ corresponds to the number of channels each cell requires. Matrix $\mathbf{C} = [c_{ij}]$ is so-called compatibility matrix, it describes the minimum channel separation between cells i and j. p, q are the channel labels for those channels used in cell i and j. So the objective of DCA in cellular networks is to minimise the total number of channels required by the system, and at the same time, meet the channel demand for each cell expressed by condition (1) and ensure that the resulted channel assignment does not lead to any interference between different calls in any cells defined by condition (2). Other alternative objective functions can be set as to minimise the call dropping or call blocking probability.

By investigating the already published approaches, DCA schemes can be implemented as centralised or distributed. In the centralised algorithms, a central controller is adopted to assign channels and assure that required signal quality is maintained. While in distributed algorithms, any decisions are made regardless of the global status of the network. So the distributed algorithms are more difficult to predict as to whether or not they can achieve optimal channel assignment. The distributed algorithms will be discussed in detail in Chapter 4. In this chapter, we will focus on centralised algorithms first.

The above channel optimisation problem formulated by Eq. (3.3) is known to be $\mathcal{NP}$-hard [42]. This means the time needed to compute an optimal solution increases exponentially with the size of the problem. Therefore, some heuristic assignment strategies and combinational optimisation tools such as Genetic Algorithm (GA), Simulation Annealing (SA), multi-colouring scheme and neural networks have emerged to deliver a near optimal solution. From these tools, GA [39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53] is categorized as an evolutionary strategy, which can be used to find a sub-optimal channel assignment from a search space with relatively fast convergence speed. The SA based approach [54, 55] achieves the global optimum asymptotically but with a slow rate of convergence, and requires a carefully designed cooling schedule. Multi-colouring techniques [56, 57, 58, 59, 60] are usually used to find the minimal number of channels needed to satisfy a certain traffic load, while neural network heuristics [61, 62, 63] provide suboptimal solutions because they easily converge to local optima. Among these algorithms, some of the research works laid the foundation for using heuristics to solve channel allocation problems, thus are worth discussing with more details.

[52] is one of the first several works trying to use GA to solve the channel allocation problem. The general principles involved in the design of the algorithm were discussed in detail, such as the genetic representation of the channel assignment and fitness function design etc. It reveals two major advantages with GA. One is its simplicity and the other is the large speed-up through implicit parallelism.

Most of the following work on applying GA to DCA problems are based on this work.

An evolutionary strategy (ES) approach to the optimisation of DCA, hybrid channel assignment (HCA) and borrowing channel assignment (BCA) are proposed in [47]. Sandalidis *et al.* formulated channel assignment as a combinatorial optimisation problem with solutions represented as vectors of binary digits. The size of a solution is always equal to the total number of channels available. The scheme allows the simultaneous reassignment of the calls that are being served in the cellular networks, which takes place together with the allocation of new calls. This process improves the blocking performance of incoming calls, but also has been found to have large complexity both in terms of time and computation. Vidyarthi *et al.* [53] then provided a detailed comparison study in [47]. More importantly they proposed a better genetic representation of the solution (using integers rather than binary digits) and also designed a different fitness functions and a mutation scheme. The simulation shows that the newly designed algorithm outperforms Sandalidis's scheme in terms of less computation complexity.

Different from the previous solely cost-function based heuristics, Beckmann *et al.* uses GA to decide an optimal call list which will not violate any of the interference constraints first and then assign them with a "frequency exhaustive assignment" scheme [41]. The simulation shows that the resulting channel assignment is very close to the optimum, and can easily cope with the local optimality issue which is very common to GA based schemes.

Kunz's method is based on neural networks [62]. It shows that neural network algorithms are also feasible to solve DCA problem. It uses Hopfield and Tank's method to create one neuron for each channel at each base station. A cost function representing frequency-separation constraints and channel demand is formulated and is then minimised by the neural network algorithm. It demonstrated that for some specific examples, neural networks algorithms can achieve optimal solutions, but for larger and more complex networks, it may easily converge to sub-optimal solutions. Another disadvantage with neural networks is its long calculation time with respect to graph coloring schemes and the difficulties to find appropriate parameters.

By using SA, a cost function with the frequency-separation constraints and the channel demand is formulated in [55]. The cost function reaches its minimum of zero if all constraints are satisfied. While in [54] the optimisation criterion is blocking probability. Although these two independent approaches use different models and different neighbourhood structures, both of them pointed out the same conclusion that SA appears to be a quite valuable approach for practical radio networks design.

In [64], the authors discuss the implementation of IEEE 802.11 based WLANs for enterprise customers with limitations such as performance under heavy load, deployment issues and the network management. They suggest using dynamic resource management instead of static radio resource management to improve performance of large scale WLANs. The centralised DCA problem in WLANs is very briefly addressed in [65]. APs are recommended to select an orthogonal channel that none of their neighbours has used if possible. But it was found to become unstable and with limited performance gain in large networks. A DCA strategy is proposed in [66] based on a real-time estimation of the number of the active stations (users) in the network. Then authors developed a DCA scheme in the MAC layer to minimise the throughput of the heavily loaded APs and maximize the channel utilizations considering the co-channel interference from other neighbouring APs. This work is closely related to the well known Bianchi model [67], but too complicated to implement.

All these works have provided a useful insight for investigating the DCA problems. We extend these works with specific focus on HD-WLANs. Below we describe our own work in DCA with a centralised control mechanism. Novel distributed channel allocation algorithms have also been developed from this work and will be described in Chapter 4.

3.4 Channel Allocation Based on Genetic Algorithm

The DCA problem is an instance of non-linear combinatorial optimisation problem, which is computationally hard to solve. Therefore, instead of using algorithms to find the exact optimal solution, considerable interest has been shown in using heuristic methods. The previous research work reveals that GA and SA have the potential to achieve good performance in DCA problems in terms of fast convergence speed and close approximation. In this chapter, we will focus on these two techniques in a HD-WLAN environment and provide indepth analysis.

3.4.1 Introduction of Genetic Algorithm

Genetic Algorithm (GA) [36] is a heuristic derived from biological evolution. Different from other heuristics, it is a population-based method and can deal with many solutions simultaneously. To use GA, we have to first define the genetic representation of the solution domain and the fitness function to evaluate the solution quality, which is usually referred to as encoding. Figure 3.1 shows the typical flow chart of a Genetic Algorithm. The procedure starts by generating an initial population of solutions. Then a loop is performed until some termination criterion is met. Most applications use the number of iterations or the stabilization of the population as the terminate condition. Each iteration in this loop handles one generation of the population. In one iteration, new solutions are generated by recombination operators such as Crossover and Mutation. After being generated, these solutions will be further evaluated in terms of their fitness, which in most cases corresponds to the value of the objective function itself. In some implementations, the fitness value of a solution may also account for penalties due to infeasibilities. Finally, the best results among the solutions are selected to form a new generation of solutions and a new iteration starts.

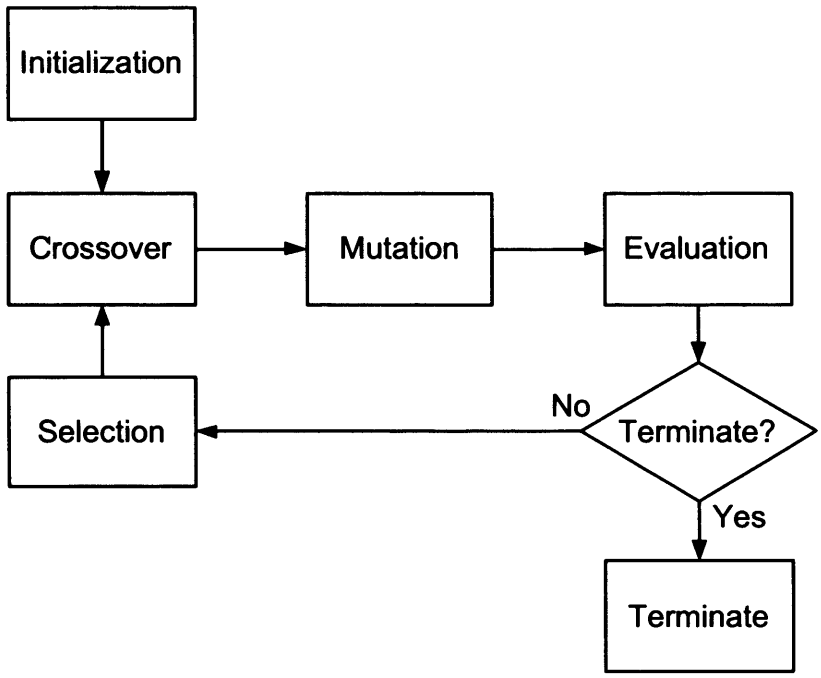

FIGURE 3.1: Flow chart of original Genetic Algorithm

Solutions (also called individuals or chromosomes) in GA are usually represented by string entities with fixed length. Previous research observed that the encoding is relevant to the performance of the algorithm, and a good encoding can result in high-fitness solutions that have small length and orders [25]. Figure 3.2(a) shows an example of representation of individuals used in our work. Assume there are 7 APs in the system, the second string shows a possible channel assignment for each AP when only orthogonal channels 1, 6 and 11 can be chosen. The fitness value associated with each solution has been set as total interference in the system. During the evolution, new solutions are introduced into the population by using the genetic operators Crossover (Figure 3.2(b)) and Mutation (Figure 3.2(c)). Crossover happens between a pair of previous solutions, called *Parents*, by exchanging a part of their solutions with each other to form two new solutions, called *Children*. Mutation usually happens to one *parent*. As for the analogy of GA in channel allocation, mutation means one of the APs randomly selects another channel for communications. Following that, new generations are formed based on their fitness value by the Selection operator. Among these three operators, Selection and Crossover effectively search the problem space and keep the offspring with high fitness values, while Mutation can prevent the loss of important information in the generation. By applying GA, the notion of "survival of the fittest" plays a central role, which is to ensure that the fittest solutions of the population survive and their information content is preserved and combined to produce even better offspring.

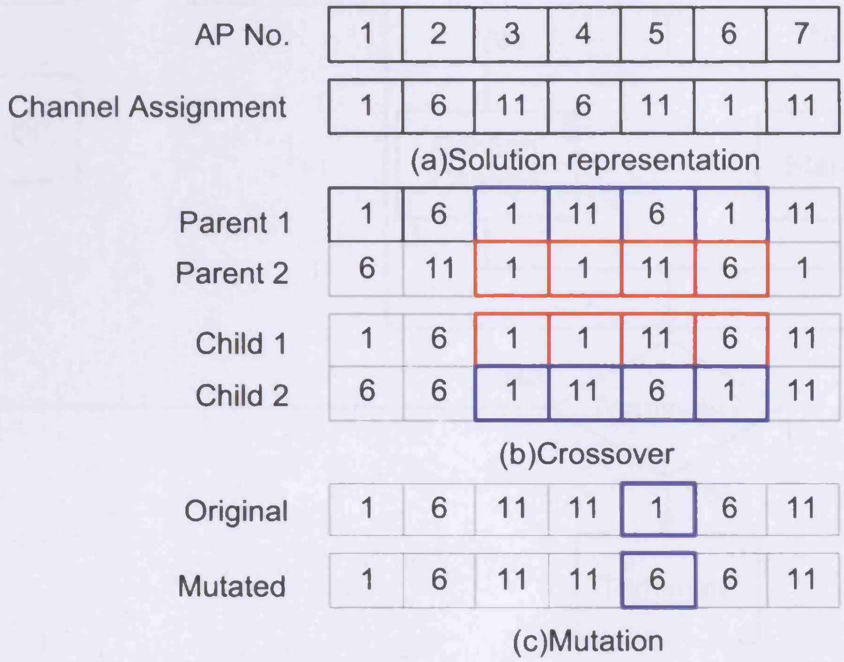

FIGURE 3.2: Solution representation, crossover and mutation operator in GA

3.4.2 Algorithm Implementation

In this section, we provide a detailed algorithm implementation for applying GA in DCA problem. The steps of the proposed GA are similar to the original version except we have enhanced the Evaluation process. Our algorithm adopts the dynamic characteristics of a WLAN and intends to find a way to quickly adjusting the channel selections in order to converge to an equilibrium state that can provide high per-user SINR. Figure 3.3 shows the flow chart of the proposed algorithm.

The steps for implementing the proposed GA are as follows:

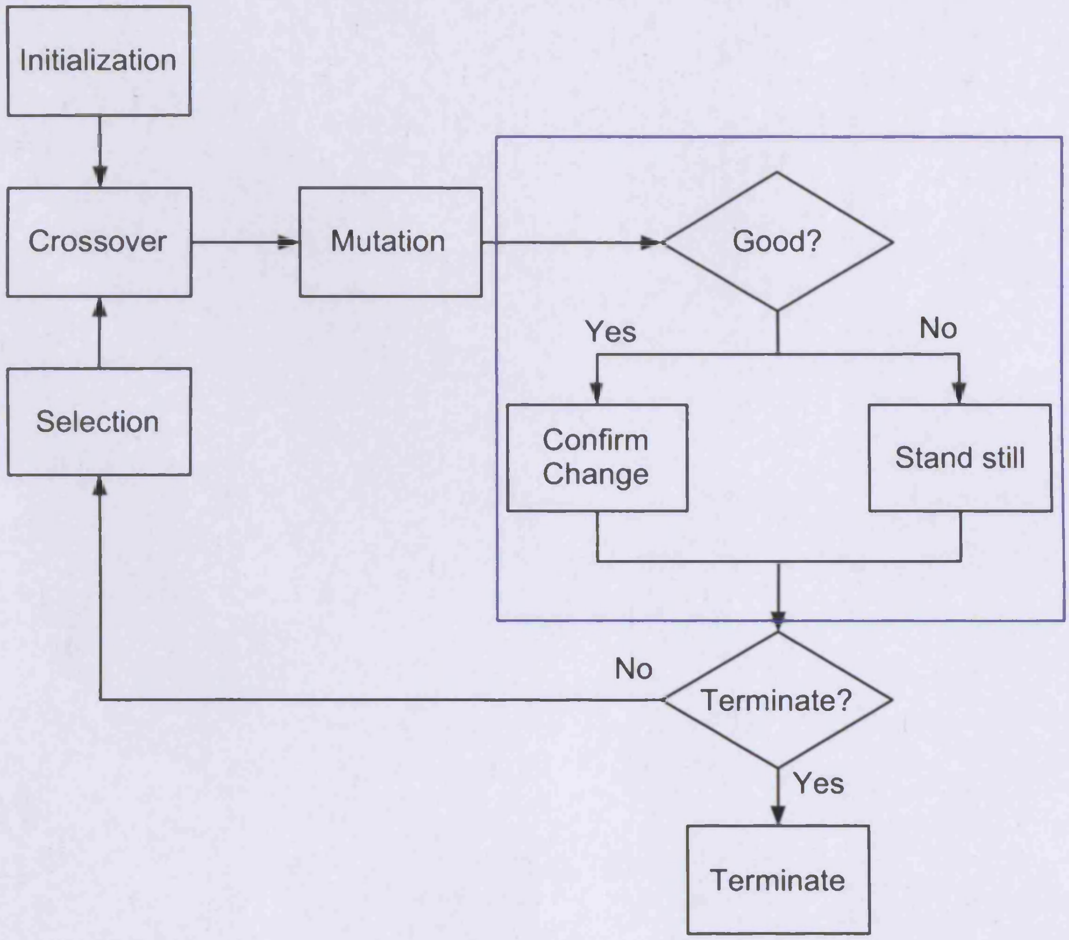

FIGURE 3.3: Flow chart of modified Genetic Algorithm

1. The system starts with a population of M channel assignments (possible solutions). Each solution starts with the worst condition that all APs are assigned to the same channel.

2. Randomly combine the M solutions into $M/2$ pairs for Crossover and generate $2M$ possible channel assignments.

3. Carry out Mutation for all the $2M$ solutions, that is, selected APs randomly pick channels to switch to. In each solution, only one AP is allowed to switch to another channel at one time.

4. Examine all potential switches according to local interference level. If the switch is beneficial to all its associated users, i.e. it reduces the current

interference level and increase its users' SINR, then the AP confirms the switch. Otherwise, it will stay at the previous channel.

5. Evaluate every solution based on the defined fitness function, that is, the network's total interference, by adding the local interference from individual APs together.

6. Select half of the population that have highest fitness value to survive and contribute to the next generation.

7. Repeat Steps 2 to 6, until the termination condition is met, that is, the generation number reaches the maximum number of generations.

According to the above steps, we can see that the main difference between the proposed GA and the original GA is that we have introduced more efficient evaluation strategy. In the original algorithm, following Crossover, the Mutation operation makes one of the APs randomly switch to another channel, no matter what impact that has on itself and the whole system. Afterwards the Evaluation operation places the best half of the population into the next generation. Therefore, it is not sure that by passing one iteration, the quality of the solutions can be improved, or maybe even worse.

Instead, by adopting the improved GA, the improvement of the solution through one generation can be guaranteed and made in earlier generations. This is due to the fact that in the improved GA, each AP will examine the interference level for itself before switching to any new channels. It will confirm the switch as long as the local interference is reduced. Otherwise, it will stay in the previous channel. On one hand, this makes fewer mutations actually take place, thus prevents the APs switching too frequently between different channels. The system will then become more stable. On the other hand, only good mutation is allowed to go through to the next generation due to the new Evaluation, which enables the system to find an improved condition more quickly.

In Figure 3.4, we compare the performance of these two types of GA in a network with 10 APs. The location of these 10 APs is randomly generated within 1 km^2

area. The total interference in the system is the performance measurement. We can see that the modified GA reaches the same final interference level as the original GA's, but with faster convergence speed.

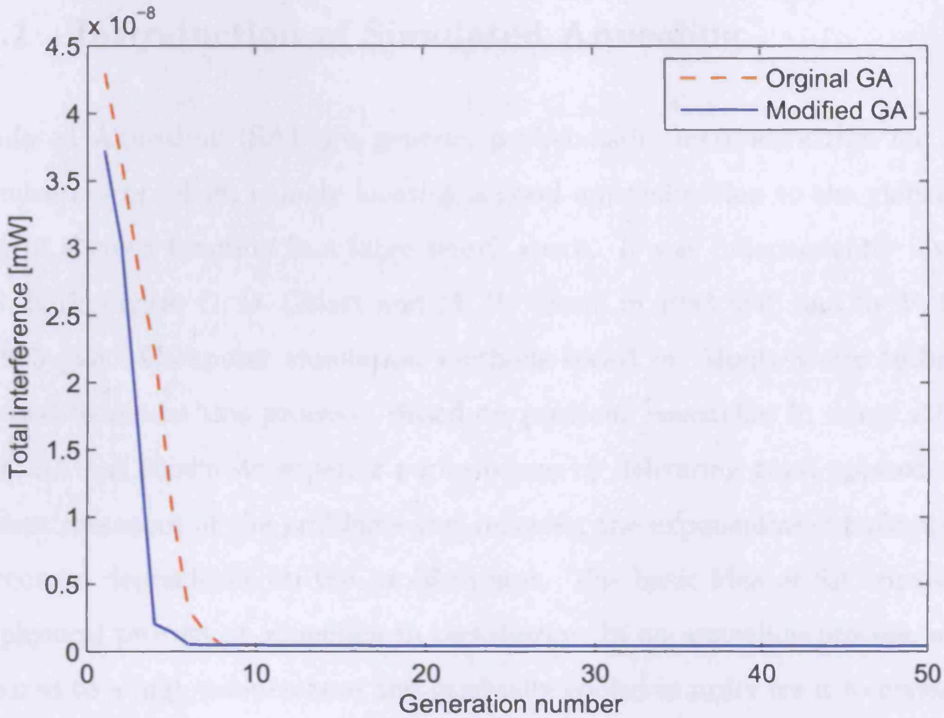

FIGURE 3.4: Comparison of total interference by running the original GA and modified GA

However, the well known limitation of GA is its sub-optimality (GA usually converges to a sub-optimal solution). Therefore, we continue our investigation in the next section for another heuristics, Simulated Annealing.

3.5 Channel Allocation Based on Simulated Annealing

3.5.1 Introduction of Simulated Annealing

Simulated Annealing (SA) is a generic, probabilistic, meta-algorithm for global optimisation problem, namely locating a good approximation to the global optimum of a given function in a large search space. It was independently invented by S. Kirkpatrick, C. D. Gelatt and M. P. Vecchi in 1983 [34], and by V. Ċerný in 1985 [35]. Computer simulation methods based on Monte Carlo techniques are used to model this process. Based on previous researches in many different areas, SA has shown its superior performance by delivering good approximation on most instances of the problems and reducing the exponential complexity to a polynomial dependence on the problem size. The basic idea of SA comes from the physical process of annealing in metallurgy. In an annealing process, a solid is heated to a high temperature and gradually cooled in order for it to crystallize. At high temperatures the atoms move randomly and at high kinetic energy but as they are slowly cooled they tend to align themselves in order to reach a minimum energy state.

In order to apply SA to solve a discrete optimisation problem - the channel allocation problem - here in this case, one has to express the problem as a cost function based optimisation problem by defining the configuration set, ρ, the cost function, $I(\rho)$ and the neighbourhood, ρ'. More specifically, the problem formulation of channel allocation can be transferred to an SA problem by defining following mappings:

1. The state of the solid = feasible channel allocation, ρ.
2. The energy of each state = total interference of each channel allocation, $I(\rho)$.
3. The state with minimum energy = the optimal channel allocation, ρ^*.
4. Temperature in annealing process = a network parameter, T.

SA uses a stochastic approach to direct the search. It allows the system to explore and occupy new states even if the perturbation causes the value of the objective function to increase temporarily. More precisely, it guides the original local search method in the following way: if ρ is the present channel assignment in the system and $I(\rho)$ is the corresponding interference level, then a move to a new neighbouring state, i.e. to a new set of channel assignment ρ' is always accepted if it is of benefit to the system, i.e. $\Delta I = I(\rho') - I(\rho) \leq 0$. In this case the interference in the system is reduced. If on the other hand the new channel assignment increases the interference level, it will be accepted with probability which depends on the change in interference and the present "temperature" level,

$$\Pr\left[\Delta I, T\right] = \exp\left(-\frac{\Delta I}{T}\right) \tag{3.4}$$

where the "temperature" T is an externally controlled parameter. To implement this selection process in MATLAB, we generate a uniformly distributed variable. If the variable is smaller than the probability, the AP will accept the worse channel, otherwise it will stay in the previous channel. This stochastic selection scheme helps SA avoid being stuck at a local optimum. The pseudo-code of an SA is described as follows.

Pseudo code of Simulated Annealing

Set $\rho \leftarrow \rho_0$ (Initialization).

Set $T \leftarrow T_0$ (Initial "temperature")

While (stopping criterion is not satisfied) **Do**

 Generate a new solution (ρ') by perturbing ρ

 Evaluate objective function $I(\rho)$

 Compute $\Delta I = I(\rho') - I(\rho)$

 If ($\Delta I \leq 0$), **then**

  $\rho \leftarrow \rho'$

 Else

  Generate a uniformly distributed random variable α, $0 \leq \alpha \leq 1$

  If $\alpha \leq e^{-\Delta I/T}$

   $\rho \leftarrow \rho'$

  End

 End

 Update T (decrement)

End

The value of T varies from a relatively large value to a small value close to zero. These values are controlled by a cooling schedule which specifies the initial and present "temperature" values at each stage of the algorithm. When the "temperature" is high, stochastic influence is strong, but as the "temperature" goes down the stochastic factor becomes less important. Therefore, the process gradually turns from a stochastic behavior to a more deterministic one. Finding the right cooling schedule is generally the most critical issue when using SA for optimisation. Even though there is some theory indicating how to decrease the "temperature" for some physical systems, it is not the case for the system here under consideration. For this reason, we compared several cooling schedules in the simulation and used fast cooling in this work.

3.5.2 Algorithm Implementation

As a rule of thumb, SA is quite slow in solving practically large problems, therefore in many applications SA has a variety of speedy versions which are strictly problem specific. By applying it to the DCA problem, we introduce several neighbouring state transition methods. A neighbouring state is defined as a new channel assignment produced from its previous assignment with one or a few APs selecting new channels. During the transition, the target AP could switch to a channel randomly or to a channel that has not been used by its neighbouring APs if possible. In order to complete this transition, we assume the APs can sense the surrounding area and choose any channels available for communication.

We design three transition methods and compare them in terms of total interference. In *Algorithm a*, we adopted the original version, where only one AP is allowed to switch to a random channel at one time. In *Algorithm b*, AP is more "intelligent". It can sense the interference in the channel before swapping, and choose the one with the least interference. While in *Algorithm c*, we adopted a pure random scheme, where several APs can simultaneously switch to any other channels in a random way. The objective of the proposed algorithm is to minimise the total interference. The details of the algorithms implementations are described as follows:

1. Initially, each AP randomly selects one of the available channels and measures the experienced interference under current condition.

2. neighbouring state transition:

   - *Algorithm a*: Randomly select an AP, say AP i, with current total interference level, $I(\rho)$. Then AP i randomly chooses another channel, with perceived new total interference, $I(\rho')$, assuming that all the other APs stay in previous channels.

   - *Algorithm b*: Randomly select an AP, say AP j, with current total interference level, $I(\rho)$. AP j then scans all three channels, and pick up one with the least interference, which results a new total interference, $I(\rho')$.

- *Algorithm c*: Randomly select several APs, say AP $k_1, k_2, \ldots, k_l$, with current interference, $I(\rho)$. And then they simultaneously and randomly switch to several other channels and results a new channel assignment with total interference, $I(\rho')$.

3. Calculate the total interference level after transition, if the new total interference is less than that of the previous generation, i.e. $I(\rho') \leq I(\rho)$, then keep the new assignment for further evolution, otherwise accept it with a probability of $\exp(-\Delta I/T)$, where $\Delta I = I(\rho') - I(\rho)$, is the difference of total interference between current and previous channel assignment.

4. Update "temperature" T with fast cooling schedule, $T = T_0/(1+t)$, where t is the generation number, T_0 is the initial "temperature"

5. Repeat Step 2 - Step 4, until the system converges.

It is obvious that the probability of channel switching is determined by two parameters, ΔI and T. In each generation, the larger the ΔI (large increment in the interference), the less likely the new channel assignment will be selected. And running the algorithm at very high and constant "temperature" will therefore not lead to any systematic improvements in interference levels.

3.5.3 Comparison of Neighbouring State Transition Schemes

In this section, we will first run a simulation to identify the most appropriate neighbouring state transition scheme for the DCA problem. We test the algorithms in a medium-sized network with randomly allocated 20 APs. 1000 different AP layouts have been tested, and the final channel assignment of one of the layouts has been extracted for comparison. Total interference figure shows an average value based on these 1000 different layouts.

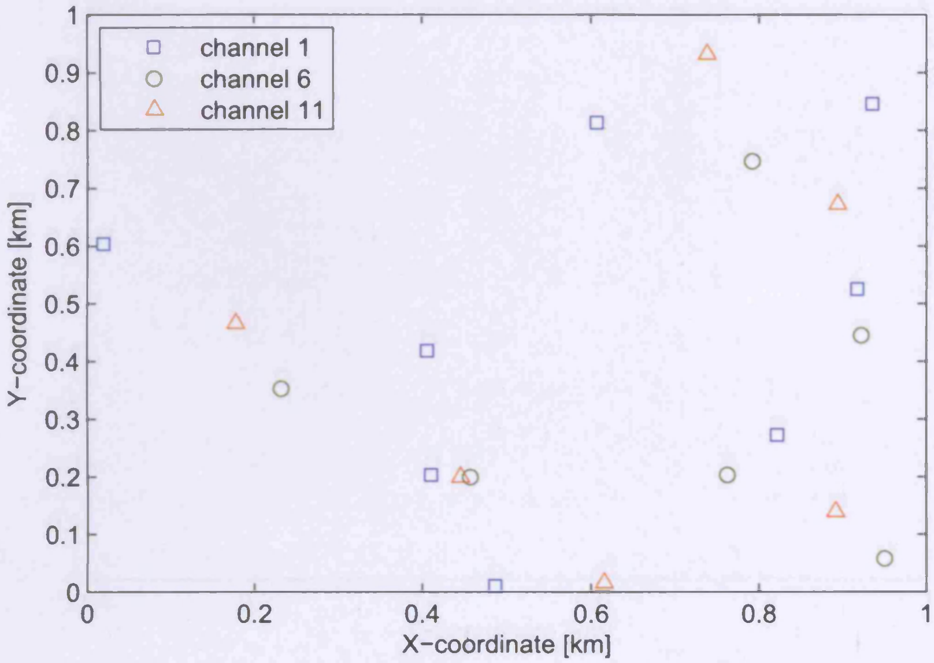

FIGURE 3.5: Channel assignment generated by *Algorithm a*

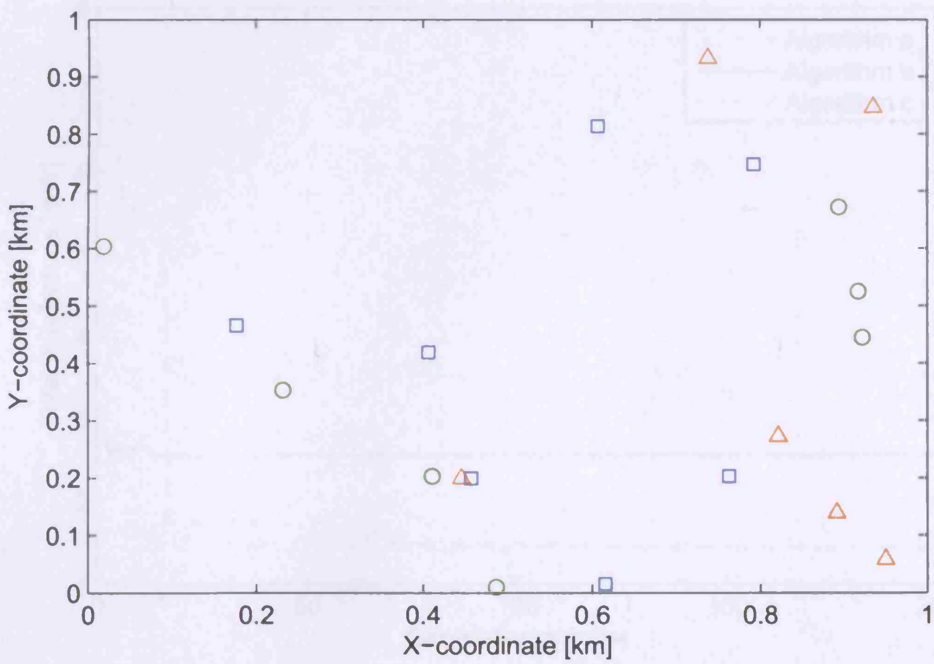

FIGURE 3.6: Channel assignment generated by *Algorithm b*

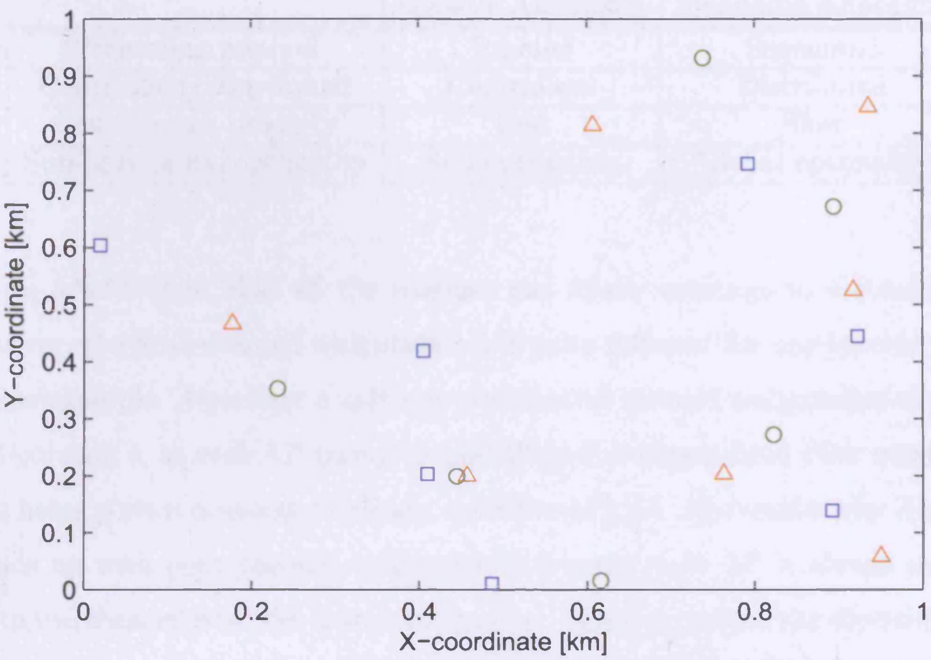

FIGURE 3.7: Channel assignment generated by *Algorithm c*

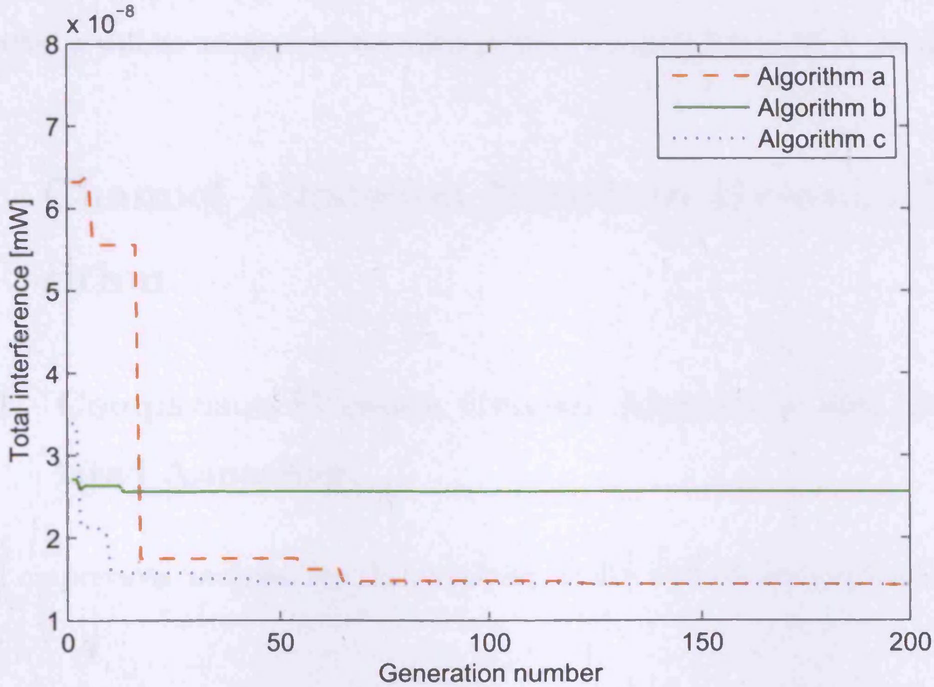

FIGURE 3.8: Comparison of total interference by running *algorithm a, b, c*

TABLE 3.1: Comparison between Genetic Algorithm and Simulated Annealing

	Genetic Algorithm	Simulated Annealing
Processing method	Parallel	Sequential
Centralised/Distributed	Centralised	Distributed
Convergence property	Fast	Slow
Sub-optimality/optimality	Sub-optimality	Global optimality

Figure 3.5-3.8 show that all the schemes can finally converge to a steady state. However, the final channel assignments are quite different for one specific layout. In this example, *Algorithm a* and *c* provide better channel assignments than that of *Algorithm b*, as each AP trying to use different channels from their neighbours. This helps system converge to a lower interference level. The reason why *Algorithm b* ends up with poor channel assignment is because each AP is always selfish to try to use channel with the least interference. This may reduce the diversity of SA and make the system easily stuck into a suboptimal solution. Although, it has the fastest convergence rate compared with two other schemes. Compare *Algorithm a* with *Algorithm c*, *Algorithm a* is more computation efficient, as in each iteration, only one AP is allowed to change channel. Therefore, in the following chapters, *Algorithm a* will be adopted as the main method to apply SA in DCA problem.

3.6 Channel Allocation Based on Hybrid Algorithm

3.6.1 Comparison Between Genetic Algorithm and Simulated Annealing

Based on previous analysis, the characteristics of GA and SA are summarized in Table 3.1.

In GA, its parallelized processing scheme makes the system evaluate several solutions at the same time, which consequently speeds up the algorithm. While in SA, the intelligent selection scheme provides a higher probability of finding an optimal solution. It worth to notice that, since both GA and SA are heuristics, the last feature of the algorithms stated in Table 3.1 is not always guaranteed. It only means GA has a high probability to converge to sub-optimal solutions, while SA is more likely to achieve global optimum. Besides, the "Distributed" characteristic for SA means it can be implemented in a distributed way. But in this chapter, we will first propose a centralised algorithm for SA. Therefore, we combine them together to design a hybrid algorithm that can provide a good trade-off between large computational time and local optimality.

3.6.2 Hybrid Algorithm

In this section, we propose a hybrid algorithm for DCA. In the proposed hybrid algorithm, some useful features from both GA and SA are combined: the global optimality from the SA and explicit parallelism from the GA. The hybrid algorithm starts with a very high "temperature" T, and generates a large number of random channel assignments (initial population). Then Crossover and Mutation operators are applied to generate a new solution (channel assignment). This is conducted as follows:

1. In one generation, new solutions can be generated by Crossover on every pair of channel assignments.

2. Mutation is applied to each of the solution, which is to randomly select a channel for an AP.

3. Channel assignments in current generation are selected by evaluating the integrated interference. If the current channel assignment is better than that of the last generation by eliminating interference, keep it for next generation. Otherwise, accept it with a probability of $\exp(-\Delta I/T)$.

4. Slightly decrease the "temperature" T according to the fast cooling schedule ($T_i = T_0/(1+t)$) and then check if the termination condition is met, such as

reaching the maximum generation number. If it is, end the process, otherwise repeat Steps 1 to 3.

3.7 Performance Evaluation

In order to thoroughly assess the features of the proposed algorithms, we have implemented networks with different scales. The simulation scenario is based on Figure 2.5, wherein a number of APs and users are randomly deployed in a 1 km^2 area. The scenario is simulated 1000 times to ensure accurate performance comparison.

3.7.1 Small Network Topology - 10 APs

We start the simulation with a small-sized system to verify the proposed algorithm. In this experiment, there are 10 APs randomly deployed in the area.

Figure 3.9 shows that by running all these three algorithms, their resultant interference converges to a low lever in this small system. Compare these three algorithms, SA converges to the lowest interference level with with slowest speed, while GA converges to the highest interference with the fastest speed. The hybrid algorithm presents a trade-off between these two performance metrics. This is consistent with our analysis in previous sections. The reason why the hybrid algorithm converges to a higher interference level than SA is that, in hybrid algorithm, when performing Crossover, it might change the current good channel selection into a worse choice. Therefore, it might lead to a final channel assignment with higher interference.

3.7.2 Large Network Topology - 50APs

In order to evaluate the algorithm's capability to handle a large network, we increase the number of APs to 50.

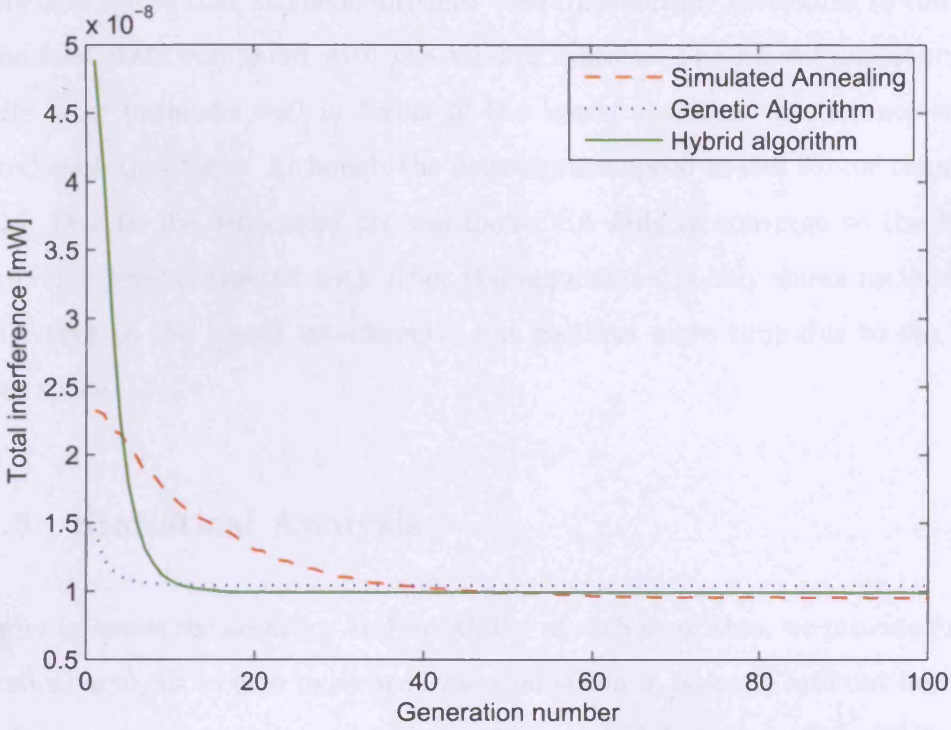

FIGURE 3.9: Total interference for different algorithms in small networks (10 APs)

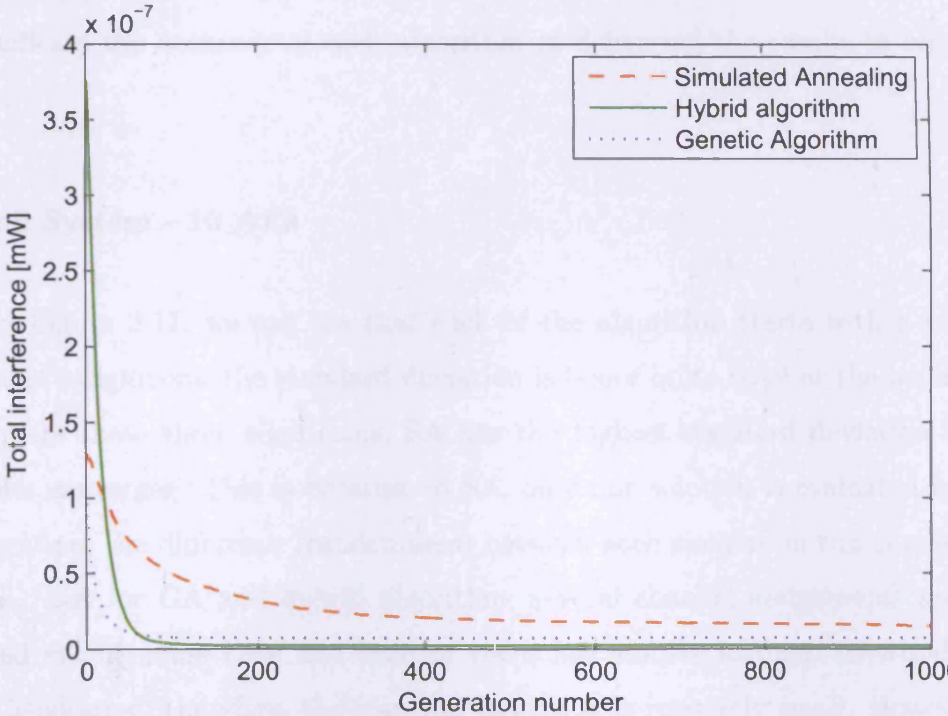

FIGURE 3.10: Total interference for different algorithms in large networks (50 APs)

Figure 3.10 shows that all the algorithms take considerably more time to converge to the final state compared with the smaller system. The hybrid algorithm can handle large networks well in terms of the lowest resultant interference within limited evolution time. Although the convergence speed is still slower than that of GA. Due to the sequential process mode, SA fails to converge to the lowest interference level compared with other two algorithms, it only shows its tendency to converge to the lowest interference, but requires more time due to the large search space.

3.7.3 Statistical Analysis

In order to assess the accuracy and suitability of each algorithm, we provide further statistical analysis to give more accurate evaluation in order to find out how each algorithm suits a particular network topology with different number of APs.

Since we run the algorithms for thousands of times and the results (in Figure 3.9 and 3.10) present average values, we choose the standard deviation measurement to indicate the accuracy of each algorithm in delivering the results in one time shot.

Small System - 10 APs

From Figure 3.11, we can see that each of the algorithm starts with a random channel assignment, the standard deviation is hence quite large at the beginning. Compare these three algorithms, SA has the highest standard deviation before system converges. This is because, in SA, only one solution is evaluated in each generation, the difference (randomness) between each simulation run is relatively large. But for GA and hybrid algorithm, several channel assignments are processed at the same time and each of them has similar features inherited from last generation, therefore, the standard deviation is relatively small. However, as the algorithms evolving, the system starts to follow the similar way of choosing

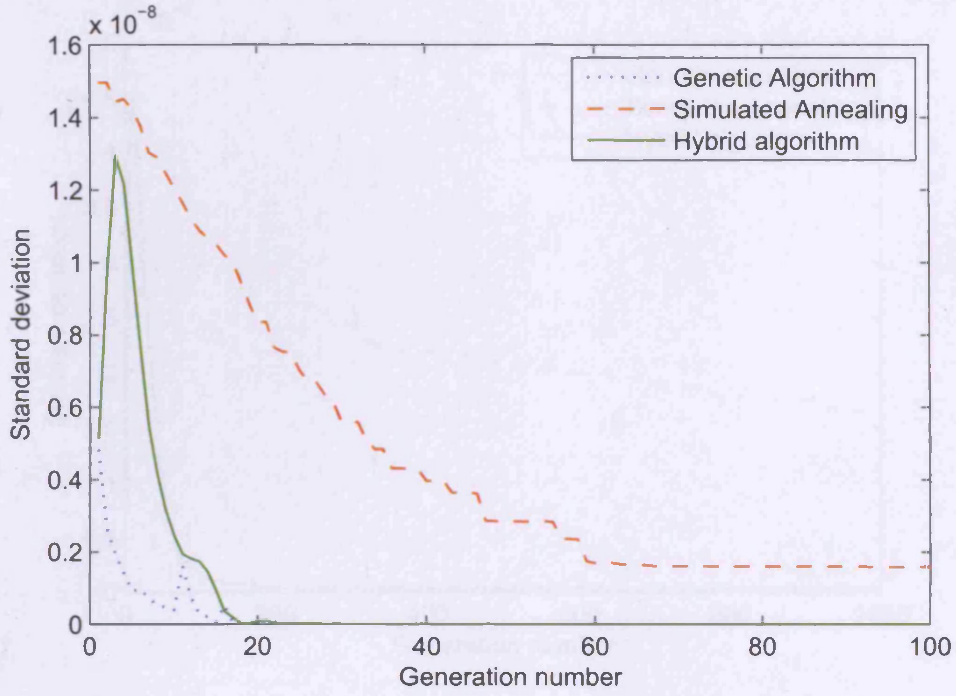

FIGURE 3.11: Standard deviation for different algorithms in small networks

channels, which means the standard deviation is decreasing gradually. When the system converges, all these three algorithms reach their lowest standard deviations.

Large System - 50 APs

When the system becomes larger, the hybrid algorithm shows its superiority in handling a large system in terms of achieving steadier and lower standard deviation when the system converges as shown in Figure 3.12.

3.8 Summary

In this chapter, we have investigated DCA problems using biologically inspired approaches in 802.11 WLANs with multiple APs. We have developed a framework of using GA, SA and a hybrid form to solve the problem. Extensive simulations have been carried out in order to evaluate the performance of each algorithm with statistical analysis. We have found that in general the proposed hybrid algorithm

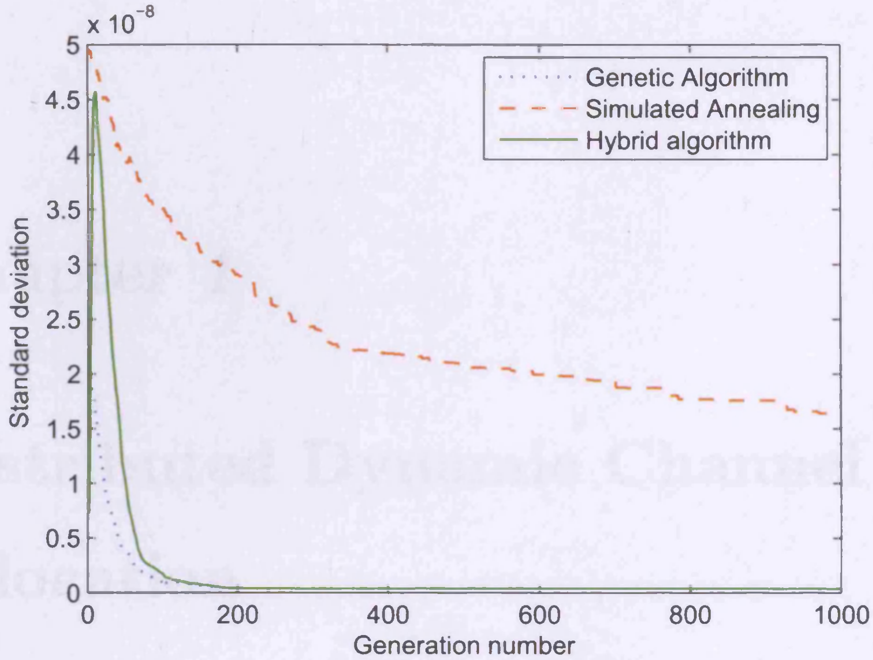

FIGURE 3.12: Standard deviation for different algorithms in large networks

provides a good trade-off between the fast convergence speed and lowest achievable interference.

Chapter 4

Distributed Dynamic Channel Allocation

4.1 Introduction

In the majority of the HD-WLAN deployments, APs are managed by different network administrators. In order to provide guaranteed service to their own customers, un-authorized access will not be allowed from the external networks. Therefore, the degree of cooperation between different APs is limited in the network. However, all these APs are essentially accessing the common unlicensed frequency band. It is inevitable that interference cannot be easily controlled. For a large and growing system, by taking all these factors into account, the problem of low interference DCA among all the APs is $\mathcal{NP}$-hard. Therefore, a centralised control unit is simply not feasible to cope with this problem. This challenging issue motivates us to fully investigate a feasible sub-optimal approach for sharing the common spectrum among all the APs to minimise interference across the whole network.

In this chapter we propose a distributed algorithm called Simulated Annealing channel allocation (SACA) to solve the channel optimisation problem in an HD-WLAN. Our approach still concerns the channel selection by APs, where channels can be selected among orthogonal frequencies. The proposed SACA algorithm is based on a local implementation of the SA technique. The network model and problem formulation is the same as in Chapter 3 for the centralised algorithms. We will summarize several existing distributed DCA methods relevant to this work in Section 4.2. Section 4.3 introduces the implementation details of distributed SACA. Section 4.4 analyses the interference performance and complexity of the algorithm.

4.2 Related Work

Distributed DCA in cellular networks has a flavor of distributed mutual exclusion but not exactly a mutual exclusion problem [68]. In distributed DCA, the decision regarding the channel acquisition and release is taken by the associated base station according to the information from its own and several possible surrounding cells. As the decision is not based on the global status of the network, it can achieve suboptimal allocation as compared to the centralised DCA and may cause forced termination of ongoing calls. Authors in [69, 70, 71, 72] realized the importance of preventing interference among nearby cells, thus adopted models and principles from the mutual exclusion problem, established the relationship between these two problems, and more importantly emphasized the differences in between. One of the main differences is that in standard mutual exclusion, two processes are not allowed under any circumstances to use the resource at the same time, but in DCA the same channel can in fact be used simultaneously by several cells, what is not allowed is two (or more) cells within the minimum reuse distance of each other doing so [72]. Based on their analysis, many researchers proposed token-based [73, 74, 75] and non-token based [76, 77, 78] algorithms to solve the distributed DCA based on mutual exclusion.

Other works on distributed DCA in cellular networks [79, 80, 81] are on maximizing channel reuse in various cells, which ensures that neighbouring cells do not make conflicting decisions that may lead to interference between on-going calls. Other works are well documented in a survey paper by Narayanan [82].

The state-of-the-art channel assignment using non-overlapping channels in WLAN is described as follows: Each AP periodically checks other data transmissions in the channel it is using. If the volume of traffic in that channel (from other APs or clients of that APs) is greater than a threshold, then the first AP tries to move over to a less congested channel. This scheme is called least congested channel search (LCCS). In [83], Mishra *et al.* pointed out that the LCCS is not efficient with continued growth of WLANs. They formulated the channel assignment problem as a weighted vertex coloring problem and proposed two distributed algorithms that outperform the LCCS in terms of interference reduction. In [84, 85], authors introduced a number of techniques based on graph colouring algorithms, and demonstrated their effectiveness using simulations. They also suggested a preliminary message format the APs could employ to exchange information regarding the wireless channel, and elaborated on the possible protocol architectures that could be used in the actual channel allocation process.

A generalised, distributed DCA algorithm that can be used in different systems is proposed in [86] by Leith and Clifford, with the aim of minimising system interference by offering unlimited non-overlapping channels. The whole network is modeled as a graph with links representing potential interference between neighbouring APs. This distributed algorithm can converge quickly when the number of required channels is no less than the chromatic number of the graph. However, for a high density network with a large number of APs, the difficulty for calculating the chromatic number is that the complexity of the algorithm can be extremely high. We will compare it with our proposed algorithm, to show that even the number of channels is not adequate, we can still find an acceptable solution with fast convergence rate.

Kauffmann's *et al* developed a distributed algorithm based on Gibbs sampler for channel selection and user association in WLANs [14]. They constructed a distribution function which dictates the channel selection made by each AP at any given time is from all available channels. It is more complicated and computationally expensive than the binary selection made in our algorithm. Since they consider the user association along with channel selection, their algorithm implicitly relies on a time parameter to control an AP's channel selection probabilities.

Luo and shankaranarayanan [87] proposed a distributed DCA algorithm with the aim to maximise per-user throughput in dense WLANs, particularly for non-uniform traffic condition. In this algorithm, every AP determines the best channel it should use in the next time slot solely based on the traffic load of its neighbouring APs and the channels used by them in the current time slot, and switches to that channel with some fixed probability. Therefore, they assume that each AP knows and periodically broadcasts the number of active stations associated with it and let APs simultaneously change their channels. However, this assumption is too strong for practical networks.

Paper [88] studied the fairness problem for uncoordinated WLAN deployments from the channel assignment perspective by using the channel hopping technique. The design considerations include distributed algorithm design, minimum of coordination (to zero) among APs belonging to different hotspots, ease of implementation and interoperability with existing standards. The motivation of the work is based on a situation when in a crowded unlicensed spectrum with large number of APs, it is not possible to compute a perfect fair channel assignment for each AP. Therefore, the objective is to use channel hopping technique allowing the network as a whole to timeshare between different static channel assignments, such that the long-term throughput obtained at an AP becomes an average of the throughput achieved over individual channel assignments used by the network as a whole.

Authors in [89] designed a DCA algorithm to minimizing channel interference among APs. They developed a mathematical model to evaluate the amount of interference between overlapping channels for IEEE 802.11 WLAN systems. In this algorithm, APs periodically run the algorithm and each AP in turn picks it own channel that minimize the interference, where "in turn" is a strong assumption. This work used overlapping channels, but the interference calculation with overlapping channels is not accurate. And the network size (4, 6, 9, and 25 APs) for simulation is relatively small.

Authors in [90] proposed graph colouring based distributed algorithms for channel assignment among interfering APs, in order to improve the utilization of wireless spectrum - when considering user distribution. In this work, overlapping channels are employed. They considered hidden node problem caused by clients and applied weighted colouring techniques to take traffic load (in terms of number of clients) into account and allocate non-overlapping channels to heavily loaded APs, and overlapping channels to APs with light load.

4.3 Simulated Annealing Channel Allocation (SACA) Algorithm

The objective of the proposed SACA algorithm is to minimise the total interference. Each AP can choose, with a probability, any available channel at any time according to the interference level at the current channel and a randomly selected alternative. The details of the algorithm are described as follows:

Pseudo code of SACA algorithm

Set $\rho \leftarrow \rho_0$ (Initial channel allocation).

Set $T \leftarrow T_0$ (Initial "temperature")

While (stopping criterion is not satisfied) **Do**

randomly select one AP: AP i

Evaluate $I_i(\rho_i)$ (interference for AP i in channel ρ_i with current channel assignment ρ)

AP i then randomly selects a new channel ρ_i'

Evaluate $I_i(\rho_i')$ (perceived interference for AP i in channel ρ_i' with new channel assignment ρ')

Compute $\Delta I = I_i(\rho_i') - I_i(\rho_i)$

If $(\Delta I \leq 0)$, **then**

$\rho \leftarrow \rho'$

Else

Generate a uniformly distributed random variable α, $0 \leq \alpha \leq 1$

If $\alpha \leq e^{-\Delta I/T}$

$\rho \leftarrow \rho'$

End

End

Update $T = T_0/(t+1)$, $t = t + 1$

End

In this procedure, the system starts with an initial random channel allocation. Before the systems converges, a randomly selected AP i senses its interference in the current channel $I_i(\rho_i)$. After that, AP i randomly selects another channel ρ_i', and estimates the new interference $I_i(\rho_i')$. If a move to the new selected channel is of benefit to AP i itself, i.e. $\Delta I = I_i(\rho_i') - I_i(\rho_i) \leq 0$, in this case the interference experienced by AP i is reduced. AP i will switch to the new channel. On the other hand, if the new channel increases the interference level, the new channel will be accepted with a probability which depends on the change in interference and the present network parameter T, i.e. $\Pr[\Delta I, T] = \exp(-\Delta I/T)$. After AP i makes its decision, it will update its parameter T based on a predefined cooling schedule, which is studied in the following section. This process will be repeated at all APs in a random way until system converges to a steady state. This can be realised by installing a timer in each of the APs. Individual timer countdown from a randomly set time interval. Once it gets time out, the AP will be triggered to sense the channels and starting channel selection process.

4.4 Performance Evaluation

In this section, we evaluate the convergence, feasibility and scalability properties of the proposed SACA algorithm. We compare our algorithm with three other algorithms. The base line is a pure random channel selection scheme. In this scheme, any APs can choose any channels they want to transmit, regardless the interference to itself. The upper-bound is the global optimal solution, which is found by the Branch and Bound method [91]. The last algorithm for comparison is a distributed algorithm based on multi-colouring approach proposed in [86]. For simplifying the notation, we use pure random, Branch and Bound and Leith and Clifford algorithm to represent these schemes respectively.

The simulation scenario is based on Figure 2.5, wherein a number of APs and users are randomly deployed in a 1 km^2 area. Network size ranges from 10 to 100 APs. The transmission power at all the APs is set to 100 mW. Both final channel assignment and total interference performance will be examined. The performance metric is total interference in the system. It is calculated by adding local interference from each of APs in the network. It is worth to notice that, the quantity of total interference in the system cannot be executed in reality without a central controller. Therefore, in this performance evaluation we would rather consider it as a virtual external monitor to measure the algorithm performance.

4.4.1 The Impact of Different Cooling Schedules

As briefly mentioned in Section 4.3, the parameter T has a major impact on convergence rate and solution quality. When T is large, the stochastic influence is strong, but as it goes down the stochastic factor becomes less important. Therefore, the process gradually turns from a stochastic behavior to more a deterministic one. Cooling schedule is a strategy to control the way of decreasing T. Hence, finding the right cooling schedule is a very important issue when using SA for optimisation. Here we compare the performance of 10 different cooling schedules (shown in Figure 4.1) under different network sizes. Cooling 3 is considered as the fastest cooling schedule. For the detailed definition of these cooling schedules, please refer to Appendix A.

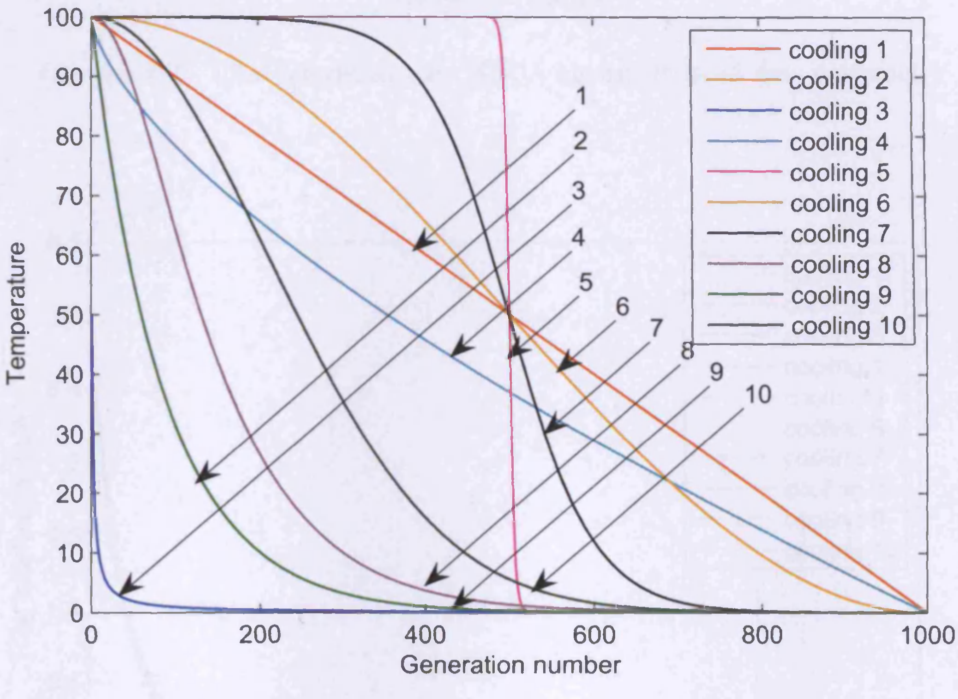

FIGURE 4.1: Different cooling schedules

Figure 4.2 shows that for small systems (with 10 APs) the total interference almost evolves in the same way as the "temperature" is cooling down. While Figure 4.3 shows that for large systems, the slower the cooling the better channel allocation (with lower interference) the system can achieve, although the advantage is not

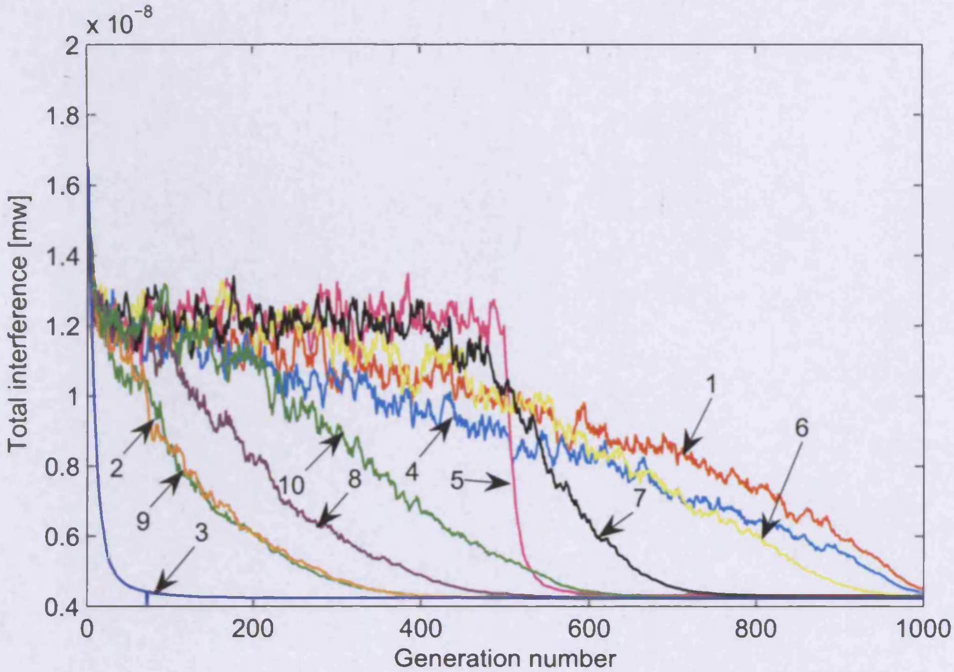

FIGURE 4.2: Total interference for SACA algorithm in 10 APs networks

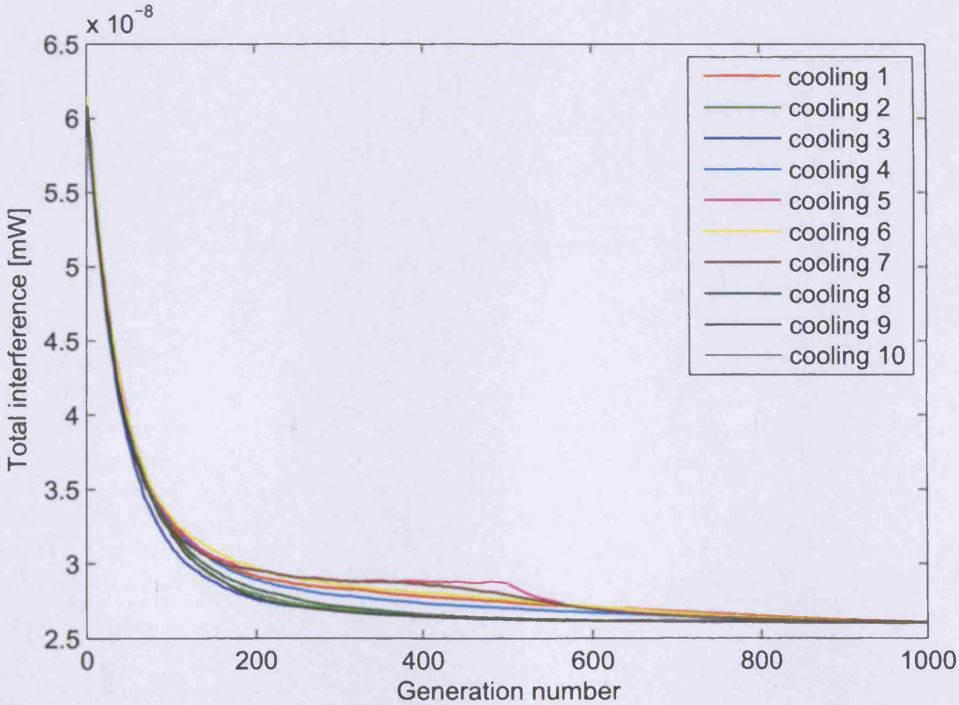

FIGURE 4.3: Total interference for SACA algorithm in 50 APs networks

significant. This is because when we increase the number of APs in the system, the objective function of the DCA problem, which is a discrete function, varies significantly in different simulations. Take a network of 50 APs and 3 available channels as an example, it has 3^{50} possible channel assignments and each assignment is associated with a total interference level. Therefore, slow cooling can provide more opportunities to hit good channel assignments compared with the fast cooling, which will then have higher possibilities to find better solutions compared with fast cooling. However, for a small system, since the fast and slow cooling can both provide the same result, fast cooling is preferable due to its fast convergence rate. For consistence, we will select fast cooling to be used in following simulations.

4.4.2 Feasibility

We present the feasibility of the proposed SACA algorithm in a medium (20 APs) and a large (100 APs) sized network with APs randomly located in a 1 km^2 area.

From Figure 4.4-4.7, we can see that the proposed distributed algorithm can solve the channel allocation problem, even in an extremely dense deployed network (100 APs in 1 km^2 area). Within the network, all three channels have been fully used and spread evenly across the network. By running the SACA algorithm, total interference in the system quickly converges to a steady state.

4.4.3 Comparisons with Leith and Clifford Algorithm

In this subsection, we compare the channel assignment and interference performance of the proposed SACA algorithm with Leith and Clifford algorithm. In [86], Leith and Clifford proposed a fully distributed learning algorithm to solve the traditional $\mathcal{NP}$-hard graph colouring problem. In their algorithm, each AP maintains a vector that indicates the probability of using each channel. The algorithm details are as follows [86]:

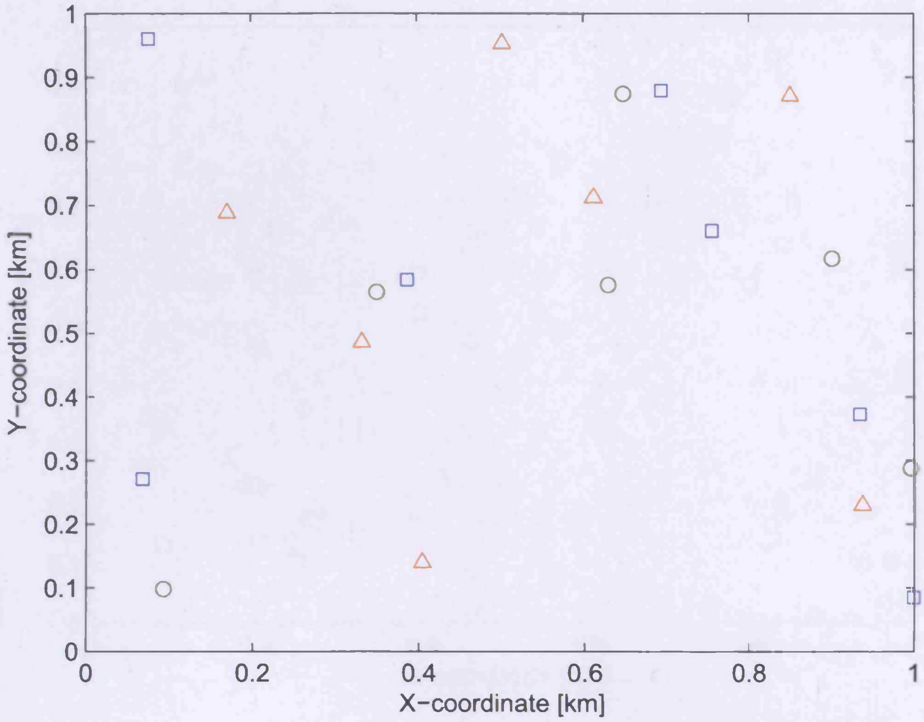

FIGURE 4.4: Channel assignment generated by SACA algorithm in a 20 APs network

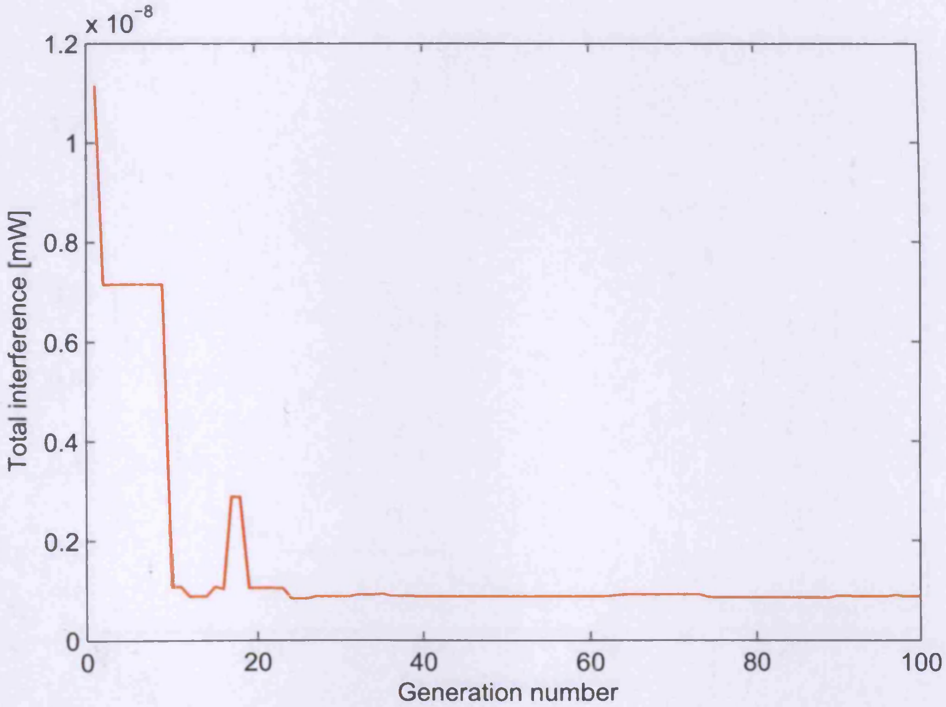

FIGURE 4.5: Total interference for SACA algorithm in a 20 APs network as channel allocation evolves

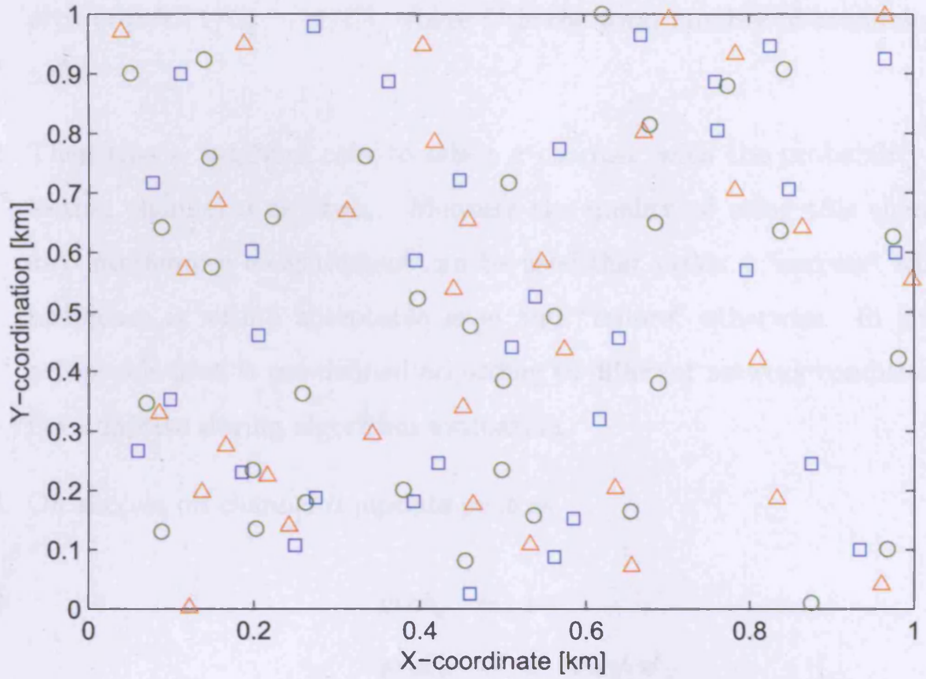

FIGURE 4.6: Channel assignment generated by SACA algorithm in a 100 APs network

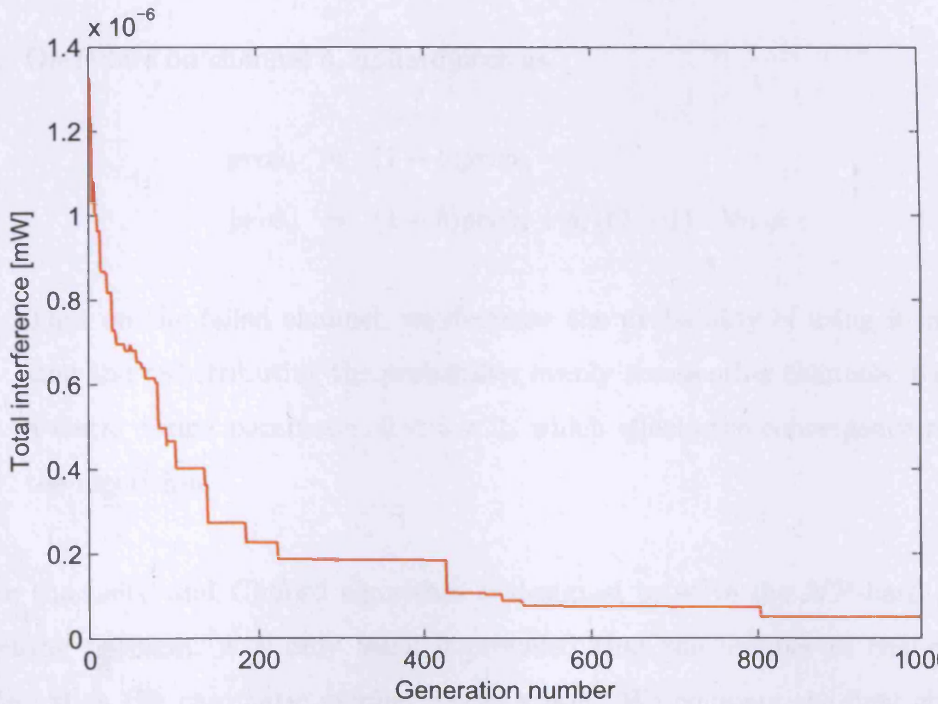

FIGURE 4.7: Total interference for SACA algorithm in a 100 APs network as channel allocation evolves

1. Initially the probability of using each channel is normalised to $prob = [1/C, 1/C, \ldots, 1/C]$, where C is the total number of available channels.

2. Then toss a weighted coin to select a channel, with the probability of selecting channel u as $prob_u$. Measure the quality of using this channel u: any interference measurement can be used that yields a "success" when interference is within acceptable level and "failure" otherwise. In [86], the acceptable level is pre-defined according to different network conditions and not adaptive during algorithm evaluation.

3. On success on channel u, update $prob$ as

$$prob_u = 1 \tag{4.1}$$

$$prob_v = 0 \quad \forall u \neq v \tag{4.2}$$

   This creates a degree of "stickiness" for AP to use channel u in next step. v represents the other channels that have not selected by this AP.

4. On failure on channel u, update $prob$ as

$$prob_u = (1-b)prob_u \tag{4.3}$$

$$prob_v = (1-b)prob_v + b/(C-1) \quad \forall u \neq v \tag{4.4}$$

   Thus on the failed channel, we decrease the probability of using it in next step and redistributing the probability evenly across other channels. b is also a static design parameter, $0 < b < 1$, which affects the convergence rate of the algorithm.

Since the Leith and Clifford algorithm is designed to solve the $\mathcal{NP}$-hard graph colouring problem, it is only feasible provided that the number of channels is no less than the chromatic number of the graph. We compare the final channel assignment of our proposed algorithm with the Leith and Clifford algorithm under two conditions, one in chromatic-number-of-channel scenario and the other in three-channel scenario. As it is difficult to compute chromatic number of a graph with more than 30 nodes, we choose a network with 30 APs as an example for comparison.

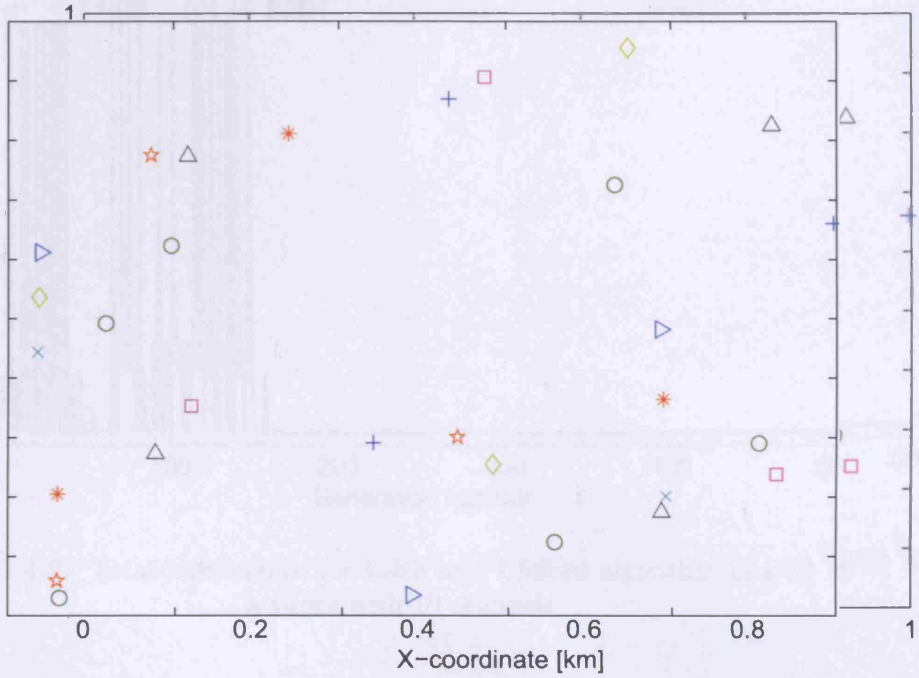

FIGURE 4.8: Channel assignment generated by Leith and Clifford algorithm in a 30 APs network with 10 channels (different symbols representing different channels being selected by APs)

In this experiment, we test two algorithms in the same network configuration. We define the APs as neighbouring APs, if the distance in between each other is less than 0.5 km. Chromatic number is computed before performing DCA algorithms. Figures 4.8-4.11 show that both algorithms converge to a steady state offered by 10 channels, with similar total interference level in the system.

Figures 4.12-4.15 show the results with the same configuration when only three channels are available. Both algorithms are simulated.

We can see that the Leith and Clifford algorithm could not find a sensible solution to converge to. This is because the Leith and Clifford algorithm is only feasible provided that the number of channels is no less than the chromatic number. Once the number of channels is insufficient, APs will become clustered and use the

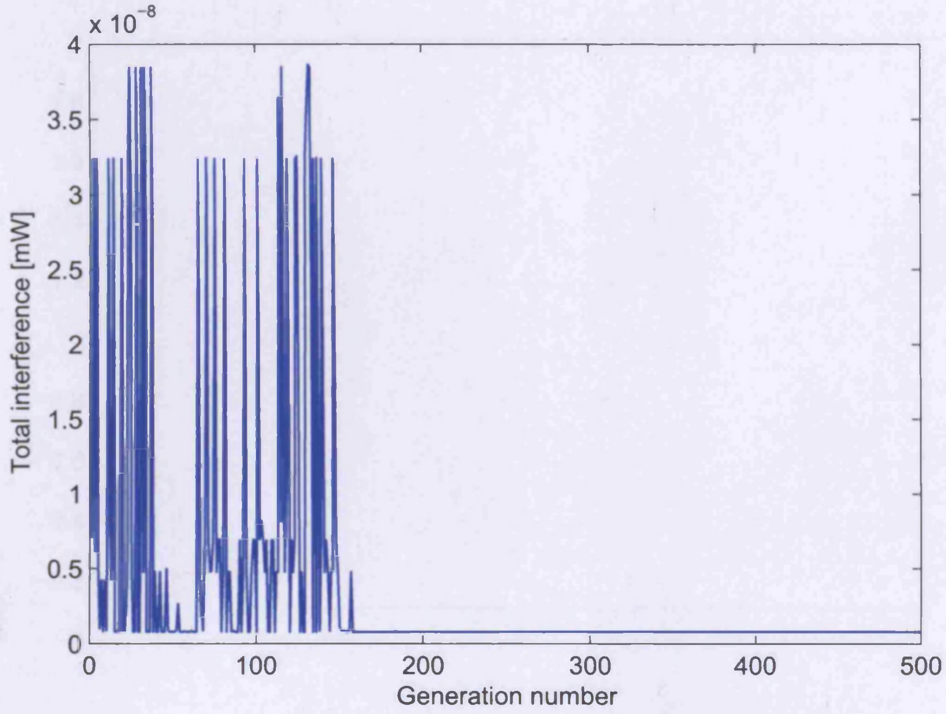

FIGURE 4.9: Total interference for Leith and Clifford algorithm in a 30 APs network with 10 channels

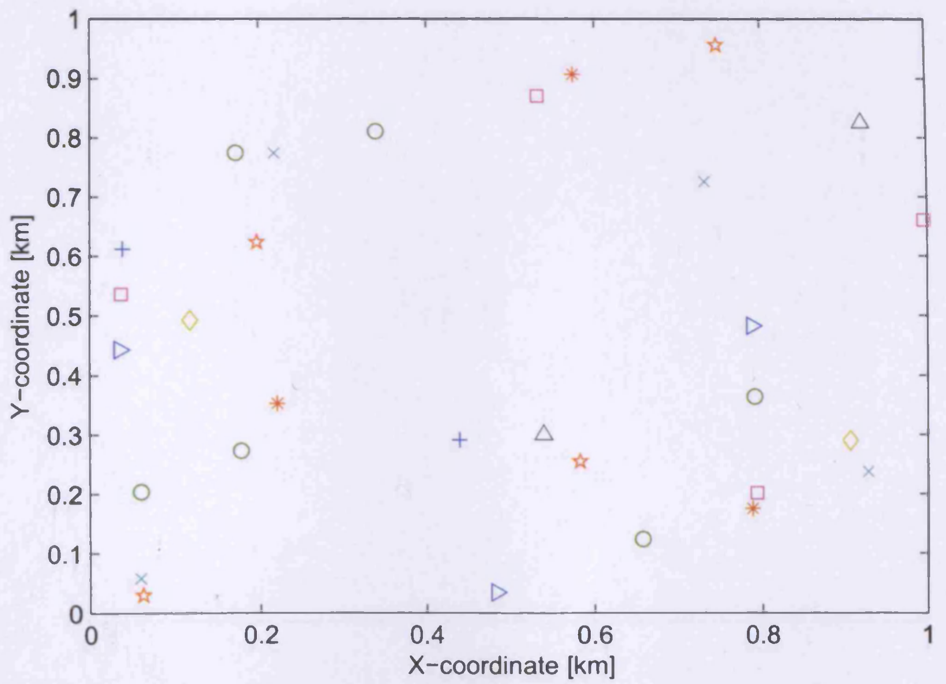

FIGURE 4.10: Channel assignment generated by SACA algorithm in a 30 APs network with 10 channels

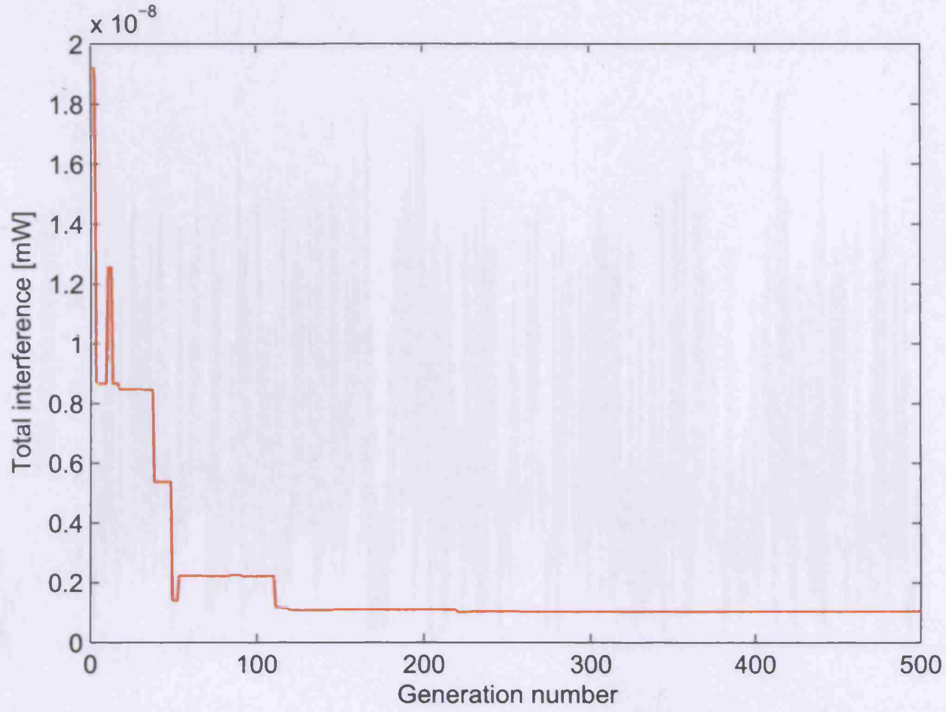

FIGURE 4.11: Total interference for SACA algorithm in a 30APs network with 10 channels

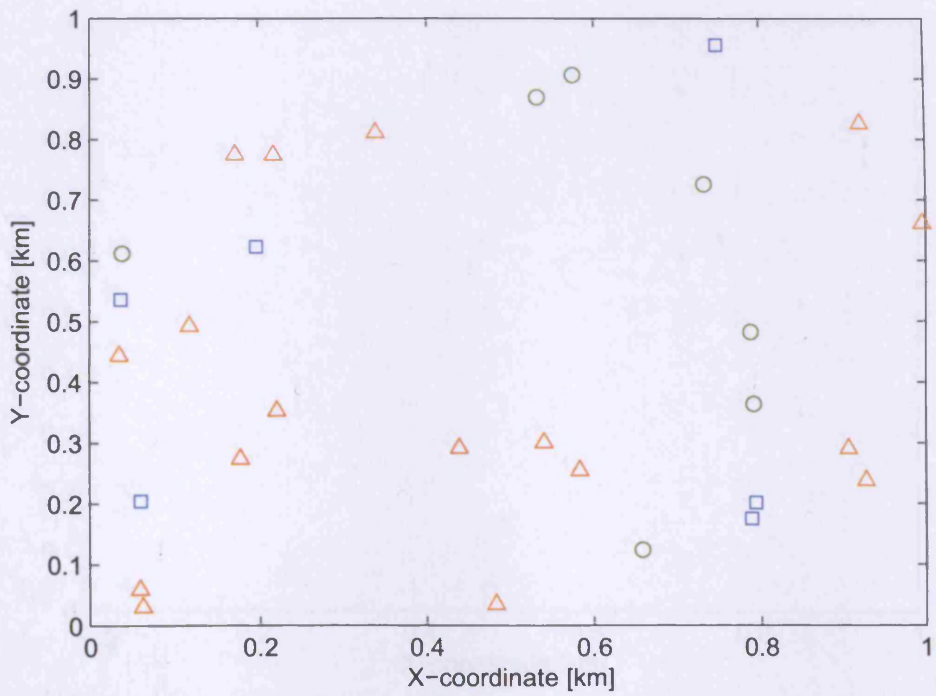

FIGURE 4.12: Channel assignment generated by Leith and Clifford algorithm in a 30 APs network and only 3 channels

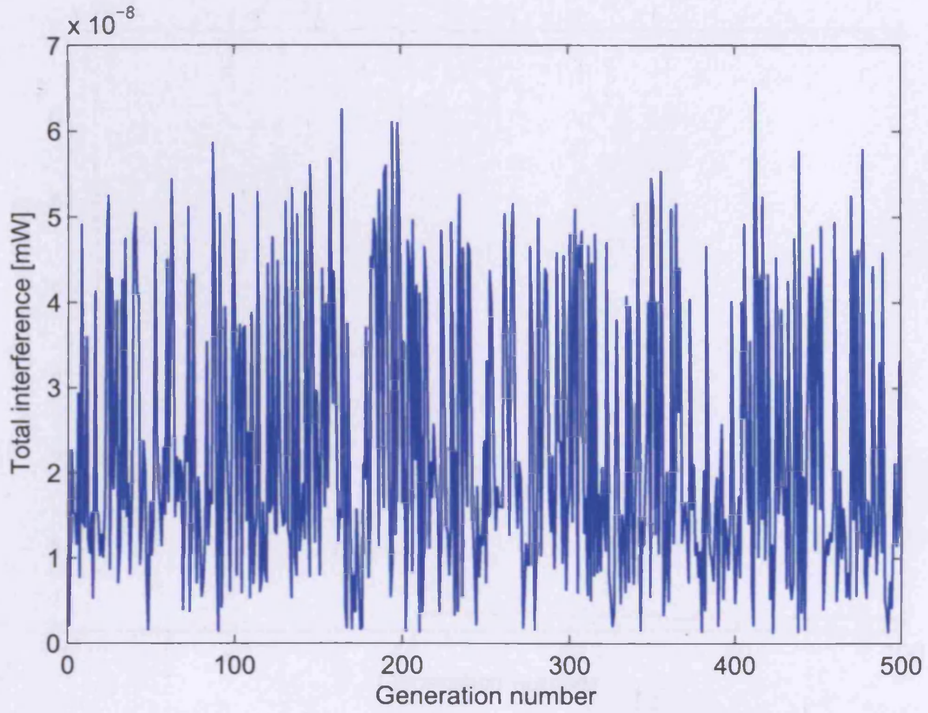

FIGURE 4.13: Total interference for Leith and Clifford algorithm in a 30 APs network with only 3 channels

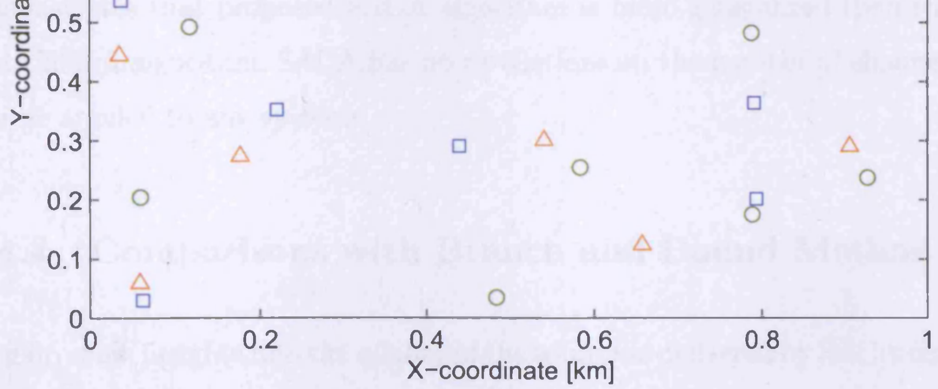

FIGURE 4.14: Channel assignment generated by SACA algorithm in a 30 APs network with only 3 channels

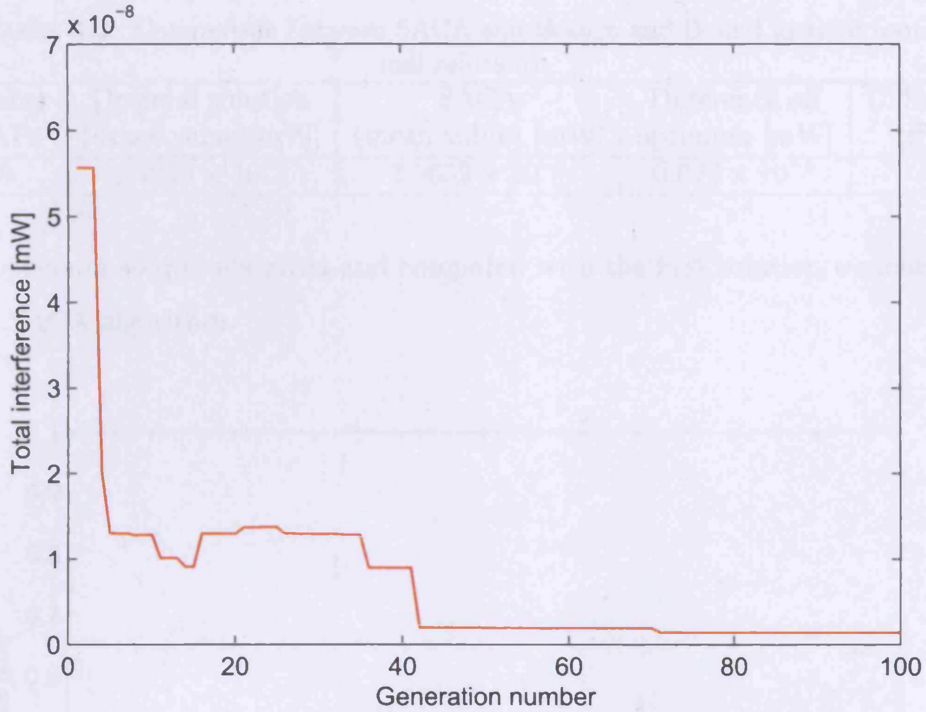

FIGURE 4.15: Total interference for SACA algorithm in a 30 APs network with only 3 channels

same channels as their neighbours, which result in severe co-channel interference in the system (Figure 4.12-4.13). However, the proposed SACA is feasible to solve the channel allocation problem and mitigate interference in the system with a rapid convergence speed. By investigating the final channel assignment found by the SACA, all 3 channels have been fully used and spread evenly across the network, and each AP selects a different channel from its nearest neighbours. This demonstrates that proposed SACA algorithm is more generalized than the Leith and Clifford algorithm, SACA has no restrictions on the number of channels, thus can be applied to any systems.

4.4.4 Comparisons with Branch and Bound Method

To gain some insights into the quality of the solutions delivered by SACA algorithm we compare it with the optimum solution found by Branch and Bound method. We use a network configuration with 20 APs randomly deployed in the 1 km^2 area.

TABLE 4.1: Comparison between SACA and Branch and Bound method (optimal solution)

Number of APs	Optimal solution (exact value)[mW]	SACA (mean value) [mW]	Difference off optimum [mW]	Difference in [%] off optimum
20	1.4930×10^{-8}	1.5652×10^{-8}	0.072×10^{-8}	4.8

The optimum solution is given and compared with the first solution we found by using SACA algorithm.

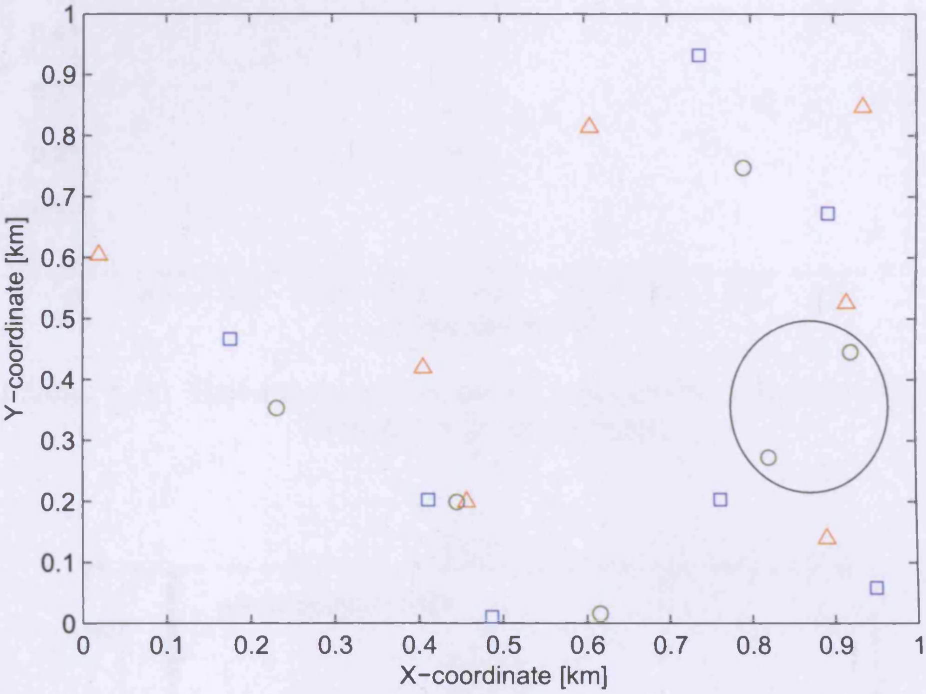

FIGURE 4.16: Channel assignment generated by SACA algorithm in a 20 APs network

Figures 4.16-4.17 show the comparison of channel assignment found by these two algorithms. The channel assignment found by SACA algorithm seems not as good as the Branch and Bound method, since one pair of neighbouring APs (indicated in the Figure 4.16) is using the same channel. Figure 4.18 shows the distribution of final total interference with all possible channel assignments found by SACA by running the algorithm for a specific network configuration over 1000 times. The relative numbers are summarized in Table 4.1.

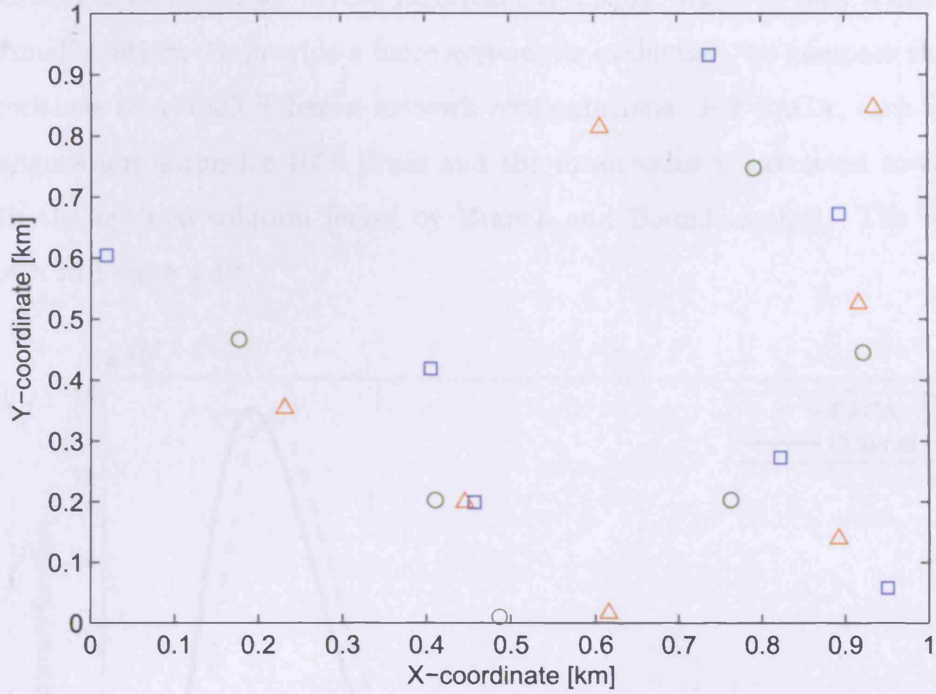

FIGURE 4.17: Optimal channel assignment generated by Branch and Bound method in a 20 APs network

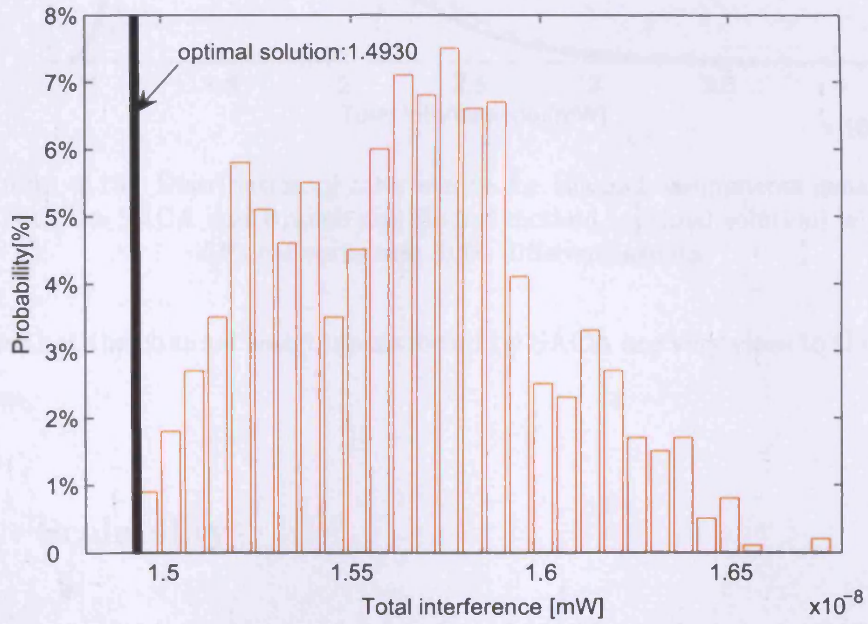

FIGURE 4.18: Distribution of interference from channel assignments generated by SACA algorithm over 1000 networks

From the results in Table 4.1, we can see that repeated 1000 times, the mean total interference obtained by SACA algorithm is 1.5652, which is only 4.8% off the optimal solution. To provide a more systematic evaluation, we compare these two algorithms over 1000 different network configurations. For SACA, each network configuration is run for 1000 times and the mean value is extracted to compare with the optimal solution found by Branch and Bound methed. The result is shown in Figure 4.19:

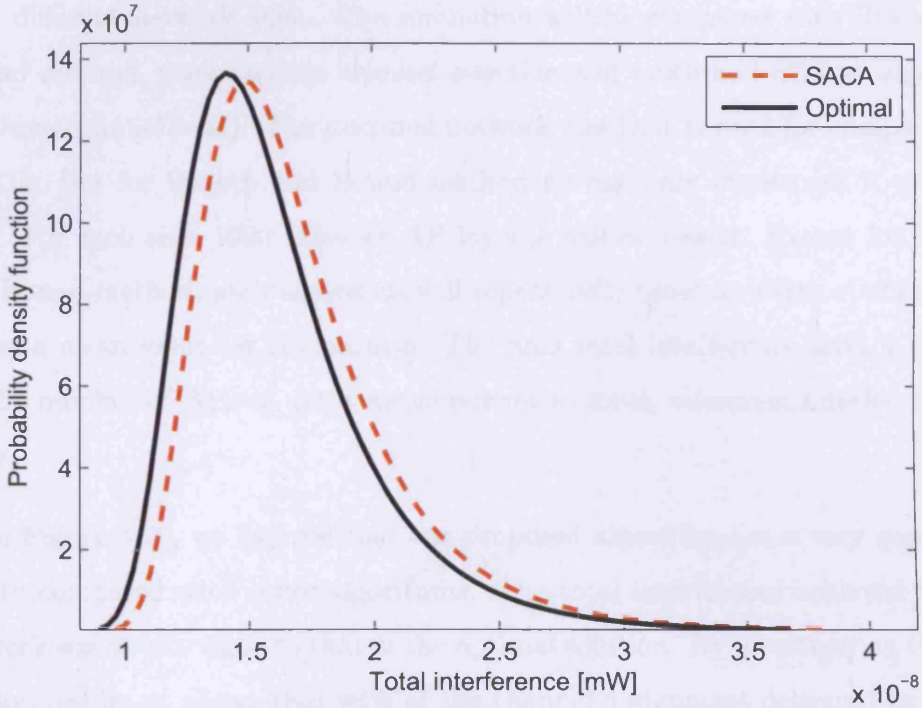

FIGURE 4.19: Distribution of interference for channel assignments generated by both the SACA and Branch and Bound method (optimal solution) with 20 APs networks over 1000 different layouts

It shows that the channel assignments found by SACA are very close to the optimal solutions.

4.4.5 Scalability

For relatively small problems of the order of 10 APs, it is easy to find a global optimum for the three-channel scenario. The resulting channel assignment leads to the lowest possible total interference. The problem however is that the optimisation problem is $\mathcal{NP}$-hard and the time it takes to find the optimal solution grows exponentially with the size of the problem. Optimum solutions for network sizes up to 30 APs are feasible. However, finding the global optimum for three channels and more than 40 APs within a reasonable time scale does not seem to be possible.

In this section, we investigate the scalability of our proposed SACA algorithm with different network sizes. The simulation will be compared with Branch and Bound method, pure random channel selection and Leith and Clifford algorithm (in three-channel case). The maximal network size that is used for comparison is 50 APs, but for Branch and Bound method we can only implement it up to 30 APs. For each size, 1000 different AP layouts will be tested. Except for Branch and Bound method, each algorithm will repeat 1000 times for every configuration to get a mean value for comparison. The final total interference level is divided by the number of APs to get a measurement as mean minimum interference per node.

From Figure 4.20, we can see that the proposed algorithm has a very good scalability compared with other algorithms. The total interference achieved in each network size is very close to that of the optimal solution. By investigating the simulation results, it shows that 98% of the channel assignment delivered by SACA are less than 5% away from the optimal solution. For pure random and Leith and Clifford algorithm (with three channels), interference level is increased significantly against the network size.

4.4.6 Interference Distribution

Since the number of APs is rapidly increasing in the public areas, from the operator's perspective, it is very important to know where are the most suitable places to deploy additional APs and which APs are offering the worst service quality that can be switched off to reduce cost. Using this measurement, not only it can show

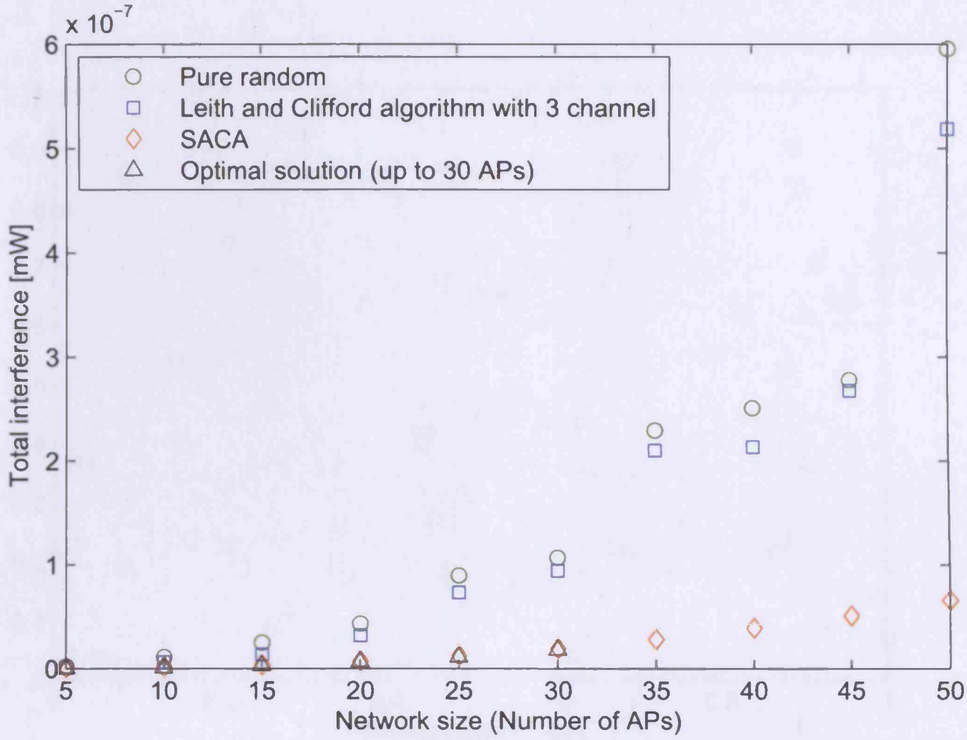

FIGURE 4.20: Scalability

the current channel usage and interference distribution in the network, but also can indicate which area is the best place to deploy new APs with what channel. We demonstrate this feature under an already densely deployed network, with 100 APs, and find out further possibilities to add more APs to the places that experience low interference.

Figures 4.21-4.24 show a clear image of channel usage and interference level in this area. Using this metric, APs deployed near high interference spot could be removed or switched to other channels in order to provide better services. Moreover, according to the service quality defined by operators, one can make a decision whether it is profitable to add new APs or not. If it is, what location and with what channel could be the best choice? This metric also raises an interesting issue that, DCA method is not only restricted to the optimisation problem to minimise the total interference or maximize user throughput, but can also be designed to maximize the percentage of area with low level interference (better service).

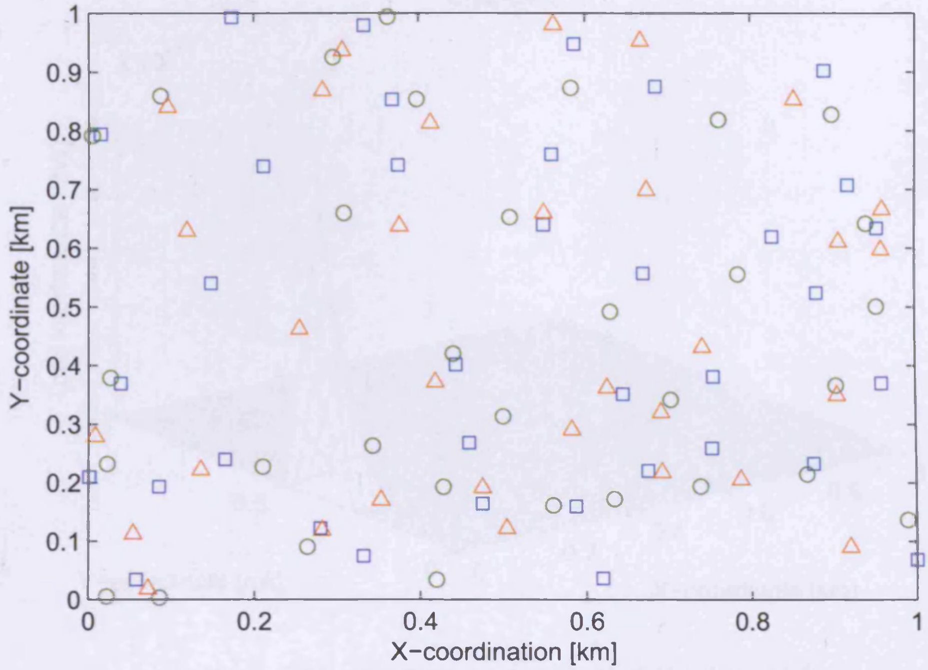

FIGURE 4.21: Channel assignment generated by SACA algorithm for a 100 APs network

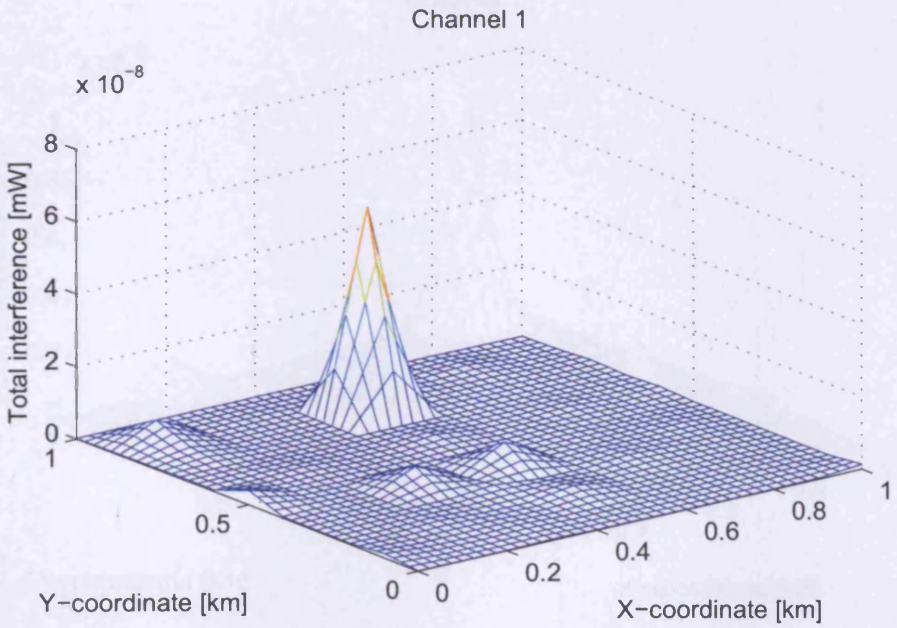

FIGURE 4.22: Interference distribution for channel 1

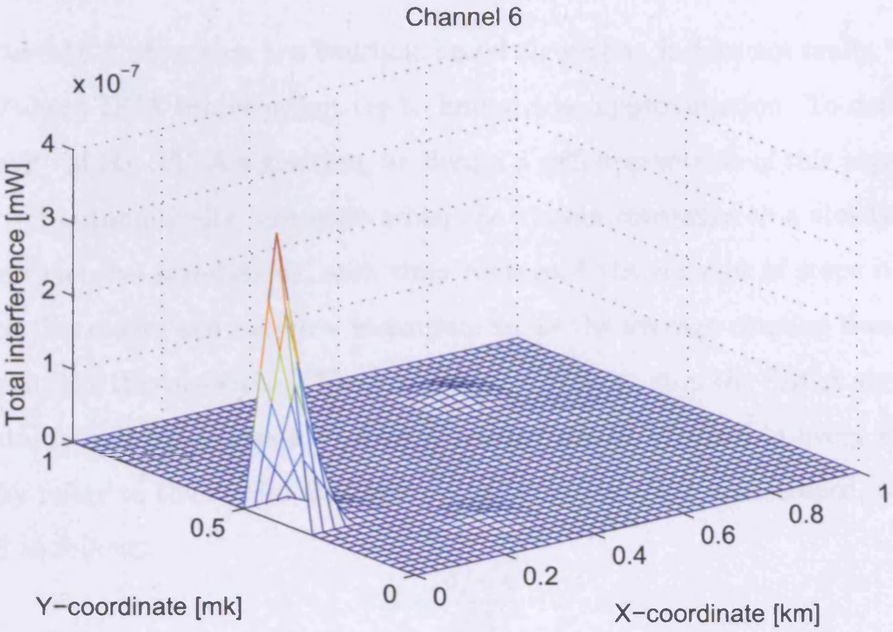

FIGURE 4.23: Interference distribution for channel 6

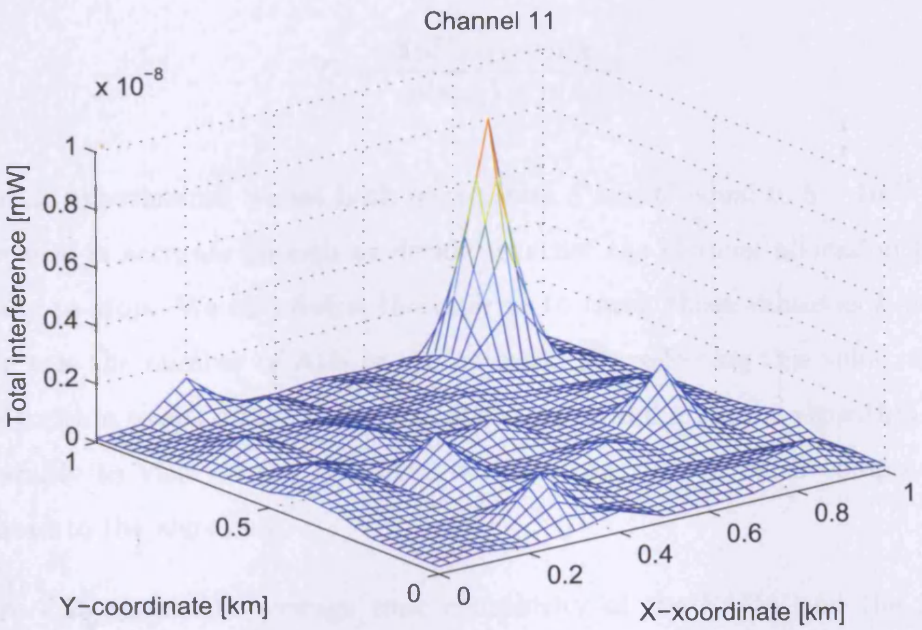

FIGURE 4.24: Interference distribution for channel 11

4.4.7 Complexity Analysis

Since the SACA algorithm is a heuristic based algorithm, it does not really "solve" the $\mathcal{NP}$-hard DCA problem, but try to find a close approximation. To define the complexity of the SACA algorithm, we design a self-stop version of this algorithm, which will automatically terminate when the system converges to a steady state. We run extensive simulations, each time we record the number of steps it needs to reach this stage, and obtain a measurement as the average running time (time complexity) of this algorithm. The two major criteria to stop the SACA algorithm are stability and convergence, and those values will be checked in every k steps. Stability refers to the small variations on the curve of total interference, which is defined as follows:

$$S = \frac{\delta/\sqrt{k}}{\mu(k)} \tag{4.5}$$

where δ is the standard deviation of the total interference in the current n steps, $\mu(k)$ is the mean total interference value in this time period. While for the convergence criterion, we measure the difference of the average total interference for every k steps and define it as follow:

$$C = \frac{2(\mu(k_{i+1}) - \mu(k_i))}{\mu(k_{i+1}) + \mu(k_i)} \tag{4.6}$$

Based on experiments, we set both parameters S and C equal to 5×10^{-4}, which we believe is accurate enough to decide whether the channel allocation process is ready to stop. We also define the interval to check those values as $k = 2 \times n$ where n is the number of APs in the network. By selecting this value, it helps the algorithm to self-adapt to the size of the input and gives the algorithm higher probability to visit all the APs, but without causing too much computational overhead to the algorithm.

Figure 4.25 shows the average time complexity of the SACA and the Branch and Bound method against the network size. The running time is presented in the log-scale. As the convergence moment varies depending on many network configuration parameters, especially on network layout. For each network size,

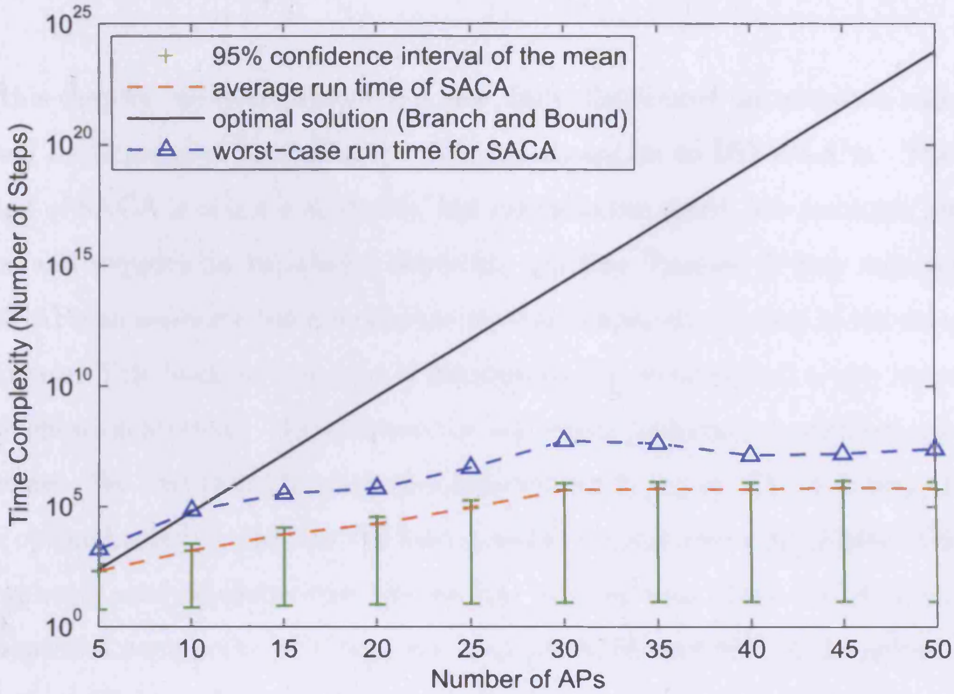

FIGURE 4.25: Algorithm complexity of SACA algorithm and Branch and Bound method

1000 different network layouts have been tested. By investigating the simulation results, we find that for smaller networks, the distribution of the running time is long tailed. This is because, for smaller networks, the SACA can easily and quickly converge to the optimal or suboptimal solutions. While for larger networks, as the solution space is expanded, the algorithm takes longer time to converge which ends up with symmetric distribution. By comparing the two algorithms, we can see that, as the network size increases, the time complexity of the SACA is much lower than that of Branch and Bound. Even for the worst-case scenarios, the difference in running time between the two algorithms is dramatically increased. Moreover, it is about 95% confident that by doing more simulations, the average running time will be caught inside the intervals representing by the green bars.

4.5 Summary

In this chapter, we have presented a new, fully distributed optimisation algorithm based on Simulated Annealing for channel allocation in HD-WLANs. The algorithm of SACA is of low complexity, fast convergence speed, low resultant interference and requires no knowledge about the wireless channel. It only requires that each AP can estimate the interference it would experience in any of the selectable channels. This leads to a minimum computational overhead and a very simple implementation strategy. We compare the algorithm performance with several other schemes. We find that the minimum interference found by SACA is very close to the optimal solution and has the best scalability compared with others. The time complexity analysis shows that the average running time of the SACA reduces the exponential complexity to a very low level provided that 98% of the solutions are less than 5% away from the known optima.

Chapter 5

Joint Design of Distributed Transmit Power Control and Dynamic Channel Allocation

5.1 Introduction

DCA techniques have been increasingly used to improve the network capacity, because of its ability to reuse wireless channels more flexibly by taking into account local propagation environment. However, when an AP decides to change to a new channel, it has to suspend the ongoing service connection and establish another one with the corresponding user-devices via the new channel. Therefore, in practice, all channel allocation schemes are susceptible to service disconnection, or at least degrade QoS over the network. TPC can be incorporated into DCA with the potential to compensate this deficiency. It can adjust the transmit power to reduce the overlapping coverage areas and hence enhance the channel access efficiency. In addition, by always using the minimum required power, the battery life for mobile devices can be greatly extended. In this chapter we analyse the problem of joint channel allocation and power control and develop three practical algorithms to interactively perform DCA and TPC on each AP in a distributed way.

The rest of this chapter is organized as follows. System model and problem formulation are described in Section 5.3. Some existing DCA algorithms and TPC methods relevant to this work are summarized in Section 5.2. Section 5.4 analyses convergence of the joint design and specifies the design criterion. Section 5.5 presents the algorithm development. Section 5.6 shows the performance evaluation results. Conclusions are given in Section 5.7.

5.2 Problem Formulation

The system model we consider for joint design is similar to the one described in Chapter 2, with an additional assumption that, transmission power can be adjusted continuously within a predefined range. The joint design objective of TPC and DCA algorithms is to maximize the average user throughput, given the number of wireless users and APs in the system. This goal is achieved by fully utilizing the three non-overlapping frequency channels with lowest possible interference across the network, and at the same time, maintaining the required SINR target for each user at minimum transmit power. Mathematically, this problem is formulated as follows:

$$\begin{aligned} \text{maximize} \quad & \frac{1}{n}\sum_{i=1}^{n} q_i \\ \text{subject to} \quad & (1) 0 < p_i < p_{max} \quad \forall i \\ & (2) r_i(t) \geq \gamma_i \quad \forall i, t \\ & (3) \text{Each AP can only use one channel at a time} \end{aligned} \tag{5.1}$$

where q_i is the throughput for the i-th AP's current active user. The SINR level for i-th user, $r_i(t)$, is defined as follow:

$$r_i(t) = \frac{g_{ii}p_i(t)}{\sum_{j\neq i} g_{ij}p_j(t)\omega_{ij} + \eta} \tag{5.2}$$

where g_{ij} is the path-loss between j-th AP and i-th user. The link path propagation matrix between all users and APs are defined as $\mathbf{G} = [g_{ij}]$. $p_i(t)$ is the transmission power of i-th AP at t-th iteration. The power vector for all the APs in the system is defined as $\mathbf{P} = [p_i]$. The power level is limited by a predefined maximum level, p_{max}. $\mathbf{\Omega} = [\omega_{ij}]$ is an interference coefficient matrix showing the instantaneous interference relationship among all APs. $\omega_{ij} = 1$ if i-th AP and j-th AP use the same channel and they are within each other's communication range, otherwise $\omega_{ij} = 0$. It is required that the SINR level for each user should be always above the target γ_i. η is the power of Additive White Gaussian Noise, which is assumed to be the same for all user-devices.

Since the transmit power can be adjusted continuously[1], a decision on channel selection is a discrete variable and the objective function has a non-linear relationship with respect to the number of channels, this problem can be classified as a non-linear mixed discrete and continuous optimization problem. This is one of the most generic optimization problems [92]. This class of problems does not have a formally defined structure. Both continuous and discrete variables and constraints are included in the problem definition. No restrictions are imposed on the functional form of the objectives. Therefore, no effective methods have been developed to tackle this problem, which means the optimal solution can not be found by using conventional optimization solvers. Therefore, we propose three heuristic algorithms which perform recursively and can find sub-optimal solutions.

5.3 Related Work

Traditionally, DCA algorithms and TPC schemes [14] are considered as the most efficient techniques to manage limited resource available to the system. They were separately proposed to improve spectrum utilisation using DCA algorithms to avoid strong co-channel interference while using TPC to minimize transmit power

[1]This assumption is made for research purpose in order to find the minimum required power to satisfy SINR requirements. In real networks, transmit power can only be adjusted through finite discrete power level.

and suppress the co-channel interference. Some of the research works have demonstrated that additional improvement of the network capacity can be achieved by combining these two techniques together. Major work in joint design was carried out in cellular networks [93, 94, 95, 96, 97], with the aim to minimize call dropping/blocking probability and thus increase the system capacity.

Work in [93] is the earliest attempt to try to combine DCA and TPC in an interactive manner. In this work, DCA determines paired radio channels for both downlink and uplink directions that experience the least interference on a call-by-call basis and then TPC algorithm periodically updates the transmit power to adjust users SINR by 1dB in each step. This work has demonstrated a low level of interactive design between channel and transmit power. Foschini and Miljanic [94] extended the work in [93] by proposing a distributed algorithm with a tighter integration. They consider initial channel access and monitor SINR performance throughout the lifetime of a call by using TPC, once the maximum transmit power can not provide the required service level, DCA is applied to search for a better frequency band with the potential to have better service quality. A family of integrated algorithms were proposed in [97] considering pedestrian mobility of the devices with a low update rate of power. As there are different groups of calls simultaneously processed in the system, the algorithm assigns different SINR threshold to different groups to protect ongoing calls from dropping due to the new incoming calls.

Despite those early works, due to the new concept of opportunistic spectrum access raised in the cognitive radio, the joint design is also considered in [98] with the aim to maximize the spectrum utilization by allowing secondary cognitive network to opportunistically exploit the unused spectrum without causing excessive interference to primary users. Li and Wu addressed the problem of optimum TPC and DCA for delay sensitive applications over a multi-channel, multi-user system in [99]. They proposed a joint Knopp and Humblet/round robin (K&H/RR) scheduler to allocate both power and channel among users with the aim to minimize the resource usage while explicitly satisfy the QoS requirements of users. In [100], authors formulated the channel assignment and load balancing problem as ILP optimization problem. It adjusted the power transmitted by the most congested AP as long as all users can be accommodated by the APs. Then the final transmitted power level on each APs is applied to allocate channels efficiently to the APs.

Yu *et al* formulated a min-max optimization problem regarding channel utilization with constraints of data rate, channel quality and transmit power [101]. They derived an expression to evaluate the channel utilization when incorporating channel conditions, SINR and transmit power. In this algorithm, channels are assigned to minimize the channel usage of the most heavily loaded APs, on the condition that traffic demand for an AP and all its users should be less than the maximum data rate it can support. The constraints include 1) QoS should be maintained, 2) transmit power is limited by a maximum level and, 3) all traffic has to be sent out eventually.

5.4 Joint Design of Transmit Power Control and Dynamic Channel Allocation

A distributed power control algorithm with single channel was first conceived by Foschini and Miljanic [94] in 1993, where all the users are sharing the same channel. We will extend their work to a multi-channel scenario and use the DCA algorithm to maximize the spectrum utilization with the lowest possible interference between neighbouring APs. For power control in a multi-channel scenario, the formulation is based on a set of differential equations describing a closed-loop performance for each user as follow:

$$\dot{r}_i(t) = -\beta\left[r_i(t) - \gamma_i\right] \quad i = 1, 2, \ldots, n \tag{5.3}$$

where $\dot{r}_i(t) = \frac{d}{dt}r_i(t)$ denotes the derivative of i-th user's SINR level, β is a constant determining the convergence rate of $r_i(t)$ towards the target γ_i. Eventually as $\dot{r}_i(t)$ goes to 0, $r_i(t)$ approaches γ_i as required. Under the assumption that interference will not change at the moment of i-th AP updating its power [94], we substitute Eq. 5.2 into 5.3 and yield the following differential equation for the dynamics of the power behavior:

$$\frac{g_{ii}\dot{p}_i(t)}{\sum_{j\neq i} g_{ij}p_j(t)\omega_{ij} + \eta} = -\beta \left[\frac{g_{ii}p_i(t)}{\sum_{j\neq i} g_{ij}p_j(t)\omega_{ij} + \eta} - \gamma_i \right] \tag{5.4}$$

By manipulating Eq. 5.4, we have the expression in terms of transmit power,

$$\dot{p}_i(t) = -\beta p_i(t) + \beta \frac{\gamma_i \eta}{g_{ii}} + \beta \sum_{j\neq i} \frac{g_{ij}}{g_{ii}} \gamma_i \omega_{ij} p_j(t) \tag{5.5}$$

Expand Eq. 5.5 into a matrix form, we explicitly characterize the dynamic behavior of the complete set of transmit power:

$$\begin{bmatrix} \dot{p}_1(t) \\ \dot{p}_2(t) \\ \vdots \\ \dot{p}_n(t) \end{bmatrix} = -\beta \mathbf{I} \begin{bmatrix} p_1(t) \\ p_2(t) \\ \vdots \\ p_n(t) \end{bmatrix} + \beta\eta \begin{bmatrix} \frac{\gamma_1}{g_{11}} \\ \frac{\gamma_2}{g_{22}} \\ \vdots \\ \frac{\gamma_n}{g_{nn}} \end{bmatrix} + \beta \underbrace{\begin{bmatrix} 0 & \frac{\gamma_1 g_{12}}{g_{11}} & \cdots & \frac{\gamma_1 g_{1n}}{g_{11}} \\ \frac{\gamma_2 g_{21}}{g_{22}} & 0 & \cdots & \frac{\gamma_2 g_{2n}}{g_{22}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\gamma_n g_{n1}}{g_{nn}} & \frac{\gamma_n g_{n2}}{g_{nn}} & \cdots & 0 \end{bmatrix}}_{\mathbf{B}'} \bullet \underbrace{\begin{bmatrix} 0 & \omega_{12} & \cdots & \omega_{1n} \\ \omega_{21} & 0 & \cdots & \omega_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{n1} & \omega_{n2} & \cdots & 0 \end{bmatrix}}_{\mathbf{\Omega}} \begin{bmatrix} p_1(t) \\ p_2(t) \\ \vdots \\ p_n(t) \end{bmatrix} \tag{5.6}$$

where $\mathbf{I}$ is an $n \times n$ identity matrix. The operation between matrix $\mathbf{B}'$ and $\mathbf{\Omega}$ is element-wise multiplication. Matrix $\mathbf{\Omega}$ shows the instantaneous interference relationship between APs, it changes accordingly as the APs are reselecting their channels. This relationship is updated by the DCA algorithm. One of the design criteria for DCA is to generate an appropriate channel assignment with minimal interference, such that TPC can operate in an interference free environment.

Combining the first and the third term of the right hand side of Eq. 5.6, yields:

$$\underbrace{\begin{bmatrix} \dot{p}_1(t) \\ \dot{p}_2(t) \\ \vdots \\ \dot{p}_n(t) \end{bmatrix}}_{\dot{\mathbf{P}}} = \beta \underbrace{\begin{bmatrix} \frac{\gamma_1 \eta}{g_{11}} \\ \frac{\gamma_2 \eta}{g_{22}} \\ \vdots \\ \frac{\gamma_n \eta}{g_{nn}} \end{bmatrix}}_{\mathbf{\Gamma}} + \beta \underbrace{\begin{bmatrix} -1 & \frac{\gamma_1 g_{12} \omega_{12}}{g_{11}} & \cdots & \frac{\gamma_1 g_{1n} \omega_{1n}}{g_{11}} \\ \frac{\gamma_2 g_{21} \omega_{21}}{g_{22}} & -1 & \cdots & \frac{\gamma_2 g_{2n} \omega_{2n}}{g_{22}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\gamma_n g_{n1} \omega_{n1}}{g_{nn}} & \frac{\gamma_n g_{n2} \omega_{n2}}{g_{nn}} & \cdots & -1 \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} p_1(t) \\ p_2(t) \\ \vdots \\ p_n(t) \end{bmatrix}}_{\mathbf{P}} \tag{5.7}$$

In a compact form, it can be written as

$$\dot{\mathbf{P}} = \beta \mathbf{\Gamma} + \beta \mathbf{B} \mathbf{P} \tag{5.8}$$

To solve the differential equation Eq. 5.8, we have [39]

$$\mathbf{P(t)} = e^{-\beta \mathbf{B} t} \beta \mathbf{\Gamma} \int_0^t e^{\beta \mathbf{B} \tau} d\tau + e^{-\beta \mathbf{B t}} \mathbf{P(0)} = \left(\mathbf{P(0)} + \mathbf{B \Gamma}^{-1}\right) e^{\beta \mathbf{B} t} - \mathbf{B \Gamma}^{-1} \tag{5.9}$$

Here we encounter the convergence property of the TPC algorithm, since

$$\lim_{t \to \infty} \mathbf{P(t)} = \lim_{t \to \infty} \left[\left(\mathbf{P(0)} + \mathbf{B \Gamma}^{-1}\right) e^{\beta \mathbf{B} t} - \mathbf{B \Gamma}^{-1}\right] \tag{5.10}$$

In order to find a power level for each AP such that they can simultaneously transmit on these channels, we have to ensure the following condition is satisfied:

$$\lim_{t \to \infty} e^{\beta \mathbf{B} t} = 0 \tag{5.11}$$

Therefore, the sufficient condition for power convergence is

1.	**B** is a diagonalizable matrix.
2.	**B** is a diagonally dominant matrix, i.e. $\lvert b_{ii} \rvert \geq \sum_{j \neq i} \lvert b_{ij} \rvert$ for all i.

Proof: As matrix **B** contains off-diagonal elements from link gain matrix **G**, they are all random components, thus in most of the cases, **B** will have n distinct eigenvalues and their corresponding eigenvectors are linearly independent. Therefore, we assume $\mathbf{B}$ is a diagonalizable matrix (although in very rare case it can be non-diagonalizable). Matrix $\mathbf{B}$ can be factored as follow:

$$\mathbf{B} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q} \tag{5.12}$$

where

$$\mathbf{\Lambda} = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix}$$

is a diagonal $n \times n$ matrix with the eigenvalues of $\mathbf{B}$ as its entries.

$$\mathbf{Q} = \begin{bmatrix} x_{11} & x_{21} & \cdots & x_{n1} \\ x_{12} & x_{22} & \cdots & x_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1n} & x_{2n} & \cdots & x_{nn} \end{bmatrix}$$

is a matrix whose columns are the eigenvectors corresponding to the eigenvalues in $\mathbf{\Lambda}$. According to the matrix exponential function, we have

$$e^{\mathbf{B}} = \sum_{n=0}^{\infty} \frac{\mathbf{B}^n}{n!} = \sum_{n=0}^{\infty} \frac{\mathbf{Q}\mathbf{\Lambda}^n\mathbf{Q}^{-1}}{n!} = \mathbf{Q} \sum_{n=0}^{\infty} \frac{\mathbf{\Lambda}^n}{n!} \mathbf{Q}^{-1} = \mathbf{Q} e^{\mathbf{\Lambda}} \mathbf{Q}^{-1} \tag{5.13}$$

As again $\mathbf{\Lambda}$ is a diagonal matrix, we have

$$\begin{aligned}
e^{\mathbf{\Lambda}} &= \sum_{n=0}^{\infty} \frac{\mathbf{\Lambda}^n}{n!} = \sum_{n=0}^{\infty} \frac{1}{n!} \begin{bmatrix} \lambda_1^n & 0 & \cdots & 0 \\ 0 & \lambda_2^n & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n^n \end{bmatrix} \\
&= \begin{bmatrix} \sum_{n=0}^{\infty} \frac{\lambda_1^n}{n!} & 0 & \cdots & 0 \\ 0 & \sum_{n=0}^{\infty} \frac{\lambda_2^n}{n!} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sum_{n=0}^{\infty} \frac{\lambda_n^n}{n!} \end{bmatrix} \\
&= \begin{bmatrix} e^{\lambda_1} & 0 & \cdots & 0 \\ 0 & e^{\lambda_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & e^{\lambda_n} \end{bmatrix}
\end{aligned} \tag{5.14}$$

Thus

$$\lim_{t\to\infty} e^{\beta\mathbf{B}t} = \lim_{t\to\infty} \begin{bmatrix} e^{\beta\lambda_1 t} & 0 & \cdots & 0 \\ 0 & e^{\beta\lambda_2 t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & e^{\beta\lambda_n t} \end{bmatrix} \tag{5.15}$$

Therefore, as long as the real part of the eigenvalues of matrix $\mathbf{B}$ are negative, $\lim_{t\to\infty} e^{\beta\mathbf{B}t} = 0$. In the case of this particular problem, instead of tracking the eigenvalues with large amount of computational effort, the condition can be interpreted alternatively and more intuitively by using Gershgorin Circle theorem [102]. As stated in the theorem, the sum of the magnitude of the off-diagonal elements of i-th row in $\mathbf{B}$ is defined as follow:

$$R_i = \sum_{j\neq i;j=1}^{n} |b_{ij}| = \sum_{j\neq i;j=1}^{n} \left| \frac{\gamma_i g_{ij} \omega_{ij}}{g_{ii}} \right| \tag{5.16}$$

Each eigenvalue of $\mathbf{B}$ is at least in one of the disks $\{\lambda : |\lambda - b_{ii}| \leq R_i\}$, as shown in Figure 5.1. All the n disks have the same center, $b_{ii} = -1$. The radius of the circles, which is R_i could be larger or smaller than "1". In the case of smaller than "1", the real part of all the eigenvalues are negative; while in the case of larger than "1", the real part of the eigenvalues can be positive, which violates the previous condition. Therefore, the sufficient condition for power convergence is, $\mathbf{B}$ is a diagonally dominant matrix, where $|b_{ii}| \geq \sum_{j\neq i;j=1}^{n} |b_{ij}|$. By satisfying these conditions the power will converge to $\mathbf{P}^* = -\mathbf{B}\mathbf{\Gamma}^{-1}$.

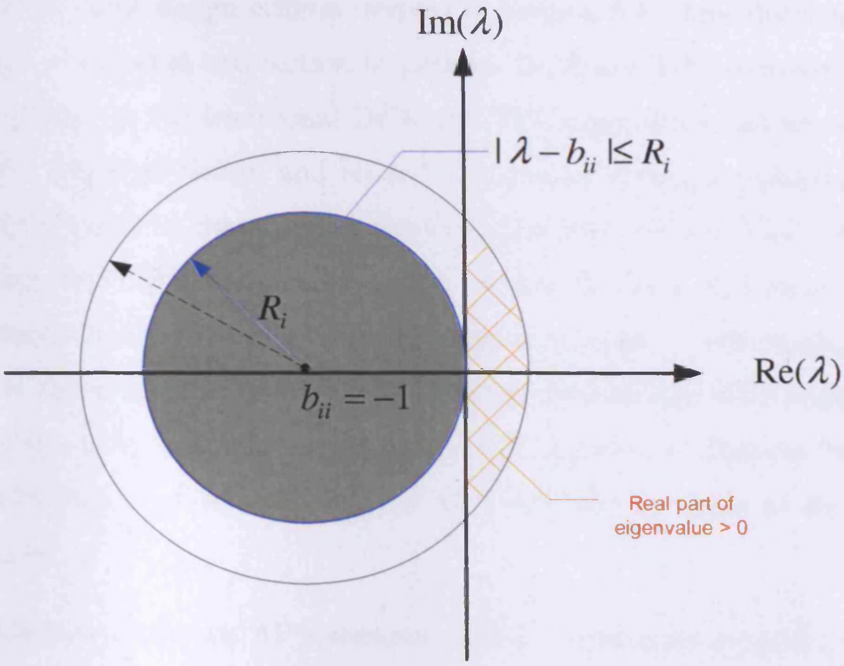

FIGURE 5.1: Convergence property analysis

Since the off-diagonal elements in $\mathbf{B}$ are all non-negative numbers, to minimize the radius, the key is to force those ω_{ij} with large weight $\gamma_i g_{ij}/g_{ii}$ to become zero, such that the matrix $\mathbf{B}$ will then have higher probability to become a diagonally dominant matrix. In the context of DCA in WLANs, that means close APs have to use different channels if possible to avoid strong co-channel interference. If users are assigned to channels experiencing low interference, they will be more likely to encounter good quality of service and as a result, more likely to maintain sufficient quality with reduced transmit powers [97]. Therefore, in the case of optimal channel assignment, the stability condition of the TPC can be strengthened. The criterion of joint design requires the DCA algorithm to provide an optimal channel assignment, such that TPC can avoid strong interference from close neighbors, while TPC has to adjust the power level carefully to minimize the coverage overlap between neighbouring APs.

5.5 Algorithm Development

Based on the joint design criteria derived in Section 5.4, three distributed algorithms are proposed in this section to perform DCA and TPC recursively at each AP. Comparing to the traditional DCA and TPC algorithms that are separately developed, this joint design and recursive operation strategy enables an AP to effectively respond to time-varying wireless channel conditions and network dynamics, e.g. new APs are added into the system. In these algorithms, each AP independently and periodically checks its channel and power configuration, as long as it could discover better channel or lower power to fulfill the SINR requirements, the AP will activate the joint algorithm for reconfiguration. This can be realized by implementing a countdown timer at each AP, which expires at an arbitrary time interval.

During the procedure, an AP's transmit power (continuous variable) and communication channel (discrete variable) evolves simultaneously, which subsequently affects its neighboring AP's configurations. As it is not possible to derive the exact close-form solution for this non-linear joint optimization problem, the following sections describe three heuristics based joint DCA and TPC algorithms, which are performed in a distributed and real time manner. These proposed algorithms are flexible and scalable, and can adaptively achieve better throughput performance and energy efficiency. The flow chart in Figure 5.2 shows the general idea of these joint algorithms.

Based on the flow chart, we propose three algorithms to implement the joint design of DCA and TPC.

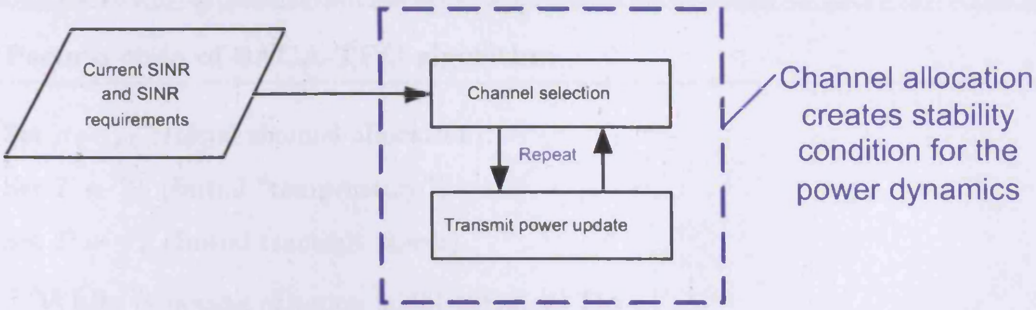

FIGURE 5.2: Flow chart of interactive design of the DCA and TPC

5.5.1 Simulated Annealing Channel Allocation with Transmit Power Control (SACA-TPC)

SACA-TPC integrates a SA-based channel allocation algorithm with a SINR-based TPC scheme. Under SACA-TPC, each AP can choose and switch to another available channel at any time. The channel selection decision is made according to the interference experienced in the current channel and the selected alternative. In this way, SACA-TPC enables every AP to probabilistically choose a new channel with less interference for communication. After that, the AP assesses the SINR for its current active user in the newly-selected channel and updates the transmit power accordingly to satisfy the SINR target. The algorithm of SACA-TPC is detailed as follows.

Pseudo code of SACA-TPC algorithm

Set $\rho \leftarrow \rho_0$ (Initial channel allocation).

Set $T \leftarrow T_0$ (Initial "temperature")

Set $P \leftarrow P_0$ (Initial transmit power)

While (stopping criterion is not satisfied) **Do**

randomly select on AP: AP i

Evaluate $I_i(\rho_i)$ (interference for AP i in channel ρ_i with current channel assignment ρ)

AP i selects a new channel ρ'_i

Evaluate $I_i(\rho'_i)$ (perceived interference for AP i in channel ρ'_i with new channel assignment ρ')

Compute $\Delta I = I_i(\rho'_i) - I_i(\rho_i)$

If $(\Delta I \leq 0)$, **then**

$\rho \leftarrow \rho'$

Else

Generate a uniformly distributed random variable α, $0 \leq \alpha \leq 1$

If $\alpha \leq e^{-\Delta I/T}$

$\rho \leftarrow \rho'$

End

End

Compute $r_i(t)$

Update $p_i(t) = p_i(t) \cdot \gamma_i / r_i(t)$, $T = T_0/(t+1)$, $t = t+1$

End

5.5.2 Greedy Channel Allocation with Transmit Power Control (GCA-TPC)

GCA-TPC combines a greedy channel allocation algorithm with a SINR-based TPC scheme. Under GCA-TPC, between the current channel and a randomly selected alternative, each AP always greedily selects the one with the less interference for communication. The transmit power is then adjusted to meet the SINR target for the current active user in that selected channel. The algorithm of GCA-TPC is given as follows.

Pseudo code of GCA-TPC algorithm

Set $\rho \leftarrow \rho_0$ (Initial channel allocation).

Set $P \leftarrow P_0$ (Initial transmit power)

While (stopping criterion is not satisfied) **Do**

randomly select on AP: AP i

Evaluate $I_i(\rho_i)$ (interference for AP i in channel ρ_i with current channel assignment ρ)

AP i selects a new channel ρ_i'

Evaluate $I_i(\rho_i')$ (perceived interference for AP i in channel ρ_i' with new channel assignment ρ')

Compute $\Delta I = I_i(\rho_i') - I_i(\rho_i)$

If $(\Delta I \leq 0)$, **then**

$\rho \leftarrow \rho'$

End

Compute $r_i(t)$

Update $p_i(t) = p_i(t) \cdot \gamma_i / r_i(t)$, $t = t + 1$

End

5.5.3 Transmit Power Control with Minimum Channel Switching (TPC-MinCS)

Since DCA algorithms are usually susceptible to service disconnections, TPC-MinCS aims to minimize the number of channel switches in the joint DCA and TPC procedure, and meanwhile try to use the minimum required power to satisfy users' SINR targets. Specifically, under TPC-MinCS, an AP first checks that, in the current channel, whether it is possible to decrease the power while still keeping users' SINR level. If it is possible, decrease the power. If it is not, a new channel will be selected. And then, the AP adjusts the transmit power to meet the user's SINR target in the new channel.

The AP won't attempt to increase the power without knowing if there is a better channel available, because this will cause un-necessary interference to the neighboring APs and users. Therefore, in TPC-MinCS, the AP will only increase the power if it is already in the best channel and the current power is still not high enough for users' SINR target. The algorithm of TPC-MinCS is described as follows.

Pseudo code of TPC-MinCS algorithm

Set $\rho \leftarrow \rho_0$ (Initial channel allocation).
Set $P \leftarrow P_0$ (Initial transmit power)
  While (stopping criterion is not satisfied) **Do**
    randomly select on AP: AP i
    Evaluate $r_i(t)$ and $I_i(\rho_i)$
    If $r_i(t) < \gamma_i$
      AP i selects a new channel ρ_i'
      Evaluate $I_i(\rho_i')$
      Compute $\Delta I = I_i(\rho_i') - I_i(\rho_i)$
      If $(\Delta I \leq 0)$, **then**
        $\rho \leftarrow \rho'$
      End
    Else
      Update $p_i(t) = p_i(t) \cdot \gamma_i / r_i(t))$, $t = t + 1$
    End
  End

5.6 Performance Evaluation

In the following, we demonstrate the throughput performance and energy saving of the proposed algorithms. We concern the benefit of conducting joint design and the impact of the network density. Several network scales are simulated ranging from 50 to 200 APs. In each case, 1000 instances of the network are randomly generated in order to obtain the average performance.

TABLE 5.1: SINR target and data rates (throughput) for 802.11g

Data rates (throughput) [Mbps]	SINR level [dB]
6	16
9	18
12	19
18	21
24	24
36	28
48	33
54	36

5.6.1 Throughput Performance

We compare the throughput performance of the three proposed algorithms. The throughput performance is defined as the maximum fraction of users which have reached the pre-defined targets. Based on engineering experiments [103], the throughput specifications are listed in Table 5.1. It provides a one to one mapping between SINR target and user throughput. We define that as long as the user can achieve a certain SINR target, it can reach the corresponding throughput level.

Figure 5.3 compares the throughput performance of three proposed algorithms in different network sizes. In all cases, the fractions of users achieving predefined throughput targets are decreasing as the throughput targets and network densities increase. Algorithm TPC-MinCS consistently outperforms the other two algorithms by allowing more users to reach their throughput targets. This is because by using TPC-MinCS, each AP always first seeks the possibility to reduce the power while still keeping the required SINR level, only when it is not possible of doing so, channel switching will be triggered. Therefore, there are two optimization occurred at the same time: 1) minimize the power level as much as possible, and 2) minimize the frequency of channel switching. While for the other two algorithms, they are triggered by channel switch, which sometimes might cause APs choose worse channels with higher interference. This will consequently cause power boosting and eventually bring more interference in the system. Comparing algorithm SACA-TPC with GCA-TPC in dense networks, they are using the same power updating scheme but different channel allocation policies, the impact

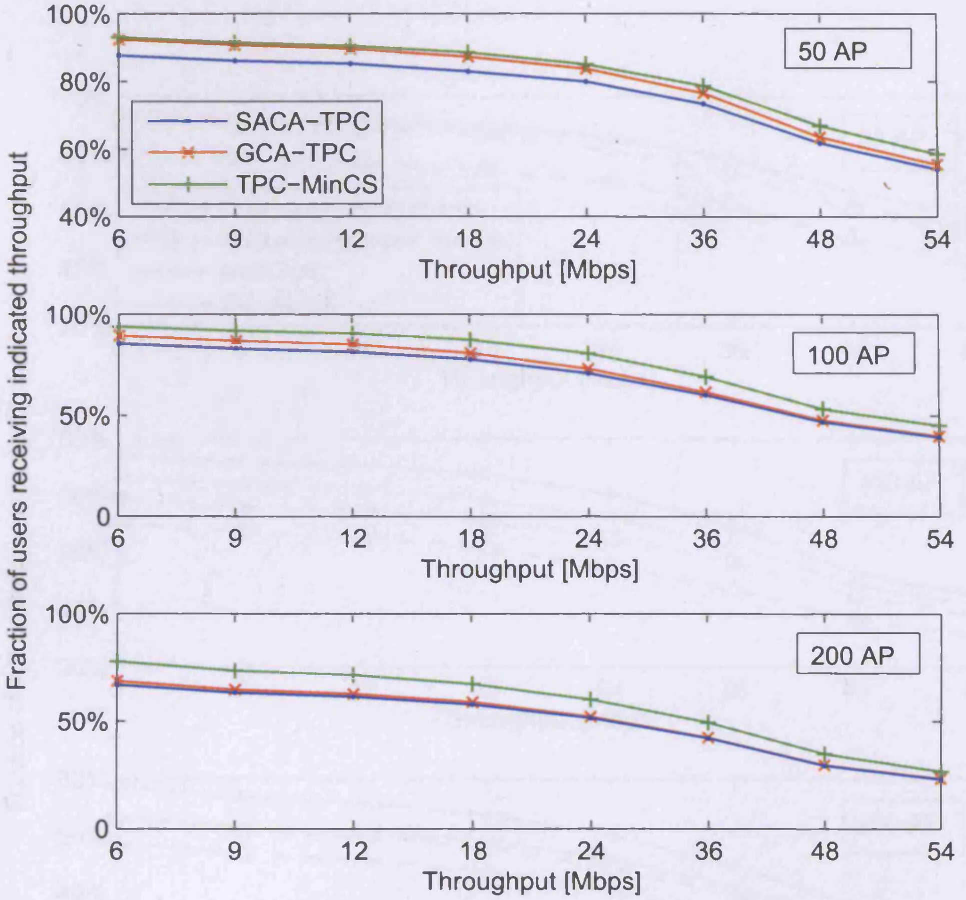

FIGURE 5.3: Fraction of users (y-axis) that achieve the throughputs indicated on the x - axis by using different algorithms under different network densities

of DCA on the throughput performance is smaller than that in sparse network. This is because in a dense network, as the distances between APs are shortened, it is almost impossible to avoid co-channel interference by providing only 3 non-overlapping channels.

In order to demonstrate the benefit of conducting joint design, we compare the performance of proposed algorithms with two benchmark schemes. Since the algorithm GCA-TPC has the medium level performance, the improvement will be bounded by only running algorithm SACA-TPC and TPC-MinCS. The two benchmark schemes for comparisons are: (i) fixed transmit power with random channel allocation and (ii) fixed transmit power with optimised channel allocation. The throughput profile is presented in Figure 5.4.

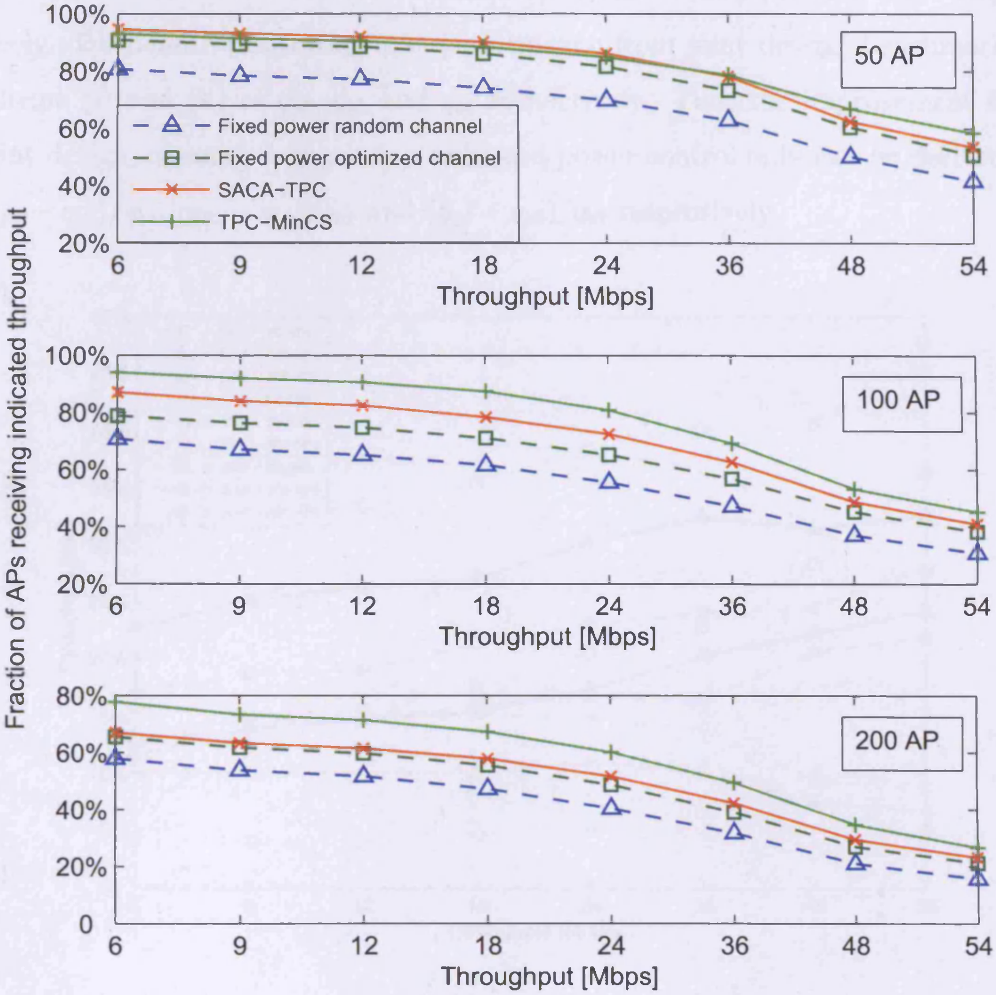

FIGURE 5.4: Fraction of users (y-axis) that achieve the throughputs indicated on the x - axis by using joint design compared with two other benchmark schemes

The throughput benefits from channel optimisation and power control presented in Figure 5.4 are obvious. In conventional deployment, the default transmission power is often set to the maximum (100 mW) without consideration of the distance between APs and clients. Such a default configuration causes increased interference among co-channel APs.

In the following, we use the SACA-TPC algorithm as an example to quantify the throughput benefits achieved by implementing joint design in percent terms and separate the contributions from channel optimisation and power control respectively. We denote the throughput performance from joint design, benchmarking scheme (i) and (ii) as q_{jd}, q_{b1} and q_{b2} respectively. Thus the improvement from joint design, channel optimisation only and power control only can be derived by $(q_{jd} - q_{b1})/q_{b1}$, $(q_{b2} - q_{b1})/q_{b1}$ and $(q_{jd} - q_{b2})/q_{b2}$ respectively.

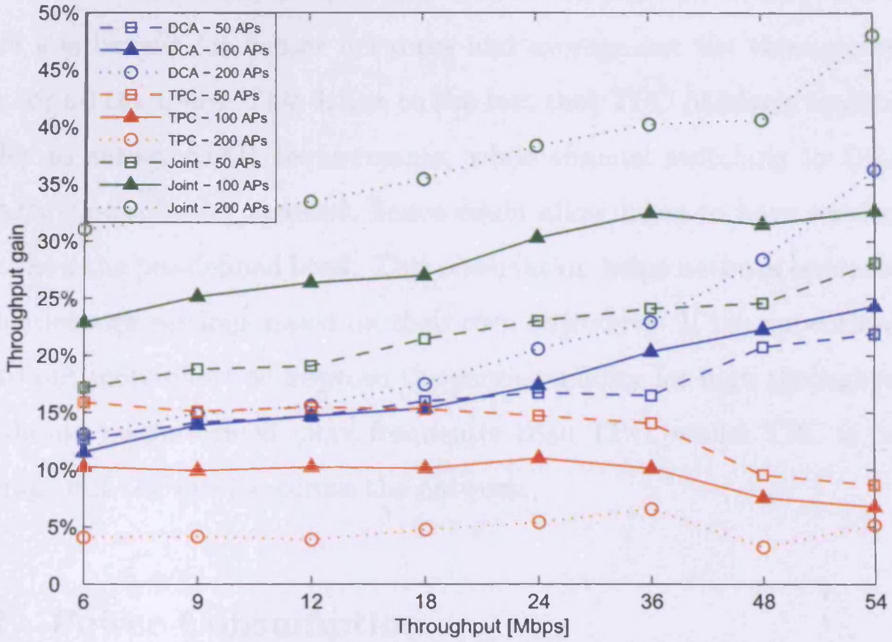

FIGURE 5.5: The percent throughput benefits by joint design and by TPC only

The green curves in Figure 5.5 represent the percent throughput improvement by applying joint design. As we can see, the improvements from joint design can be up to 48%. More throughput benefits are achieved for higher range throughputs, which means the joint design helps more clients to achieve higher throughput. There is also a noticeable dependence on the network density, where the benefits are more obvious in denser networks. This is because when the number of APs is relatively small while the number of channels is relatively large, there is not much gain of using optimisation schemes to reuse the spectrum, as there are enough channels to compensate the sub-optimality effect of random scheme. However, with more APs and less channels, there is real necessity in reducing the interference by reusing the channel, which can be achieved by our joint design scheme.

The blue and red curves in Figure 5.5 show the benefits achieved from TPC only and DCA only. We can see that if other things being equal, the throughput improvements from DCA tend to be somewhat higher than those achieved by TPC. Furthermore, DCA appears more beneficial to higher level throughput. It can bring more user from low throughput range to high throughput range. Whilst TPC, on the other hand, is more sensitive to the network density and tends to provide less benefit for denser networks and average out the throughput performance for all the users. This is due to the fact that TPC passively updates power in order to satisfy SINR requirements, while channel switching in DCA might help APs choose better channel, hence could allow users to have service quality higher than the pre-defined level. This observation helps network operators to adjust the network settings based on their own objectives. If the network operators want to put more effort to improve the service quality for high throughput users, DCA should be performed more frequently than TPC, whilst TPC is preferable to average out the service across the network.

5.6.2 Power Consumption

The power consumption is defined as the average final power level for all APs. Figure 5.6 shows the power consumption for three proposed algorithms. In conjunction with Figure 5.3, it can be seen from Figure 5.6 that algorithm TPC-MinCS uses least power to achieve the best performance compared with other two algorithms. As more and more users are added into the network, each AP boosts its power level to improve (or keep) users' service quality, which forces others to do the same and creates a chain effect throughout the entire network.

In the following, we quantify the power saving by using joint design. In the conventional scheme, transmit power is fixed at their maximum level, i.e. 100 mW

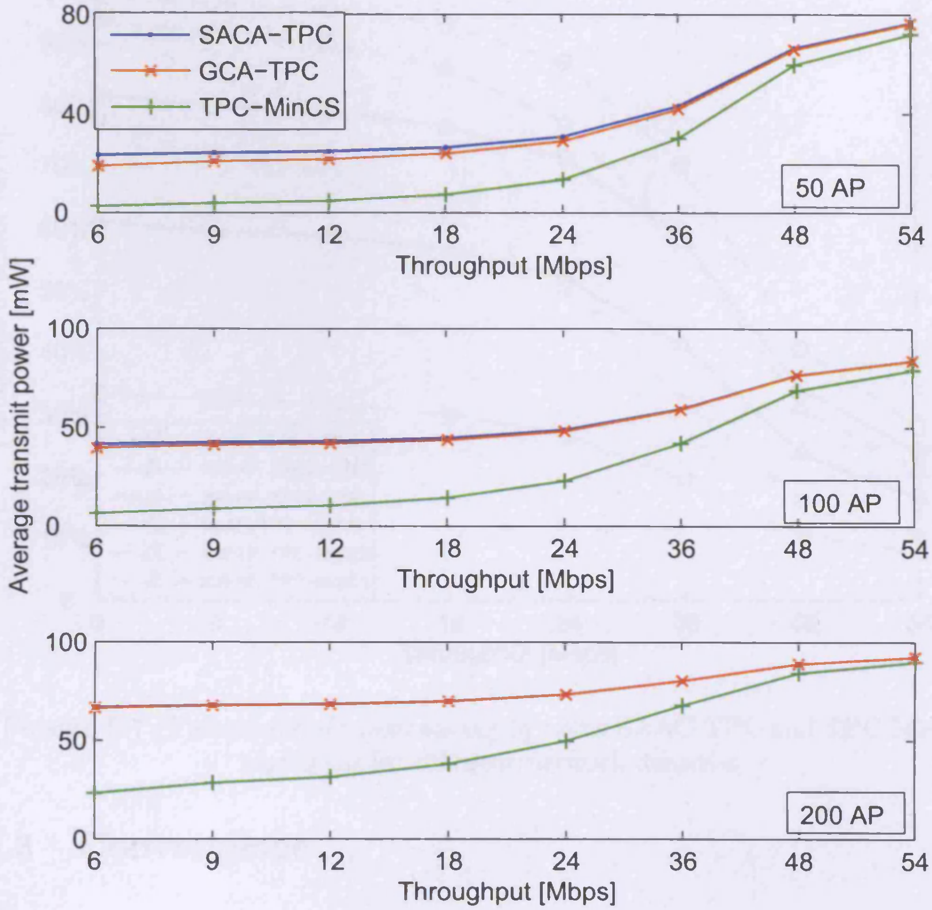

FIGURE 5.6: Average power consumption by using different algorithms under different network densities

(20 dBm). We define the percentage of power saving as $(p_{max} - p_i)/p_{max}$, where p_i is the final power level for i-th AP by using joint design.

We can see from Figure 5.7 that for both algorithms SACA-TPC and TPC-MinCS, large power saving can be achieved when the throughput target is low and the network is relatively sparse. In dense network, each AP is trying to increase its transmit power to overcome the surrounding interference and guarantee the user's SINR target. Therefore, to have further power saving, the better solution is to allow more channels to be available to the system.

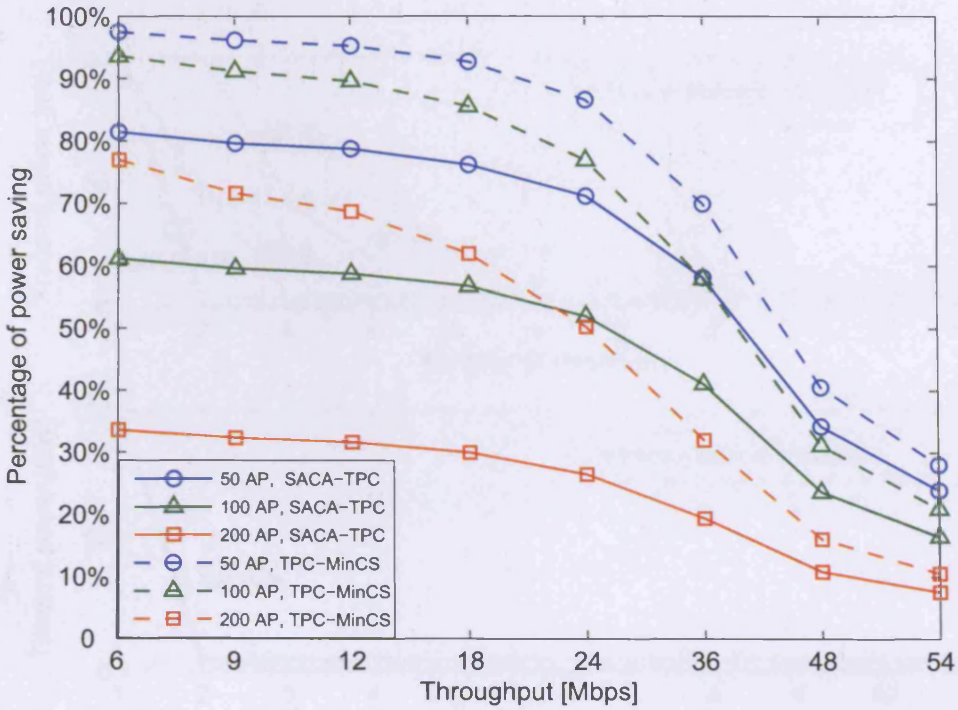

FIGURE 5.7: Percentage of power saving by using SAAC-TPC and TPC-MinCS algorithm for different network densities

5.6.3 Convergence

Recall to our finding in Section 5.4, in the case of optimal channel assignment, the convergence property of the TPC algorithm will be strengthened. In practice, this means with the optimal channel assignment, the power level for each AP will converge quickly to a low level and meanwhile satisfy the SINR requirements. Here we use a simulation case to exemplify this finding.

In this simulation case, 15 APs are randomly deployed in an area along with 15 users. We will first find out the optimal channel assignment for these 15 APs to minimize the total interference across the network, and then perform the TPC algorithm based on the channel assignment in a synchronized way for each AP and user link. The other random scheme used here for comparison performs TPC upon a randomly selected channel assignment. The SINR target for each user in both schemes is the same and set to 16dB.

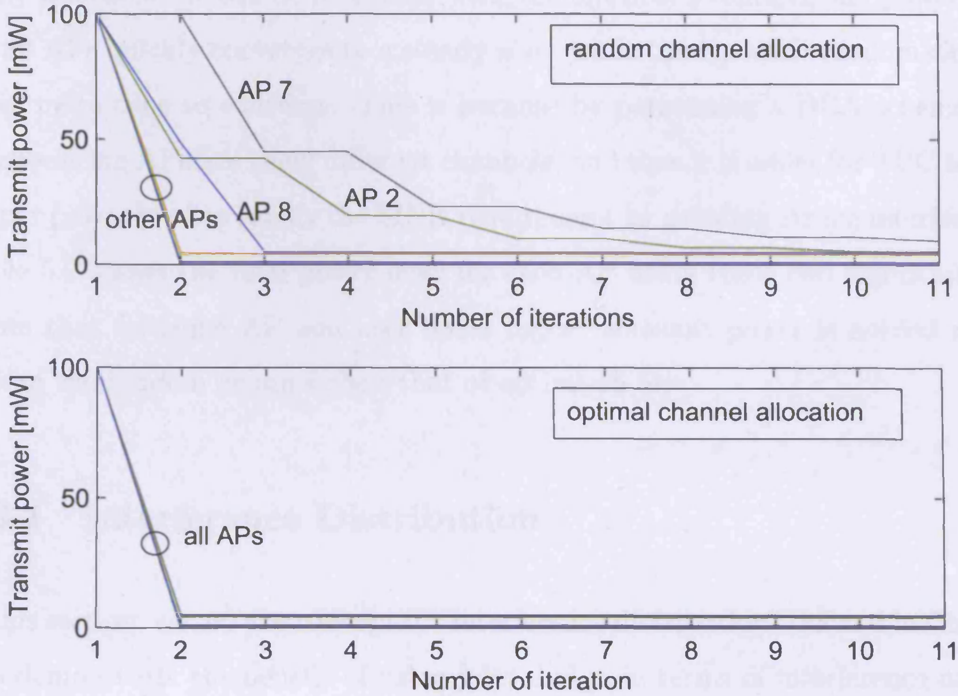

FIGURE 5.8: Power behavior for all 15 APs under the case of randomized and optimised channel assignment

TABLE 5.2: Final power level in the case of optimal and random channel assignment

	Optimal channel (mW)	Random channel(mW)
AP-1	0.2204	0.2204
AP-2	**0.7312**	**5.3048**
AP-3	4.2075	4.2075
AP-4	0.0159	0.0159
AP-5	0.0362	0.0362
AP-6	**0.0159**	**0.0163**
AP-7	**4.5608**	**9.6258**
AP-8	**4.9545**	**4.9616**
AP-9	3.9085	3.9085
AP-10	0.0176	0.0176
AP-11	0.1445	0.1447
AP-12	0.1469	0.1469
AP-13	3.8371	3.8371
AP-14	0.0288	0.0288
AP-15	0.9977	0.9977

Figure 5.8 shows the power behavior when the channels are randomly and optimally allocated. It can be seen that with the optimised channel, the power level for all APs quickly converges to a steady state while the one with random channel takes more time to converge. This is because by performing a DCA scheme, the neighbouring APs are using different channels, and thus it is easier for TPC to find proper power level to satisfy the SINR requirement by avoiding strong interference. Table 5.2 shows the final power level for each AP using these two algorithms. It shows that for some AP and user links, higher transmit power is needed in the case of the random channel than that of optimised one.

5.6.4 Interference Distribution

In this section, we use the concept of "interference distribution" defined in Chapter 4 to demonstrate the benefit of using joint design in terms of interference mitigation. In Figure 5.9, we compare the interference distribution of the SACA-TPC algorithm with a random scheme, where channels are allocated in a random way and power has been set to a fixed level. The network size for comparison is 100 APs.

Figure 5.9 shows a clear image of the interference level in each channel across the whole network by using different algorithms. Generally, for both algorithms, APs deployed near a high interference spot could be removed or switched to another channel in order to provide better services. Moreover, according to the service quality defined by operators, one can make decision on whether it is profitable to add new APs or not. If it is, which area with what channel and power level could then be the best choice?

Comparing these two cases, we can see that by conducting a joint design, all the APs are trying to use the minimum required power level to reduce the impact to neighbouring APs, and channel allocation is also optimised to minimise co-channel interference. It actually can reduce the interference up to the order of 10^2 in this simulation case. Figure 5.9 shows the results in the same magnitude to

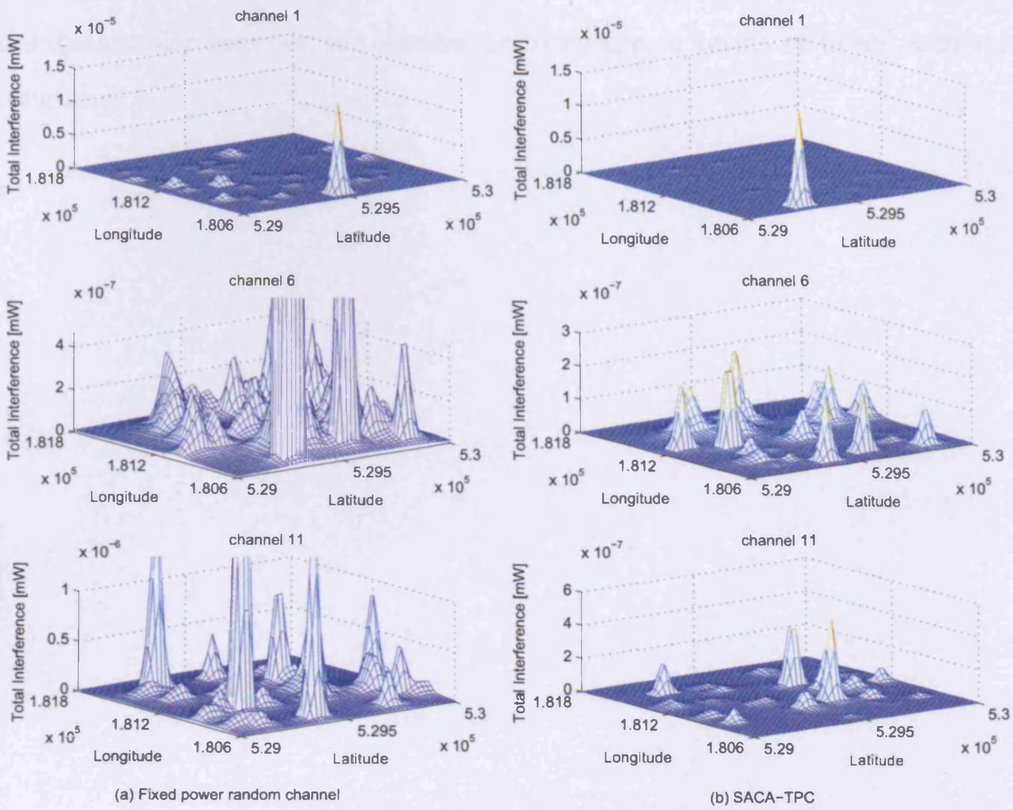

FIGURE 5.9: Interference distribution for benchmark scheme (i) and SACA-TPC

demonstrate the difference. Therefore, we can conclude that the network running SACA-TPC algorithm has more room to accommodate new APs than the one without optimisation, which consequently increases the potential capacity of the system.

5.7 Summary

In this chapter we present three real time and open ended distributed algorithms through joint design of DCA and distributed TPC. In these three algorithms, all APs are capable to choose any available channels for communication to respond to the current radio propagation environment, and can independently adjust their transmission powers to explicitly guarantee users' SINR requirements. We also show that in the case of optimal channel allocation, the convergence probability can be strengthened further. The simulation results show that the proposed algorithms can substantially improve the system performance in terms of users' achievable throughput.

Chapter 6

Algorithm Validation with Real Data

6.1 Introduction

In this chapter, we validate our proposed channel allocation and power control algorithms by using measurement data from a real WLAN deployed by BT in SOHO area of London. The objective is to explore the nature of evolving interference and its impact on the network performance and also demonstrate the improvement resulting from conducting the proposed algorithms. It is well known that, with the existing channel assignment and power settings, current 802.11b/g is confronted with severe interference problems. This study offers a valuable insight on how to improve the service quality of Wi-Fi clients via interference management. Since centralised algorithms are generally believed impractical for implementation in large scale networks, only distributed algorithms will be validated in our system, including the distributed DCA algorithm, i.e., SACA, and joint design algorithms of DCA and TPC, i.e., SACA-TPC, GCA-TPC and TPC-MinCS.

6.2 Experiment Environment

The algorithm validation is carried out by running performance evaluation simulations in a roughly 1 km^2 residential (SOHO) area, which comprises 200 APs. Figure 6.1 provides a top view of this residential area.

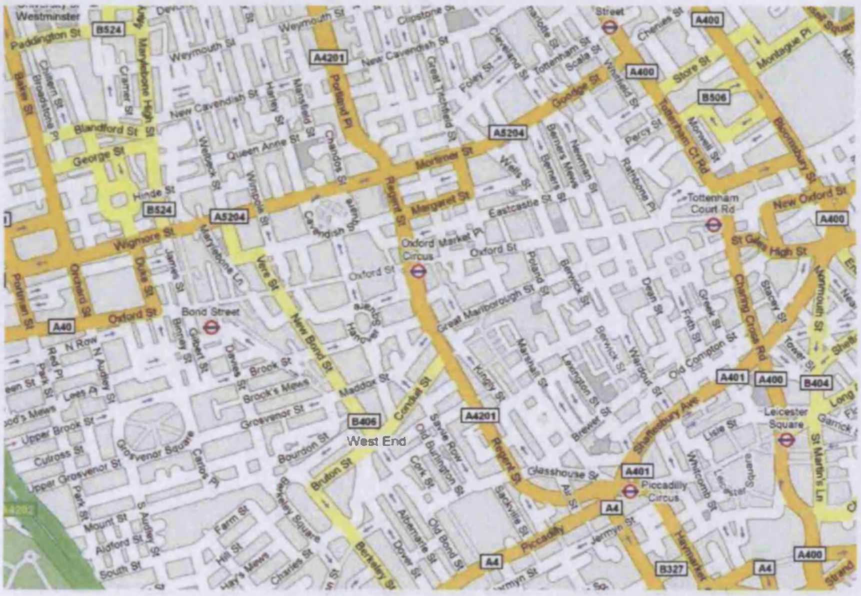

FIGURE 6.1: Residential area for algorithm validation (source: Google map)

In this area, 200 houses are selected and each of them is deployed with a customer home hub (AP), with which a home network is set up. Each home network is associated with a number of home clients. The maximum distance from a client to its corresponding AP is set to 8 meters. This empirical value is chosen in such a way that it gives a coverage area within which almost all residential property boundaries are fully covered. The location of APs and clients are determined by a stochastic process. Channels are distributed to home networks based on a particular channel distribution scheme, which will be discussed in detail later. For 802.11b/g technology, each AP is allocated with one of the three non-overlapping channels, i.e., channel 1, 6 and 11. Only downlink performance is considered in our validation. MAC layer overheads are not taken into account at a detailed level in this phase of validation. Instead, a rough approximation of 30% degradation of raw data rate is assumed. Antenna radiation pattern is assumed to be isotropic. No specific assumption is made on the type of clients, since our interest mainly lies on Wi-Fi data rate rather than a particular device to device scenario. Backhaul capacity is assumed to be large enough, such that we do not need to worry about the performance bottleneck stemming from backhauling. All APs and clients conform to the 802.11g standard. The maximum power level for APs and clients are 20 dBm at the current regulatory Effective Isotropic Regulated Power (EIRP).

6.3 Validation Results

In the following, the proposed distributed DCA algorithm, i.e. SACA, and other joint design algorithms, i.e. SACA-TPC, GCA-TPC and TPC-MinCS, will be validated in the above mentioned system. Final channel assignment, throughput performance and transmission power level are among the key performance metrics to be evaluated for the proposed algorithms.

6.3.1 Distributed DCA-SACA

We first validate the DCA algorithm, SACA. The user throughput is taken as the performance metric and measured in our system. System performance by running SACA algorithm is compared with two other cases, namely the baseline and random cases. A baseline performance represents the best achievable throughput in an ideal situation. It is assumed that the channel number in this case is unlimited. Therefore, there is no interference existing among APs. Path loss is the only factor for signal degradation and is influenced by factors such as distance, number of walls/floors between them. While in the random case, the channels are distributed to APs in a random manner regardless of the contention between neighboring APs. That is, no interference management/avoidance scheme is adopted during channel allocation. These two cases stand for two extremes - no interference and random interference.

In our validation, we examine the performance degradation induced by interference for every home network. As the modeled scenario focuses on the video delivery, capacity sharing will commonly occur at the APs whereas the interference will primarily affect the clients. This is due to the contention caused by the 802.11 CSMA/CA protocol. It occurs when a home hub is able to perceive signals coming from neighboring home hubs that operate on the same channel. Furthermore, the clients will also be affected by the interference from neighboring home hubs operating on the same or overlapping channels.

The modeling assumes saturated downlink traffic in a peak hour scenario, but can be extended to other traffic mixes for a given traffic-demand correlation matrix. This simulation method is generic in nature and can be mapped to any service or scenario.

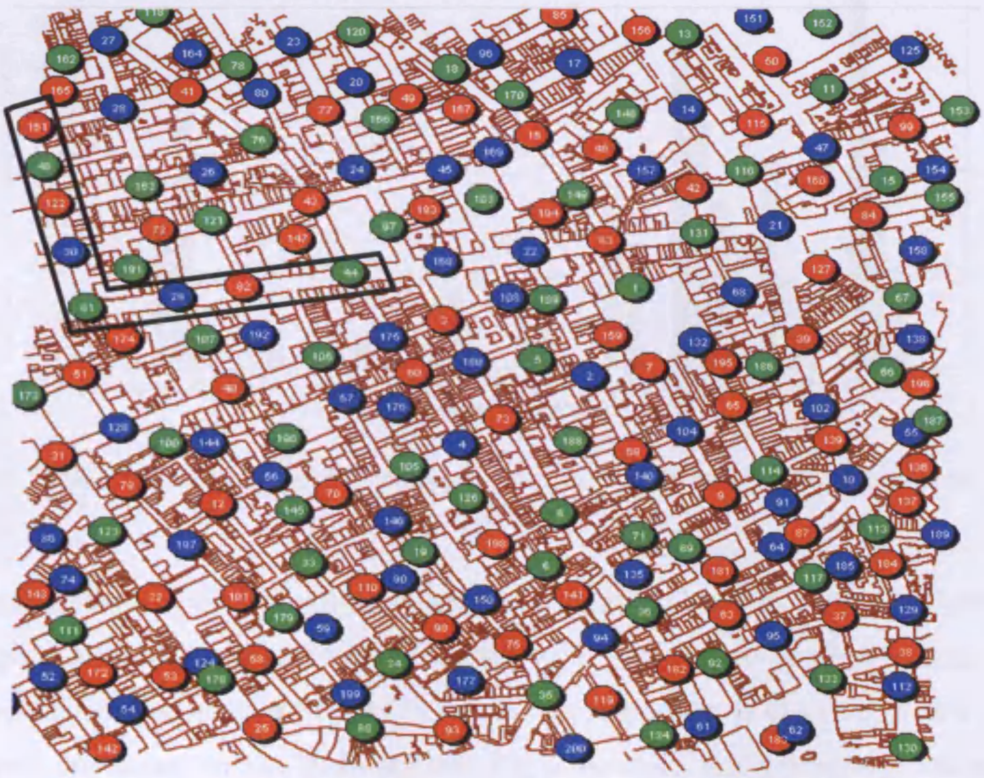

FIGURE 6.2: An instance of channel assignment generated by SACA algorithm

Figure 6.2 shows the channel assignment obtained by running SACA algorithm. APs with different colors represent different channels assigned to them. It is not straightforward to conclude whether this is an optimal channel assignment or not. But it can be seen that the algorithm takes into account of the interference restriction when allocating channels to APs. Take APs No. 161, 48, 122, 30

81, 29, 82 and 44 for example (framed region). APs along the same street are using different channels to avoid co-channel interference. Signal degradation in this residential area is mainly caused by propagation through walls and floors. Therefore, even if two APs are closely located (in term of distance) to each other, they can still use the same channel so long as they are separated by walls or floors. Propagation loss profile is one of the key measurements provided by BT, which is used as an input of the validation for the proposed algorithms.

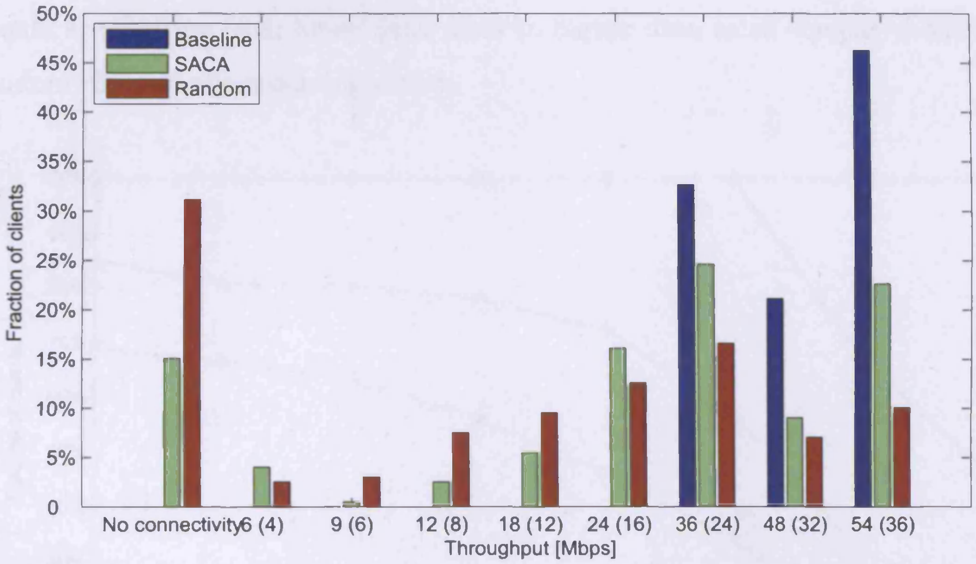

FIGURE 6.3: Histogram of throughput performance for various algorithms using 802.11g

Figure 6.3 shows the histogram of user throughput achieved by employing various channel allocation algorithms. The x-axis values denote the average throughput rates that can be achieved by the clients and is referred to as link-rate. The x-axis offsets are based on the standard 802.11g rate which is a function of adaptive coding and modulation (or ultimate SINR). The values quoted in the parenthesis are obtained by considering 30% degradation due to MAC layer overheads. The y-axis denotes the percentage of clients that are expected to meet their throughput targets corresponding to the x-axis values. The "No connectivity" region on the x-axis represents the percentage of clients that are unable to achieve the minimum 802.11g data rate of 6 Mbps due to interference.

The baseline bar-plots show the average throughput performance of the clients with the absence of any interference and represent the best performance with maximum throughput using the 802.11g technology. The baseline throughput distribution is purely a reflection of the client location statistics, as it is assumed that the channel number is unlimited to the system. Other bar-plots represent the throughput performance with random and SACA channel allocation respectively with the presence of interference. One trend which can be observed is that, by using the SACA algorithm with the aim to minimize interference, a number of clients are shifting from lower data rates to higher data rates compared with the random channel allocation algorithm.

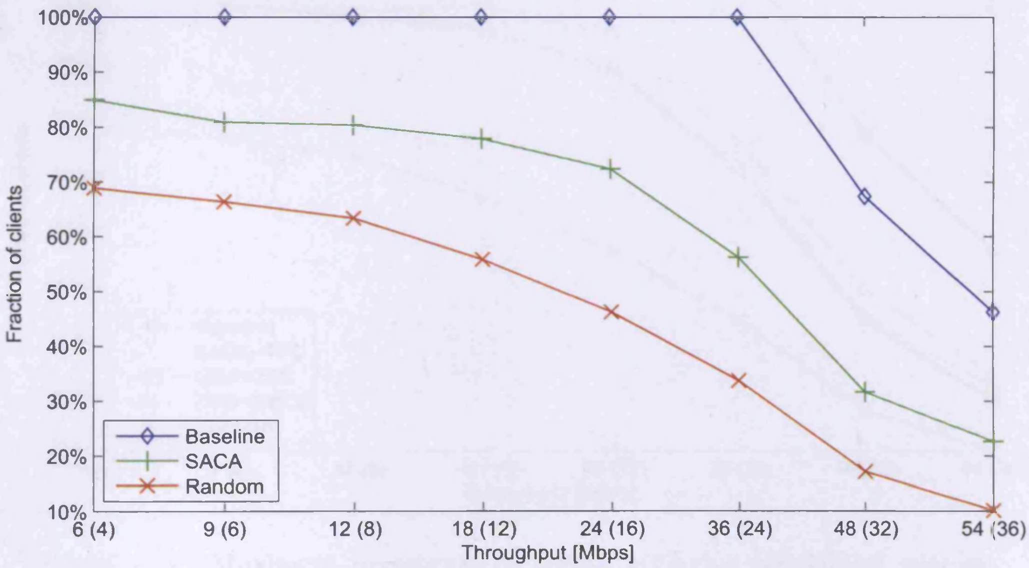

FIGURE 6.4: Complementary cumulative distribution plot showing percentage of clients exceeding pre-defined average throughput requirements

Figure 6.4 depicts the same results as Figure 6.3 in the form of complementary cumulative distribution plot. This representation helps to readily understand what percentage of the clients can meet the specific criteria. For the three different approaches, the y-axis values show the percentage of clients that can achieve or exceed throughputs corresponding to x-axis values. It can be seen that by applying SACA algorithm, the throughput performance can be improved by around 15% compared with random channel allocation scheme.

6.3.2 Joint Design of DCA and TPC

The objective of combining the DCA and TPC together is to further improve the user throughput. In this subsection, we validate the algorithms with joint design, i.e. SACA-TPC, GCA-TPC and TPC-MinCS. The performance criterion is the maximum achievable user ratio to the pre-defined user throughput target. In the following validation, each throughput target will be tested for all the algorithms and the maximum percentage of clients that can achieve their targets will be measured. Figure 6.5 presents the performance comparison among these algorithms.

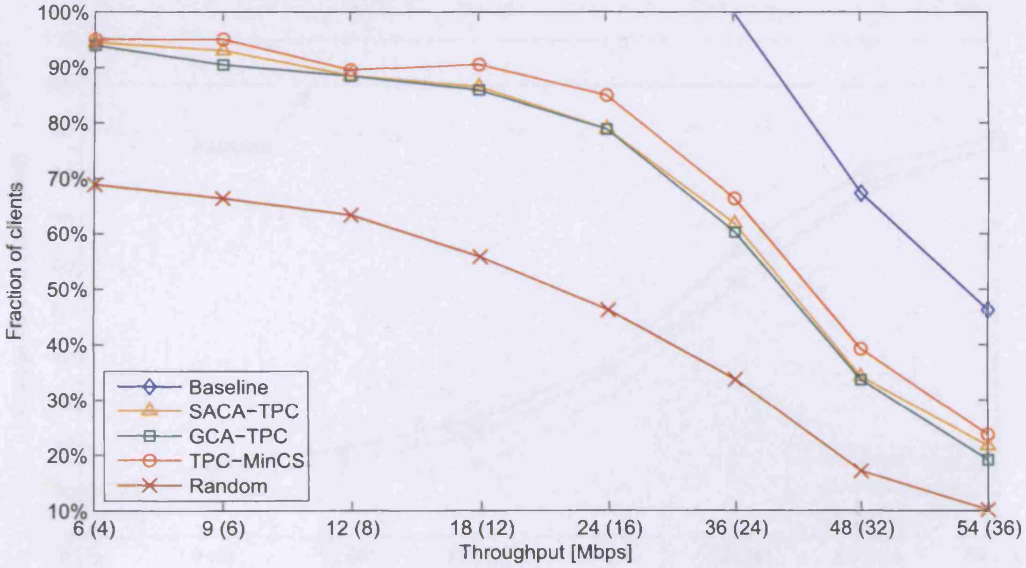

FIGURE 6.5: Maximum percentage of clients achieving pre-defined average throughput requirements

It can be seen that, compared with the throughput performance achieved by SACA algorithm, the throughput performance is further improved by applying the joint design algorithms and apparently brought closer to the baseline by around 10%.

As introduced in Chapter 5, in the joint design algorithms, in order to improve the channel access efficiency and reduce coverage overlap, power level for each AP can be adaptively adjusted by using TPC algorithm. This technique significantly reduces power consumption in the system. In what follows, we demonstrate the power consumption for all APs in each algorithm running under different throughput requirements.

Figure 6.6 shows the average power consumption for three proposed algorithms. In conjunction with Figure 6.5, it can be seen from Figure 6.6 that algorithm TPC-MinCS uses least power but achieves the best performance compared with the other two algorithms. As more and more users are added into the network, each AP boosts its power level to improve (or maintain) its users' service quality, which consequently forces others to do the same and creates a chain effect throughout the entire network.

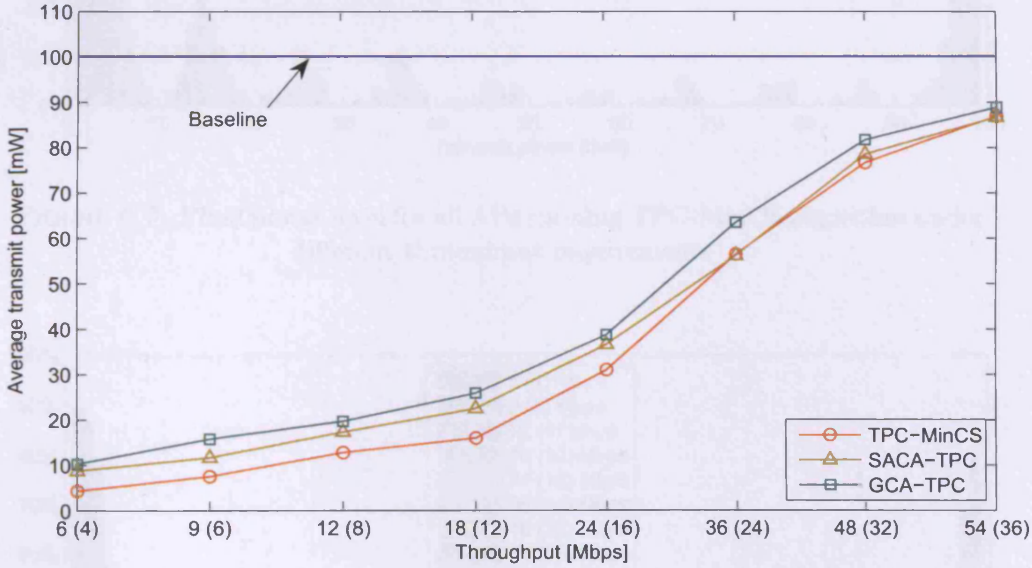

FIGURE 6.6: Average power consumption for different algorithms under different throughput requirements

Figures 6.7-6.9 show the final power distribution for all the APs running each algorithm under different throughput requirements. The power level for three algorithms is similar. They all have a trend that when the throughput target is low, the majority of APs tend to transmit using low power, but as the target increases, APs are starting to use high transmit power. This is because, when the throughput target is low, all the APs are using minimal required transmit power just to satisfy their own transmission requirements. But as the target goes up, APs have to increase the power not only to fulfill the throughput requirement, but also endeavor to compensate for the evolving interference.

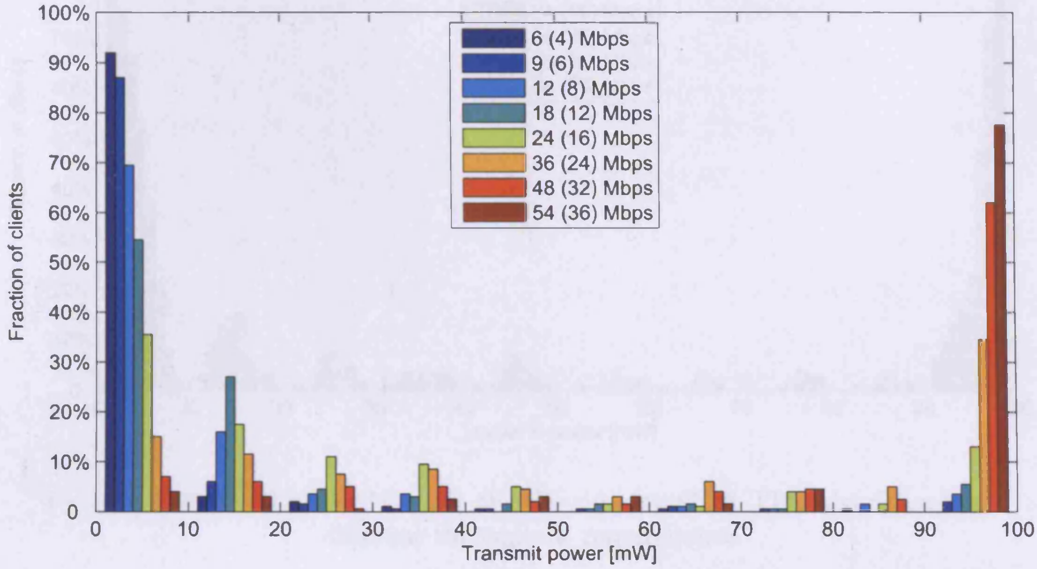

FIGURE 6.7: Final power level for all APs running TPC-MinCS algorithm under different throughput requirements

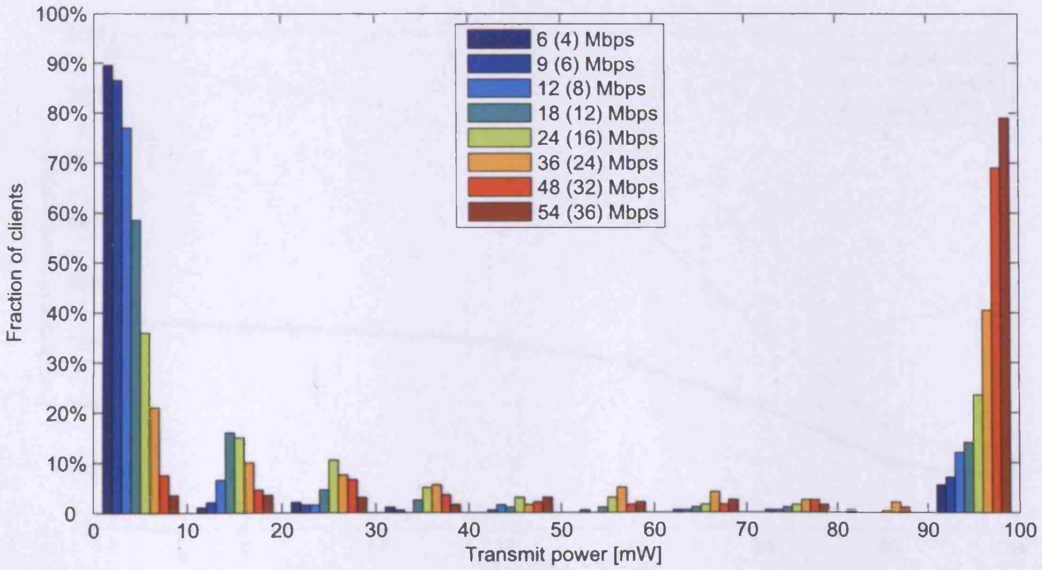

FIGURE 6.8: Final power level for all APs running SACA-TPC algorithm under different throughput requirements

In the following, we quantify and assess the power saving after adopting joint design approaches. In the conventional scheme, transmit power is fixed at their

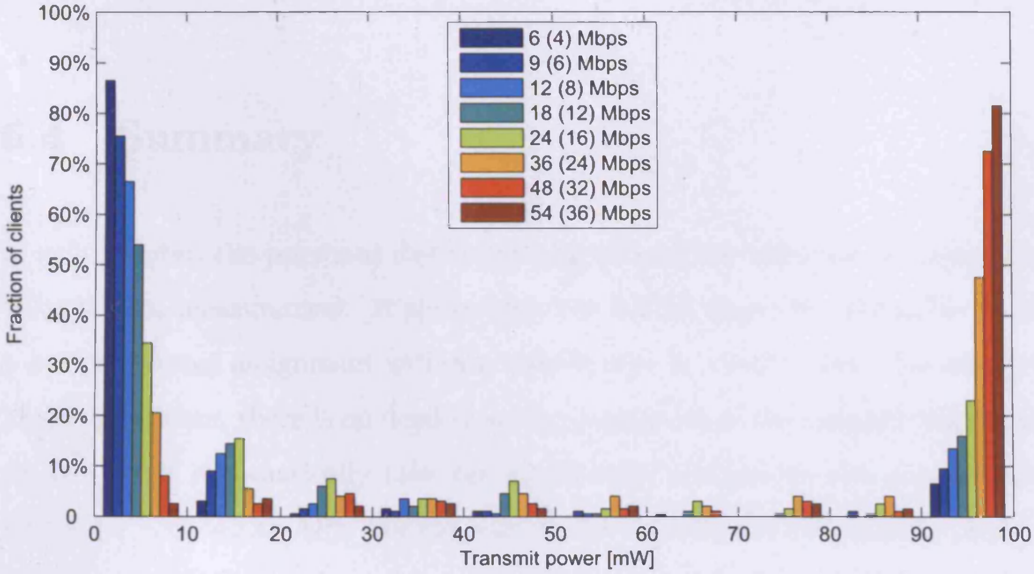

FIGURE 6.9: Final power level for all APs running GCA-TPC algorithm under different throughput requirements

maximum level, i.e. 100 mW (20 dBm). We define the percentage of power saving as $\frac{p_{max}-p_i}{p_{max}}$, where p_i is the final power level for i-th AP by using joint design.

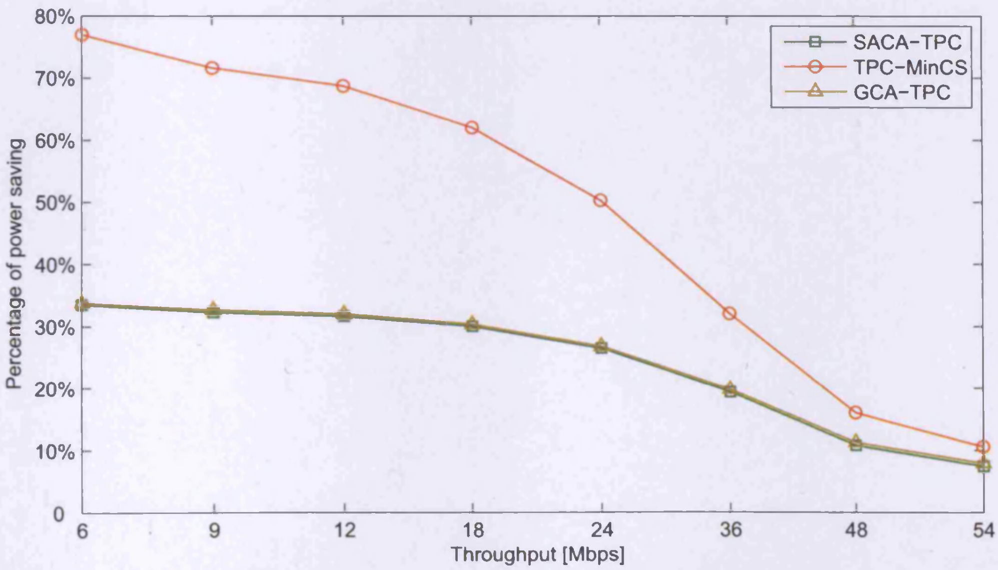

FIGURE 6.10: Power saving for different algorithms

We can see from Figure 6.10 that for all algorithms SACA-TPC, GCA-TPC and TPC-MinCS, substantial power saving can be achieved when the throughput target is low. This result is well consistent with our previous findings.

6.4 Summary

In this chapter, the proposed distributed algorithms are validated by using a real WLAN data measurement. It shows that the SACA algorithm is feasible to find a proper channel assignment with low interference in a real system. By using this SACA algorithm, there is no need to make assumption of the channel propagation model, it will automatically take the interference restrictions into account when allocating channels to APs. For the joint design algorithms, a substantial improvement in terms of user throughput and power saving is presented and compared with traditional schemes, in which channels are allocated in a random way and the power is set to the maximum level.

Chapter 7

Conclusions and Future Work

This research project has aimed the investigations on the resource allocation and optimisation problems and techniques for multiple access wireless networks. Whilst it is not possible to present the full research framework and all of the results in the current form of the thesis, this chapter concludes and highlights the major results from the project, and provides a summary of the simulation and analysis results we have obtained. Based on the achieved results and findings, we also point out some possible and useful directions for future works.

7.1 Conclusions

In this thesis, we have presented a concrete framework of using heuristic based algorithms to solve DCA and TPC problems in 802.11 HD-WLANs. To the best of our knowledge, this work has original contributions to the optimisation problems in licence-exempt wireless systems.

To solve the DCA problems with a low complexity condition, we have applied the heuristic based Genetic Algorithm and Simulated Annealing into the $\mathcal{NP}$-hard channel optimisation problem, and then proposed an algorithm with the hybrid form to combine the advantage of individual algorithms. Extensive simulations and statistical analysis have been carried out in order to evaluate the performance of each algorithm. We have found that, in general, the proposed hybrid algorithm provides a good trade-off between the convergence speed and near optimality. We also find that, Simulated Annealing appears to be the best choice to dynamically allocate channels in small networks, while for large networks, the proposed hybrid algorithm appears to be a better solution.

In the second step, the poor scalability of the centralised algorithm has been taken into consideration, and a fully distributed channel allocation scheme has been proposed to accommodate the situation that each AP in the network belongs to different service providers. The proposed algorithm is based on the distributed Simulated Annealing technique, namely Simulated Annealing channel allocation (SACA). The implementation of SACA is effective and requires no knowledge about the wireless channels. It only requires that each AP can estimate the interference it would experience in any of the selectable channels. This leads to minimum computational overheads and a simple implementation strategy. We compare the final interference values obtained by SACA with the optimal solutions using the Branch and Bound method. As the SACA delivers stochastic results, we evaluate the distribution of the results over thousands of network topologies with optimal solutions and other schemes. We have found that the minimum interference simulated by SACA is very close to the optimum solution and has the best scalability compared with other algorithms. The time complexity analysis shows that the average running time of the SACA reduces the exponential complexity to a very low level provided that 98% of the solutions are less than 5% away from the known optima.

By learning the potential to further improve the system capacity by incorporating TPC into DCA, we then investigate the joint design problem of these two techniques. We analyze the convergence property of TPC in multi-channel scenario and highlight the design criterion when considering joint design. We have followed the design criterion and develop three practical algorithms to interactively perform DCA and TPC on each AP in a distributed way. In the proposed algorithms, all APs are capable of choosing any available channels for communication to respond to the current radio propagation environment and then independently adjust their transmit power to explicitly satisfy user-devices' SINR requirements. The simulation results show that the joint design can lead to substantial throughput improvement and power saving compared to the benchmark schemes. By analyzing the simulation results, we provided key insights to the deployment of HD-WLANs, including the selection of new added APs location, operating channel and proper power level. We also have demonstrated the impact of different techniques in the network operation. We found that DCA can be used to improve the service quality of higher throughput users, while TPC is preferable to provide mid range throughput to the majority of the clients.

In the end, we have successfully validated all the distributed algorithms by using measurement data from a real WLAN in the SOHO area of London, UK. The algorithm validation confirmed the feasibility of proposed algorithms and showed the performance improvement by conducting DCA and TPC algorithms.

7.2 Future Work

Up to the results presented so far, the subject of interference mitigation is investigated by jointly implementing DCA and TPC. The user throughput instead of total interference is the objective function, with the pre-defined user SINR target and power minimization being added to the problem formulation. The joint design contains two dynamics: one is the discrete channel and the other is the continuous transmit power. Any of the APs changing the power or channel settings will affect the interference distribution in the network and cause other APs to adjust their own previous configurations accordingly to maintain the QoS. Therefore, the investigation of searching the optimal channel and power setting becomes more complex. Whether this joint design problem can be solved with low complexity remains a challenging question. Therefore, one of the possible extensions of this research is to precisely define and more importantly find the optimal channel and power configuration, such that the quality of sub-optimal solutions found by heuristics can be measured.

When analyzing the convergence property of TPC in the multi-channel scenario, we obtain the sufficient condition in terms of the feature of the propagation matrix. During the algorithm evolution, the sufficient condition is being examined to see if the algorithm will build convergence condition to the system. However, even though sometimes the sufficient condition is not satisfied, the system still can converge. Therefore, for the next step, it would be highly desirable to derive the necessary and sufficient condition for the system to converge in the multi-channel scenario. With the necessary condition, it would be helpful to adjust the algorithm parameter to ensure that the convergence property is satisfied.

In this thesis, the impact of MAC protocol on system performance has not been considered in a detailed level. The throughput degradation due to contention is counted for 30% less of the original level. If we consider the impact from MAC protocol, a statistical model has to be built to mimic the access activities from all APs and user-devices. By using this MAC model, the percentage of time that actually used for transmitting, sensing or even setting back and waiting, has to be recorded to accurately compute the system throughput.

We assume that the traffic model in the system is saturated, which means the APs always have data to be transmitted to the user-devices[1]. In addition, we also assume that the user-devices are all of the same type. However, a realistic HD-WLAN is envisaged to provide multi-media service, including data, video and voice traffic, and each service has unique traffic model. In order to guarantee the QoS of all the traffic flows running in the system, the traffic models have to be taken into consideration.

The resource allocation scheme proposed in this thesis is not limited to HD-WLAN only. All the algorithms can be extended to other systems by giving the specific channel configuration. However, for a more complicated system, such as wireless mesh networks, the management of channel allocation and power control is quite different. In mesh networks, the devices can be equipped with multiple antennas, simultaneous transmission is allowed on a single device. Therefore, channel

[1]This is a worst-case downlink interference scenario for a peak hour traffic condition, but our work can be extended to other traffic mixes for a given traffic-demand correlation matrix.

separation for a single device is one of the constraints for channel allocation and different power on each antenna should also be carefully adjusted to avoid interference. Another issue in the mesh network is the connectivity, since the transmission scheme in mesh network is multi-hop based, neighbouring devices are required to use the same channel to set up a connection. This is different compared with HD-WLANs, where communication is mainly in single hop mode. Channels tend to be different for neighbouring APs to avoid co-channel interference. Therefore, to operate DCA and TPC in wireless mesh networks is another potential research direction in the future.

Appendix A

Simulated Annealing Cooling Schedules

Below are 10 cooling schedules that have been frequently used in Simulated Annealing optimization. T_i is the temperature for iteration i, where i increases from 0 to N, N is the maximum iteration number. T_0 and T_N are initial temperature and final temperature respectively.

- cooling 1

$$T_i = T_0 - i \times \frac{T_0 - T_N}{N} \tag{A.1}$$

- cooling 2

$$T_i = T_0 \times \left(\frac{T_N}{T_0}\right)^{\frac{i}{N}} \tag{A.2}$$

- cooling 3

$$T_i = T_0 + (T_0 - T_N) \times \frac{i(N+1)}{(i+1)N} \tag{A.3}$$

- cooling 4

$$T_i = T_0 + i^{\frac{\ln(T_0 - T_N)}{\ln N}} \tag{A.4}$$

- cooling 5

$$T_i = T_N + \frac{T_0 - T_N}{1 + \exp\left(0.3\left(i - \frac{N}{2}\right)\right)} \tag{A.5}$$

- cooling 6

$$T_i = T_N + \frac{T_0 - T_N}{2} \times \left[1 + cos\left(\frac{i\pi}{N}\right)\right] \tag{A.6}$$

- cooling 7

$$T_i = T_N + \frac{T_0 - T_N}{2} \times \left[1 - \tanh\left(\frac{10i}{N} - 5\right)\right] \tag{A.7}$$

- cooling 8

$$T_i = T_N + \frac{T_0 - T_N}{\cosh\left(\frac{10i}{N}\right)} \tag{A.8}$$

- cooling 9

$$T_i = T_0 \exp\left(-i \times \frac{1}{N} \times \ln\left(\frac{T_0}{T_N}\right)\right) \tag{A.9}$$

- cooling 10

$$T_i = T_0 \exp\left(-i^2 \times \frac{1}{N^2} \times \ln\left(\frac{T_0}{T_N}\right)\right) \tag{A.10}$$

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