Self Organising Cognitive Radio Networks

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Abstract

This thesis investigates the application of learning and cognition to self organisation of ad hoc and green small cell networks in order to improve performance in terms of throughput, delay and the network energy consumption to achieve 'green communication'.

Initially, an attempt is made to improve the spatial re-use of the network by dividing it into disjoint sets of nodes through a clustering process. A novel distributed clustering algorithm is developed that exploit cognitive radio based principles in that they have the ability to learn from received signal strength indicator (RSSI) beacons, to form clusters which reduce the average distance between nodes, as well as reducing the level of overlap between clusters. By making nodes repeatedly learn about their environment through RSSI, nodes effectively compete to become a cluster head, with the winning nodes being those that are located in an area of locally high node density. It is demonstrated that the resulting cluster formation through repeated learning is better than with no learning and node degree.

The benefit of applying a hierarchical architecture to ad hoc and green small cell networks via two-hop backhauling is examined with respect to its energy efficiency. Energy efficiency is investigated in terms of the energy consumption ratio (ECR) and the energy reduction gain (ERG). The results are compared to that of a traditional single hop architecture with no hierarchical formation. It is shown that under certain conditions, dual hop clustered networks can potentially be more energy efficient that single hop transmission, but care needs to be taken to ensure that the backhaul links within the network do not become bottlenecks at high offered traffic levels.

The application of directional antennas at a Hub Base Station significantly helps to reduce the total energy consumption of the network as well the backhaul connectivity of a dual-hop clustered network. Introducing Reinforcement Learning to channel assignment on the first hop reduces end to end delay and thus minimises the amount of time and energy for the nodes in the network to be in transmission or reception mode. The reinforcement learning schemes can exploit the spectrum in which it perceives as a good option based upon individual channel historical information and thereby further improve the network spatial re-use.

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Declaration

Some of the research presented in this thesis has been published. A list of the publications is provided below

- Aizat Ramli , "Clustering Protocol for a Self-Organizing Network using RF Signal Strength*"* , *URSI(International Union for Radio Science) workshop,* Birmingham, 2009.

- Aizat Ramli and David Grace, "RF Signal Strength based Clustering Protocols for a Self-Organizing Cognitive Radio Network," in *Proceedings of the 7th International Symposium on Wireless Communication Systems (ISWCS),* pp. 228-232, 2010.

- A. Ramli and D. Grace, "Reducing Energy Consumption in Future Broadband Wireless Networks through a Hierarchical Architecture", *Mobile VCE Green Communications Workshop*, Brussels, 23 June 2011

All contributions presented in this thesis as original are as such to be the best knowledge of the author. References and acknowledges to other researchers have been given as appropriate.

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1.1 Overview

The future trend in wireless communication networks is that they are becoming more reliant on data based transmission which can be in the form of VoIP (voice over Internet Protocol), web browsing, video teleconferencing, email messaging, etc. A 2012 report by ERICSSON highlights that in 2011 the data traffic in mobile networks was more than 3 times that of voice traffic and by the end of 2017 it is expected to grow by 15 times [1]. Furthermore, the current global political agenda has made a big impact on the public perception of manmade global warming and thus is influencing government policies worldwide towards a higher funding allocation on green technologies. With the escalating price of energy bills, cellular network operators also have an interest in green technologies in order to reduce the power consumption of their networks. As a result, one of the main objectives of the next generation wireless communication systems is to greatly enhance the network capacity with higher efficiency in spectrum and energy utilization.

Despite the continuous development on advanced coding, modulation and channel assignment schemes, the current cellular system architectures are believed to be unable to cope with the future growth of wireless data demand. The added complexity of these novel techniques will also increase the energy consumption of the networks. Therefore the issue of increasing network capacity to support future demands whilst reducing the energy consumption appears to be a contradictory set of challenges.

In [2] it was pointed out that the most effective way to increase network capacity is to maximise spatial reuse which can easily be achieved by reducing propagated interference through lowering the radiated power of a node. Therefore, the transmission distance between a transmitter and receiver pair has to be reduced which would require the access points to have small coverage areas. These small cell access base stations (ABS) can be deployed en masse creating a dense high capacity network. The low power and low cost nature of these access points can potentially reduce the network energy consumption. Therefore small green cell networks (SCNs) are seen as a viable solution to next generation networks that are economical and ecological [2].

Unlike the implementations of microcells and picocells in cellular networks, SCN deployments are envisioned to be more ad hoc in nature with the lower powered ABSs installed on street lamps or in localised areas such as buildings where the number of subscribers are high. This concept negates the need for costly site acquisitions and top-down network planning design. The offloading of mobile data to femtocells, whose coverage lies in the region of 10m to 30m, can be seen as an initial step towards these unplanned green SCNs [2].

Moreover, the system capacity can be enhanced by the small cells using distributed radio resource allocation schemes and allowing spectrum utilization of each small cell to be flexible and able to adapt to different environmental conditions.

1.2 Ad hoc networks

The ability for wireless devices to establish communication link with each other in an environment where there is limited or no fixed infrastructure, such as in the aftermath of natural disasters, military missions and environmental monitoring in remote areas require different approach in designing its network compared to that of cellular network. The term ‘ad hoc networks’ has been used to describe the type of network mentioned earlier as communication can only be established among devices within range of one another, connectivity are usually temporary and devices can be added or removed from the network [3]. The dynamic of the network and the absence of established fixed infrastructure require wireless ad hoc networks creation to incorporate the ability of self-configuration/healing and organisation for reliable connections. Devices (also known as nodes) in wireless ad hoc networks not only have to receive packets but also be able to transmit and forward it. Wireless ad hoc networks can be divided into various types and can be classified according to their applications and their limitations.

One example of ad hoc networks is the wireless sensor networks (WSN). These networks comprise of hundreds to thousands of low cost sensors which have limited memory and processing capability and are required to operate for long period of time using small batteries. These sensors are typically deployed for monitoring environmental conditions by performing distributed sensing and are generally stationary after deployment. Information gathered through sensing is relayed to the destination on multi-hop basis. The limited energy supplies require the implementation of wireless sensor networks to consider the energy consumed by the sensors so that the network lifetime can be prolonged.

Wireless Mesh Networks (WMN) is another example on the type of ad hoc networks. Just as in wireless sensor networks, wireless mesh networks are generally compose of static and/or slow moving devices, can dynamically join the network and collaborate with other devices in the network acting as an end user or routers to forward packets [4]. However, WMN are not as restricted in its capabilities as WSN since WMN’s devices are powered by a relatively large battery or connected to the main power supply. WMN provides significant reduction on the installation cost for Internet access compared to IEEE 802.11 – based access point [4]. This is made possible as WMN eliminates the need for each node to have a cabled connection to the wired backhaul. Instead, the connection is achieved through a wireless multi-hop as depicted in Figure 1-1. The relatively cheap, inexpensive and self-configured nature of WMN’s nodes can therefore readily be installed to provide additional capacity (or removed) from the network across wide and densely populated geographic areas such as in stadiums and office buildings. Unlike the highly instable network topologies of mobile ad hoc networks (MANET) and the limited processing power of WSN, WMN have the capabilities to provide a higher quality of service (QOS) to the end users.

1.3 Challenges of SCNs

For realisation of SCNs to be financially feasible, the cost of operations, administration and maintenance has to be greatly reduced compared to the standard cellular network architecture. The unplanned deployment of low-powered ABS of SCNs exhibits similar limitations to that of an ad hoc network namely a wireless mesh network and thus requires self-configuration/healing and organisation capability and limited use of a centralised coordinator. Thus, the implementation of SCNs can be seen as a cross paradigm between decentralised operation such as ad hoc and sensor networks with that of a centralised cellular network.

The unplanned deployment of SCNs can give rise to high intercell interference which can be relieved by having all the cells in the network continuously cooperating and exchanging information regarding their spectrum usage. However, in order to ensure network scalability and minimise energy consumption, an individual ABS of an SCN may need to be able to autonomously and intelligently make decisions to optimise its performance. The reduction in centralised monitoring also means that it may be more difficult to identify incorrect operations, e.g. broken backhaul links.

As in ad hoc networks, a wireless self-backhauling capability can significantly reduce the total investment of SCNs. The scarcity of radio spectrum coupled with the dense deployment means that network performance can be crippled at the backhaul links. Therefore the backhaul links need to be able to support the flexible deployment feature of these small cells and provide high speed backhaul data rates by line of sight or spatially reused multi-hop relays [2].

1.4 Objective

As aforementioned, SCNs and ad hoc networks (particularly mesh networks) share similar limitations due to the total absence of or limited centralised coordination. This thesis investigates the application of a hierarchical formation of ad hoc and green small cell networks through self-organisation. Learning and cognition shall be incorporated in the Self-organisation algorithm in order to improve the network performance in terms of throughput, delay and the network energy consumption to achieve ‘green communication’.

The multi-hop relaying capability has been a topic of research for decades especially on its application to wireless ad hoc networks. One of the main benefits of the multi-hop architecture is that the transmission power can be significantly reduced as according to the Friis transmission equation, the power received at a receiver and transceiver’s distance follows an inverse square law. However, mathematical analysis by Guptar and Kumar [5] found that the multi-hop wireless ad hoc network’s per node capacity decreases rapidly with increasing network size. This is because as the number of hops between source and destination also grow larger, resources have to be shared not only with the originating traffic but also with the relaying traffic needs to be forwarded on the behalf of other nodes. This thesis shall investigate and examine on how multi-hop relays together with intelligent channel assignment schemes can be applied to SCNs and ad hoc networks such that the network total energy consumption can be reduced without significantly compromising network capacity.

1.5 System Scenario

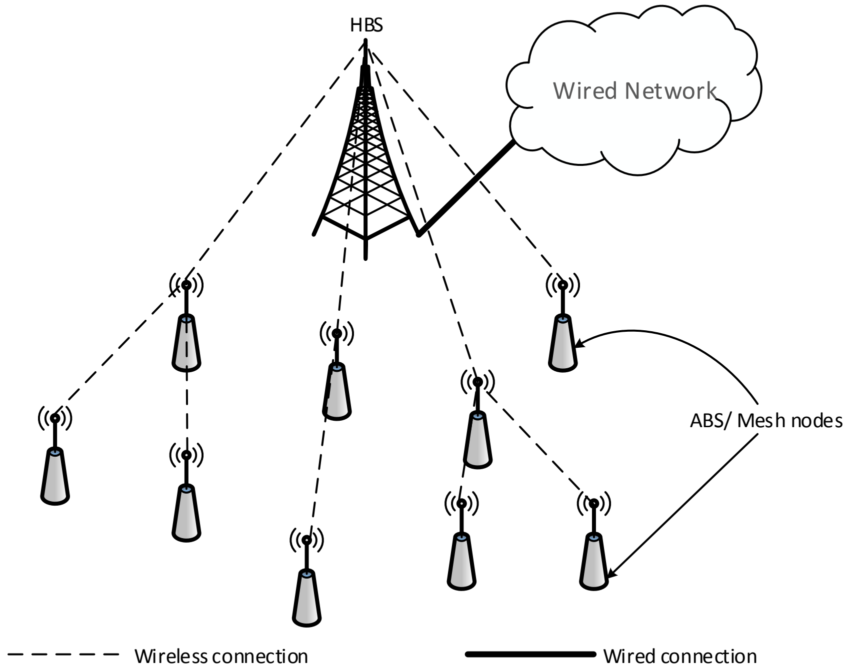

Figure 1-1: Network Architecture

The system scenario used in this work will consist of a high density deployment of Access Base Stations in SCNs or mesh nodes which each have a radio transceiver and have the capability of functioning as a router when used in wireless mesh networks. The research shall focuses on improving the efficiency of the wireless backhaul links as large portion of the energy consumption of a typical wireless cellular network is due to the base stations [6] for which 50% to 80% of the power is used by the power amplifier. As illustrated in Figure 1-1, the network will also be composed of Hub Base Stations (HBSs) which serve as a gateway connecting the backhaul links to the external and back bone network. An open spectrum scenario is considered where all the ABS or mesh nodes have equal access to the spectrum.

1.6 Thesis Outline

This thesis consists of 7 chapters; chapter 2 provides the motivation, background knowledge and literature that are related to the same area of research as this thesis. Chapter 3 starts by outlining the selection of simulation software. The modelling methodology is then presented along with a list of performance measures and verification strategy.

In chapter 4, a novel clustering algorithm which utilises RSSI (receive signal strength indicator) to enable nodes in the network to learn and ‘compete’ to become a cluster head is presented. The objective of the proposed clustering algorithm is to minimise cluster overlap and the distance between nodes to its cluster head to facilitate spatial re-use and reduce network energy consumption. To understand the merits of a hierarchical structure via clustering, network performance measures were conducted through simulation in chapter 5 to understand the behaviour of the network in terms of its energy efficiency.

To further improve the hierarchical network energy efficiency, the application of reinforcement learning on channel assignment is investigated in chapter 6. A variation of reinforcement learning algorithm is proposed to enhance the rate of exploration thereby allowing it to begin exploiting at an earlier stage.

Finally in chapter 7, a summary and conclusions of the work in this thesis are provided. Novel contributions are highlighted and lists of potential future work areas are provided.

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2.1 Introduction

In the past two decades the usage of wireless communications has been widely and rapidly expanded. Today, wireless communications are embedded in almost every aspect of people's daily life, from mobile networks to wireless broadband, from civil utilization to military applications.

With the continuously increasing number of wireless users, the usable communication channel spectrum which ranges from 9 kHz to around 300 GHz, is becoming an ever rare and expensive resource. Governing bodies such as Office of Communication (Ofcom) in the UK and the Federal Communications Communication (FCC) in the US manage and regulate the usage of radio spectrum in order to maintain a certain quality of service (QOS). This is necessary as interference can occur when radio waves are transmitted simultaneously from multiple users at the same frequency. These governing bodies divide the radio spectrum into non overlapping bands and license it to an authorised user for a certain price as shown in Figure 2-1. Licensed users or operators have the exclusive rights to use the radio frequency band under certain rules and regulations that are specified by the regulator. However, with the ever increasing demand for wireless communications, the exclusive spectrum usage to a specific users or operators has caused a shortage of spectrum. Despite this policy issue, research from both Ofcom [8] and the FCC [9] have shown that the utilization of spectrum is very inefficient due to the fact that an authorized user may not fully utilize the spectrum at all times.

In order to meet the spectrum demand of emerging wireless applications, numerous novel policies and techniques have been introduced to improve the spectrum efficiency. It is believed that the key to an efficient channel utilization scheme is the ability for an individual radio network to share or re-use the resources as efficiently as possible [8]. One domain of resource sharing that is explored in this thesis is the ability of spatial reuse through Self-organisation in decentralised networks such as Ad Hoc (specifically mesh networks) and small green cell networks.

The purpose of this chapter is to provide the challenges, novel paradigms and literature reviews which are related to this thesis. The challenges in spatial re-use in wireless networks and the concept of a Self-organising network (SON) are introduced in section 2.2 and 2.3 respectively. Under subheading 2.3, literature reviews on clustering processes which will be relevant on the formation of a hierarchical structure for wireless networks are provided. A novel paradigm known as cognitive radio will be discussed in 2.5 and finally, conclusions are drawn in section 2.6.

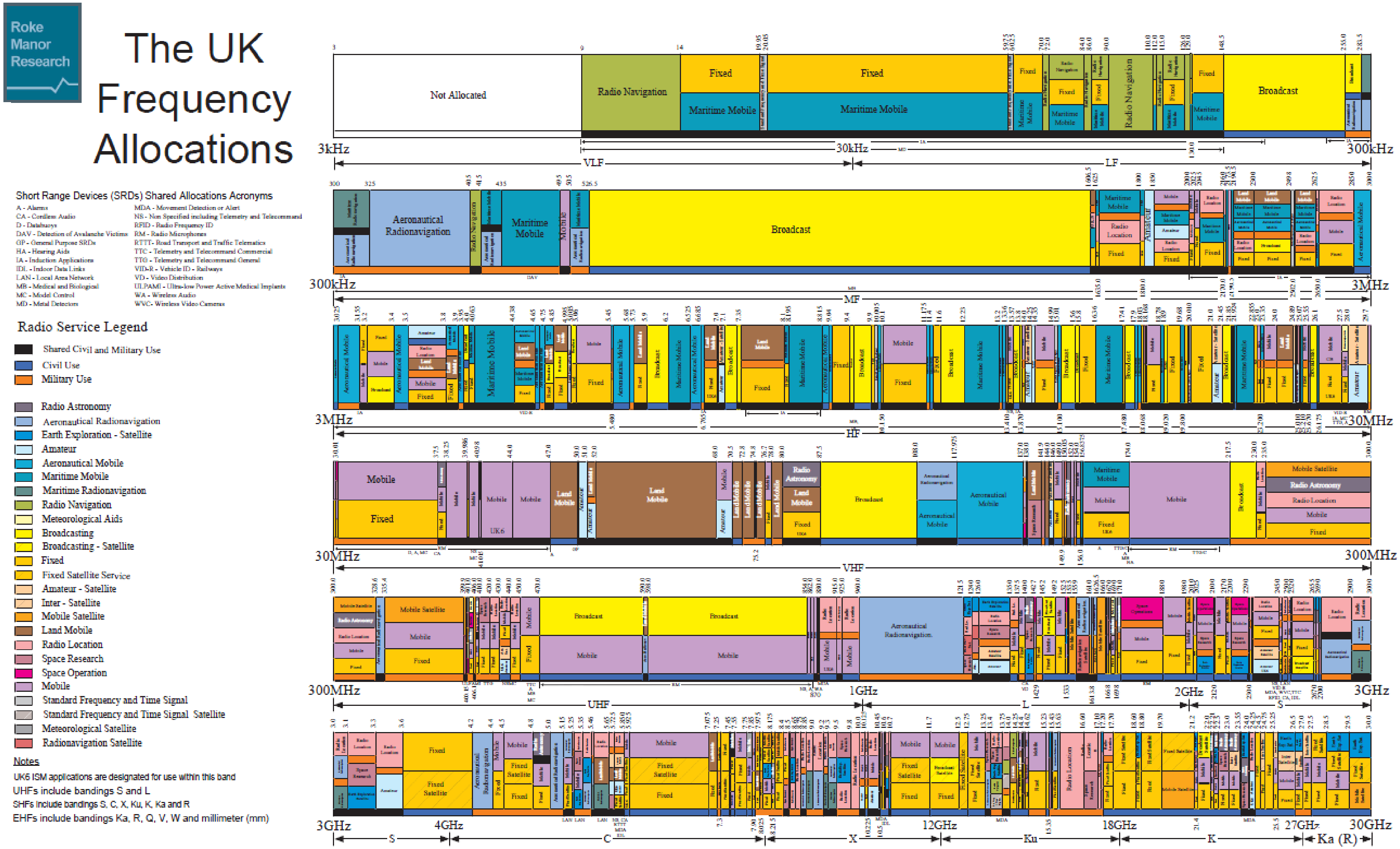

Figure 2-1 UK Frequency allocation chart. (Directly reproduced from [7])

2.2 Spatial Re-use

The main benefit of spatial reuse is the ability to reuse the same set of frequency bands simultaneously in another part of the radio network provided that there is no or little interference. This happens due to signal fading or the fact that one part of the network is shielded from other areas perhaps by obstructions such as hills or buildings. As stated in chapter 1, spatial reuse and the subsequent enhancement on the frequency reuse factor is a simple and efficient mean to improve the network capacity. As shown in Figure 2-2 , more efficient frequency reuse has enabled wireless network capacity to grow by almost 3000 times between the periods of 1950 to 2000 [2].

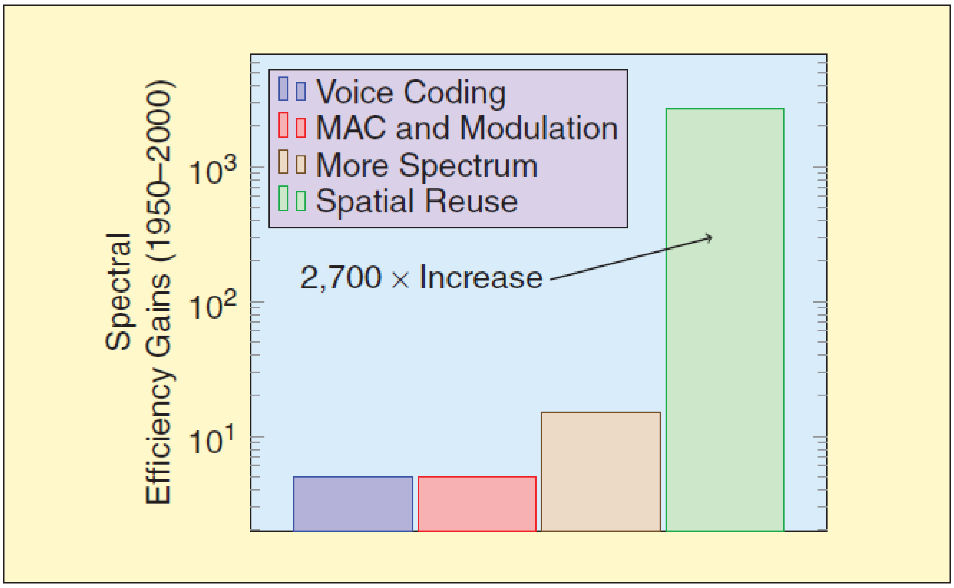

Figure 2-2: Wireless network capacity gains from 1950 to 2000 (Directly reproduced from [2])

The topology of spatial reuse has been extensively studied and utilised in the current cellular network architecture. The basic concept of a cellular system is shown in Figure 2-3, a base station is generally located in the middle of each cell and allocates channel for mobile users. An early channel assignment scheme was Fixed Channel Assignment (FCA) in which the frequency planning is based on geography and locations of base stations. The frequency allocation is then divided into assignments [10] and an assignment given to each base station. Each frequency assignment is reused at a suitable distance away from each another such that mutual interference is kept below an acceptable level.

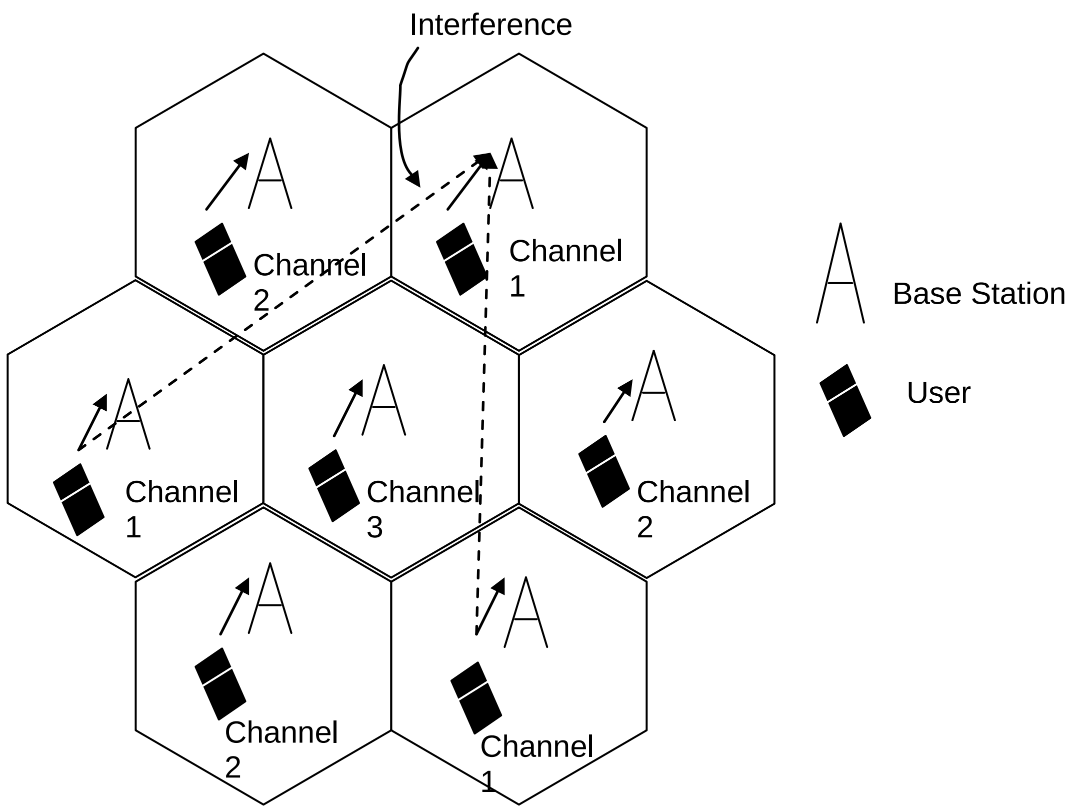

Figure 2-3: Hexagonal cell concept in cellular network architecture

The current 4G networks incorporate novel technologies, such as Orthogonal Frequency Division Multiplexing Access (OFDMA) on the downlink, Single carrier FDMA, multi layer transmission MIMO, and beam forming. The physical layer technologies as described enable 4G networks to provide high channel capacity, possibility of adaptive data rate and higher resistance to frequency selective fading compared with single carrier system. Moreover, through cooperation, the 4G base stations can dynamically alter the bandwidth allocation to its users to optimise channel quality. Reducing the cell sizes whilst increasing the number of base stations for coverage is one of the key proposals for achieving high network capacity for next generation wireless communication systems.

Orthogonal Frequency-Division Multiplexing (OFDM) is a modulation scheme in which a frequency band or a channel is divided into smaller but distinct bands known as subcarriers. The subcarriers are orthogonal to enable the receiver to distinguish the signals carried by different subcarriers. The much smaller bandwidth of each subcarrier provides immunity to inter-symbol interference and that the signals on each subcarriers experience flat fading. In OFDM, each user transmits over the entire frequency band and multiple access can be achieved by allocating different users to different time domain. OFDMA as employed in 4G and IEEE 802.11a provides a greater flexibility compared to OFDM as users can be partitioned in time and frequency domain. In 4G and beyond networks, one of the primary issues that can affect the quality of service of users is due to the inter-cell interference [11]. The quality of service experienced by a user depends upon its location within the cell. Typically, users at the edge of a cell will experience a lower data rate on the downlink due to an increase in path loss and a higher received inter-cell interference [12]. To reduce the effect of inter-cell interference caused by users at the edge of a cell, fractional frequency reuse FFR as illustrated in Figure 2-4 propose that the total available subcarriers in a cell should be divided into two groups [12]. One group of subcarriers is known as *super group* is reused by the users near the central of a cell, where as the other group known as *regular group* is reused by the users near the boundary of a cell. The *regular group* is further divided according to the cell sectors. FFR not only provide improvements on the downlink data rate of users on the cell edges but it can also improve the overall cell capacity and throughput.

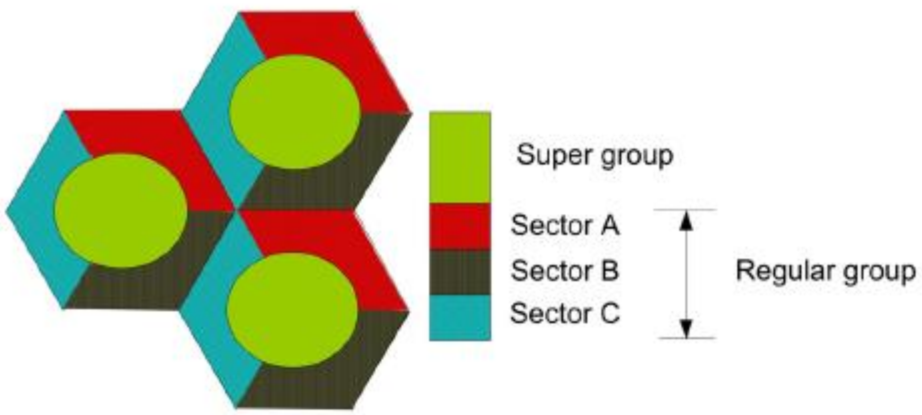

Figure 2-4: Fractional Frequency reused (FFR) (Directly reproduced from [12])

In a bottom-up network in which no pre-existing infrastructure exist such as ad hoc and sensor networks, each node participates in routing by forwarding data for other nodes (multi-hop). As pointed out by [13] this gives rise to several topological problems for the network analysis. The locations and topology patterns of a node in the network plays a significant role in the network behaviour, as it dictates how individual nodes communicate and interfere with their neighbours. Two topology structures that studied by [13] with regards to the ability of spatial re-use in multi-hop packet radio:

I. Regular topology: Nodes are uniformly positioned in the network or in a regular and repeated pattern in the network. This simplifies the analytical behaviour on the performance of the network as it can be assumed that all the nodes in the network will have similar communication capability and how it will impact the network performance.
II. Random topology: Nodes are randomly distributed in the network. In this scenario it is harder to predict the existence or the number of nodes in the area of interest within the network. However using the Poisson distribution model given in *2.1*, probability of finding *n* nodes in a region of area *A* can be predicted

$$Pr[n;A] = \frac{\lambda_a A^n}{n!} e^{-\lambda_a A} \tag{2.1}$$

Where λ_a is the density of node per unit area.

Based on their findings, [13] predictably concluded that multi-hop transmission in a regular topology has significantly higher throughput compared to a random topology. In order to optimise the network performance, nodes in the network need to limit transmission distance. They suggested that for regular networks, node transmission range should ideally be within only three neighbouring nodes, where as 6-8 nodes are needed in random topology in order to guarantee the existence of a repeater to its intended destination.

Time Division Multiple Access (Time Division Multiple Access) as employed in second generation cellular network, enables multiple users to share the same channel by allocating different time slots to each user. To increase network capacity, Spatial TDMA was developed for multi-hop environment by allowing the same time slot to be reused provided that there is a sufficient spatial separation [14]. However, the technique requires all transmissions from the nodes in the network to be synchronised to slot boundaries.

2.3 Self Organizing Networks

SCNs and An ad hoc network must be able to operate under very dynamic conditions and in most cases the network will operate with very limited centralised control thus creating an autonomous network. In a large scale network, distributed algorithms are fast becoming an area of research due their scalability and robustness.

To realise such network, the concept of self-organization protocols was introduced. In [15] self organization is defined as '*'structure with function*'', where the structure is the particular arrangement of components such that it meets common goals, i.e. functions. This definition can be applied to a wireless network provided that the network still maintains its basic communication necessity, e.g. maintains signal capacity, while achieving its functions or goals, e.g. saves energy or bandwidth usage. Self organizing networks must also be robust, i.e. be able to adapt if there is a change in the structure that causes its function to deteriorate.

Algorithms for self-organizing networks can be divided into several classes depending on the goal or the function of the network [3]. Some of the notable classes are communication, density control and clustering.

I. *Communication*: Basic functionality of the communication network and amongst earliest class of algorithms to be developed, considering the self-organizing approach, especially in ad hoc and sensor networks [16]. The problem is to create a communication infrastructure, such as the establishment of backhaul links and routes between nodes, and maintain this infrastructure in the presence of topological changes.

   Currently, there are several proposals for routing protocols focusing on both ad hoc and sensor networks, considering some self-organizing aspects due to the ad hoc nature of these networks that do not use a fixed infrastructure. Thus, routes must be discovered and maintained based on local cooperation. An example to be considered is the ad hoc on-demand distance vector algorithm (AODV) [16] that creates routes only on demand, that is, when the source nodes need them. Basically, the AODV protocol has two phases: the first one is route discovery, based on a flooding process started by the node that wants to send a message; and the second phase is route maintenance, realized by all nodes of a discovered route to update it.

II. *Density control*: In wireless sensor networks (WSN), the implementation of this network must consider the energy consumption of individual sensor nodes as they are expected to operate for a lengthy period of time without the need of frequent battery replacement.

The node transceiver consumes energy not only during transmission and reception, but also in channel listening (idle state). In general, the more expensive states, in terms of energy consumption, are transmission followed by reception. A possible strategy to save energy is to turn off the sensor radio that is in idle state. When this happens, the node is no longer capable of communicating with other nodes, thus there is one less active node changing the network topology and density.

III. *Clustering:* The objective of clustering to divide objects or data into disjoint sets of 'groups'. In wireless ad hoc and sensor network, clustering algorithms can mimic the hierarchical topology of a cellular network without the need for a fixed infrastructure. The nodes in the network are split and grouped according to their location in the network, usually with one node selected as a cluster head which is ideally located in the centre of the 'grouped' nodes. In addition to supporting network scalability and facilitating spatial reuse [17] and [18], clustering has numerous advantages. It can localize the route set up within the cluster, thus reducing the size of the routing table stored at the individual node [19]. By partitioning the network into non-overlapping clusters, an inter-cluster routing map table is stored and performed by the cluster head. This can reduce the amount of routing information propagated in the network [19]. In intra-cluster routing, ordinary nodes send packets to their cluster head and forward them to a gateway node to be delivered to other clusters. As illustrated in Figure 2-5, only cluster heads and/or gateways nodes participate in the propagation of routing control/update messages. In dense networks this significantly reduces the routing overhead, thus solving scalability problems for routing algorithms in a large ad hoc network [20], [21].

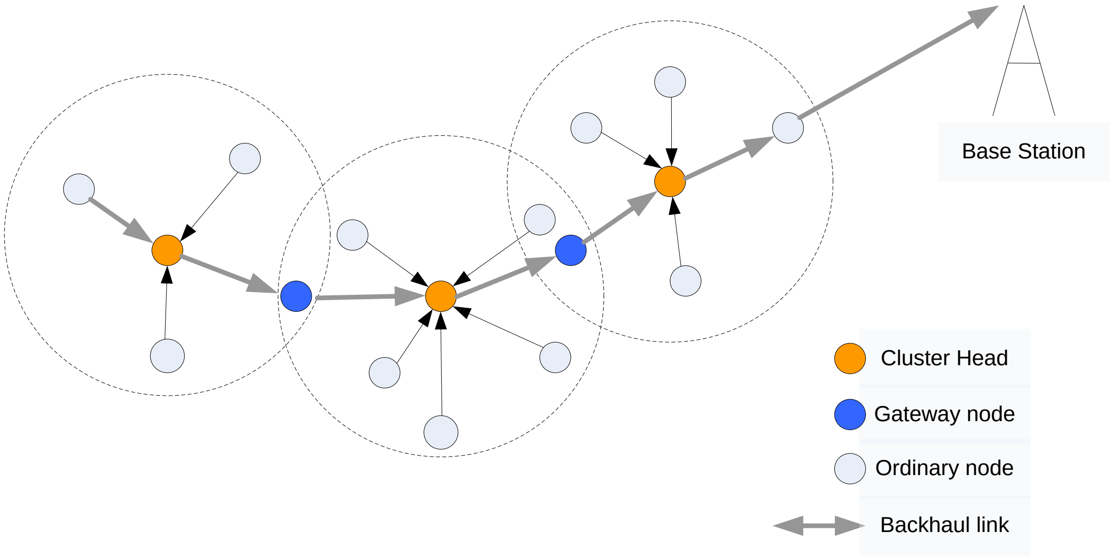

Figure 2-5: Relaying messages in clustered network

2.4 Clustering strategies – Literature Review

Generally, the process of clustering a network is performed by selecting potential nodes within the network to become a cluster head. Nodes elected as a cluster head will broadcast their status to other nodes in the network. Each node determines which cluster they want to belong to by typically choosing the cluster heads that require the minimum communication energy [20]. Any nodes in the network can become a cluster head provided they have enough power and processing capability. Choosing a cluster head optimally is an *NP*-hard problem [22]. Broadly speaking, cluster head selection strategies can be divided into two categories; heuristic and weight based.

In a heuristic algorithm, nodes selected as cluster heads change periodically to maximise the purpose of clustering. The main issue with heuristic techniques is that the frequent change in cluster-head also requires frequent information exchange amongst nodes, thus resulting in high computation overhead. In a weighted based algorithm, cluster head nodes are selected based upon certain merits. The purpose of a weighted clustering algorithm is to preserve the topology when the first batch of cluster heads was elected. The problem with this technique is that there is a possibility that a non-ideal node was selected to become a cluster head.

The implementation of clustering in an ad hoc network does not necessarily require the selection of a cluster head node. This type of algorithm divides the network into a set of clusters, each of which contains a certain number nodes. The clusters are only a logical arrangement of the nodes in the network. The nodes are organised into a cluster such that the distance between any two nodes in the cluster is at most a certain number of hops away. The advantages of not having a cluster head is that the tasks of cluster administration such as forwarding of data packets and communication scheduling are shared by all the nodes in the cluster. This distributes the energy consumption that would otherwise be required by a single node elected as a cluster head. However, clustering a network without a cluster head can potentially be more complex to implement and it is shown in [18], that for large scale ad hoc networks, a cluster head based scheme outperforms a non-cluster head based schemes in terms of reducing the traffic overhead.

2.4.1 Clustering Algorithms in Wireless Networks

Clustering is an effective means for managing high populations of nodes. Often the clustering objective for a wireless network is set in order to facilitate meeting the applications requirements. In this section some of the merits and disadvantages of several proposed clustering protocols for wireless networks shall be discussed according to their objectives.

a. Maximising network lifetime in sensor networks through load balancing

LEACH is one of the first topological hierarchal techniques to be implemented in wireless sensor networks [20], [21]. Energy consumption in wireless systems is directly proportional to the distance, single hop communication is expensive in terms of energy consumption. However, provided that transmission distance is short and/or the radio electronics is high, direct transmission energy is more energy-efficient on a global scale than minimum transmission energy (MTE) routing protocol. LEACH protocol uses only two layers for communication. One is for communication within the clusters and the other is between the cluster heads and sink. Given the duties, a cluster head consumes significantly more energy than a normal node. In order to spread this energy usage over multiple nodes, the role of being a cluster head is rotated periodically among the nodes of the cluster in order to balance the load. LEACH forms clusters by using a distributed algorithm, where nodes make autonomous decisions without any centralised control. Initially a node decides to be a cluster head with a probability p and broadcasts its decision via an advertisement message. Clusters are formed depending upon the signal strength of the advertisement message each node receives. Nodes will go for the one which has the strongest signal. The role of the cluster head is then rotated periodically by getting each node to choose a random number ‘‘T’’ between 0 and 1. A node that has not become a cluster head for the previous round can become a cluster head for the current round if the number is less than the following threshold:

$$T(n) = \frac{p}{1 - p(o \; mod \frac{1}{p})} \qquad 2.2$$

Where p is the desired percentage of cluster head nodes in the sensor population, o is the current round number. According to LEACH [20], simulation shows that LEACH performs over a factor of 7 reductions in energy dissipation compared to the power aware routing protocols. The problem with the LEACH protocol lies in the random selection of cluster heads and that LEACH uses one hop intra- and inter cluster topology where each node transmits directly to the Cluster head and thereafter to the base-station. Therefore there is a possibility that the selection of cluster heads is unbalanced and they may be in some unreachable parts of the network unreachable.

An extension of the LEACH protocol uses a centralised cluster formation algorithm for the formation of the clusters [21]. The algorithm execution starts from the base station where the base station first receives all the information about each node regarding their location and energy level and then it runs the algorithm for the formation of cluster heads and clusters. Here also the number of cluster heads is limited and selection of the cluster heads is also random but the base station makes sure that a node with less energy does not become a cluster head. The problem with LEACH-C is that it is not feasible for larger networks because the nodes which are far away from the base station will have difficulty in sending their status and may not reach the base station in time.

HEED (Hybrid Energy-Efficient Distributed clustering) [23] is a distributed clustering algorithm scheme. Cluster heads are elected according to a hybrid of their residual energy and a secondary parameter, such as node proximity to its neighbours or node degree. In the initial stage of the algorithm, all nodes in the network are given a percentage value, *Cprob*, which is used to limit the number of cluster heads. Each node then calculates their probability to become a cluster head, *CHprob*, as follows:

$$CHprob = Cprob\frac{Eresidual}{Emax} \tag{2.3}$$

Where *Eresidual* is the current energy in the sensor, and *Emax* is the maximum energy, which corresponds to a fully charged battery.

After the first batch of cluster heads is generated, the algorithm goes through a *repetition phase*. In this phase every node (including the cluster head node) finds the Cluster head that it can transmit to with the least transmission power. If no cluster head are within the node transmission range, it elects itself to become the cluster head and sends an announcement message to its neighbours, informing them about the change of status. At each cycle of the algorithm, a cluster head nodes double its *CHprob* value. A cluster head is called a tentative cluster head if its *CHprob* value is less than 1. It can change its status to a regular node at a later cycle if it finds a cluster within its transmission. However, a node permanently becomes a cluster head if its *CHprob* has reached 1. HEED has several advantages over LEACH in that it forms a set if cluster head that are more evenly distributed in the network and that energy consumption is not assumed to be uniform for all the nodes.

b. Facilitates Spatial reuse

As mentioned before, clustering a network can facilitate spatial reuse. However if a network is poorly clustered, i.e. a network is not completely covered by clusters or there is high degree of overlapping clusters then the benefit of clustering for spatial reuse is significantly reduced.

In clustering with less overlap, the number of repeated broadcast transmissions over any area will be small, thus reducing the amount of transmission collisions and channel contention, allowing communications to become faster, more efficient and more reliable.

ACE (Algorithm for cluster establishment) [24] is an emergent algorithm that minimises overlapping clusters and the clusters generated can provide full coverage to the network in time proportional to the deployment density of the nodes. The algorithm consists of two parts, spawning a new cluster and migration of existing clusters. An un-clustered node will decide to become a cluster head provided it can find a certain number of loyal followers. A loyal follower is a follower of only one cluster. The new cluster head broadcasts an invitation message to recruit its neighbours. Upon getting the invitation, a neighbouring node joins the new cluster and becomes a follower of the new cluster head. During the process of clustering, some nodes are within the range of more than one cluster. Each cluster head periodically checks its cluster member if they have higher number of loyal followers. If any of its cluster members has a higher loyal follower, then the current cluster head will terminate and a node that has the largest number of loyal followers will become the new cluster head. This process of electing a cluster head by the former cluster head is called migration. The overall effect would appear as clusters are applying a repulsive force to spread out and reduce their overlap. Figure 2-6, which is taken from [24], shows the progression of the ACE algorithm after 3-iterations and compares ACE to a simple node-ID based scheme. Some of the weaknesses of ACE are pointed out by [25], the main criticism is that the threshold function is used in ACE to control the formation of new clusters uses two manually adjusted parameters. ACE's performance relies on these parameters which are usually manually adjusted according to the size and shape of a sensor network.

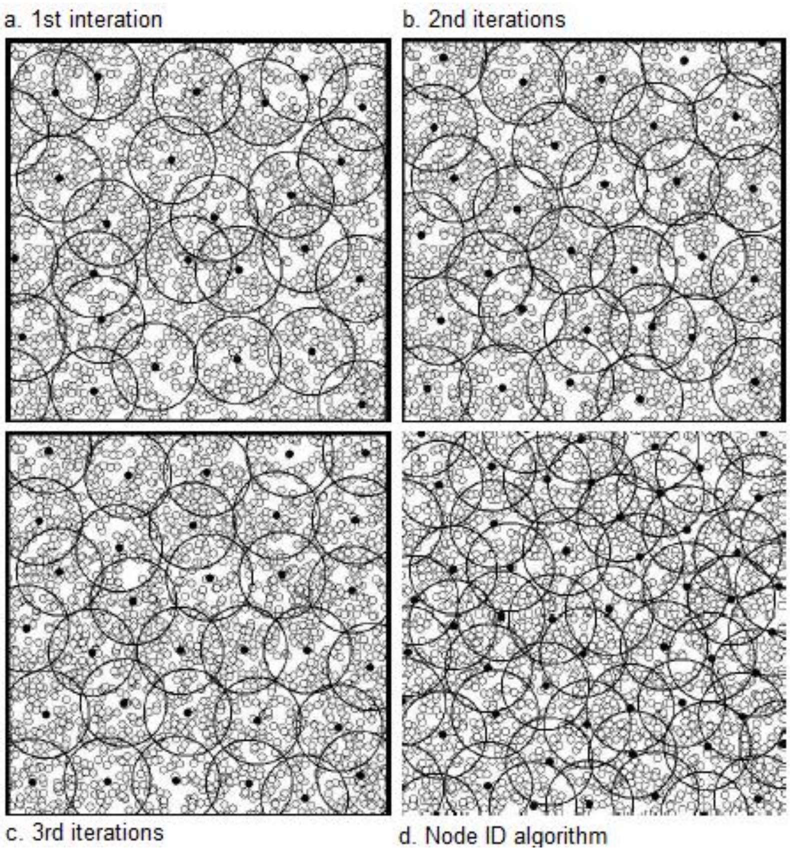

Figure 2-6: Illustration of ACE algorithm after 3 iterations as compared to node ID algorithm (reproduced from [24])

In [25], they argued that minimising the number of cluster heads would not only provide an efficient cover for the whole network but it would also minimize the cluster overlaps. This reduces the amount of channel contention between clusters, and also improves the efficiency of algorithms that executes at the level of the cluster-heads. In the initial stage of the algorithm, a node which has the maximum number of neighbouring nodes is selected as a cluster head by a central coordinator. When the cluster is formed, each cluster member finds neighbouring un-clustered nodes within its transmission range. A node with the highest number of followers that can communicate to the respective clustered node is selected to become the cluster head. This process is repeated until the entire network is clustered. The algorithm requires nodes to count the number of its neighbour by a unique Identification Number (ID). The node has to count the number of its neighbours by exchanging IDs one by one without collision. [25] Reports that the required number of clusters at a various communication distance (30m -100m) to cover the network of randomly deployed 2500 and 5000 nodes are reduced by an average of 11% to 12% compared to ACE. The main drawback of this algorithm is that the process of finding a node with the highest number of followers requires high overhead. Each node has to compare the number of its followers with all neighbouring node.

Clustering processes are often employed in data mining in order to discover pattern in large data sets. They are used to organise and separate large set of data into clusters in such a way that the data belonging to a particular cluster are more identical than that of other clusters. One of the simple and widely used clustering algorithms in statistical analysis is the *k-means* [26]. Assuming a Euclidian sample space, *k-means* attempts to minimise the intra-cluster distance whilst maximising inter-cluster distance. This is achieved through iteratively re-calculating and minimising the distance between the data with its centroid .The objective function of *k-means* is given below

$$arg\,min \sum_{j=1}^{n_{ch}} \sum_{i=1} \left\| x_i - y_j \right\|^2 \qquad 2.4$$

Where n_{ch} is the number of clusters, $\left\| \mathrm{x_i} - \mathrm{y_j} \right\|^2$ is a distance between a data point x_i and its centroid y_j.

The steps of *k-means* are as follows:

1. Randomly position n_{ch} points (initial centroids) within the sample space.
2. Determine each data nearest centroids and assign this data to that group (cluster).
3. For each group, calculate the new centroid position through averaging the coordinates off all the data in the group.
4. Repeat step 2 and 3 until the centroids no longer change position

The simplicity of the *k-means* algorithm enables it to be implemented in wireless network to form clusters as a means of increasing spatial reuse with nodes nearest to the calculated centroid elected as a cluster head. However, applying *k-means* to wireless network would require a central coordinator to determine and calculate the positions of centroids.

c. Establishing and facilitating network communication

Unlike [25] and [26], the authors of [27] argued that that allowing some degree of cluster overlaps overlap can facilitate applications, such as inter-cluster routing through gateway, network discovery, node localisation as well as being more robust towards cluster head failure. [27] propose a randomised distributed Multi-hop Overlapping Clustering (MOCA) for wireless sensor networks. The objective of their algorithm is for each node to either becomes a cluster head or at least a within *k* hops away to the nearest cluster head. To execute the proposed algorithm, nodes do not need to be aware of their geographical position therefore mitigating the need to be equipped with GPS. At the start of the algorithm, all the nodes in the network are assumed to have a probability *p* to become a cluster head. A node that decides to become a cluster head will make an advertisement broadcast to other nodes that are within its radio range. Through flooding, the advertisement is forwarded to all other nodes that are within *k* hops away from the cluster heads. All the nodes that receive the advertisement will update its cluster head table and send a request to the respective cluster head in order to become a cluster member.

A node will elect itself as a boundary node (also known as gateway node) if its cluster head table contain more than one cluster head ID. Each cluster head has a list of its cluster members and the number of hops required to reach to neighbouring clusters through boundary nodes. A node can also becomes a cluster head in the event that it does not receive an advertisement from a cluster head after a certain period of time. Their results suggest that the initial probability *p* has little or no impact on the average overlapping degree.

In Max-Min D [28] cluster, the authors propose a heuristic based distributed clustering algorithm to guarantee that a node is at most *k* hops away from a cluster head. The algorithm is designed assuming that the nodes in the network are subjected to constant topological changes due to node mobility i.e. mobile ad hoc network. Cluster heads provide a communication route for nodes in their cluster. Therefore, one of the objectives of Max-Min D cluster is to re-elect existing cluster heads when possible, thereby maintaining network connectivity and reduce communication overheads. The selection of cluster heads selection process is based on their node ID rather than degree of connectivity as well as requiring $2k$ round of flooding. The 1^{st} *k* round of flooding is to broadcast largest node IDs. The 2^{nd} *k* round propagates the ID that exist at each node after the completion of 1^{st} *k*-round. After the completion of 2^{nd} *k*-round, a node will become a cluster head if it has received its original ID. Remaining non-cluster head nodes will elect nodes in which their ID occurs at least once during the 1^{st} and 2^{nd} *k* round of flooding. If such nodes are not found, the maximum node ID in the 1^{st} round will be elected as a cluster head. Once cluster heads selection process has been completed, each node will determine if it is gateway node by broadcasting its elected cluster head to its neighbours. A node will become a gateway node if its neighbour's cluster head selections are different to itself.

Facility location problem

Facility location problem is branch of operations research which seeks to optimise the geographical placements of new facilities to provide a form of service such that the desired objectives can be maximised or minimised. An example of facility location problem is the placement of fire stations in a city whose objectives are to provide a good coverage (distance) of the city as well as being close to hot spot areas. Clustering algorithms which partition the network on a plane can be viewed in a context of a facility location problem [29], [30].

In [30], the authors developed a distributed facility location algorithm for wireless sensor network to self- organise the network consisting of servers or client nodes. In clustering terminology, servers and client nodes corresponds to cluster heads and cluster members respectively. Each server incurs an additional cost for establishing connections to the client nodes in order to provide services as forwarding traffic. Each client has a communication cost that is proportional to the distance to its associated server. The goal of their distributed algorithms is to optimise the overall cost of the connections between servers and client nodes. They proposed a separate distributed optimisation algorithms for one hop and multi-hop connections. In both instances, nodes eligible to become a server can be selected beforehand based on its capabilities such as processing power, remaining energy level or communication bandwidth. In the algorithms, an unconnected client can also be elected as a server if it has the lowest cost efficiency number compared to the remaining unconnected clients. The cost efficiency *c* is defined as:

$$c = (f_c + \sum_{i=0}^{B} cx_i)/|B| \tag{2.5}$$

Where f_c is the opening cost of a server, *B* is the number of clients establishing connections with the server and *cx* is the connection cost of a client to the server.

Just as in clustering, the optimisation of facility location problem is *NP*-hard. Approximation algorithms that complete in polynomial time are often employed to provide approximation solutions for optimising *NP*-hard problems. In [31], the authors investigated the approximation solution to the facility location problem in a distributed setting. They proposed algorithms that are able to achieve an approximation solution with a time complexity that is dependent on communication rounds *k*. The goal of the algorithms is to open new facilities and having each client to establish connections to a facility such that it minimises the sum of connections and facilities opening costs. Facilities and clients execute two different algorithms. The basic idea of the facility algorithm is for each facility to increase its variable y_i during the iteration so that clients are more likely to establish connections with a facility a with good cost efficiency. The cost efficiency is calculated based on (*2.5*).

However, the distributed algorithms proposed by [30] require an initial neighbour discovery process so that each client can assess connection cost to all servers. The algorithms proposed by [31] require nodes to constantly update its neighbour in every communication step and therefore incurs high communication overhead and increase power consumption.

2.5 Cognitive Radio

The inefficient usage of the existing spectrum can be improved through opportunistic access to the licensed bands without interfering with existing users. A cognitive radio technique which was introduced in [32] has been considered as a potential solution for such task. Cognitive Radio is an evolution of the Software Defined Radio paradigm. Technologies and concepts employed in Software Defined Radio enable cognitive radio to adjust the configurations and parameters of its transceiver to adapt to various communication requirements. There are three core requirements for cognitive radio devices: observe, decide and act [33], [34].

A cognitive radio is defined by [35] as *'a radio that is aware of and can sense its environment, learn from its environment and adjust its operation according to some objective function'*. The cognitive radio definition utilizes and build upon the concept of the spectrum hole [33] defined as '*a band of frequencies assigned to a primary user (licensed user), but, at a particular time and specific geographic location, the band is not being utilized by that user*'. The efficient use of the spectrum will be promoted by exploiting the spectrum holes. If the spectrum hole is requested by a primary user, the cognitive user will move to another spectrum hole or stay in the same band, changing their transmit parameters to avoid interference.

Spectrum awareness provides the opportunity to fundamentally change the way governing bodies and wireless network operators manage the radio spectrum. Through this capability, a cognitive radio user can make a decision to dynamically alter its operating parameters such as transmit power, carrier frequency, modulation, to acclimatise itself with the environment whenever there is a statistical change in the incoming radio frequency with the sole purpose to take advantage of the available spectrum.

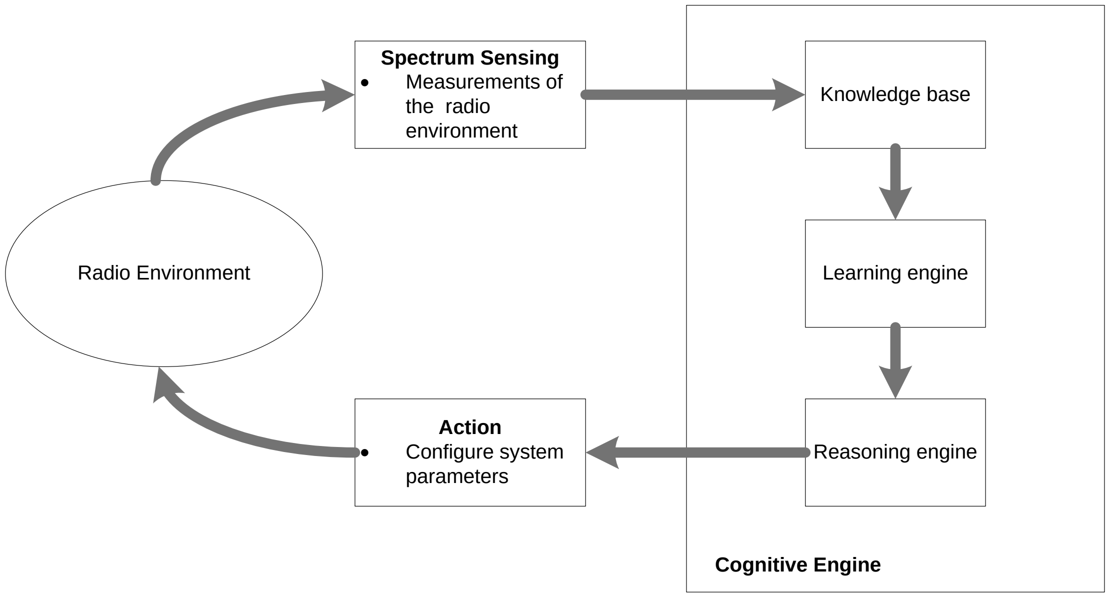

Figure 2-7: Cognitive Radio Cycle

Figure 2-7 illustrates the main components of a cognitive radio. The purpose of spectrum sensing is to observe and collect information regarding the radio environment. The information obtained from spectrum sensing is passed to the cognitive engine. The cognitive engine is the primary component in which cognitive radio can be termed ‘intelligent’. The historical information about the environment is stored in the knowledge base. The learning engine deciphers the historical information through classification and organisation of the information such that the reasoning engine can decide upon the course of actions to optimise its desired objective, for example increasing spectral efficiency thorough appropriate channel selection. Once a decision has been made by the cognitive engine, the appropriate parameters are configured by the system based upon the settings set by the cognitive engine. The consequences of the actions made by the cognitive engine will be observed by the spectrum sensing and the whole process is repeated.

The work in this thesis will particularly focus on the means in which the cognition aspect of a cognitive radio can improve the self organisation ability of ad hoc and green small cell networks.

2.6 Conclusion

This chapter has presented important background information and a literature review that are closely related to the work in this thesis. Firstly, background knowledge of current spectrum management policies and techniques have been reviewed, which indicates the potential issues that cause spectrum scarcity. The importance of spatial reuse and how efficient self organisation in wireless communications can optimise the network performance were addressed. Afterwards, the concept self organising networks concept is defined and several classes of its makeup are discussed. In addition, a comprehensive review on the clustering algorithms. As the essential part of this thesis, the background theory of cognitive radio has been particularly discussed regarding to the issues of functionality, learning algorithm, and the importance of decision making. The balance between data rate and energy consumption in this type network will be explored later in the thesis.

Chapter 3 Performance Modelling and Evaluation Techniques

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3.1 Introduction

In order to understand and analyse the novel proposed approaches, performance evaluation is needed to quantify the degree of improvement over existing approaches. Such performance evaluations can either be conducted via experiments or through system modelling by mathematical analysis and computer simulation [10]. The experimental approach incurs a high cost due to the need for the design and manufacturing of hardware prototypes as well as being a time consuming process since a large data size is required in order to have a representative sample of a real world scenarios. Due to the availability of financial support and the time constraints, the performance evaluation implemented in this research will not include any field experiments.

The complexity of a current and future wireless communication network coupled with the real world environment makes it ever harder to model its behaviour through mathematical descriptions only. However, the rapid pace of the development of computing processing speed and the availability of sophisticated programming software has made it possible for a detailed description of a real world communication environment to be programmed and simulated on a personal computer (PC). The relative ease in which simulation models can be modified to accommodate various modelling scenarios and novel approaches makes it a more attractive method for performance evaluation of cognitive radios than a purely mathematical descriptive method. Therefore, computer simulations have been adopted as a primary method in order to conduct the research and evaluate the proposed novel approaches.

The purpose of this chapter is to provide an overview on the modelling and performance evaluation techniques which have been applied to the reminder of this thesis. Firstly this chapter addresses the selection of the software available to conduct the research. A general framework of the system modelling using simulation is discussed in section 3.3. Afterwards, the relevant simulation parameters and performance evaluations criteria are provided. In order to verify the simulations, the resulting performances are compared with a well known closed-form analytical expressions to describe the behaviour of a relative simple communication network in section 3.5. At the end of the chapter a brief conclusion is drawn.

3.2 Simulation Software

There are numerous programming languages and software available for radio engineers to analyse the performance of a radio network at various OSI (Open System Interconnection) layers. Although most of these programming languages are able to simulate cross layer design, each has its particular advantages and limitations.

One of the most widely used programming languages is ‘C’ which was developed in the 1970s. The relatively straightforward process in which ‘C’ programming source codes are compiled and converted into binary executables makes executing codes very efficient with very low run-time[1]. Simulations of a detailed radio network environment will require manipulation of large data sets which is easily achieved through grouping the data set into an array or matrix form. In ‘C’ programming, users

[1] Run-time is the amount of time required for a computer program to be executed

will need to write unnecessary lines of codes or functions to perform a matrix arithmetic compared to a high level programming language.

MATLAB is commercially available software developed by MATHWORKS Inc. It is an example of a high level programming language known as an interpreted language. Unlike ‘C’ programming, the source code in MATLAB is converted into binary executables one line at a time in a sequence and thus has a much higher run-time. The main advantage of MATLAB is that code development and debugging time can be significantly reduced compared to ‘C’ and a program can be written more easily and shorter length[36], [37].

The research as presented in this thesis will focus mainly on simulating the behaviour of radio network on the transmission process and data link layer. Unlike MATLAB or ‘C’ programming, OPNET simulation software was specifically designed to model and analyse the performance of a communication system. OPNET introduces a highly detailed network environment; the software requires an in depth modelling at various layers which would overly complicate and increase code development time of introducing novel algorithms.

After weighing the benefits of the available programming languages, MATLAB was concluded to be the most suitable software to conduct the research. Compared with either ‘C’ or OPNET, MATLAB is a superior mathematical tool to handle arrays and matrices. Although, MATLAB code typically runs 10 times slower than ‘C’ code, with the rapid growth of a personal computer processing speed, the run-time of code is less of a concern than in the time in developing a simulator. Instead, MATLAB provides programmers with the flexibility of developing transmission algorithms in wireless communication systems with relatively, low code development time, and it allows for easy modification to try out new algorithms.

3.3 Modelling Techniques

The process of simulation and data gathering is broken down into two main parts; the first part is to assess the performance of the resulting distribution of clusters generated from randomly positioned nodes under various clustering schemes as shown in Figure 3-1.

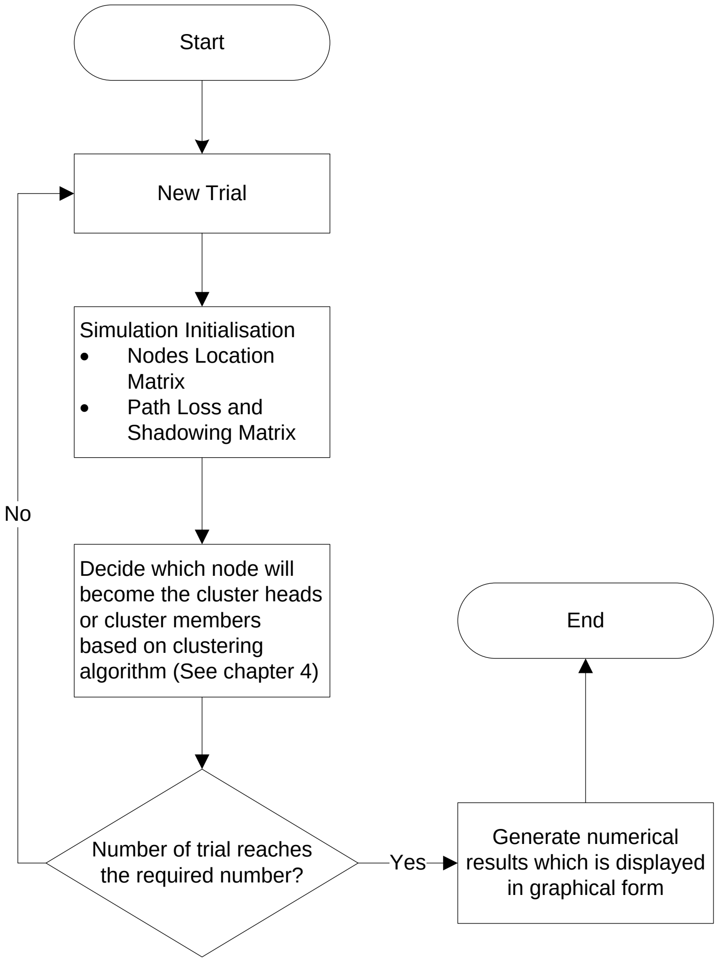

Figure 3-1: Clustering Simulation Data Gathering Process

The second part of the simulation is simulating and modelling the transmission behaviour of the resulting network formed via the clustering algorithms. The general simulation methodology is shown in Figure 3-2. Greater detail on the specific of the MAC scheme and the associated parameters are discussed in chapter 5. The simulation is also be conducted under various channel assignment schemes to deduce the QOS (quality of service) that a clustered network can support.

Note that in Figure 3-1 and Figure 3-2, to obtain statistically accurate results, a process known as Monte-Carlo simulation is adopted in which data is only obtained after a certain number of trials. This process reduces the effect of random fluctuations which arise due to the random placements of nodes. In the simulation as shown in

Figure 3-2, the randomness is not only due to the geographical distribution of cluster heads and cluster member distributions but also on the transmission arrival rate. In Monte-Carlo simulation, the results become more statistically accurate with a larger number of trials.

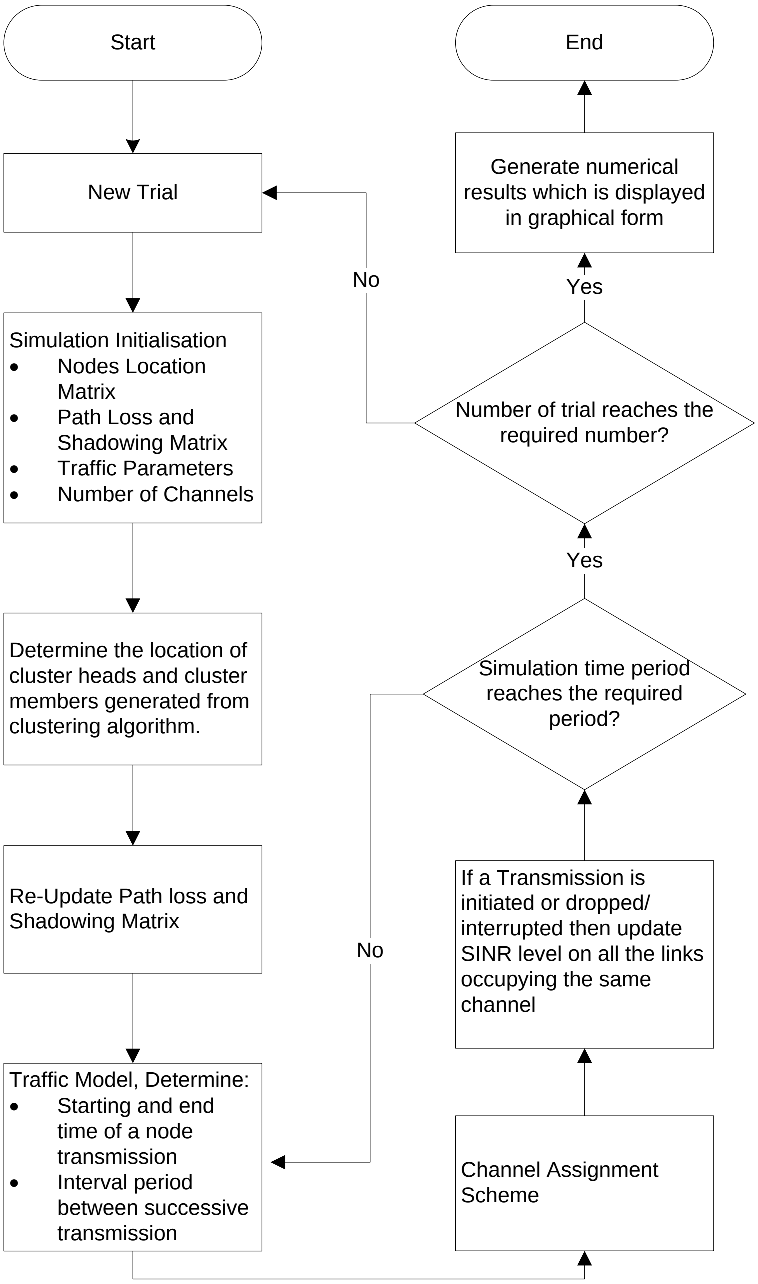

Figure 3-2: Transmissions Behaviour Simulation Data Gathering Process

3.3.1 Traffic Modelling

In order to evaluate the performance of a cognitive radio multiple access control protocol, a traffic model is required to be able to capture the statistical characteristics of the actual traffic that will have a significant impact of the network and protocol performance, i.e. the information flows from different users to the receiver in the proposed cognitive radio network scenario. Traffic modelling in a computer simulation needs to be able to imitate the real world scenario within a certain margin and typically, a mathematical model is employed to calculate the probability of a transmission departure rate.

The performance evaluation of the proposed radio network (chapter 5 and 6) will be measured against the generated offered traffic *G*. The offered traffic is defined as the number of concurrent calls or average data rate that can be obtained when there is no medium of contention.

The oldest and most widely used traffic model in communication system is the Poisson traffic model. The model states that the number of transmission occurring in a time interval from 0 to *t* is according to the Poisson distribution as given in 3.1.

$$P_k(t) = \frac{e^{-\lambda t} \lambda t^k}{k!} \qquad 3.1$$

Where λ is the average number of transmissions occurring per unit time and *k* is the probability of *k* transmission occurrences.

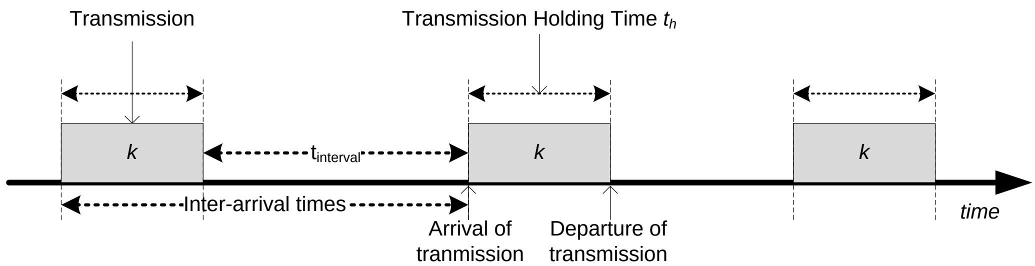

Figure 3-3: Transmission traffic

In modelling traffic in which the probability of transmission follows that of a Poisson distribution, each transmission inter-arrival time needs to be allocated i.e. the time period between two successive transmissions as shown in Figure 3-3. The average inter-arrival time μ i.e. is given by:

$$\mu = \frac{1}{\lambda} \qquad 3.2$$

The probability that no transmission occurs from 0 to t is achieved by setting k equal to zero in 3.1, which gives:

$$P_0(t) = e^{-\lambda t} \qquad 3.3$$

Then, the probability that a transmission will be generated after a period t_h for a predefined offered traffic G and number of users n is given by:

$$P = 1 - e^{-\lambda t_h} = 1 - e^{\frac{-t_h}{\mu}} = \frac{G}{n} \qquad 3.4$$

Therefore, the expected time interval between two successive transmissions:

$$\mu = -\frac{t_h}{\ln(1 - \frac{G}{n})} \qquad 3.5$$

From the above discussion, it is clear that for the transmission arrival rate to achieve a Poisson traffic distribution, each user will need to generate a transmission that has a $t_{interval}$ period that follows a negative exponential distribution[2]. Therefore the probability that a transmission is generated after $t_{interval}$ is:

$$P = 1 - e^{-\frac{t_{interval}}{\mu}} \qquad 3.6$$

In a computer simulation, the arbitrary length of $t_{interval}$ can be calculated using 3.7, where $P(t)$ is the probability that a transmission is generated and is uniformly

[2] The probability density function of exponential distribution is given by $P(t) = \lambda e^{-\lambda t}$ and its cumulative distribution function is the same as in 3.4.

distributed with a mean of 0.5. The *rand* function in MATLAB allows for quick calculation of $P(t)$.

$$t_{interval} = -\mu \ln(1 - P(t)) \quad 3.7$$

The offered traffic of each user is set to be no greater than 1 Erlang in order to prevent $t_{interval}$ to be less than zero. This setting ensures that the system will not overflow by each user generating more than one transmission at a given time.

For the purpose of system level simulation of the network, a file based transmission with a file arrival rate that follows a Poisson distribution to simulate the behaviour of a data transmission in a clustered network (chapter 5 and 6) was adopted. Unlike a packet based model, the holding time of a file is dependent upon the transmission rate of a channel which in turn is influenced by the interference. A file model can simplify the protocol behaviour whilst enabling the effect of interference and channel re-use to be clearly observed.

It was demonstrated in [38] through measurement and an analytical study on LAN traffic, that packet arrivals come in burst periods over time scales of 10s to 100000s. Paxson and Floyd in [39] did a further investigation on the traffic behaviour for different applications. The authors found that the Poisson model is only valid for modelling user generated traffic where as machine arrivals are best modelled using a self-similar process.

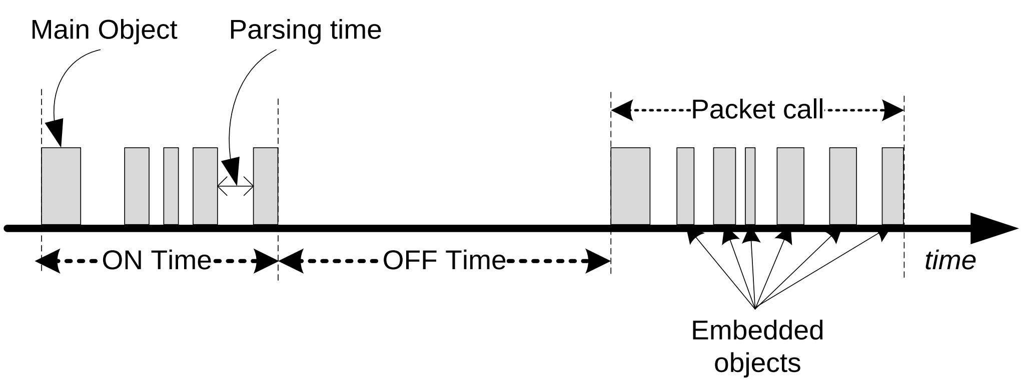

Figure 3-4: Packet transmissions in HTTP

In 3gpp [40], WWW (World Wide Web) browsing is modelled by dividing the session into ON/OFF periods as illustrated in Figure 3-4. The total duration of web-page download (ON time) initiated by a user is referred as packet call. The interval periods between packet calls (OFF time) follow an exponential distribution and represent the periods of users viewing web pages. The self-similar nature of WWW is generated in 3gpp by having each packet call consist of a burst of packets (known as embedded objects) caused by machines interactions through HTTP (Hypertext Transfer Protocol). The distributions of the main parameters in WWW as modelled in 3gpp are summarised in Table 3-1.

Parameter	Distribution
Main Object Size	Truncated Lognormal
Embedded object size	Truncated Lognormal
Number of embedded objects	Truncated Pareto
OFF time	Exponential
Parsing time	Exponential

Table 3-1: HTTP traffic parameters distribution

Best Effort traffics such as FTP (File Transfer Protocol) and Email are modelled by having files size that follow truncated lognormal distribution and with inter-arrival time of exponential distribution.

Despite the findings of Paxson and Floyd in [39], researchers are still using Poisson arrival process to analyse the performance of their schemes such as novel channel assignment selection or routing schemes in a multi-hop environment. The well analysed behaviour of Poisson model in queuing theory allows researchers to predict the performance of various applications such as blocking probability and the achievable throughput in MAC designs.

3.3.2 Propagation Model

In this work, nodes are assumed to be randomly deployed in a network area in which the access points are mounted on roof tops.

The Winner II channel models [41] are based on statistical channel measurements which measured the behaviour of RF signals between the frequencies of 2 – 6 GHz at up to 100 MHz RF bandwidth. The path loss model for Winner II is as follows

$$PL = A\log_{10}(d[m]) + B + C\log_{10}(f_c\,[GHz]\,/5.0) + X \qquad 3.8$$

Where PL is the estimated path loss

The model can be applied in the frequencies range from 2-6 GHz for various scenarios such as indoor hot spots, urban and rural environments, moving networks and many others. This thesis shall concentrate on modelling stationary and slow moving nodes and that antenna heights will not considerably impact the path loss. The B5a scenario in Winner II channel model is chosen as it consist of a strong line of sight signal (LOS) and single bounce reflection and in which transmitting h_{te} and receiving nodes h_{re} are positioned at rooftop height h_{te} = h_{re} = 25m. The variables for B5a scenario are as follow:

A = 23.5, B = 42.5, C =23 and X is an optional, environment specific term such as wall attenuation.

3.4 Performance Evaluation Methodology

A few key parameters will be discussed in this section. In chapter 4, a novel clustering schemes are proposed in an attempt to produce clusters with a high packing efficiency as well as clusters with low overlap, yet ensure network coverage such as hexagonal close packing architecture that is usually employed in analysing cellular network performance. Measuring the average transmission distance length to a cluster head, the number of nodes which are not part of a cluster and the number of nodes that are within the range of more than one cluster gives an indirect measurement on the compactness of the proposed clustering scheme.

In section 3.4.2 of this chapter, a discussion is provided on the parameters that are employed in chapter 5 to understand the achievable clustered network performance, constraint and behaviour. The parameters were also used in chapter 6 to compare the performance of the system under various channel assignment schemes.

3.4.1 Clustering Evaluation

a. Transmission distance

As mentioned in [2] and [42], reducing the transmission distance can significantly reduce energy dissipation. Therefore measuring the average Euclidean distance between nodes to a cluster head can provide indications of the energy consumption in the system. The average Euclidean distance between a cluster member node located at (x_1, y_1) and cluster head at (x_2, y_2), is given by:

$$d(x,y) = \sum_{i=1}^{n_{Td}} \sqrt{\left((x_1 - x_2)^2 + (y_1 - y_2)^2\right)_i} \Big/ n_{Td} \qquad 3.9$$

where n_{Td} is the total number of clustered nodes.

b. Number of nodes within the range of more than one cluster

To reduce contention between clusters and improve the channel re-use factor, it is important to minimise cluster overlap. To study the degree of overlapping clusters is as illustrated in Figure 3-5, the number of nodes that are within the coverage radius of more than one cluster is counted. Higher node counts will indicate that many clusters are overlapping one another.

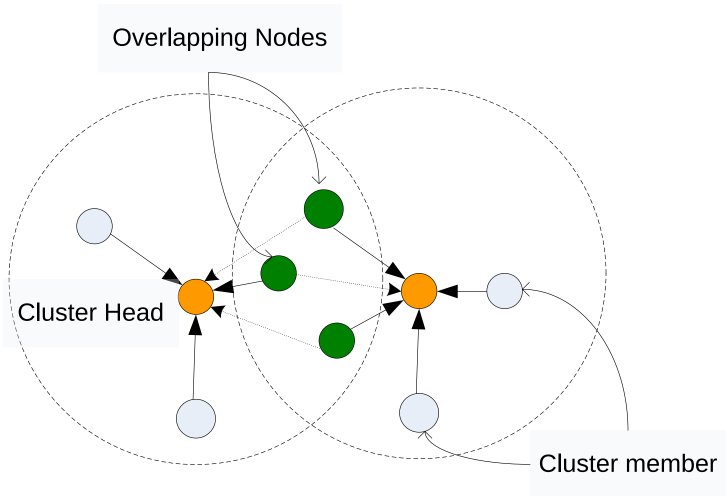

Figure 3-5: Nodes in overlapping clusters region

c. Number of un-clustered nodes

As mentioned earlier, clustering algorithms need to provide coverage for the network whilst minimising the number of cluster overlaps. Aggressively reducing cluster overlap can result in inefficient network coverage which can lead to some nodes not being part of a cluster as demonstrated in Figure 3-6. These nodes can be disruptive to the overall network energy performance as they may need to send directly to the HBS or through multiple-hops using intermediate cluster members to relay their data to the nearest cluster head. Therefore to compare the efficiency of the proposed clustering scheme in providing network coverage, the number of nodes which are not part of a cluster as a function of the coverage radius of a cluster heads are measured.

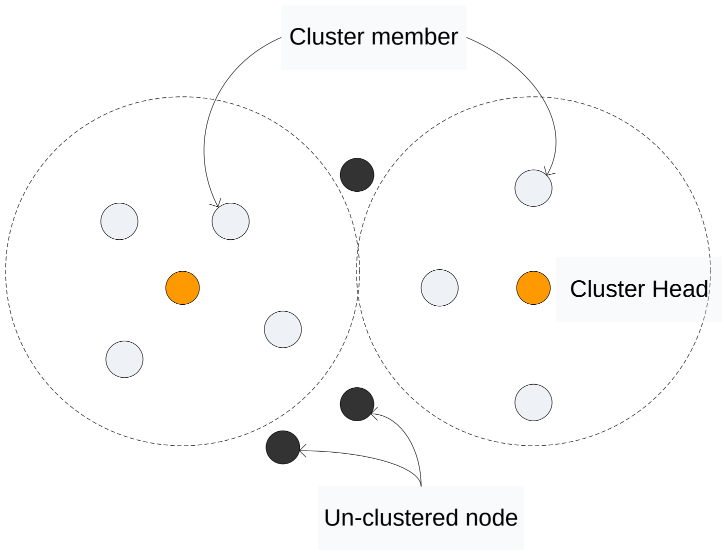

Figure 3-6: Illustration of un-clustered nodes

3.4.2 Network Performance Evaluation

a. Channel Capacity

In order to illustrate the benefits of applying cognitive radios, coupled with self organisation to an ad hoc and green small cell network, understanding is needed on the fundamental channel capacity limit for a specified bandwidth in the presence of noise and interferences. The Shannon equation as seen below specifies the upper bound limit of a channel capacity for a given channel bandwidth *B* and Signal to Interference Noise Ratio (SINR).

$$Channel\ capacity = B\ log_2\,(1 + SINR) \tag{3.10}$$

Based on (3.10), it is clear that a low value of SINR due to high interference can significantly degrade the performance of a communication link. Although increasing bandwidth is an effective means of improving transmission rate, the continuous investment on radio spectrum by network operators to support the demand of wireless data is unsustainable due to its scarcity and escalating price.

b. Signal to Interference Noise Ratio

Signal to Interference and noise ratio (SINR) or otherwise also known as Carrier to interference and noise ratio (CINR) which is the un-modulated value of SINR, is an important parameter which can heavily influence wireless communication link quality and the overall network performance. The SINR of a link between node *tr* and receiver *rx* can be obtained from the following equation:

$$SINR = \frac{Pr_i}{\sum_{k=0}^{Tx} I_k + \sigma^2} \tag{3.11}$$

Where Pr_i is the signal strength received by *rx* from *tr*, *I* is the power received by *rx* from source *k*, *Tr* is the total number of nodes (other than *tr*) transmitting on the same channel and time slot as *tr* and σ^2 is the noise power level.

The received signal strength at *rx* can be influenced by various factor. The received signal power level Pr_i in logarithmic decibels is calculated as follows:

$$Pr_i(dB) = Pd_i(dB) + Gr_i(dB) + Gt_i(dB) - PL_i(dB) \tag{3.12}$$

Where Pd_i is the radiated power transmitted by node *tr* on a particular channel, Gt_i and Gr_i are the transmitter and receiver gains respectively.

In the absence of interference, the signal can still be corrupted by the presence of noise σ^2 and the SINR as given in equation in 3.11 becomes just:

$$SNR\ (Signal\ to\ Noise\ Ratio) = \frac{Pr_i}{\sigma^2} \qquad 3.13$$

c. Blocking and Dropping probabilities

The blocking and dropping probability are measurements used in chapter 5 in describing the grade of service of a wireless network. The blocking probability is used to measure the probability that a user is unable to access a channel or medium as all the available channels are 'sensed' to be occupied by other transmissions. The blocking probability at time *t* is defined as follows:

$$B(t) = \frac{T_b(t)}{T_s(t)} \qquad 3.14$$

Where $B(t)$ is the probability of blocking at time *t*, $T_b(t)$ is the total number of blocked transmissions and $T_s(t)$ is the total number generated transmissions.

The dropping probability provides a measurement of the probability that an ongoing transmission fails. The probability of call dropping at time *t* is defined as:

$$D(t) = \frac{T_d(t)}{T_s(t)} \qquad 3.15$$

Where $D(t)$ is the probability of dropping at time *t*, $T_d(t)$ is the total number of dropped transmissions.

d. Throughput

In chapters 5 and 6, the throughput measure is used to understand the network behaviour in providing quality of service (QoS). In this thesis, throughput is defined as the total information that is successfully received at the destination. Due to blocking, dropping and interference the throughput cannot exceed the total offered traffic *G*, where both can either be expressed in Erlang or Bits per second (Bits/sec). The offered traffic *G* in Erlangs can be derived from Little's law as given in 3.16. One Erlang of throughput for two Erlangs of offered traffic means that only 50% of the information is successfully delivered.

$$G = \lambda t_h \tag{3.16}$$

Since this work focuses on modelling data based transmissions, the results in chapter 5 and 6 are presented in Bits per second as it allows for an understanding of the achievable network data rate and capacity. The offered traffic and throughput in Bits per second were obtained respectively:

$$Offered\ traffic\left(\frac{Bits}{sec}\right) = \frac{Total\ files\ generated\ by\ users\ in\ bits}{Length\ of\ simulation\ time\ in\ seconds} \tag{3.17}$$

$$Throughput\left(\frac{Bits}{sec}\right) = \frac{Total\ files\ received\ in\ bits}{Length\ of\ simulation\ time\ in\ seconds} \tag{3.18}$$

e. Delay

The period from which a file or packet is generated at a user to the time that it is successfully received by the receiver is known as the delay. The total delay is an accumulation of several factors namely the processing delay, propagation delay, transmission delay and queuing delay. The processing time is the amount time taken by users to determine the destination of the information by examining the packet's header. Propagation delay is the amount of time taken by a radio signal from a user to travel across a transmission link to the intended destination. Transmission delay is the duration required for all the bits of a packet or file to be transferred from a user to the receiver across the transmission link, the duration of transmission delay is linked to the date rate of the transmission link. In multi-hop transmissions, a relaying node can receive several incoming packets or file which have to be retransmitted. Assuming that a node can only re-transmit one packet at a time, the additional packets have to be queued in a buffer until it can be transmitted, this delay is known as queuing delay.

In this thesis, the files are processed immediately upon being generated by the users and thus have no processing delay. The propagation time is considered to be negligible; therefore the files transmission end to end delays are affected by the channel capacities (transmission delay) and queuing delay. Note that the network scenario as presented in chapter 5 assumes that a node can concurrently process more than one files or packets. However, queuing delay can still takes place on the relaying nodes if the number of available channels for transmissions at the relaying nodes is less than the number of received files.

f. Energy consumption and efficiency

In chapter 5, the energy consumption model of a user is presented. The model describes the amount of energy usage in Watts during transmission, reception and idle periods. Rather than simply presenting the total energy consumed for a given length of simulation, the results are displayed in Joules/bit as it conveys the energy efficiency which takes in the account on the QOS for the various scenarios of the network. More details on the energy efficiency metrics in Joules/bit will be discussed in chapter 5.

3.5 Performance Verification Techniques

3.5.1 Clustering Validation

As aforementioned in chapter 2, clustering is an *NP*-hard optimisation problem with respect to minimising the inter-cluster distances (reduce transmission range) and maximising the intra-cluster distances (cluster overlap). In chapter 4, for a given transmission range and network area, a closed form solution of the expected number of cluster heads and of un-clustered nodes is derived for the non-learning scenario. The solution provides guidance on to the verification of the proposed clustering scheme by comparing the amount of deviation on the resulting number of clusters and un-clustered nodes with a non-learning scheme.

3.5.2 Network Performance Validation

Queuing theory is a mathematical study of system behaviour and its ability to provide service to random demands for example approximating the waiting period for customers at supermarket checkouts. Queuing theory has also played an important role is assessing the performance of communication systems.

Kendall's notation is often employed to classify the various scenarios in queuing system [43]; the format of Kendall's notation is as follows:

$$A/B/q/K/N$$

The terms A and B describe the inter-arrival rate and the service time distribution respectively. The q denotes the total number of servers in the system or the number of channels available. K is used to specify the amount of storage available and finally N is the total number of customers or nodes in the system. The following symbols are frequently used in placed of A and B to describe their distribution:

- M: exponential distribution
- D: deterministic (Constant time interval)
- G: General (Arbitrary interval)

The Erlang loss model - *M/M/q/q*

The Erlang loss model is a well known queuing system and its behaviour is used in classic telephone exchange systems to determine the achievable Grade of Service (GoS). The model assumes that the average arrival rate λ remains constant, with inter-arrival times as well as service times following a negative exponential distribution. In the event of q being fully occupied, additional calls will be blocked and are assumed to be lost i.e. no waiting time which would affect future arrivals. Hence the Erlang loss model can be summarised under Kendall's notation as *M/M/q/q*. The expected probability of blocking $P(b)_b$ of such system is known as Erlang B formula which is denoted by:

$$P(b)_b = \frac{\frac{G^q}{q!}}{\sum_{i=o}^{q} \frac{G^i}{i!}} \qquad 3.19$$

The main assumption on the derivation of Erlang B is that the arrival rate follows a Poisson traffic model and thus the formula is still valid for any service time distribution [44]. Therefore, the Erlang B formula can be used as a means of verifying the traffic model where the arrival rate conforms to Poisson distribution. Figure 3-7 ,illustrates the comparison between the Erlang B formula and the probability of blocking of a system whose traffic is generated as described in section 3.3.1 and simulated using MATLAB and with $N = 100$.

The upper bound performance (throughput in Bits/s) of the clustered network as presented in chapter 5 can be derived assuming that there is no interference. The theoretical upper-bound performance is compared with the simulation results under two different channel assignment schemes. It can be seen from the result of offered traffic against throughput in chapter 5, the channel assignment scheme that best mitigates interference at the receiver has a comparable throughput with the upper bound performance.

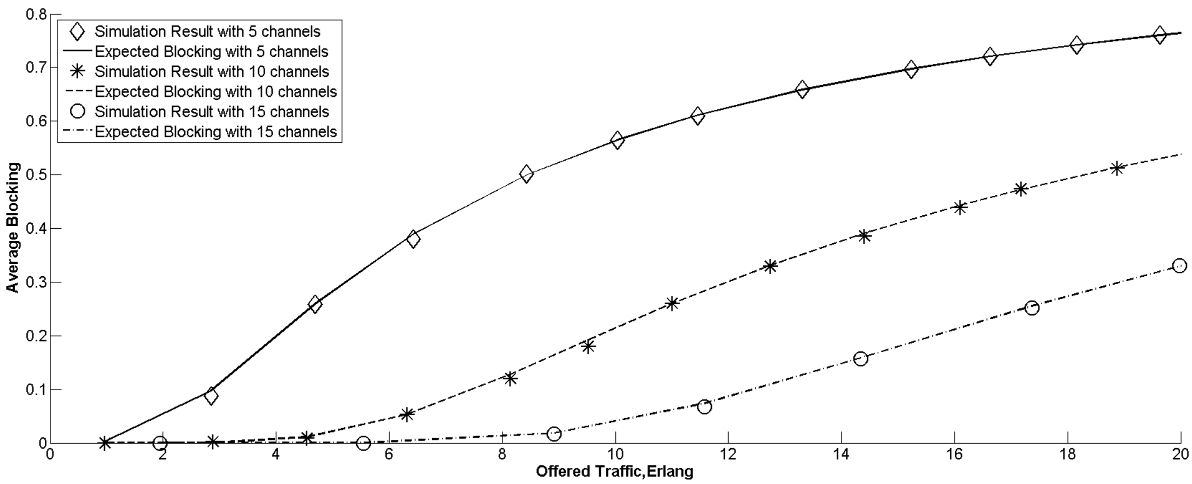

Figure 3-7: Comparison between theoretical Erlang B probability of blocking with the simulated results.

In chapter 6, it is difficult to fully describe the behaviour of the network mathematically due the incorporation of fully and partially distributed learning on the channel assignment scheme to maximise the network performance. Most research conducted on multi-agent learning scenario mainly uses Monte Carlo simulation to assess the performance of different schemes [45]. The same approach is employed in chapter 6 and a detailed analysis is provided to discuss the performance of users in specified cases.

3.6 Conclusion

The frameworks of the system modelling for the simulations implemented in the reminder of this thesis have been outlined in this chapter. After weighing the cost and development time of several performance evaluations; MATLAB software was selected as the primary research tool. The software selection was made due to its efficiency in code development time and the imbedded numerical. To achieve statically reliable results, Monte Carlo simulations with a sufficient number of events need to be employed to reduce the random fluctuations in order to determine the behaviour of the system. Several performance parameters have been defined to quantify the clustering algorithm efficiency and clustered network performance. Despite lacking an analytical model due to difficulty in analysing network interference for the scenario in chapter 5 and 6, the traffic model validations presented in this chapter ensure that the foundation of network modelling through simulation is correctly implemented.

Chapter 4 Clustering Protocols for a Self-Organizing Cognitive Radio Network

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4.1 Introduction

A wireless ad hoc network provides the ability for multiple nodes of a similar type to interact without the need for an established infrastructure, with the added advantage of supporting distributed sensing. A wireless ad hoc network must be able to operate under very dynamic conditions and in most cases the network will operate without centralised control. The lack of a central administration means that these networks are required to be able to independently organise themselves thus creating an autonomous network.

Due to hardware limitations, one of the major hurdles in wireless ad hoc networks is to prolong the network lifetime and maintain the connectivity of the nodes. It has been identified that hierarchical techniques namely clustering can help reducing energy consumption [20], [21] and [23]. Clustering is particularly useful for applications that require scalability where there are hundreds or thousands of nodes. Scalability in this context implies the need for load balancing and efficient resource utilization.

The purpose of this chapter is to propose a novel distributed clustering algorithm in an attempt to minimize the number of unconnected nodes and to reduce the distance of nodes to the cluster head within each cluster. The algorithm will also attempt to minimise the number of clusters whilst maintaining full connectivity. The purpose of minimising the number of cluster heads is to provide efficient coverage of the network, while minimising cluster overlap [46]. As shown in the previous chapter, overlapping cells can significantly reduce multiple access protocol efficiency and can increase the amount of intra- and inter-cluster channel contention between clusters.

In order to reduce the transmission link length, a cluster head must be situated in areas of high node density [24], [25]. Similar to [47] the proposed cluster-head selection algorithm utilizes the RF signal strength for head selection. The novel aspect of this algorithm is that the received signal strength indication (RSSI) will be sensed by a node multiple times, taking into account changes in the environment over time, thereby making it able to learn its significance in relation to other nodes. Individual nodes will then make a decision whether to become a cluster head using the information provided by these multiple RSSI measurements.

The learning process undertaken by nodes is consistent with the definition of cognitive radio as suggested by [35]. One vital element of cognitive radio is learning from the interactions between the environment and itself. Using cognitive radio techniques enable individual nodes to a make decision whether to become a cluster head based on its sensed environment.

This chapter is organized as follows. Section 4.2 introduces the transmission range assignment problem and how it can affect the network clustering performances. Section 4.3 provides derivation on the expected number of clusters when a random node can become a cluster head. The proposed algorithm is presented in 4.4, the section also includes the assumptions made in deriving the cluster head selection algorithm. Simulation results are discussed in section 4.5. Finally, conclusions are drawn.

4.2 Transmission Range Assignment Problem

In [20] and [23] it is assumed that nodes are able to communicate with their respective cluster heads over any distance, and that the number, or percentage, of cluster heads is predetermined. However, this is impractical for large scale deployments, since each node will have a limited transmission power. Therefore, if the number of cluster heads and/or the transmission power is low, nodes located far away from the cluster head will be unable to send their data to the base station hence increasing the data loss.

In order to increase the energy efficiency of a network, the range r at which a node transmits is an important parameter to consider as the energy consumed by a node for communication is directly dependent upon its transmission range. The transmission range r can also be considered based on the *SNR* threshold with which a node can successfully receive a packet from another node without the presence of interference. In [48] the author investigates how large the transmission range (r) of a node must be in an ad hoc network such that it can form a strongly connected network. In the paper they considered the scenario whereby n homogenous nodes are randomly distributed over d_x dimensional region and that all the nodes have the same transmission range. They noted that for a square area with $l_1=l_2$ side lengths, taking into account that nodes could be concentrated at opposite corners of the area A, thus for nodes to be strongly connected then the transmitting range r should be $r \approx \sqrt{A}$ However, this scenario could be unrealistic and random placement of nodes may lead to some local areas having no nodes. This reduces potential spatial diversity and thus may lead to a lower capacity. They showed that the probability of n homogenous nodes all having the same transmission range r placed randomly in area A with sides $l_1=l_2$ length will connect with the probability:

$$P[cn] = 1 - (l_1 - r)(1 - \frac{r}{l_1})^n \qquad 4.1$$

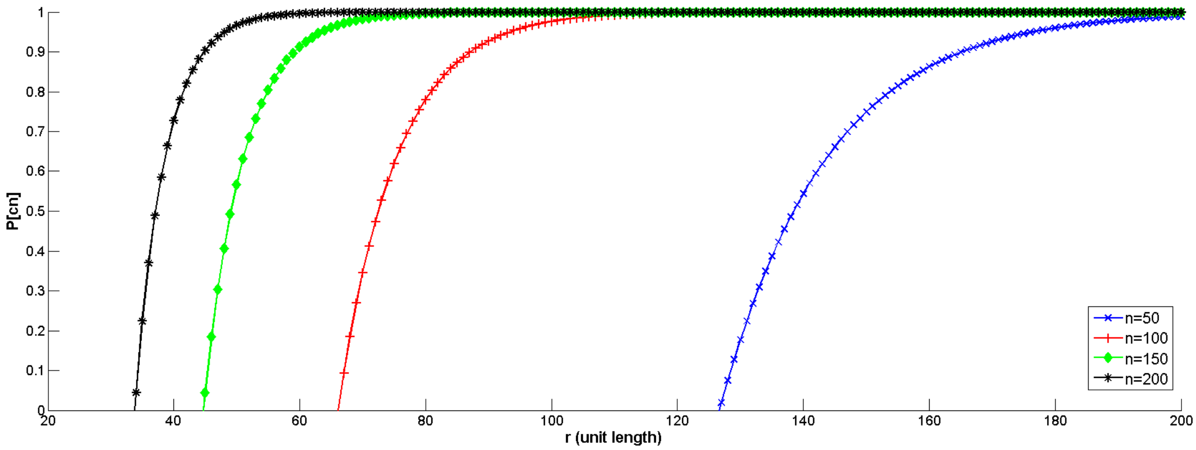

Figure 4-1 : Illustrates the relation between r and l_1=l_2 given that l_1=l_2 =1000 for various numbers of nodes n.

4.2.1 Lower bound transmission range *r*

It is assumed that there are *n* uniform randomly distributed nodes in a given deployment area *A* resulting in a Poisson distribution with node density λ_a, where λ_a = *n/A* [25], [49]. Since formation of a cluster requires at least one cluster member, $\lambda_a \pi r^2$ can be used to find the expected number of nodes n_d for a given transmission range *r* [13]. Thus a cluster can be formed if:

$$\lambda_a \pi r^2 \geq 1 \tag{4.2}$$

However, using (4.2) to set the transmission range *r* can yield a *P[cn]< 0.95* thus the resulting network will have large number of nodes not belonging to any cluster. This reduces the spatial diversity gain that can be achieved through efficient spatial clustering and will lead to a lower capacity. To maintain network coverage i.e. network is sufficiently covered by clusters, (4.1) can be used to set the lower bound of transmission range *r* such that *P[cn]> 0.95*.

4.2.2 Upper bound transmission range *r*

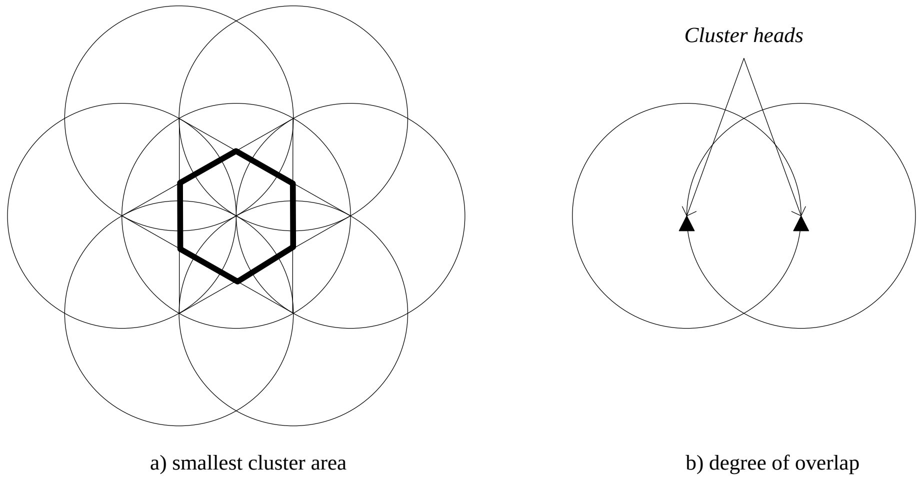

Figure 4-2 : Smallest cluster area is $(\sqrt{3r^2})/_{2}$.

As mentioned in the earlier chapter, one of the benefits of clustering is that it can improve the spatial re-use of a network, thus increasing capacity. However, to optimise the spatial re-use that can be gained via clustering it is important to reduce the amount of cluster overlap. In this thesis cluster overlap is defined as the number of nodes that are within the transmission range of more than one cluster. The increase in the number of cluster overlaps is not only dictated by the poor selection of nodes to become a cluster head but also a node's transmission range *r*.

Assuming that *n* nodes are randomly deployed around 2 cluster heads (n_{ch}) and that each cluster consists of $n/\ n_{ch}$ nodes, then the expected the number of nodes that is in the overlapping region $E[n_o]$ (nodes within transmission range of more than one cluster) for the network as presented in Figure 4-2b is

$$overlap\ area\ (A_o) = \ 2r^2\cos^{-1}\left(\frac{d_c}{2r}\right) - \frac{1}{2}\ d_c\sqrt{\left(4r^2 - {d_c}^2\right)} \quad 4.3$$

$$E[n_o] = \lambda_a A_o \quad 4.4$$

Where d_c is the distance between the two cluster heads

Ideally a cluster head should not be selected if it is within the transmission range r of other cluster heads, thus the largest overlap area occurs when a cluster head located on the perimeter of its neighbouring cluster head coverage disc r with a radius of r, thus $d_c = r$.

$$\arg\max_{d_c} A_o(d_c) = r \quad (4.5)$$

$$n_o = \lambda_a r^2 \left({}^{2\pi}/_{3} - \frac{1}{2}\sqrt{3} \right) \quad (4.6)$$

From the above analysis it is evident that the number of nodes in the overlapping region n_o is dependent not only the positioning of cluster heads (selecting nodes to become cluster with large d_c) but also upon the transmission range r.

Since the network assumes a squared network area A with n homogenous nodes randomly deployed then given a transmission range r, several of these nodes will become cluster heads in order to provide network coverage. It is important to note that increasing a node's transmission range r would yield fewer cluster heads but at the expense of energy consumption and increasing the number of nodes in overlapping areas. To minimise the channel contention amongst n nodes, the upper bound limit on the transmission range r shall be selected such that the number of nodes in the overlap region n_o to be no more than $n/2$. In [50], the authors have shown that cluster area A_c is at its smallest when $A_c = \frac{\sqrt{3r^2}}{2}$, which occurs when 7 cluster heads are on the perimeter of its neighbours broadcasting range r (see Figure 4-2 a). In the case of Figure 4-2a, A_o can be approximated to

$$A_o = \pi r^2 + 6\left(r^2 \left({}^{2\pi}/_{3} - \frac{1}{2}\sqrt{3} \right) - \left(\frac{\pi r^2}{6} + 2\left(\frac{\pi r^2}{6} - \frac{r^2}{2}\sqrt{{}^{3}/_{4}} \right) \right) \right) \quad (4.7)$$

$$A_o = 2\pi r^2 \quad (4.8)$$

The network coverage provided by the cluster heads in Figure 4-2a is slightly less than $4\pi r^2$, thus around half of the total nodes n are expected to be within the range of more than one cluster head.

$$E[n_o] \approx \frac{1}{2} n \qquad 4.9$$

4.3 Expected number of Clusters

In [52], the author states that one of the requirements of distributed clustering is that no nodes can remained un-clustered. This requirement can be difficult to achieve in a large scale network comprising of many nodes. The varying nature of radio propagation and the shadowing experienced by individual nodes can leave some nodes isolated from neighbours. Provided that no nodes are un-clustered and that no cluster can form within transmission range r of other clusters, the empirical formula for cluster density λ_c proposed by Bettstetter [52] where:

$$\lambda_c = \frac{\lambda_a}{1 + \frac{n_d}{2}} \qquad 4.10$$

Where n_d is the expected number of nodes within transmission range r; $n_d = \pi r^2 \lambda_a$. When $\pi r^2 \lambda_a > 1$

The expected number of cluster heads $E[n_{ch}]$ can thus be deduced to

$$E[n_{ch}] = \lambda_c A \qquad 4.11$$

$$E[n_{ch}] = \frac{1}{1 + \frac{\pi r^2 \lambda_a}{2}} \qquad 4.12$$

The number of expected cluster heads in (4.11) however, assumes deployment of nodes over an infinite area size and that all nodes are either cluster heads or within the range of a cluster heads. Un-clustered nodes can also be formed when clusters are sparsely distributed.

Using (4.10) it is possible to derive the combined number of the expected cluster heads $E[n_{ch}]$ and the number of unconnected nodes n_u taken into account the boundary layer for a rectangular region with dimensions $l_1 \times l_2$. According to [50], the expected number of nodes n_d within the transmission range of size r with n nodes uniformly distributed across an infinite area size but with a boundary layer ($l_1 \times l_2$) is given by:

$$n_d = \frac{n\,\pi r^2}{l_1 l_2}\left(1 - \frac{4r}{3\pi l_1 l_2}(l_1 + l_2) + \frac{r^2}{2\pi l_1 l_2}\right) \qquad 4.13$$

Using (4.10) with (4.13), the expected number of cluster heads $E[n_{ch}]$ together with the number of unconnected nodes n_u for a rectangular deployment area $A = l_1 \times l_2$ is as follows:

$$E[n_{ch}] + n_u = 1/(1 + \frac{n\,\pi r^2}{l_1 l_2}\left(1 - \frac{4r}{3\pi l_1 l_2}(l_1 + l_2) + \frac{r^2}{2\pi l_1 l_2}\right)/2\,) \qquad 4.14$$

Where $A = l_1 \mathrm{x} l_2$ assuming a rectangular deployment area

(4.14) provides the expected number of cluster heads $E[n_{ch}]$ together with the number of unconnected nodes n_u provided that no cluster can form within transmission range r of other clusters and when a random node can become a cluster head.

4.4 Proposed Distributed Clustering Algorithm

4.4.1 Clustering Goals and Assumptions

Assuming that n nodes are randomly positioned in a field with area A with l_1 and l_2 sides length. The clustering algorithm requires that a node to be mapped to at least one cluster $1 \leq i \leq n_c$, and n_c is the number of clusters. Centralised 'top down' techniques require the central administrator (typically a base station) to have complete knowledge on network parameters such as network traffic, node location, transmission power and proximity to neighbouring nodes. In a large scale network, the delay and processing power consumption requirement may be undesirable. As pointed out by [42], a base station component consumes more energy per subscriber than the node in the network. Distributed processing can reduce the burden of a base station by off loading some of the processing requirement to the nodes in the network [53].

A distributed processing is preferred over centralised techniques as it can potentially have better scalability in a large scale network since nodes can act independently in various parts of the network without having to wait for command from a central administrator. The lack of central administrator and the autonomous decision making by individual nodes means that the network is also less susceptible to protocol error due to transmission errors and node failures thus making the network more robust.

Nodes can independently make altruistic decisions such that they can improve the overall network performance by sensing the network condition. However, a distributed clustering process should be simple and efficient so that processing requirements and sensing periods can be reduced thus helping reduce node's energy consumption.

To increase the energy efficiency of the network, the proposed clustering protocol should reduce the proximity of a node to its respective cluster heads $r_,$ it has been shown in [20], [23] and [51] where the power consumption of a node's power amplifier is a function of r. The number nodes of in an overlapping cluster n_o needs to be minimised in order reduce channel contention. In [23], [24] and [54], the authors argued that clustering protocols which minimise the number of cluster heads required to provide network coverage which in turn have high number of cluster members will yield a low n_o. However, it is demonstrated in the earlier section that n_o is not only determined by the number of cluster heads but also the proximity of a cluster to other clusters d_c. Hence, cluster protocols need to produce a well distributed cluster and the nodes transmission range of a node r needs to be appropriately tuned as it will dictate the number of cluster heads required to provide network coverage. A well distributed cluster across the network is therefore desirable as it increases spatial reuse and thus reduces the number of transmission collisions and channel contention.

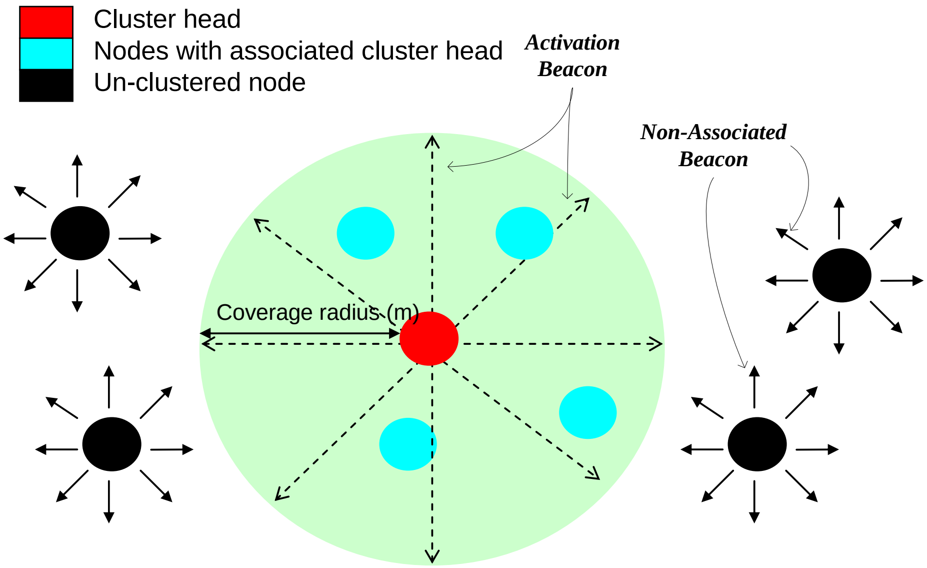

Figure 4-3: Cluster head density in accordance with the placement of all the nodes.

In order to help nodes make independent decisions, each node is able to periodically sense the accumulation of beacons or RSSI (Receive Signal Strength Indicator) transmitted by their remaining nodes in the network. This allows nodes to detect and sense the changes in its local environment and behave accordingly thus negate the need of an individual node to be aware of the location of all other nodes in the network. To minimise energy consumption and the relaying burden, intra-cluster communication is limited to a single hop. Figure 4-3 shows nodes that are associated with their corresponding cluster head. Each cluster has a specific coverage radius (m) based on the cluster-head transmit power and cluster members are able to directly communicate with its cluster head.

Assuming that nodes are randomly deployed in a field A, then the assumption on the properties of the network and nodes are as follows:

1. Nodes may only connect to only one cluster head i.e. the cluster head with the strongest RSSI. This allows a node to transmit at a lower power level hence reducing power consumption. Geographically, the clusters formed will be more compact and dense as cluster heads with the highest power level are generally the closest (in terms of Euclidian distance), therefore the network will maximise its spatial reuse factor.

2. Nodes are slow moving or fixed and are location unaware thus negating the need to be equipped with GPS (Global positioning System) and/or reduce the excessive sharing of information between nodes in the network.
3. Nodes are homogenous, exhibit same capabilities, such as transmission power level, processing power etc.

During the clustering process, a node that is a neither cluster head nor a member of a cluster, i.e. an un-clustered node, will continuously (except when receiving) transmits a *non-associated* beacon, as shown in Figure 4-3. If a node decides to become a cluster head it will stop its *non-associated* beacon and instead transmit an *activation* beacon. An un-clustered node that senses an *activation* beacon will evaluate its RSSI against the $RSSI_{threshold}$. If the *activation* beacon is above the threshold it will terminate its *non-associated* beacon and send a request to become a member of that cluster. Note that the $RSSI_{threshold}$ can be selected such that it is a function of the coverage radius of the cluster head.

4.4.2 Reinforcement Learning and Competition in Electing Cluster heads

Multiple sensing of RSSI allows each node to learn its positioning significance in terms of neighbouring node density. This mechanism can be employed by making the un-clustered nodes sense the RSSI at random 'wake up' times. The probability of node 'wake up' will be set such that at each time frame only one node out of *n* will be able to sense the network condition, this so that no cluster head is formed within the transmission range *r* of other cluster head. Nodes will also continuously sense at random times and calculate their reward *R* (to be discussed in later section 4.4.3) based on the accumulation of RSSI arising from of the *non-associated* beacons given off by other nodes it has received.

The concept of multiple sensing to reinforce decision making has been introduced by Jiang in [55], [56]. Jiang noted that the interactions of nodes with its environment and reception rewards by undertaking different actions are coherent with the definition of reinforcement learning (RL). Reinforcement learning is a sub class of Machine Learning, a discipline which deals with the ability of a system to learn and adapt. Reinforcement learning focuses primarily with the design and development of learning algorithms which uses data gained from past experience such that the performance can be optimised given certain objectives and constraints [58]. In the standard reinforcement learning model [45], each agent perceives the state of its environment S in which the agent then chooses action $a \in A_s$, where A_s is the total available actions. The performed action a changes the state of the environment in which the agent will then receive feedback via the reward R. The objective of the standard reinforcement learning model [45] is to find a policy π, mapping states S to action A_s such that the reward R can be maximised.

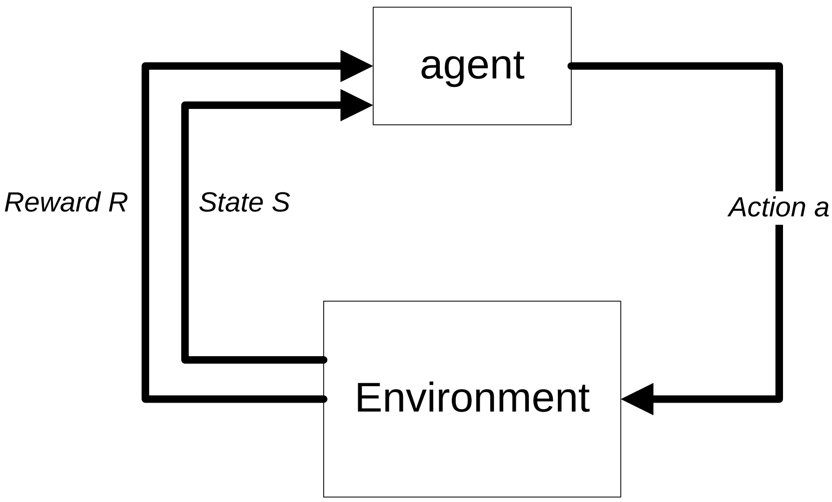

Figure 4-4: Standard Reinforcment Learning Model

In the proposed model, each node receives reward R that corresponds to the perception of its environment S (sensing) during each 'wake up' time. The accumulation of reward R will be used by a node to decide the right course of action a therefore, the objective of the proposed reinforcement learning model is to map the perceived environment or state S to the reward R. R will be designed such that its perceived environment S is dependent upon a particular node's location and neighbour density. As time progresses, nodes will have different levels of the reward R due to the differences in the levels of RSSI received. By setting a reward threshold called $R_{threshold}$, nodes 'compete' with each other to cross $R_{threshold}$ first thereby enabling them to become a cluster head. Since the reward is proportional to the RSSI of the *non-associated* beacon, nodes that are located in a high density area will receive greater RSSI thus having higher a chance of becoming cluster head earlier. The random wake time also ensures that there will be no more than one cluster head per cluster as it is assumed that only one node is active at a time. It should be noted, that a node which has become a cluster head or member of a cluster will not perform RSSI sensing and discard their priority factor.

Figure 4-5 shows an illustration of the proposed algorithm which is a combination of a state diagram and logical operations. The description of the individual states and the operation of the proposed algorithm are as follows:

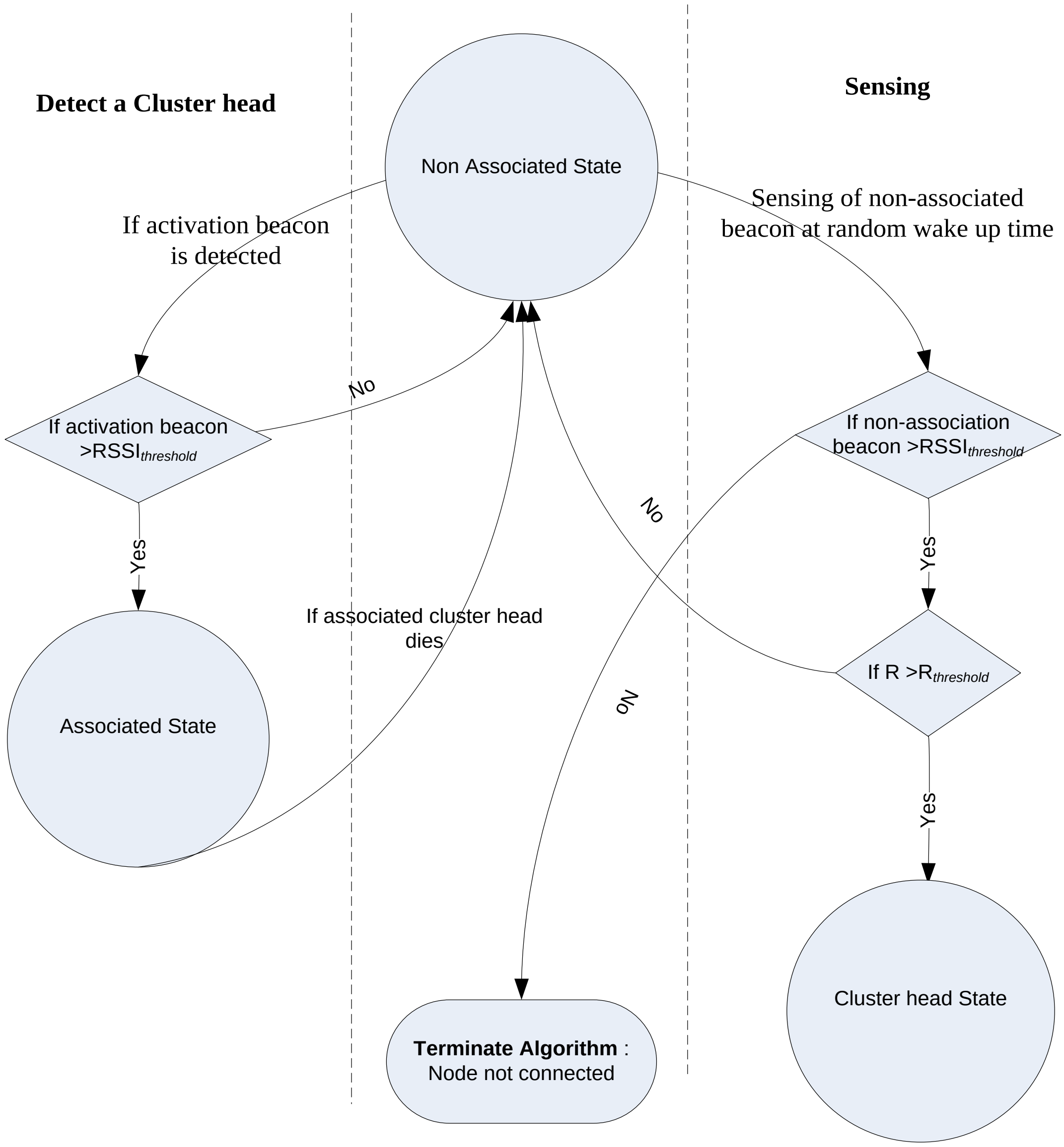

Figure 4-5: Combinations of State diagram and logical operations of the proposed clustering algorithm

- Non-associated State**.** In this state nodes are neither a cluster head nor a member of a cluster. All the non-associated state nodes will continuously (except when periodically receiving) send a *non-associated* beacon signal. Parallel to this operation, each node will have a random 'wake up' time to sense the *non-associated* RSSI given off by other node. Nodes will continuously sense and compute their reward R based on the sensed RSSI at the random 'wake up' time. If during sensing a node receives the *non-associated* beacon signal strength at less than $RSSI_{threshold}$ then the node will not continue and will discard its previous reward R. This in effect will make sure that the node will not become a cluster head. A non-associated state node will actively scan for the *activation* beacon a of cluster head. If a cluster head is detected it will evaluate for the *activation* beacon from the cluster head. If the *activation* beacon's RSSI is above $RSSI_{threshold}$ then the node will send an association request to the cluster head and become part of the cluster. It will terminate its *non-associated* beacon, discard its reward R and become an associated state node.

- Associated State. During this state the node will continuously scan (except when transmitting) for the *activation* beacon of other cluster heads. If it detects the formation of new cluster head with a higher activation signal, it will send a request to be a member of the new cluster head and break its association with the old cluster head.

- Cluster-head state. A node is able to become a cluster head if during a non-associated state the *non-associated* beacon RSSI is above $RSSI_{threshold}$ and that its reward R is greater than $R_{threshold}$. The newly self-elected cluster head will continuously transmit (except when receiving) its *activation* beacon.

In the event of the death or failure of the cluster head all the cluster member nodes move into non-associated state and will restart the algorithm with a new reward R. This allows the network to maintain its robustness.

4.4.3 Reward R and $RSSI_{threshold}$

In the non-associated state, the node will have a random 'wake up' time for sensing its environment *S* and calculate its reward *R*, provided that the sensed non-associated beacon RSSI is above the $RSSI_{threshold}$. The $RSSI_{threshold}$ will be specified in Watts and selected such that it is a function of transmission range *r*, thus a node is able to determine whether neighbouring nodes exist within one communication radius. If there are no other nodes within one communication radius then the node should not become a cluster head, thus minimising the number of cluster heads.

The proposed algorithm can be modified so that no learning is involved by simply setting $R_{threshold}$ equal to zero. This in effect makes the nodes no longer compete to become the cluster head first as it is now determined purely randomly.

The challenge is how to map the reward *R* such that it takes into account how each node perceived its environment denoting its neighbour's density and its proximity. In [59], two methodologies were presented to calculate *Reward R* (denoted as priority factor *P* in the [59]). The form of $1/[10\log(\text{RSSI})]^2$ was found to be ideal numerically as it is able to scale up RSSI in Watts while at the same time providing relatively significant differentiation between different reward levels but there is an element of arbitrariness in the equation.

As mentioned previously, nodes will continuously transmit a non associated beacon and that $RSSI_{threshold}$ will be selected such that it is a function of transmission range *r* (in Watts). At every random 'wake up' time, nodes add the newly sensed *non-associated* beacon RSSI in the form of RSSI/$RSSI_{threshold}$ to its previous figure, where RSSI is measured in Watts. Mapping the reward *R* to RSSI/$RSSI_{threshold}$, increases the probability of a node that has a high density of neighboring node will become a cluster head. Nodes in 'wake up' time that sense RSSI below the $RSSI_{threshold}$ may not have a neighboring node that is within its transmission *r* and is thus deemed unsuitable as a cluster head. This method of calculating the reward *R* in the form RSSI/$RSSI_{threshold}$ is called sumRSSI.

```
i = 0; R = 0
While ( R ≤ R_threshold)
        {
          R_i = RSSI_i/RSSI_threshold        for RSSI_threshold>0
          R = R_i+R
          i++;
        }
where i is the number of wake up times
```

Figure 4-6: sumRSSI psedo-code

A comparison can be made to the node degree schemes implemented by [25], [49] and in part by [23], [24]. In[23], [24] and [25], the authors argued that by forming clusters with nodes that have the greatest number of neighbours, fewer cluster heads will be produced subsequently reducing the number of nodes in the overlap region n_o and increasing spatial reuse. They assumed that each node has unique ID (identification) and is able to count the number of neighbouring nodes within single hop distance or transmission range r. No details were provided in [23], [24], [25] and [49] on the process of identifying the number of neighbouring nodes.

A comparison to the scheme presented in Figure 4-6 to that of node degree can be made by mapping the reward R to the number of neighbours each node has. Nodes in ‘wake up’ time will transmit a beacon and non-associated state nodes that receive the beacon above the $RSSI_{threshold}$ will respond back by sending a message containing its node ID. Just as in LEACH [21], the short message can be transmitted using a non-persistent CSMA MAC protocol (therefore, collisions are ignored in the simulation). The nodes in ‘wake up’ time will count the number of nodes ID n_{dx} it receives. If no neighbouring nodes respond by sending the short message, then the nodes in ‘wake up’ time will cease competing to become a cluster head and remain un-clustered. As time progresses, nodes with the highest number of neighbours are more likely to exceed $R_{threshold}$ and broadcast Cluster head *activation* beacon. The pseudo code for node degree is given in Figure 4-7.

```
i = 0; R = 0
While ( R ≤ R_threshold)
    {
     R_i = n_dx
     R = R_i + R
     i++;
    }
```

Figure 4-7: Node degree psedo-code

4.4.4 On Demand Beacons transmission

In the proposed clustering scheme as illustrated in Figure 4-5 and Figure 4-6, non associated state nodes will continuously transmit non-associated beacons. If node n_i and all its neighbouring nodes within transmission range r are not called to 'wake up' then continuous beacon transmission does not contribute to additional information and will increase the network energy consumption. In fact nodes that are located beyond the transmission range r of node n_i also does not yield a high information value as signal strength is proportional to the separation distance between the two nodes. The amount of non-associated beacons can be reduced by nodes transmitting the beacon only when it is called upon to do so. Nodes during 'wake up' will transmit a wake up beacon, and the remaining nodes can receive and judge whether the received wake up beacon signal strength is greater than $RSSI_{threshold}$. Only non-associated state nodes that receive the wake up beacon above $RSSI_{threshold}$ will respond by transmitting a *non-associated* beacon. The flowchart given in Figure 4-8 illustrates the actions that take place when node n_i is in the 'wake up' period.

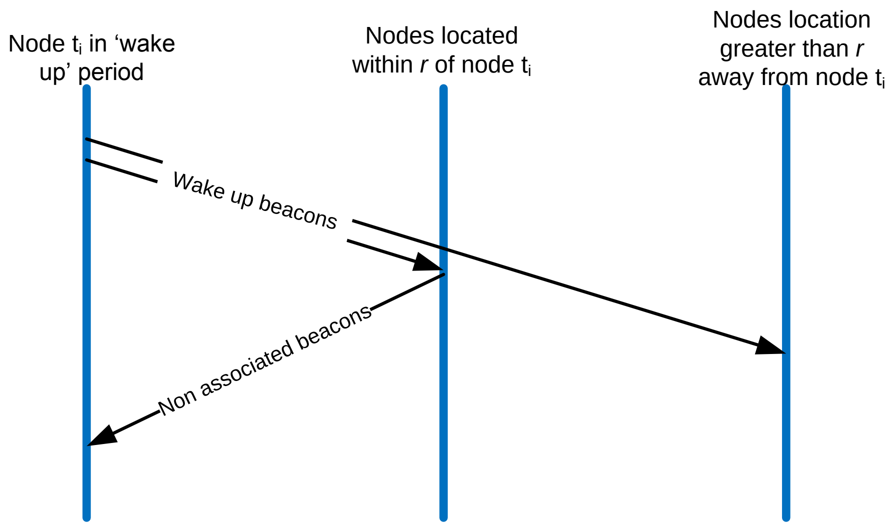

Figure 4-8: Flowchart off On Demand Beacon transmission

Reducing the number of beacons received by an individual node at a given a time would result in less accumulation of rewards therefore increase the period over which clusters are formed. The beacons efficiency e_b can be denoted from the total number of beacons transmitted over a period in which the network is covered by clusters t_x i.e. no node is still in non-associated state.

$$e_b = \frac{1}{\sum_{t=0}^{tx} bc_t \, t_x} \qquad 4.15$$

Where bc_t is the number of beacons transmitted during period *0* to t_x

4.5 Simulation and Results

This section verifies the performance of the proposed clustering scheme as presented in the aforementioned section and shows how it can reduce the distance between cluster heads and its respective cluster members while still maintaining sufficient coverage. Monte-Carlo simulations with 1,000 iterations were performed to illustrate the convergence rate of the proposed distributed clustering schemes. To understand the effect of mapping the reward *R* to the RSSI, the results are compared to that of a node degree scheme as presented in Figure 4-7 and centralised *k-means* [26] as presented in chapter 2.

4.5.1 Simulated Scenarios

100 homogenous nodes are randomly distributed on a square service area of $1x10^6m^2$ i.e. sides length $l_1=l_2=1000m$. It is assumed that nodes are located above rooftops at a height of 25m and operate at a frequency of 2.1GHz and the path loss was modelled via the Winner II channel model [41]. The maximum transmit power is -10dBW and a noise floor of -134dBW is assumed. The gains of transmitting and receive antennas are both fixed at 0dBi and the nodes have noise figure of 5dB. The $RSSI_{threshold}$ has been selected such that it is a function of the maximum transmission range r.

In order to understand the geographical distribution of clusters formed through the proposed clustering, the inclusion of shadowing in the radio propagation model was omitted in the simulations of sections 4.5.2 and 4.5.3. This resulted in a path loss affected by only the transmission distance between nodes as all the remaining parameters such as transmission power, antenna heights and antenna gains remained unchanged. However, radio signals are also affected by obstructions such as trees and buildings and the rate in which it is affected is different for every path, causing variation with respect to the mean value given by path loss model [63]. This phenomenon is known as shadowing and the typical distribution of the signal powers is a normal distribution. In the Winner II channel model [41], the shadow fading is Gaussian with a mean of zero and standard deviation of 3.4 dB. The resulting clustering performances of the proposed distributed clustering schemes under shadowing environment are provided in section 4.5.4.

4.5.2 Convergence rate

The improvement in spatial reuse can only be gained through clustering if the transmission range r of nodes can guarantee a strongly connected network such that the number of un-clustered nodes can be minimised. Using (*4.1*), it is deduced that to guarantee a probability of connectivity $P[cn]$ of greater than 0.95, the lower bound transmission range r was set to 100m. To minimise the channel contention amongst n nodes, the number of nodes in the overlap region n_o ideally should be no more than $n/2$. As illustrated in the previous section $n_o \approx n/2$, occurs when cluster heads are formed and located at the perimeter of its neighbours broadcasting transmission range

r. The expected number of clusters $E[n_{ch}]$ derived in (4.14) resulted in an upper bound transmission range r of 330m in which 7 clusters are formed.

Figure 4-9, Figure 4-10 and Figure 4-11 illustrate the performance of the clustering schemes at varying $R_{threshold}$ for the lower and upper bound transmission range r and for comparison purposes when r is 200m. By mapping the reward R to the received signal strength in the form of RSSI/$RSSI_{threshold}$, the packing efficiency of the clustering increases compared with that of the no learning algorithm, which does not calculate the reward R. This is because by allowing the nodes to learn and compete; nodes that are in a highly dense area will receive a higher RSSI, thus having a higher probability of becoming a cluster head faster. This differs from that of the no learning algorithm in which all nodes have equal chance of becoming a cluster head provided that during sensing its received beacon RSSI is above $RSSI_{threshold}$. The results also illustrate that although a node degree scheme can reduce the variation in the nodes proximity to the nearest cluster heads, on average it increases the distance and thus would result in higher network energy consumption compared to sumRSSI and the no learning scheme. It is important to note that learning algorithms performances, i.e. the sumRSSI and node degree performance saturates. This implies that any further learning and competition by nodes in the network up to a certain point no longer aids its clustering formation and can be considered a waste as it increases the overhead time for cluster formation and is therefore energy inefficient.

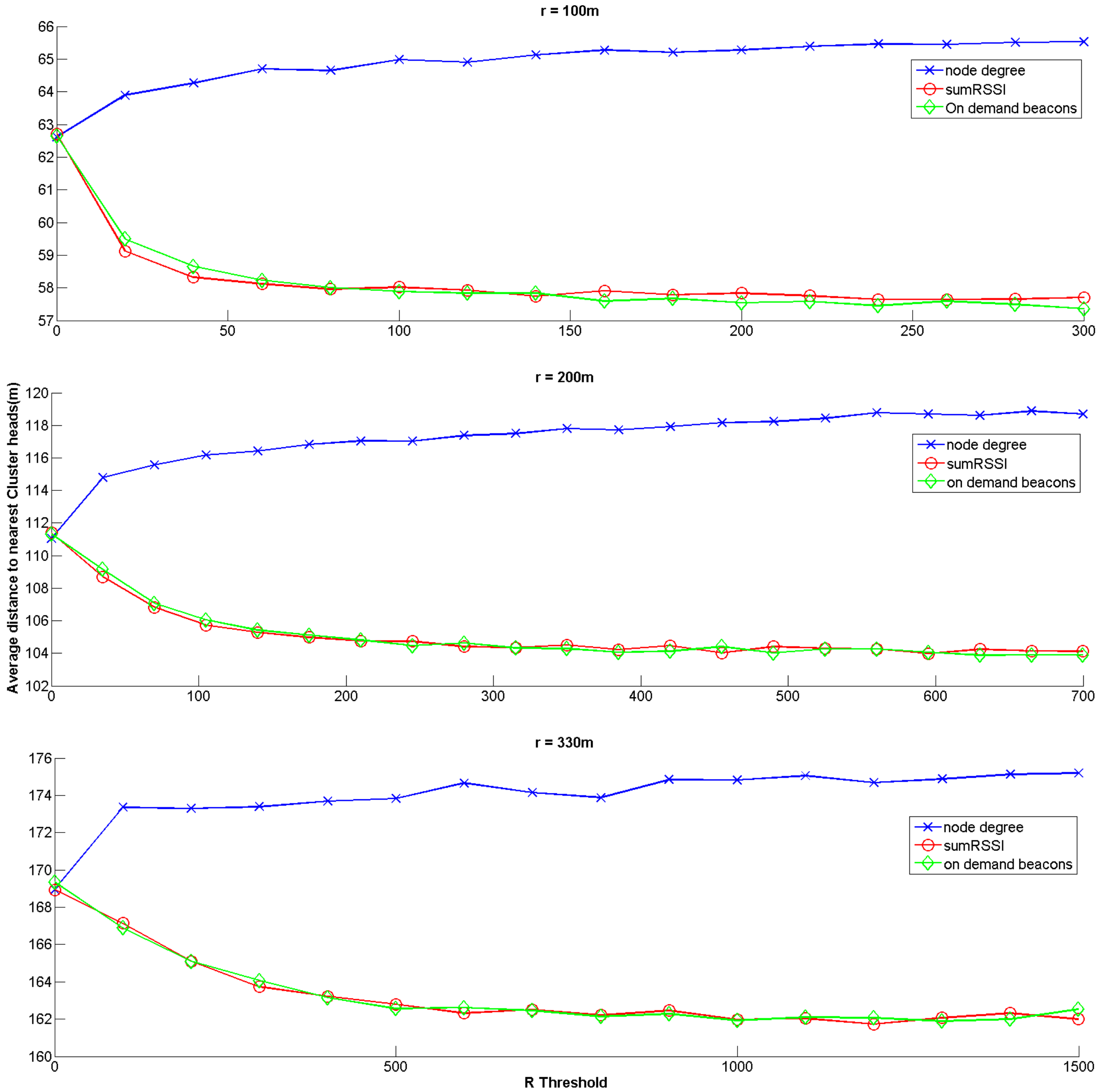

Figure 4-9: $R_{threshold}$ against average distance nearest cluster head for upper and lower bound transmission range as well at 200m

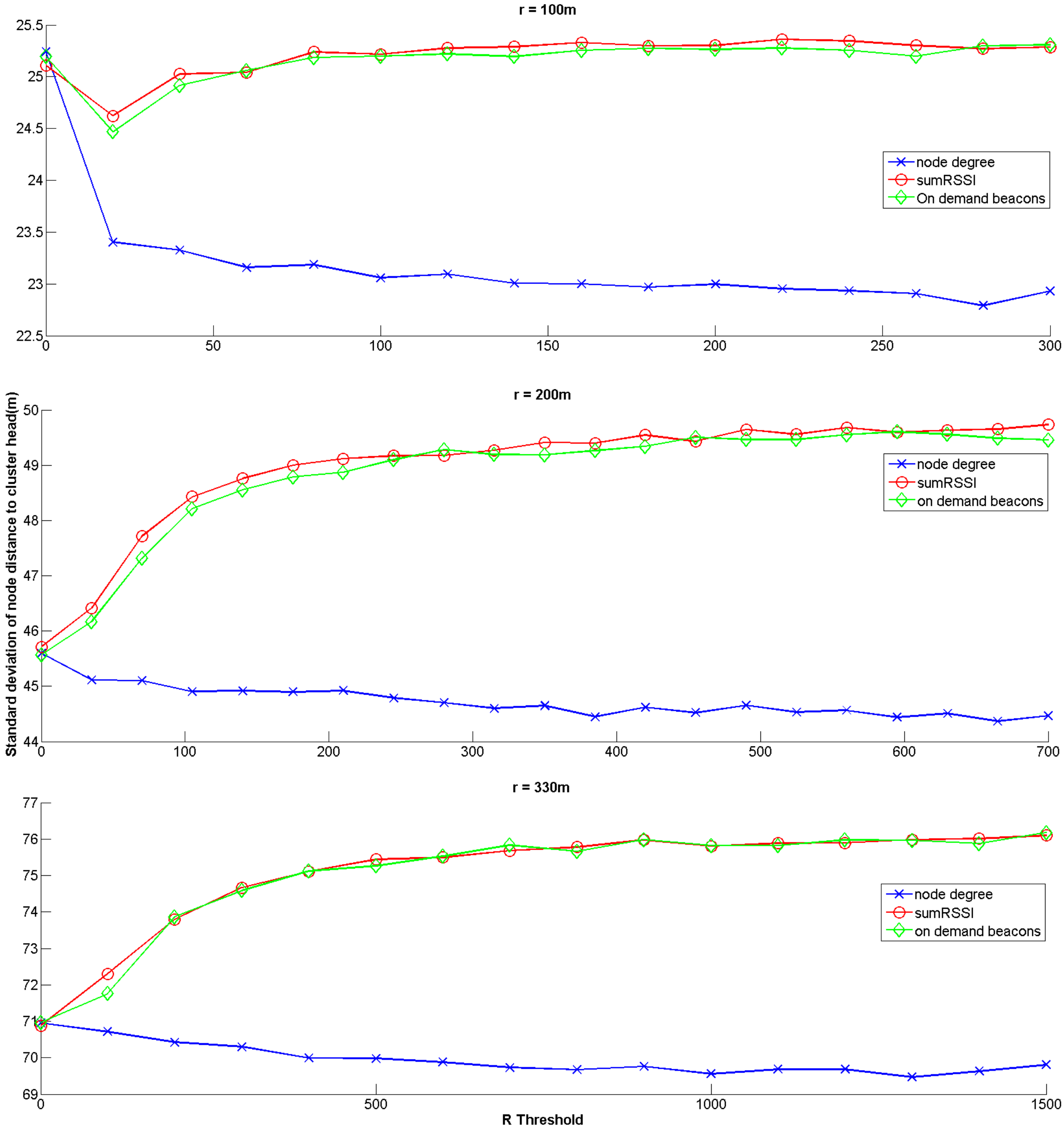

Figure 4-10: $R_{threshold}$ against standard deviation of node distance to nearest cluster head for upper and lower bound transmission range as well at 200m

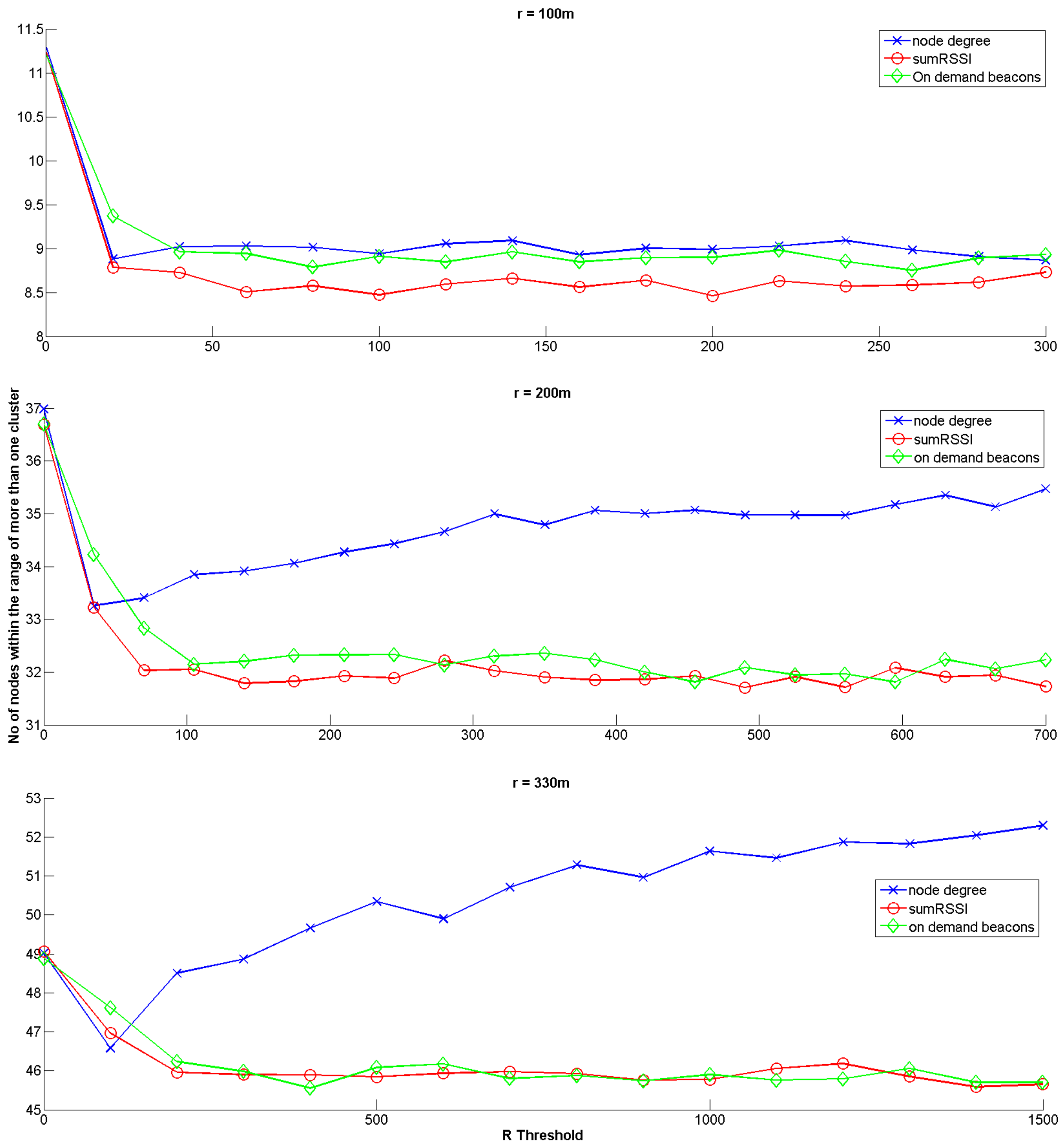

Figure 4-11: $R_{threshold}$ against n_o for upper and lower bound transmission range as well at 200m

Figure 4-12 illustrates that on demand beacon transmission can further reduce the energy consumption of the network as at a given time during the clustering process, only a certain number of nodes are required to transmit their beacons. Despite receiving less information on the network conditions, the on demand beacon approach has a similar packing efficiency to that of standard sumRSSI as evident in the results presented in Figure 4-9, Figure 4-10 and Figure 4-11. This indicates that local information obtained from neighbouring nodes within transmission range *r* presents higher information value. At the lower bound transmission range *r* =100m, the beacon efficiency e_b of On Demand Beacons is in the order of a factor 10 times more efficient than the standard sumRSSI. The beacon efficiency unsurprisingly deteriorates with an increase in $R_{threshold}$ as clusters takes longer to form. Note that the beacon efficiency increases at larger *r* as fewer clusters are needed to provide coverage for network thus reducing t_x. Also transmission range *r* increases, the difference in the beacon efficiency e_b between On Demand Beacons and sumRSSI diminishes as the On Demand Beacons requires more nodes to transmit their beacons in a given period.

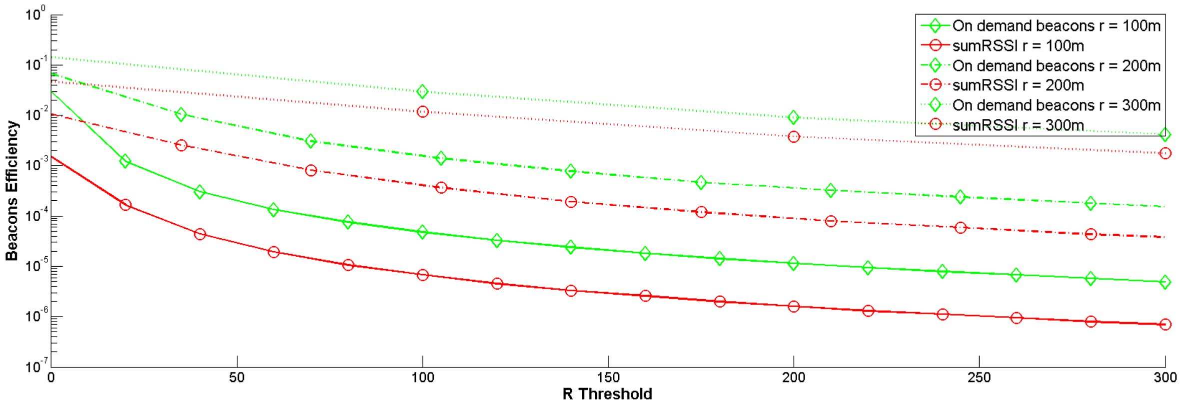

Figure 4-12: Improvement in beacons efficiency via On Demand Beacons

4.5.3 Clustering performance with varying transmission range r

a. Monte Carlo results

The number of clusters varies according to the specified cluster radius as shown in Figure 4-13. The smaller the transmission range, the larger the required number of clusters to provide coverage for the entire network. Understanding the number of cluster heads formed by varying the transmission range *r* enables us to understand and select the appropriate number of clusters such that the number of un-clustered nodes can be minimised. The simulations were performed with $R_{threshold}$ of 1000. The resulting number of clusters formed also allows us to compare the clustering performances with that to the centralised *k-means* [26] as it requires a predetermined number of clusters. In [59], the resulting distribution of cluster heads and cluster members generated through the proposed algorithm presented in this chapter were compared to that of LEACH algorithm. Details on the clustering algorithm employed in LEACH are provided in chapter 2 Note that unlike the objectives of the proposed clustering algorithm presented in this chapter, the goal of clustering in LEACH is to evenly distribute energy load among nodes in the network. Nevertheless some of the results published in [59] are reproduced in this chapter.

Note that Figure 4-13 clearly indicates that the average number of cluster heads formed ${n_{ch}}^A$ for the no learning algorithm is close to that of the expected number of clusters $E[n_{ch}]$ derived in (4.14). Note that the figures for un-clustered nodes (no learning) n_u was empirically obtained through simulations as presented in Figure 4-14.

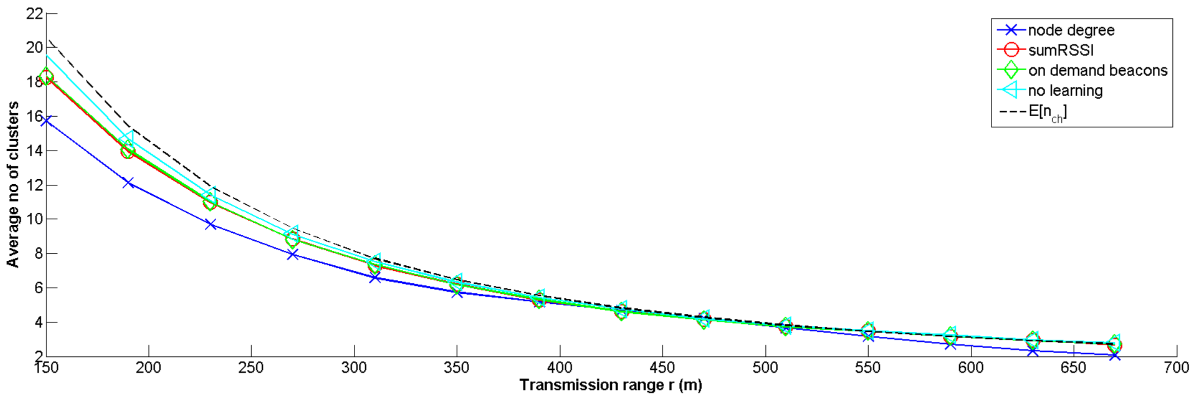

Figure 4-13 Average no of Cluster heads formed for a given transmission range r

Nodes which are not part of a cluster will be unable to send data to the cluster head and therefore have to transmit directly to the HBS (hub base station). To study this effect, the numbers of nodes which are not part of a cluster as a function of the transmission range *r* of a cluster head were measured, and the result is compared to that of *k-means* [26]. Note that unlike the proposed clustering algorithm, *k-means* [26] requires a predetermined number of clusters with each cluster cantered around an imaginary geometric centroid. The objective of *k-means* is to minimise the sum of the squares of distances of nodes to the geometrical centroid. In the *k-means*, nodes nearest to the imaginary geometric centroid are elected to act as a cluster head so that data from cluster members can be relayed to the hub base station. For a fair comparison, the *k-means* and LEACH was simulated to produce similar cluster size that conforms to the proposed algorithm at specific transmission range *r* intervals.

As illustrated in Figure 4-14 compared with no learning, the learning schemes i.e. sumRSSI, node degree and *k-means* resulted in more nodes becoming un-clustered at *r* less than *l*/3. This would result in more nodes having to transmit directly to the HBS thus potentially increasing the inter-cluster channel contention. However, this drawback is negated by the fact that the learning schemes produce fewer clusters (see Figure 4-13) thus normalising the inter-cluster channel contention to that of no learning schemes. It is also evident from Figure 4-15 that the proposed clustering algorithm produces more uniform positioned clusters than that of LEACH.

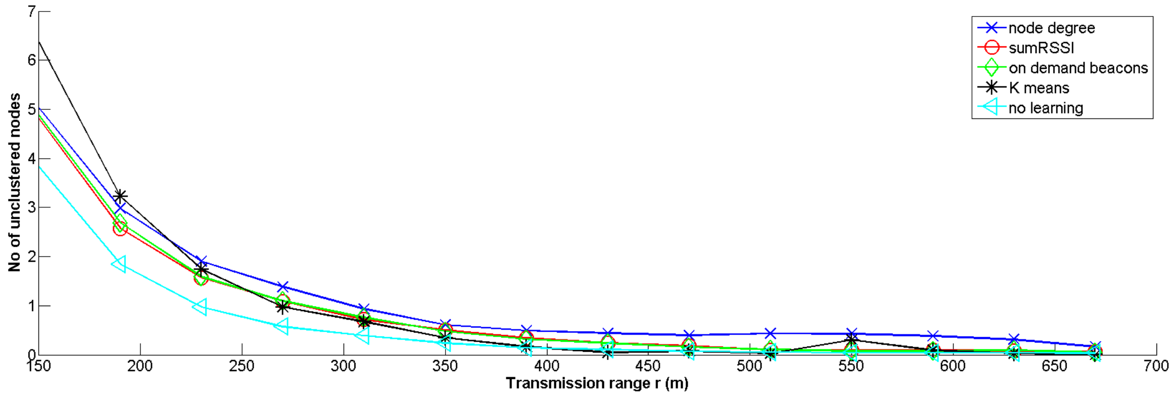

Figure 4-14: Average no of un-clustered nodes at different transmission range r

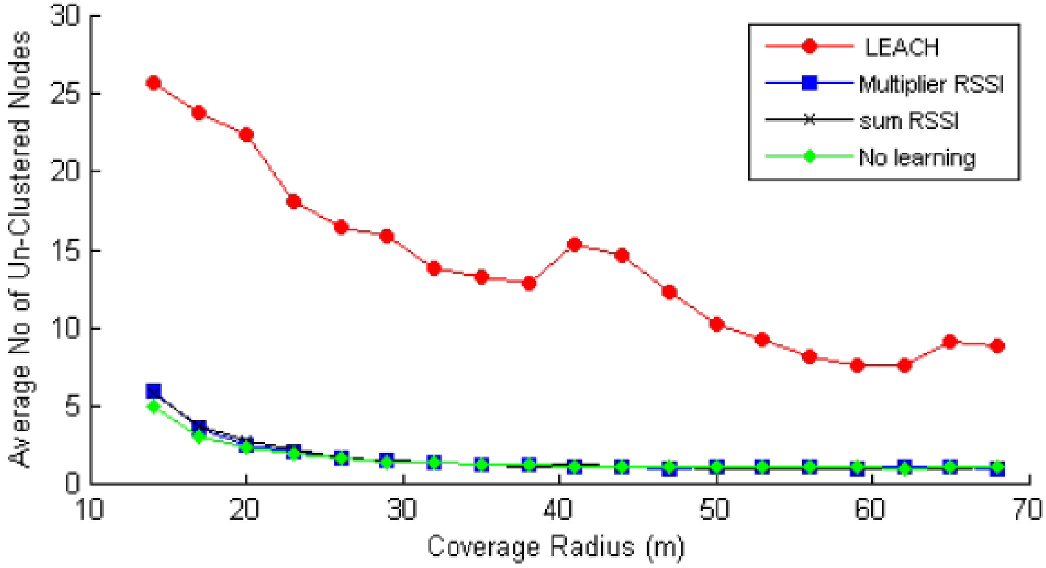

Figure 4-15: Average no of un-clustered nodes for the proposed clustering algorithm vs. LEACH (Directly reproduced from [59])

Figure 4-9 presented earlier, illustrates that the proposed algorithm reduces the Euclidean distance between cluster heads and its members when compared to no learning. As mentioned in [2], reducing the transmission distance length can significantly reduce energy dissipation assuming an energy dissipation model as proposed in [20] is directly proportional to the square of the transmission distance. Figure 4-16 shows how mapping the reward *R* to RSSI/$RSSI_{threshold}$ and the number of neighboring nodes (node degree) affect Euclidian transmission distance at various transmission ranges. An argument can be made that, the node degree has the highest average transmission distance because it produces fewer clusters compared to the no learning and sumRSSI. This argument is only partially true as illustrated in Figure 4-17 and Figure 4-18 whereby sumRSSI has the least average transmission distance for the same number of clusters compared to no learning, node degree and LEACH. The reduction in transmission distance is achieved as cluster heads are more likely to be elected by the nodes located in densely populated areas thus able to reach $RSSI_{threshold}$ at a faster rate. In *k-means*, the reduction in transmission distance is achieved through iteratively moving the centroids such that the average distance of nodes in a cluster is minimised. This process requires a central coordinator as it requires knowledge on the location of all nodes in the network and an arbiter to process and execute the algorithm.

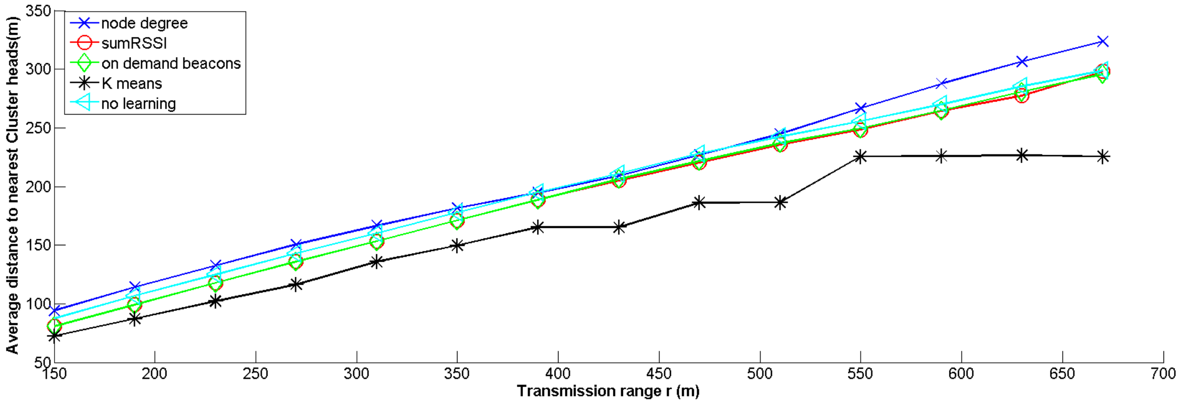

Figure 4-16: Average transmission distance to cluster heads at various transmission range r

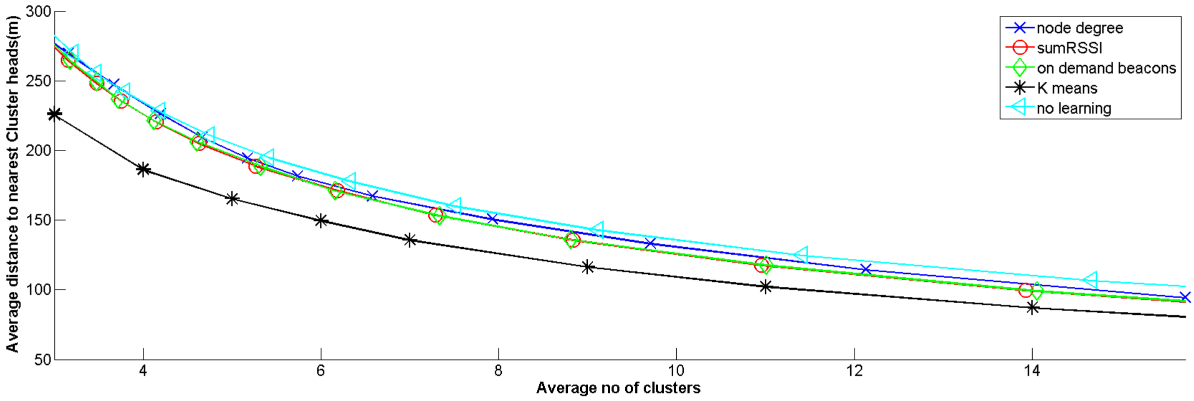

Figure 4-17: Average transmission distance to cluster heads at various number of clusters

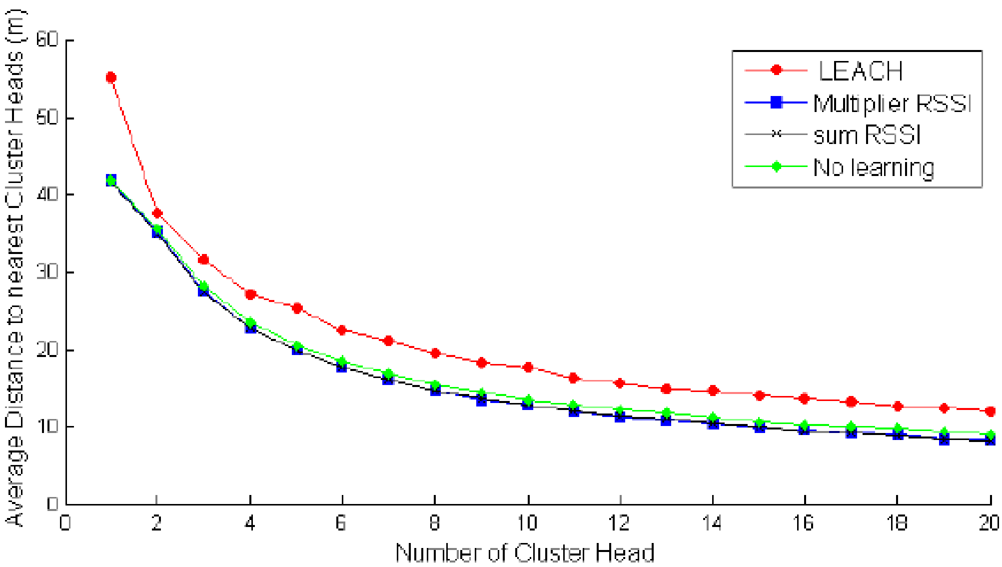

Figure 4-18: Average transmission distance to cluster heads for the proposed clustering algorithm vs. LEACH (Directly reproduced from [59])

To reduce intra-cluster channel contention and improve aggregation it is therefore important to minimise cluster overlap. The degree of overlapping clusters can be found by measuring the number of nodes that are within the coverage radius of more than one cluster n_o and two clusters. Higher node counts will indicate that many clusters are overlapping one another. Figure 4-19 shows a comparison of such measurement where; 2 clusters and 3 clusters in the legend represent the number of cluster heads that are within the transmission range r of nodes in the network. From Figure 4-19, sumRSSI and node degree produces a cluster with a lower overlap than that of *k-means*. This is achieved by the random 'wake up' time of $1/n$ which eliminates the probability cluster head is elected within the transmission range r of other cluster head.

The result also illustrates that at a transmission range r of less than $l_1/2$, the sumRSSI produces fewer n_o compared to node degree. This is because in sumRSSI, the most recently sensed *non-associated* beacon RSSI is of greater importance. Any changes to the overall global network *non-associated* beacon RSSI, e.g. formation of new cluster head will cause a reduction in RSSI as some of the *non-associated* beacons will have turned off by some nodes. Un-clustered nodes that are located close to the newly formed cluster will therefore sense significantly fewer *non-associated* beacons RSSI thus making it a relatively low priority node. Although node degree has a better n_o at r greater than $l_1/2$, the resulting no of clusters is only 4% of n. Such a low number of clusters would cause a heavy load on cluster heads as they are involve in relaying information from and to its cluster members. A high number of cluster members would also increase channel contentions amongst nodes within each cluster thus reducing the benefit of clustering. SumRSSI resulted in 7 clusters formed in the network at transmission range r of between 300m to 350m, at which point n_o is roughly $n/2$, this is consistent with the expected $E[n_o]$ derived in (4.9).

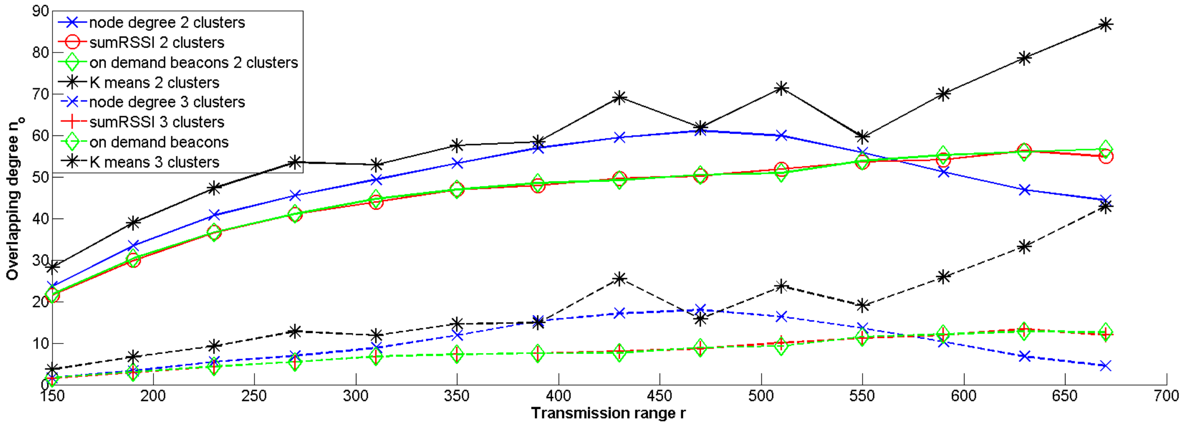

Figure 4-19:Average no of nodes in range of more than one cluster head

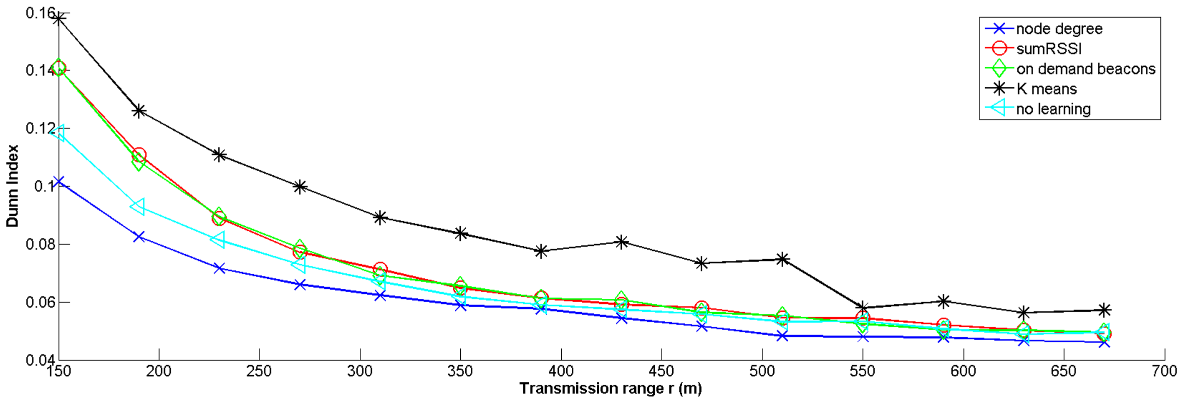

Figure 4-20:Dunn index of clustering schemes at various transmission range r

Several metrics have been proposed and surveyed in [46], [60], [61] and [62] to quantify, evaluate and validate the performance of clustering schemes. Most of these metrics are used in data mining processes to understand the similarity of objects in clusters and pattern recognition. The Dunn index [61] attempts to quantify the compactness and well distributed and separated clusters. The index allows us to compare various clustering schemes and provide an insight into the spatial diversity that can be gained. The Dunn index is defined as the ratio of minimum inter-cluster distance to the maximum intra-cluster distance, and is summarised in equation (*4.16*).

$$Dunn\ Index = \min_{1 \le i \le n_{ch}} \left\{ \min_{1 \le j \le n_{ch}, j \ne i} \left\{ \frac{d(C_i, C_j)}{\max\limits_{1 \le k \le n_{ch}} (\Delta C_k)} \right\} \right\} \qquad 4.16$$

Where $d(C_i, C_j)$ is the minimum distance between two cluster heads and $\max_{1 \le k \le n_{ch}}(\Delta C_k)$ is the maximum intra-cluster distance or diameter between all the clusters in the network.

In the scenario presented in this section, $\max_{1 \le k \le n_{ch}}(\Delta C_k)$ is obtained by measuring the maximum Euclidian distance of a node to its nearest cluster head. Clustering schemes that produce large separation distance between clusters $d(C_i, C_j)$ and a small cluster diameter ΔC_k will result in a high Dunn index. Therefore, larger values of the Dunn Index correspond to well distributed and compact clusters. Note that that the Dunn Index gives no indication on the number of clusters formed. The Dunn Index of *k-means* and the proposed clustering schemes is shown in Figure 4-20. It is clear that at up to the upper bound transmission range *r* (330m), sumRSSI produces a more dense and distributed clusters than no learning and node degree. The node degree has the lowest Dunn Index, due to the high average node transmission distance to the nearest cluster head as illustrated in Figure 4-16. These findings illustrate that although the node degree scheme, produces lower cluster count, the resulting clusters are large in diameter and are not well distributed throughout the network. This would reduce spatial diversity and therefore increase channel contention.

b. Snapshot results

In this scenario the location of 100 nodes were fixed with a transmission range *r* of 200m. $R_{threshold}$ is set at 1000, at which point the performance of the proposed clustering schemes have converged. By fixing the geographical location of nodes, the distribution of transmission distances of nodes to its nearest cluster head can be understood. Figure 4-21 illustrates the cumulative distribution function (CDF) of the nods transmission distances for various clustering schemes. The *X*- axis of Figure 4-21 corresponds to the transmission distance from a node to its respective cluster head and the *Y*-axis is the ratio of number of nodes that have transmission distance less or equal to *X*. It can be seen that sumRSSI and on demand beacon have a very similar distribution and cover a wider transmission distance (ranging from less than 10m and up to 190m) than that of node degree. This supports the result presented in Figure 4-10 in which sumRSSI has a higher standard deviation of node distances compared to node degree. Around 40% of the numbers of nodes have a transmission distance of less than *r/2* compared to only *n*/3 achieved by node degree. The result also shows that 15% of nodes in sumRSSI and on demand beacon have a better transmission distance than that of *K-means*. This shows that mapping the reward *R* to RSSI exhibits a greater bias towards electing cluster heads that minimize the transmission proximity of only several neighbouring nodes rather than the average in the local area.

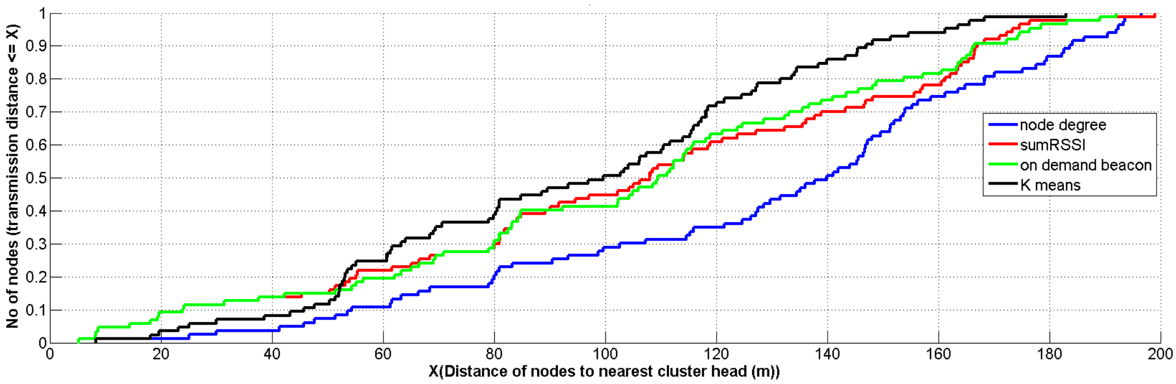

Figure 4-21: CDF of distribution of nodes transmission distance to its nearest cluster head

4.5.4 Shadowing environment

a. Monte Carlo result in the presence of shadowing

Figure 4-22 illustrates the average received transmission power (dBW) by each node with varying $RSSI_{threshold}$ in a shadowing environment with a mean of zero and standard deviation of 3.4 dB. The result shows that up to the upper bound transmission range *r* which corresponds to $RSSI_{threshold}$ of 106dB, the cluster heads in sumRSSI and On Demand Beacons on average can receive between 1dBW to 2dBW more power than no learning and node degree. This means that, assuming nodes can perform power control, sumRSSI and on demand beacon can reduce its power consumption by up to 36.7% to achieve the same signal to noise ratio (SNR) as that of node degree.

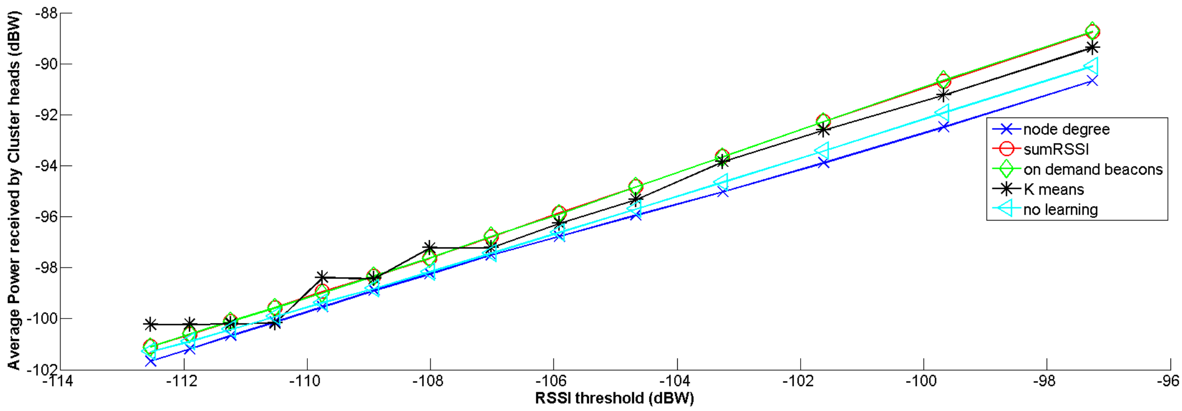

Figure 4-22: Average power received by cluster heads from each cluster member in a shadowing environment.

b. Snapshot result in the presence of shadowing

Figure 4-23 illustrates the snapshot distribution of power received by cluster heads from respective cluster members. The simulation was performed by fixing the geographical location of nodes and its shadowing properties. $RSSI_{threshold}$ and $R_{threshold}$ was set to -100dBW and 1000 respectively. Since *K*-means does not take into account the RSSI and only attempt at minimising the average geographical proximity of nodes in the local area to the centroid, several nodes received power are below that of $RSSI_{threshold}$ and can thus result in an increase in the number of un-clustered nodes. The result shows that half of the nodes in sumRSSI and on demand beacon can reduce its transmission power by 3dBW compared to the node degree. However, the snapshot result as presented in Figure 4-23 also shows that there is a negligible difference on the powers received by cluster heads formed through learning based clustering schemes (sumRSSI and on demand beacon) and no learning scheme. This differ to the findings obtained through Monte Carlo simulation given in previous section where it expected that at an $R_{threshold}$ of -100dBW, the cluster heads formed through the no learning scheme will on average receive 1.27 dBW less power compared to the sumRSSI and on demand beacon. This indicates that the learning inspired clustering schemes (sumRSSI and on demand beacon) do not always optimise the resulting clusters formation. Therefore, in a certain geographical layout of nodes in the network in which the learning schemes are unable to provide a significant improvement on the clustering performances, it is more advantageous for the clusters to be formed using no learning scheme due to its low overhead time.

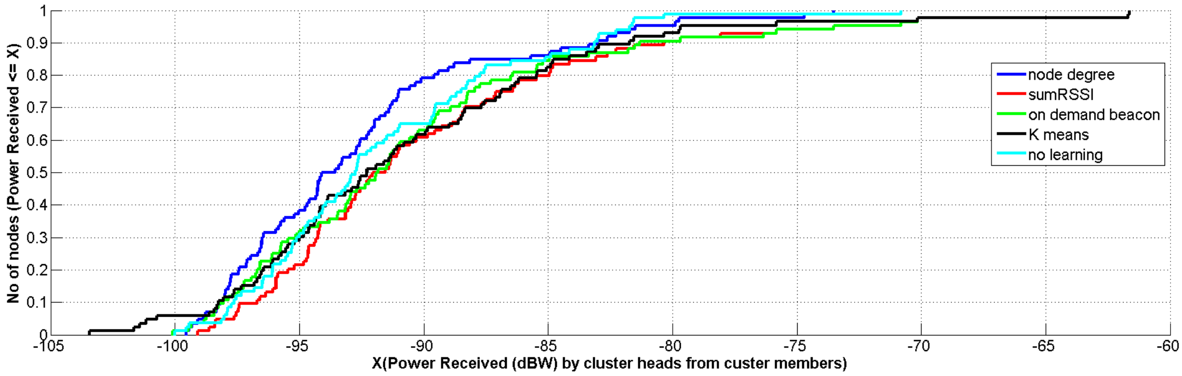

Figure 4-23: CDF of distribution of power received by cluster heads form its cluster members in a shadowing environment.

4.6 Conclusion

In this chapter a novel clustering algorithm is presented that has the ability to allow nodes to learn via RSSI and compete to become cluster heads. It is shown that by making nodes repeatedly learn about their environment through RSSI, the resulting cluster formation is better than with no learning and node degree. The proposed algorithm is distributed and reduces the transmission distance of nodes to cluster head. The resulting cluster formation of sumRSSI also provides an efficient coverage of the network and reduces the degree of overlapping clusters. Although the transmission distance alone does not model the total energy consumption, the power amplifier's energy consumption is dependent upon transmission range [42].

Unlike the claim made by in [23], [24], [25] and [49], the results presented in this chapter illustrate that through the proposed algorithm, electing nodes which have the highest number of neighbouring nodes as cluster heads (node degree) can result in an increase in the average transmission distance and degree of overlapping clusters. This can result in higher energy consumption and reduce quality of service (QOS) due to high channel contention amongst nodes due to diversity. Learning based on the RSSI of beacons eliminates the need for excessive exchange of information required to find the number of neighbouring nodes in node degrees. This means that sumRSSI can learn more efficiently and quickly compared to node degree as well as being more scalable and robust with various network sizes and shadowing properties.

A further reduction in energy consumption can be gained by reducing the number of beacon transmissions. The results indicate that nodes only need to learn through its immediate neighbours beacons (single hop) to achieve the same level of clustering performance.

It is illustrated that the proposed clustering schemes converges as $R_{threshold}$ grows larger. This indicates that up to a certain point, any further learning and competition no longer aids the distribution of clusters. Although *k-means* is able to distribute the clusters separation and reduce the geographical proximity of nodes in the local area, it requires a central coordinator as well high exchange of information. It also fails to take to take to account of showing when used in its basic form.

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5.1 Introduction

The energy efficiency of wireless communication networks is attracting considerable interest, as their increasing data rates and ever increasing use mean that they are consuming an ever increasing proportion of the world's energy usage. Today, the world is trying to reduce energy consumption, in order to ultimately reduce requirements for fossil fuels. Future wireless networks will carry not only user-to-user traffic, but also machine-to-machine data. Such machine-based traffic can include low rate data from sensors, such as periodic measurements, to high-data rate streaming video from the next generation of CCTV. User-based traffic is also seeing a considerable increase, as users expect to use the same applications on their laptops and tablets as they have in their desktops. Thus, the structure of next generation networks is likely to be more ad hoc in nature, able to cope with a wide range of traffic requirements, with the structure adapting to load requirements and spatial usage.

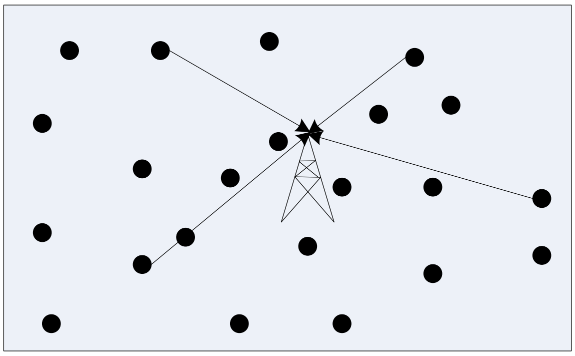
Wireless networks must take into account these data requirements, usage, cost and energy consumption. In the case of mobile devices, transmit power and the amount of processing are two important factors. Linked with this is the type of wireless communications architecture, both access and backhaul, that needs to be used with these next generation architectures. For example the FP7 BuNGee project looked at a cost effective dual hop access and backhaul wireless architecture that is capable of delivering 1Gbps/km^2 for such future wireless services [64].

This thesis shall examine the benefits and limitations of such dual hop architecture in a more general sense than BuNGee (regular topology), as a way of reducing energy consumption while maintaining throughput. Nodes collaborate with neighbouring nodes throughs self-organising techniques, in the form of clustering, to organise nodes into access networks and backhaul networks. The operation of a clustering algorithm is such that the nodes are organized into disjoint sets by selecting appropriate nodes as cluster heads. The cluster head will become an access point providing the backhaul links to the networks. They are responsible for routing data from nodes to a hub base station and vice versa.

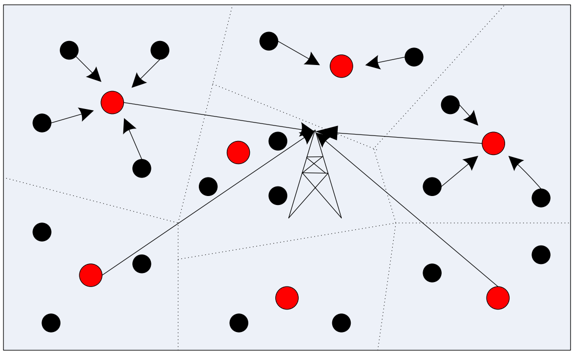
The purpose of this chapter is to understand and quantify the energy efficiency and power consumption under variable conditions such as offered traffic load, channel assignment scheme and transmission range of a hierarchical architecture in the form of dual hop clustered network. Understanding the behaviour and characteristics of such radio network, enables radio designer to optimise its efficiency. This chapter will also investigate the conditions in which the dual hop clustered network can be more energy efficient than the direct transmission architecture as shown in Figure 5-1.

The content of the chapter is as follows. First, some of the literature on the power consumption models that have been applied in sensor and ad hoc networks are presented followed by some discussions by various researchers whether it is more energy efficient to use short hops or long hops. Afterwards the energy efficiency metrics are defined, which are used to compare the network under different variables.

In section 5.3, the expected upper bound network throughput for the dual hop clustered networks is provided followed by descriptions on the system modelling for simulations in 5.4. The result under different variables based upon the system model is presented in 5.5 which and a mean to eliminate dropping in a file transfer is also presented. Finally a conclusion is drawn.



a) No hierarchical formation



b) Clustered Network with 2 hops

Figure 5-1: Network planning of Wireless Networks with hierarchical architecture

5.2 Wireless Network Energy Consumption

The annual growth sales of smartphone has recently overtaken personal computers (PCs). The increase in processing power in smartphones allow users to interact with their smartphones for a richer experience and the wireless network should provide broadband like performance to cater for the expectations and needs of subscribers. In order cope with the continuously increasing number of wireless users which have led to the usable channel spectrum becoming ever rarer and increasingly expensive, researchers have been continuously proposing new and more efficient modulation, coding, media access control (MAC) and novel architecture to meet future demands of wireless subscribers.

The tremendous growth in the amount of cellular traffic has caused concern amongst mobile network operators due to the increase in energy consumption, energy cost and carbon footprint [6]. The issue of soaring energy consumption was highlighted in [65] and [66], where 3% of worldwide energy consumption is due to information and communication technology infrastructure (ICT) and within the next decade it is estimated that the cost of energy consumption be more than double current levels [65]. During the last decade there has also been a greater awareness amongst the general public of the impact of the effect of rising CO_2 emissions on the environment. In fact ICT accounted for 2% of the global CO_2 emissions and is comparable to that of aeroplanes [66] and [67].

Various schemes have been proposed in the literature to tackle the growing concern of energy consumption and CO_2 emissions. Various solutions have been proposed in the literature with a lot of research focused on reducing energy consumption in the radio access network. The radio access network accounts for over 80% of the power consumption of mobile networks and base stations are mainly responsible for this [7]. Accordingly, novel energy efficient centric architectures have been proposed. The energy saving benefit of a multi-hop architecture that uses relays to exchange information between mobile stations and base stations was studied in [8]. Small cell deployments that bring mobile stations closer to base stations [2] and twin state deployments that allow base stations to change state from macro-cell to smaller cells by dynamically altering its coverage radius depending upon the traffic load [68].

5.2.1 Review of Energy Consumption Models in Ad-hoc and Sensor Networks

The increase in awareness amongst the general public in regard of the CO_2 emission and the additional cost incurred by mobile network operators has given researchers an extra dimension in dealings with design of wireless networks. The design and evaluation of energy saving networks and protocols requires information on the energy consumption behaviour of actual wireless devices. However, there is a lack of general consensus amongst researchers on the practical modelling of energy consumption of wireless devices.

An analytical energy consumption model was developed in [69] for a tagged device to successfully transmit a packet with the p-persistent CSMA MAC protocol. The model is based on of studying the system behaviour between the time intervals of two successful transmissions of the tagged devices, referred as the *virtual transmission time*. From a tagged device wireless standpoint, the average energy consumption is the ratio between the energy required to successfully transmit a packet in a renewal interval divided by the system efficiency.

$$E[Energy_{virtual\_transmission\_time}] = \frac{PTX\ .\, l_{th}.\, t_{slot}}{p_{energy}} for\ 0\ > p_{energy}\ > 1 \qquad 5.1$$

Where *PTX* denotes the power consumption per unit time, l_{th} is the packet length and p_{energy} is the power efficiency. $E[Energy_{virtual\_transmission\_time}]$ is the energy consumed by the tagged device during a *virtual transmission time* and it includes the energy consumed in idle periods, collisions and successful transmissions. The work conducted in [69] provides an analytical closed expression for the optimal value of *p*, such that the throughput can be maximised whilst minimising energy consumption.

Unlike [69] which provides an analytical model of the energy consumption in a wireless local area network (WLAN), Feeney and Nilsson [70] conducted a series of experiments on the IEEE 802.11 wireless network interface. The wireless network devices were operated in an ad hoc networking environment in which they obtained measurements with regards to energy consumption. In order to help developer model the energy consumption during transmission and reception, the data compiled by [70] was summarised and presented as a linear equation:

$$Energy\ consumption = m_x . l_{th} + b_x \tag{5.2}$$

m_x and b_x are the coefficients for various operational set up such as point to point, broadcast and discard traffic. Figure 5-2 presents the result from [70] on the energy consumption during transmission, reception and the idle period of the tested IEEE 802.11 interface device. It is worth noting that the result indicates that the energy consumed during reception is marginally more than during an idle period, this finding is supported by another measurement conducted by [71].

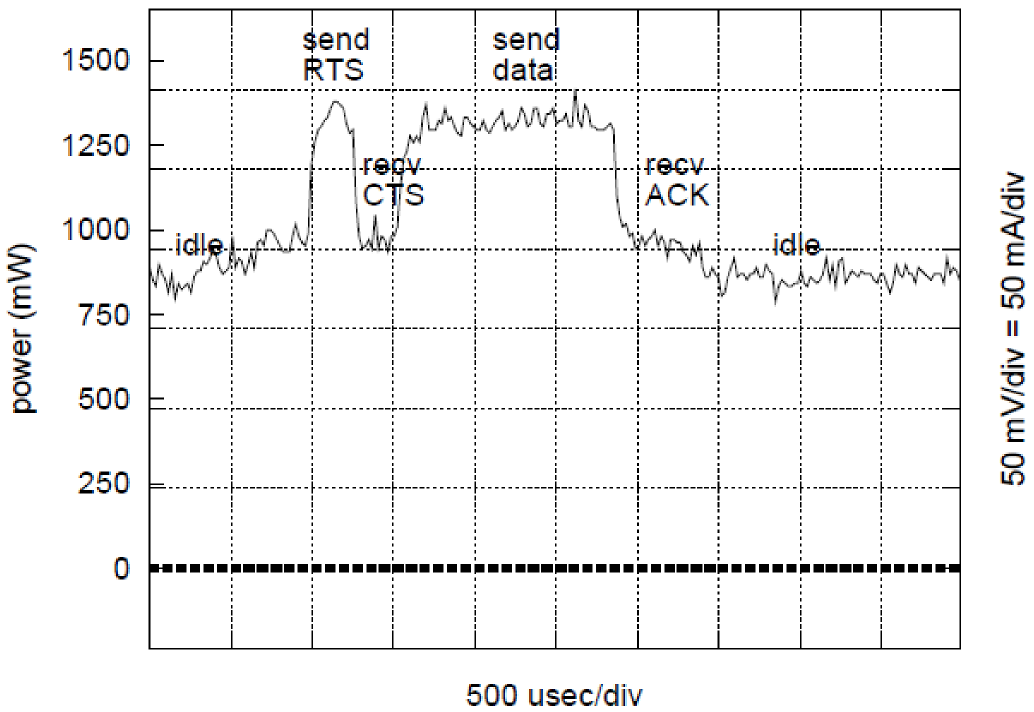


Figure 5-2: Experimental snapshot on the Energy consumption of IEEE 802.11 (directly reproduced from [70])

5.2.2 Long hop vs. Multi-hop energy consumption

In wireless sensor networks (WSN) where there is a greater emphasis on energy conservation as they are operated with limited battery power and computing capability. The discussion of whether it is more energy efficient to transmit over many short hops or few long hops has been a topic debated by various researchers [20], [73], [74], [75] and [76]. One of the drawbacks of the multi hop approach is that using other nodes as relays can cost more energy due to the additional effort for multiple transmission and reception as well as the increase in delay and bottleneck. In contrast, a single hop needs to go over a longer distance with more transmit energy. Over the last few years, some researchers such as [77] claimed that multi-hop network implementations can reduce energy consumption by 40% less compared to an equivalent single-hop network. However, some researchers [74], [75] and [76] argue that long-hop implementations consume less energy in relaying data compared to equivalent multi-hop networks due to simpler routing protocols, lower communication overhead, and higher overall efficiency.

In [20] and [21], the authors examine the energy consumption of a direct communication to the base station versus minimum energy multi-hop routing protocols in a wireless sensor network as shown Figure 5-1. Using the energy modelled summarised in Table 5-1, their analysis and simulation results indicate that when the transmission distance is small, transmission and receive energy are identical and a direct transmission is therefore more energy efficient than minimum energy routing protocols.

Operation	**Energy Consumption**
Transmission	$E_{Tx}(k_b,r) = E_{elec}\times k_b + e_{amp} \times k_b \times r^2$
Reception	$E_{Tx}(k_b,r) = E_{elec}\times k_b$

Table 5-1: Leach energy consumption model

Where k_b length of a message in bits, E_{elec} is the transmitter and receiver circuitry and e_{amp} is the transmitter amplifier.

The claim made by LEACH in regards to the energy consumption of short hops and long hops was supported by M. Haenggi in [73], [74], [75] and [76]. From their analysis in [76], M. Haenggi concluded that the total energy reduction in transmitting over short hop is negligible as the circuitry of low power transceivers will dominate the energy consumption of sensor network nodes and that relatively high transmit peak power is required to maintain network connectivity, therefore it is more beneficial to transmit via a long hop if a reliable connection can be made [76]. M.Haenggi also claimed that long-hop transmission does not necessarily produce greater interference than multiple transmissions at lower power as Signal to interference ratio (SIR) does not depend on absolute power levels. Assuming that all nodes increase their power by the same factor, the increase in transmitted energy will not reduce the probability of packet reception as SIR would actually remain constant.

In [72], they explore the conditions in which multi-hop routing is more energy efficient than a direct transmission and when two hop strategy is optimal in wireless sensor networks (WSN). They argued that the energy consumption model used in [76] were unrealistic as it does not reflect the practical performance of commercially available sensor network nodes during transmission and reception. Figure 5-3 illustrates the current consumption of commercially available wireless sensor network transceiver model used in [72]. Their experimental tests using actual sensor networking hardware showed that it is more energy efficient using multi-hop schemes and that its efficiency is dependent upon source to sink distance and energy consumed in reception.

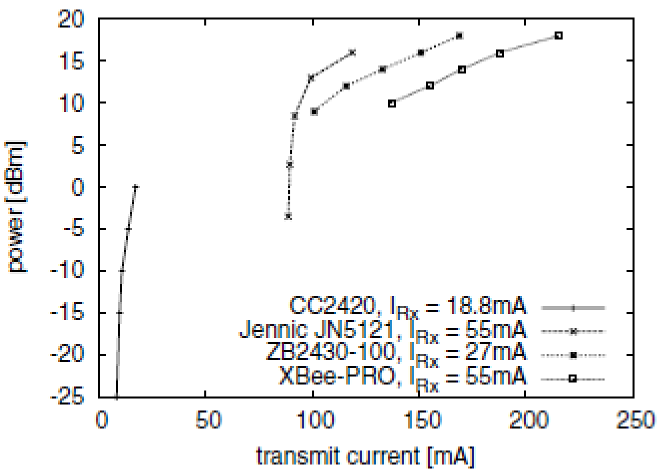


Figure 5-3: An example of Current consumption of transceivers model in Wireless Sensor Nodes (Directly reproduced from [72])

Wireless sensor network (WSN) energy efficiency has been widely based on a sensor node power consumption modelled by [20], [21]where the major impact of the energy consumption of a node is largely dependent upon the transmission range and transmitter circuitry. However, the quality of service (QOS) of a transmission also plays a vital role in the energy consumption as poor QOS will result in a longer delay thus increase energy consumption. In [51], the author analyses the energy consumption of wireless sensor devices by separating out the power consumption of each hardware component and incorporating the characteristics with RF transceivers to understand the impact on the QOS of the network. The power consumption in [51] is derived from the structure of a communication module found in a typical WSN node, in which the total power consumption for transmission $Pt_{xi}(r)$ and reception Pr_{xi} is:

$$Pt_{xi}(r) = P_{TB} + P_{TCF} + P_A(r) = Pt_0(r) + P_A(r) \qquad 5.3$$

$$Pr_{xi}(r) = P_{RB} + P_{RCF} + P_{RA} = Pr_0 \qquad 5.4$$

Where P_{TB} and P_{RB} is the power consumption in baseband DSP circuitry, P_{TCF} and P_{RCF} is the front end switching power consumption and P_{RA} is the reception power amplifier. $P_A(r)$ is the power consumption of the power amplifier and is dependent upon the transmission range r. Since P_{TB} together with P_{TCF} and P_{RB} together with P_{RCF} and P_{RA} are not dependent upon transmission range r, therefore these components can be modelled respectively as a constant Pt_0 and Pr_0. They demonstrated that the upper bound limit of power efficiency of the network is proportional to the power consumption of the transmission and reception circuitry as well as the power amplifier of the tested devices. They also concluded that multi-hop schemes are more energy efficient than single hop only if the source to sink transmission length cannot be reached via single hop.

The above discussions clearly demonstrate that whether to use single hop or multi-hop to achieve optimum energy efficient solution is still continuously analysed and debated amongst various researchers. Therefore the network will be limited to two hops, i.e. data from cluster members will be transmitted to the cluster head which in turn relay the data directly to a HBS. The limitation on the number of hops is primarily to reduce the relaying burden on the cluster heads and decrease the end-to-end bottleneck that can exist along transmission links from source to sink which therefore severely limits the network capacity.

5.2.3 Energy Efficiency Metrics

In order to meaningfully measure the energy reduction gain in a wireless system, one has to consider the impact on quality of service (QOS) brought about by using less power. The Energy Consumption Rating (ECR) metric which was employed in [78], [79] and [80] takes into account not only the energy consumed but also throughput, this a allows network planner to understand the trade off and the affect of energy conservation schemes such as power management and power control have on the network QOS. ECR defines the total amount of energy consumed to successfully deliverer one bit of information, and can be obtained by:

$$ECR = \frac{E_T}{M_s} \qquad 5.5$$

Where E_T is the total energy consumed for duration of t_e and M_s is total number of data bits successfully delivered. Although ECR can also be derived as a ratio of total power consumed by the network over the throughput S_s, such analysis however will only take a snapshot and does not convey the statistical behaviour of the total energy consumed by nodes in the network during transmission, reception and idle period.

The energy consumption model is crucial in comparing ECR of a radio network, section 5.4.8 addresses the power consumption model used in this thesis.

An Energy Reduction gain (ERG) metric will be used compare the energy efficiency between two different systems. Energy Reduction Gain is given by

$$ERG = \frac{ECR_1 - ECR_2}{ECR_1} \qquad 5.6$$

Where ECR_1 is the reference energy efficiency of a network and ECR_2 is the energy efficiency of a network being compared too.

5.3 Dual Hop Clustered Network Upper Bound Throughput

As mentioned in chapter 3, the Erlang B probability of blocking $P(b)_b$ describes the achievable grade of service for a system that is summarised under Kendall's notation as *M/M/Q/Q*, where Q is the numbers of channels or servers available [44]. The call arrival rate and service time follow an exponential distribution with a finite mean and assuming a large number of sources then the probability of calls arriving at a particular time will approximate to the Poisson process. The Erlang b probability of blocking $P(b)_b$ is also described as a lossy system as in the event blocked calls, the sources will not wait for the channel to be available and the calls are lost and will not attempt retransmissions.

In a single hop networks where the HBS (Hub Base Station) employs an Omni-directional such as those shown in Figure 5-1, assuming that all the transmissions from nodes in the network area can be reliably received by the HBS and no capture effect takes place. At a given time, the number of concurrent transmissions cannot be greater than the number of channels Q, as additional transmissions on channels $q \in Q$ would result in the received SINR at the HBS to exceed $SINR_{threshold}$ and would cause the transmissions to be dropped. The handshaking protocol eliminates the possibility of dropped calls within the single hop networks thus reducing data losses as two concurrent transmissions on the same channel would fail. Assuming that there are no retransmissions, just as in a telephone network, the performance of a single hop network can be analysed by considering the data losses only occurs when the transmissions are blocked due to inadequate number of channel to support the offered traffic in bps G_{bps}. The expected throughput for a single hop network $E[S_s]$ for a given offered traffic is as follows:

$$E[S_s] = G_{bps}.(1 - P(b)_b) \qquad 5.7$$

Where $P(b)_b$ is the expected blocking probability under Erlang B formula with Q number of channels.

In the dual hop cluster network scenario, the transmissions from cluster members to cluster heads will also be blocked if the number of uplink channels Q_u available at a particular cluster heads is less than the number of concurrent transmissions from its respective cluster members. The hidden node terminal problem can occur when a cluster head successfully receives an RTS and inaccurately perceives the channel to be sufficient for transmissions which can cause neighbouring clusters uplink transmissions to be dropped. Note that for a fair comparison with a single hop networks, all blocked and dropped transmissions from a source will not be retransmitted and is considered as loss. However the end to end transmissions, i.e. transmission from cluster members to HBS, will be delayed and buffered at the cluster heads if the transmissions are blocked due to inadequate number of 'unused' backhaul channels Q_b.

If the uplink transmissions are not blocked or dropped then the rate at which transmissions have to be relayed by cluster heads follow a Poisson arrival rate thus queuing model for cluster heads can be summarised under Kendall's notation as $M/M/Q_b$. Under such assumptions, the Erlang C formula $P(b)_c$ given in 3.19 enabled us to predict the probability that the backhaul transmissions will be delayed [44].

$$P(b)_c = \frac{\frac{G^{Q_b}}{Q_b!\,(1-P)}}{\sum_{i=o}^{Q_b-1}\frac{G^{Q_b}}{i!} + \frac{G^{Q_b}}{Q_b!\,(1-P)}} for\ 0 < P < 1 \qquad 5.8$$

Where P is given by G/Q_b

The Erlang C formula however, assumes that the offered traffic in Erlang does not exceed the number of available channels, $G < Q_b$. In a high traffic file transfer, whereby the traffic from cluster member G is greater than the number of backhaul channels $(G \geq Q_b)$, the cluster heads behaves just like a traffic source in a lossy system with call arrival rate which conforms to a Poisson process with traffic G. Assuming that no transmissions are dropped on the uplink, then upper bound throughput $U[S_c]$ for a clustered network is:

$$U[S_c] = \begin{cases} 0 \\ G_{bps}.(1 - P(b)_c) for\ 0 < G < Q_b \\ G_{bps}.(1 - P(b)_b) \end{cases} \quad 5.9$$

5.4 System Modelling

To accurately analyse the performance of the dual hop cluster networks through simulations, the system model needs to take into account a number of factors, including the approach to clustering, the propagation model and channel assignment scheme, along with how the received signal to interference plus noise ratio (SINR) is mapped to the transmission data rate. The power control and power consumption model used are addressed and how all the mentioned parameters affect the network radio environment are explained below.

5.4.1 Power Control

As mentioned in earlier chapters, power control enables individual nodes to increase or decrease their transmit power to meet certain objectives such as improve system capacity by enabling higher channel utilisation, increase coverage or to reduce power consumption. Applying power control can improve the channel utilisation by reducing the intra-cluster interference. For example consider the Figure 5-4a where there is an ongoing uplink transmission between cluster member cm to its respective cluster head *ch*, the excessive transmission power by *cm* would be detected by cluster head *dh*. Due to the hand shaking protocol, cluster head *dh* will not permit its respective cluster member dm to transmit until the channel is no longer occupied. However with power control, cluster members can adjust transmission power and transmit with minimum energy required such that its respective cluster head can successfully receive the transmission [81]. This, as shown in Figure 5-4b is not only more energy efficient but also allows a greater channel reuse, hence an improve performance. This research is not focusing on the implementation and the specifics on how power control can be achieved at the inter cluster level such as in [82], therefore it is assumed it can be performed locally by cluster heads such as in cellular network [83] i.e. cluster heads are able to tell specific cluster members to adjust their transmit by measuring their transmit powers. Power control is introduced to limit the excessive power and reduce intra cluster interference.

In LTE, uplink power control can be performed by the user simply based on signal strength measurements; such a technique is called open loop power control [84]. A user will either reduce or increase its transmission power to achieve a certain Signal to Noise Ratio target (SNR target). All the nodes in the node in the network were subjected to limit their radiated transmit power such that the SNR at their intended destination is no more or less than 40 dB. The value of SNR target was chosen to provide some margin for expected interference at the receiver, during the life time of the transmission (The TSB mapping operates effectively in an SINR range of 1.8-21dB).

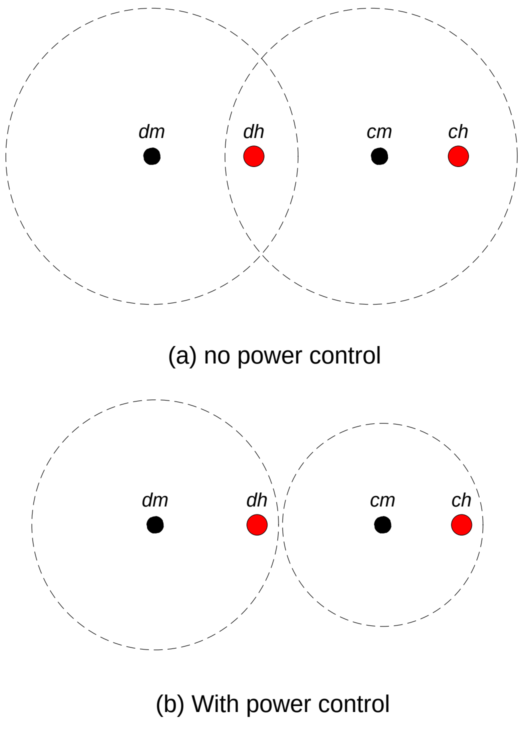


Figure 5-4: Transmission scenario of with and without power control.

5.4.2 Network Environment and Clustered Network

In chapter 3, it was demonstrated on how nodes can be made to learn about their environment through multiple sensing snapshots. The information gathered by each node is used to help the node to determine whether to become a cluster head autonomously.

The proposed clustering algorithm sumRSSI was simulated with a *Reward R* of 100, with 100 nodes randomly distributed on a square service area of 1×10^6m^2 with the HBS (hub base station) in the centre of the service area. During the clustering process, the radiated transmit powers of the nodes operate at a maximum power of 0dBW.

5.4.3 Receive Power and Path Loss model

This thesis focuses on modelling on static or relatively slow changing wireless networks such, with nodes that do not move significant distances during the measurement period as wireless mesh network. It is assumed that nodes are located above roof top height so that the height of antenna has relatively small impact on the path loss. (In practice the relative performance of the approaches here are likely to be relatively insensitive to propagation.) The propagation model that used in this chapter was developed by WINNER II (model B5a) [41] which was based on statistical measurement results as mentioned in earlier chapter.

The amount of power received in logarithmic decibels Pr_i by node *rx* on a particular channel can be calculated according to the equation presented in chapter 3 which is reproduced below:

$$Pr_i(dB) = Pd_i(dB) + Gr_i(dB) + Gt_i(dB) - PL_i(dB) \tag{5.10}$$

The node antenna patterns are assumed to be isotropic, with their transmitter and receiver gains, $Gt_i = Gr_r =$ 0dBi. The operating frequency is in the 2.1 GHz band and the channel bandwidth is 1MHz.

5.4.4 Hidden and Exposed Node Terminal Problem

Due to the limited spectrum availability and the ever increasing number of wireless devices, the design of the MAC (media access control) layer is therefore has to be efficient in reducing channel contentions amongst users. An improper channel assignment could lead to an increase in the global interference which would increase delay and hence the energy consumption of the network as nodes will be in the transmitting and receiving mode for a longer duration. The high interference will also reduce the energy efficiency as nodes will be required to retransmit messages caused by dropping.

The topology of a wireless network is such that transmitting devices may or may not interfere with its neighbours which give rise to the two well know problems of hidden-node and exposed node problems [85], [87]. Figure 5-5 illustrates such problems. The hidden node terminal problem occurs when both node *a* and node *c* simultaneously transmit on the same channel to node *b* which causes the packet to collide resulting in performance degradation. Employing the ability to sense before transmission such as CSMA (Carrier Sense Multiple Access) does not mitigate the hidden node terminal problem as in the case in Figure 5-5, node *a* is outside the transmission range of node *c* and is therefore cannot sense the existence of each other.

Consider that there is an ongoing transmission from node *b* to node *a.* as shown in Figure 5-5b and assume that the nodes access the channel via CSMA/CA (Carrier Sense Multiple Access with collision avoidance protocol). If node *c* wants to transmit to node *d*, it will first sense its environment and inaccurately deduced that there is an ongoing transmission that will cause a collision if it transmits messages onto the same channel. Such transmissions however, would only cause a slight increase in interference at node *a*. This unnecessary delay in transmission would result in the channel being underutilised and thus reduce spatial reuse; such a problem is known as the exposed node terminal problem.

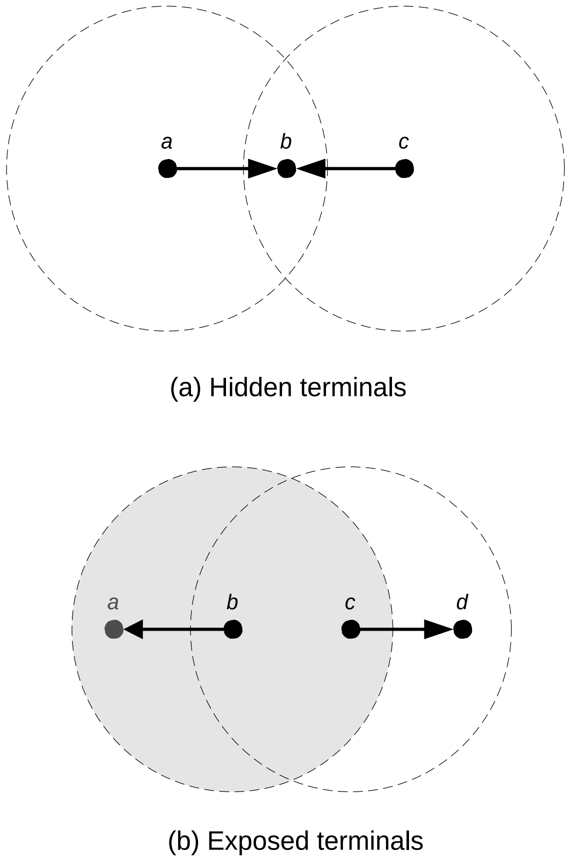


Figure 5-5: Hidden and Exposed node problems, each circle indicates the transmission range of the node at its centre

In IEEE 802.11 [85], the means in which it accesses a channel is called the distributed coordination function (DCF).DCF partially solved the issue with hidden node terminal problem in the scenario as shown in Figure 5-5 with the introduction of a hand shaking technique onto CSMA/CA [86]. The hand shaking technique requires the sender to ‘test’ the state of a channel by sending a short frame of RTS (Request to Send) to the receiver. If the RTS is successfully received by the receiver, it will respond by sending CTS (clear to send) frame to the transmitter. In the event of the channel being occupied by another transmission, the RTS frame will not be successfully received by the receiver due to collision and there will be an absence of a CTS response. The handshaking protocol avoids collision of packets and thus increases the network performance. It is worth noting that the hidden node terminal problem still exists in a multi-hop network [87] and [88]. However, the implementation of the handshaking protocol still does not solve the exposed node terminal problem [87], [89] and [90].

In a dual hop clustered network as shown in Figure 5-6, the hand shaking protocol does not mitigate the existence of hidden node terminal problem. Consider that there is an uplink communication from cluster member *bm* to cluster head *bh* and that the transmit power level of node *bm* is limited such that only its respective cluster head *bh* can successfully receive the transmission. The ongoing uplink communication from node *bm* to cluster head *bh* will be 'hidden' from cluster head *ah* and thus it will not be able to sense the ongoing communication. If there is a message to be transmitted via the backhaul link from cluster head *ah* to hub base station (HBS), it will falsely conclude that the channel is empty and began transmission. Due to the nature of the dual hop clustered architecture, some clusters are located at the edge of the network and the maximum distance of cluster head transmission range (m) assuming a squared network with *l* side lengths is:

$$dr_{mx}(m) = \frac{\sqrt{2l^2}}{2} \qquad 5.11$$

The maximum transmission range of cluster heads dr_{mx} will affect hidden uplink transmissions within an area of:

$$maximum\ transmission\ range\ area\ = \frac{\pi l^2}{8} \qquad 5.12$$

From (5.12), it can be seen that the maximum transmission range of cluster heads can cover an area of almost 40% of the network (assuming squared network area). Due to the cumulative transmission range of other cluster heads in the network, substantially more nodes are in the vulnerable region i.e. a node transmitting to its respective cluster head cannot be detected by neighbouring cluster heads and can be disrupted due a backhaul connection from neighbouring clusters occupying the same channel.

The cumulative effect of the hidden node terminal problem can severely affect the uplink transmission thus reducing the scalability of the dual hop clustered network. To mitigate the hidden terminal problem posed by the large interference range of the cluster head transmission, a split channel pool bandwidth (assuming the total number of channel available in the network >2) between the uplink and backhaul connections is proposed. The separate channels for the uplink allow the communication to be uninterrupted by the backhaul connections from cluster heads in the network. Splitting the common channel pool however limits the number of available backhaul connections which could compromise the capacity of the network.

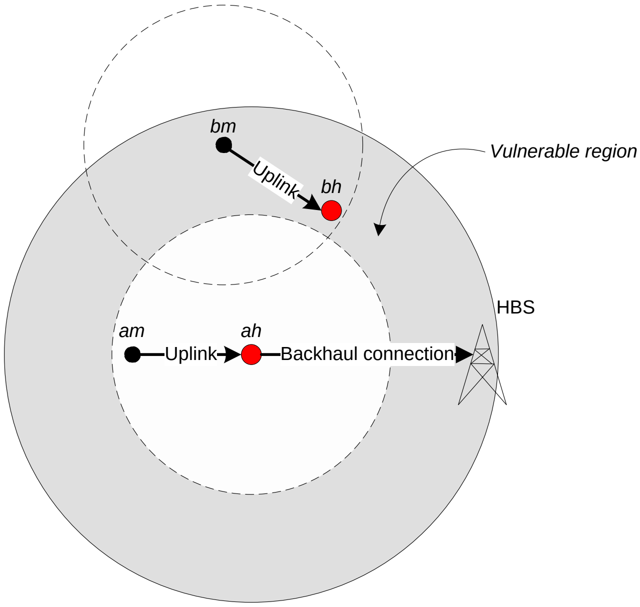


Figure 5-6: Shaded area indicates the vulnerable region in which uplink transmissions cannot be detected by cluster head ah

5.4.5 Interference Model and Channel Assignment Scheme

The interference model was calculated based upon the total transmitted power received by *xr* transmitted by nodes in the network on the same channel not including node *i*. A transmission will be dropped or blocked depending upon the level of signal to interference noise ratio (SINR) not being below than $\text{SINR}_{\text{threshold}}$ at the receiver *xr*. Nodes will have access to the channels via the Distributed Channel Assignment scheme (DCA) [91] and will implement hand shaking like protocol with its intended receiver to reduce the presence of hidden node terminal problem within a cluster. The RTS-CTS control signal power level is assumed to be low enough and of short duration such that it does not interrupt the ongoing transmission from other cluster members which can be achieved through the capture effect. In [92], to prevent the exchange of RTS-CTS from colliding with the data transmission, the bandwidth is divided into a dedicated control channel and data channels. To negate the exposed node terminal problem which would result in a channel being underutilised and reduce spatial re-use, the cluster heads will only respond to RTS packet of its respective cluster members. This can be achieved by sending RTS with a message containing the cluster head node ID, which is made known by cluster members during cluster head activation message. Note that the simulation modelling of RTS-CTS like implementation are basically used to prevent a node from transmitting onto the same channel as other nodes belonging to the same cluster.

As mentioned earlier to avoid channel contention between cluster members and cluster heads, the total channel pool Q_T will be partitioned into two separate non overlapping sub-channel sets for uplink Q_u and backhaul Q_b, i.e. $Q_b \cup Q_u = Q_T$. Figure 5-7 illustrates the flow chart in which a channel is accessed between cluster member *xi* and cluster head *xr* and the conditions of which a call can either be blocked or dropped.

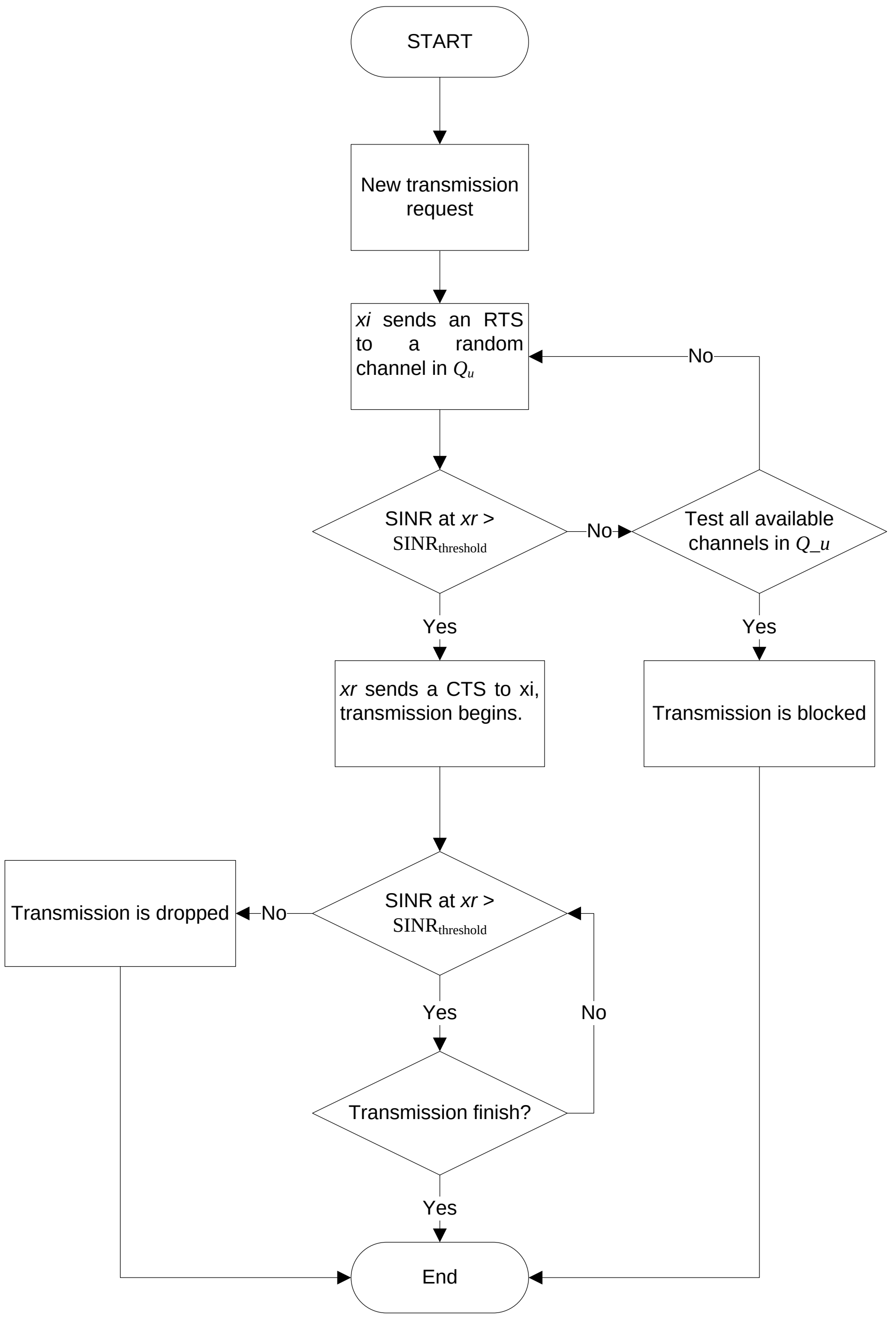


Figure 5-7: Flow chart of channel access and the conditions in which transmission is either blocked or dropped

5.4.6 Linkage to System Mapping and Traffic Models

Truncated Shannon bound (TSB) [93] was adopted to map the signal to interference plus noise ratio (SINR) level to capacity. The TSB describes the relationship between SNIR and bandwidth efficiency of different modulation scheme. According to the TSB the, achievable channel capacity for a user can be obtained by:

$$hannel\ Capacity\ C_{TSB}, \frac{bps}{Hz} = \begin{vmatrix} C_{TSB} = 0 & for\ SINR < SINR_{min} \\ C_{TSB} = \alpha C_s \quad for\ SINR_{min} < SINR < SINR_{max} \\ C_{TSB} = BC_{max} & for\ SINR > SINR_{max} \end{vmatrix}$$

Where α is the attenuation factor, B is the channel bandwidth, C_{TSB} is the channel capacity, $C_s = B(1 + log_2 SINR)$, $SINR_{min}$ is the minimum SNIR at which a signal can still be successfully received by a receiver. The parameters of the TSB are $\alpha = 0.65$, $SINR_{min}$ = 1.8 dB, $SINR_{max}$ = 21 dB and C_{max} = 4.5bps/Hz.

A Poisson traffic model was used to access and evaluate the performance of communication networks, the traffic model is required to be able to capture the statistical characteristics of an actual traffic that have a significant impact of network and protocol performance. The file lengths are fixed at 45Mbs, under optimal network conditions i.e. either no or very low interference level at the receiver *xr*, the transmission will last for 10 seconds (file length/ C_{max}). The Poisson traffic model was generated by having the inter arrival time for files generated on each transmitting node following a negative exponential distribution. The traffic load on each transmitting node will be not be higher than one Erlang as transmission buffer is not considered in this scenario, which means that a new file is only generated by a node if its previous was successfully transmitted.

5.4.7 Cluster Head Characteristics

In the presented scenario, the cluster heads not only have to transmit their own files to the HBS but they also help their respective cluster members to choose appropriate channel for uplink transmission and relay the files that it receives from its respective cluster members to the HBS. The cluster heads are assumed to be able to concurrently transmit any number of files if the numbers of backhaul channels Q_b are available to support such transmission. Under a high traffic load i.e. when the numbers of backhaul channel is less than the number of files than the cluster heads can relay, the files will be queued in an infinite size buffer within the cluster heads and the files will delayed indefinitely until a channel is available for transmission under the first in first out queuing (FIFO policy).

5.4.8 Energy Consumption Model

The purpose of this study is to understand the effect of a hierarchical architecture has on energy consumption rather than to perform power management or energy conservation techniques. However, quantifying the energy consumption of a wireless network device under various traffic conditions is more challenging than it actually first appears, because the energy performance is effected by the external radio environment, spectral efficiency and various components that make up wireless interface such as its baseband signal processing circuit, power amplifier and circuit switch with each such parameters affecting this efficiency energy metric very differently [6].

It was highlighted in [6], [51], and [94] that the power amplifier uses a significant portion of the energy used in a Macro-cell base station. The high amount of power is used to reach highly shadowed and high path loss destinations. The measurements conducted in [95] on network interface card (NIC) concluded that the RF power level should be at its lowest since it reduces the power consumption of power amplifier and it was also noted in [96] that the battery life is inversely proportional to the transmit power. Therefore to maximise the battery life (or total fixed amount of energy consumed in the case of externally powered nodes), each node has to reduce transmit power to a fixed level, which in some circumstances may result in a lower, but more energy efficient data rate per unit bandwidth. For these reasons, the scope of the energy consumption model of a device is limited to the transmission/reception components of wireless devices and combining all the various electronic components into a single module. The proposed radiated energy consumption model will be highly affected by the external radio environment unlike that of [20], [21].

The period in which a node spends time for transmission or reception t_s of a file/data is dependent upon its length f_h to be transmitted or received and the channel capacity which is mapped on to the SINR. Therefore the energy consumed by a node during transmission e_t and reception e_r for a period of t_s:

$$e_t = t_s . Pt_{xi} \tag{5.13}$$

$$e_r = t_s . p_e \tag{5.14}$$

Where Pt_{xi} is the required transmitted power such that the receiver can successfully receive the transmission and is dependent upon the required radiated transmitted power Pd_{xi}.; Pt_{xi} remains constant upon concurrent transmission and reception by a cluster head as unlike macro base station in which the power consumption scales with the number of connected users in a given time, the affect is negligible in smaller cells [97]. p_e is the power consumed by all the electronic components in a wireless network interface card and thus it is also when a device is not transmitting, i.e. power consumed during idle. As mentioned earlier, it was noted by [70] and [71] that the power consumed by IEEE 802.11 network interface during reception is only slightly greater than during an idle period, this is because during idle is continuously scanning the radio environment [98], [99].

As in [20] and [51], it is assumed that there is a linear relationship between transmitted power consumption Pt_{xi} and the required transmitted uplink radiated power Pd_{xi}. Achieving such efficiency and linearity below the saturated point of the power amplifier is still ongoing research by RF power amplifier designers [100]. The baseline measurements conducted by [95] on commercially available IEEE 802.11 wireless network card is used to understand the relationship between the radiated power and the power consumed during transmission. Their result is shown in Figure 5-8 which indicated that although the uplink radiated power Pd_{xi} and transmission power consumption Pt_{xi} is not exactly linear, a reasonable approximation can still be made using simply least squares regression.

$$Pt_{xi} = 9. Pd_{xi} + p_e \tag{5.15}$$

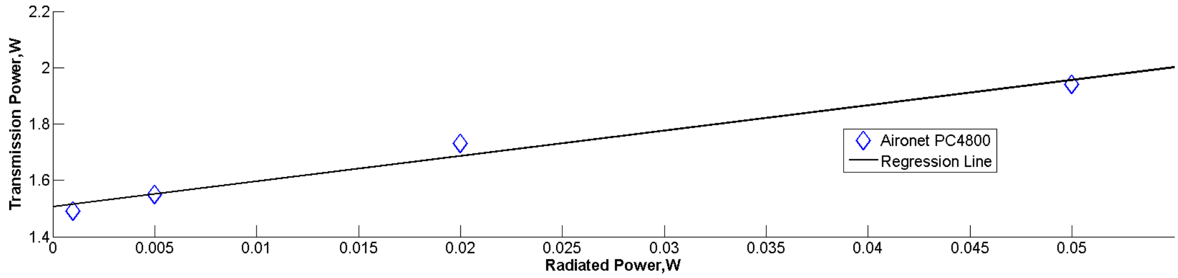


Figure 5-8: The relationship between transmission power consumption of IEEE 802.11 and the actual radiated power.

Nodes must be awake throughout t_e to be able to receive files from its neighbours, this is very energy inefficient at low offered traffic. In [20], although the authors noted that a node has to remain awake or idle during the steady state phase, it is assumed that energy is only consumed during transmission and reception only. Such assumptions however may not be applicable to higher powered devices such as network interface for IEEE 802.11b as the energy consumed during idle period is comparable to that during reception [70], [71]. Therefore the total energy consumed by the nodes in the network E_t after a period of t_e assuming that the nodes are in idle mode when it is not transmitting or receiving can be summarised as:

$$E_T(Worst) = \sum_{i=1}^{n}\left(\sum_{k=1}^{n_t}(e_t)_k + (p_e.t_e)\right)_i \qquad 5.16$$

Where n is the total number of nodes in the network, n_t is the number of times node i transmit within t_e period, note that only cluster heads can receive a file.

Equation (5.16) assumes that nodes are awake or idle throughout $t_{e,}$ which is the worst case scenario in terms of energy efficiency during very low offered traffic. Power savings can be achieved by effectively turning off or forcing nodes into sleep mode when they are not transmitting or relaying files from their neighbours [101]. The effectiveness of such power management has been discussed in an earlier chapter. Such as approach however introduces a new set of problems such as how long does a node should remain turned off or in sleep mode and under such an event, is it more energy efficient for cluster members to transmit to neighbouring nodes that are in idle period or transmit directly to HBS?.

Equation (5.17) presents the total energy consumption of nodes in the network in 'active mode' (transmission and reception), otherwise they are turned off or in a sleep mode. Since sleep mode can consume up to 100 times less energy than transmission mode it is therefore considered negligible [72]. Such an energy saving technique however assumes an ideal scenario as it would require the cluster heads to accurately predict and anticipate the occurrence of uplink transmissions such that it can serve its respective cluster members.

$$E_T(Best) = \sum_{i=1}^{n} \left(\sum_{k=1}^{n_t} (e_t)_k + \sum_{j}^{n_r} (e_r)_j \right)_i \qquad 5.17$$

Where n_r is the number of time node i receive a file within t_e period.

The energy model as described above considers the energy consumed during files lost due to dropped transmissions. Such a model enabled us to understand energy consumption behaviour of a network under various traffic load, network planning and transmitted power.

5.5 Dual Hop Clustered Network Architecture Performance

5.5.1 Simulated Scenarios

A file based traffic model was adopted, assuming a negative exponential inter-arrival time, with a fixed file sizes. The end-to-end system throughput is a summation of the throughput all users within the system, taking into account constraints (bottlenecks) within both the access and backhaul segments. In the case of the single hop, the system throughput relates to just the throughput of the access network. Nodes in the network were randomly distributed and since the transmission distance will affect the radiating interference and the energy consumption, the placement of nodes were varied at 100 randomised sites. At each site, e_t and e_r were measured over an interval t_e of 1000 seconds with the rate of transmission and reception follows that of the offered traffic. The offered traffic is the traffic arising from both newly generated and retransmitted files in bits/sec. The total number of available channels Q_T in the network is 40. In the clustered network all the simulations were conducted during the steady state phase i.e. all the clusters in the network has been formed and with geographical distribution of cluster heads and cluster members generated followed that of the sumRSSI clustering algorithm. The values of the parameters used in the simulations for the system scenario presented in this chapter are provided in previous section and summarised in Table 5-2.

Section 5.5.2 provides simulated results on the comparisons between single hop and the dual hop clustered networks performances and energy efficiency with varying offered traffic levels. In the dual hop clustered network, the channels for the uplink Q_u and backhaul Q_b are split equally from Q_T i.e. Q_u = Q_b = 20.

Section 5.5.3 provides results on the dual hop clustered networks performances and energy efficiency with varying ratio of uplink and backhaul channels allocation. In sections 5.5.2 and 5.5.3, the clusters were formed with an $RSSI_{threshold}$ which corresponds to a transmission range r of 200m (see results chapter 4 on how transmissions range r affect the number of clusters)

Section 5.5.4 provides results on energy efficiency and throughput of dual hop clustered network ranges from 2 to 13 by varying transmission range r for the cluster scheme sumRSSI. As in section 5.5.2, uplink Q_u and backhaul Q_b are split equally from Q_T i.e. Q_u = Q_b = 20.

Parameters	**Value**
Size of Network layout	1,000m×1,000m
Number of Nodes	100
Centre Frequency	2.1 GHz
Carrier Bandwidth	1MHz
Maximum Radiated Transmit Power Pd_{xi}	0dBW
Node Antenna Gain (*Gt*,*Gr*)	0dBi
Noise figure	5 dB
$SINR_{threshold}$	5 dB
$SNIR_{max}$	21 dB
Noise floor	-134dBW
File Length f_h	45Mb
Nodes antenna heights	25 m
C_{max}	4.5bps/Hz
The total number of available channels Q_T	40

Table 5-2: System Parameters.

5.5.2 Varying Offered Traffic

To study the energy efficiency, it is crucial to understand how the system throughput varies with offered traffic. Figure 5-9 illustrates the dual hop clustered network throughput at various offered traffic and channel assignment schemes.

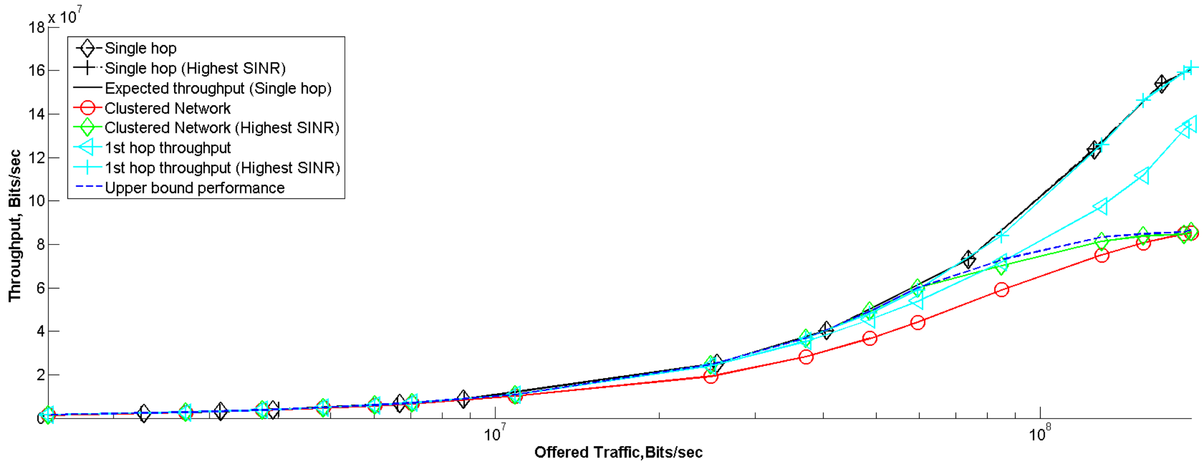


Figure 5-9: Dual hop clustered network throughput performance against various offered traffic levels.

The saturation of throughput for the cluster as presented in Figure 5-9 is caused by not only the bottlenecks on the backhaul segment due to high traffic load and limited channel availability of Q_b but also due to the high dropping due to channel contention on the uplink as illustrated in Figure 5-10. This causes the actual throughput of the dual hop clustered network to be lower than that predicted by (5.8). The dropping is induced by overlapping clusters and the hidden node terminal problem, the effects being reduced by cluster heads accessing all the available uplink channels Q_u and assigning channel with the highest SINR [103].

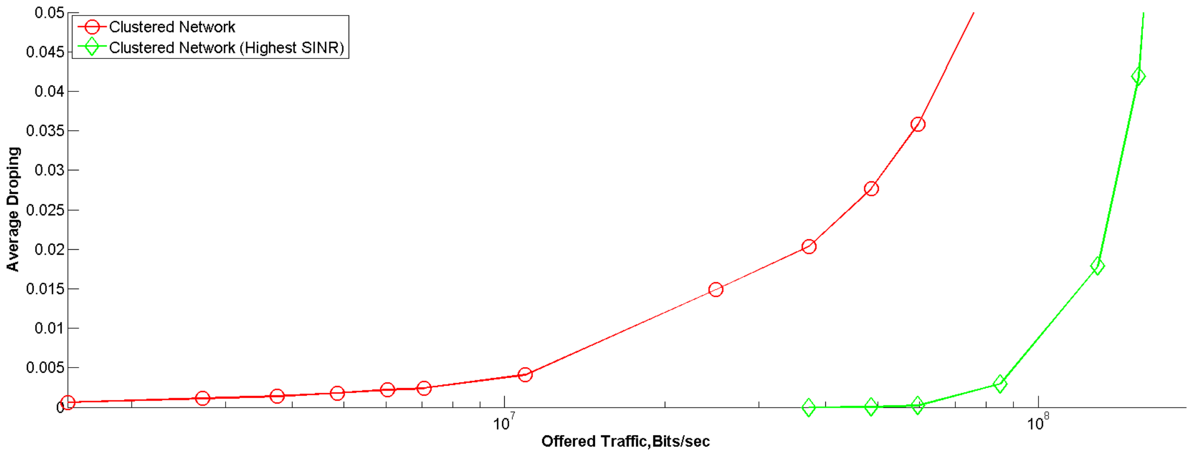


Figure 5-10: The dropping probability suffered by dual hop clustered networks for various offered traffic levels.

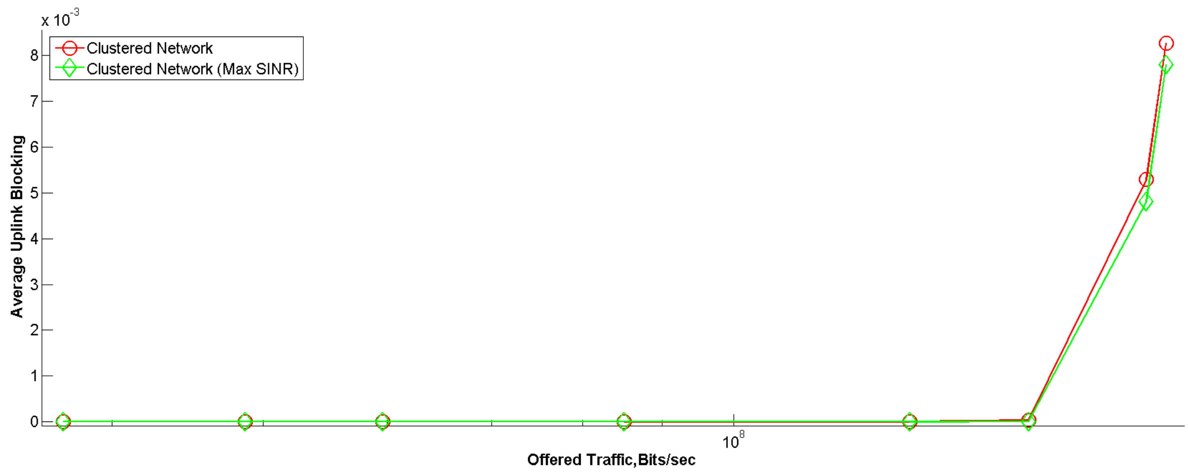


Figure 5-11: The blocking probability suffered at the uplink by dual hop clustered networks for various offered traffic levels.

The random channel assignment scheme also suffers from additional delay per file to the cluster head than highest SINR as illustrated in Figure 5-12. This is due to transmitting cluster members reusing the same channel Q_u as ongoing uplink transmissions in immediate neighbouring clusters. At high offered traffic levels, the high to end to end delay is caused by mainly by files unable to be relayed to the HBS and is buffered in the cluster heads as Q_b is too congested.

The results shown in Figure 5-10 and Figure 5-12, illustrate the need to have well distributed and low overlapping clusters in order to reduce interference on the uplink thereby reducing dropping and delay.

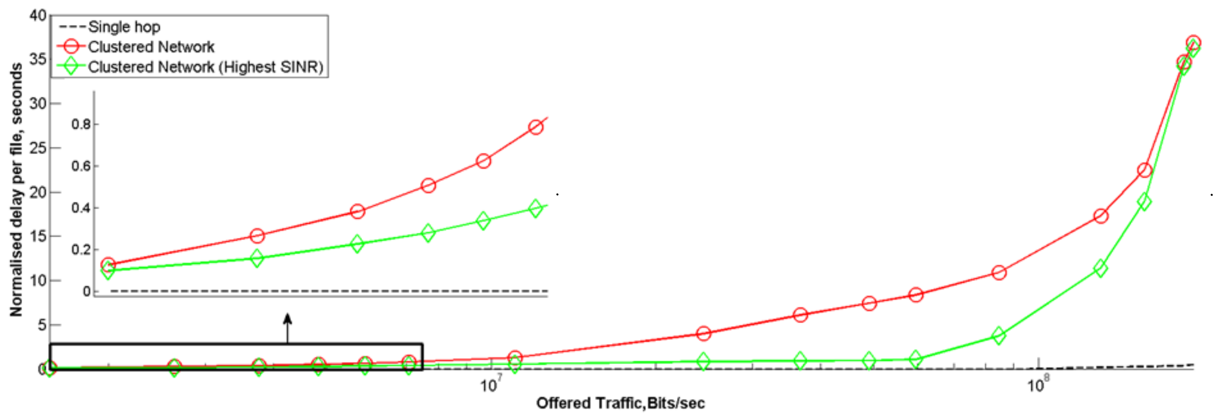


Figure 5-12: The average normalised delay per file for various offered traffic levels.

Figure 5-13 illustrates the energy efficiency in joule/bit of a single hop network and clustered networks with a random channel scheme denoted as C_n and highest SINR scheme C_{nh} under various offered traffic and with and without the energy saving (cluster heads are assumed to be in sleep mode when it is not transmitting and/or receiving) scheme denoted as *best* and *worst* respectively. Figure 5-13 also shows the power consumed for three different p_e levels in order understand how the energy efficiency of clustered networks are affected by proportion of energy consumed during receive and idle period. The result for when p_e is zero, shows the energy efficiency of clustered networks when transmission power consumption Pt_{xi} is the major dominating factor.

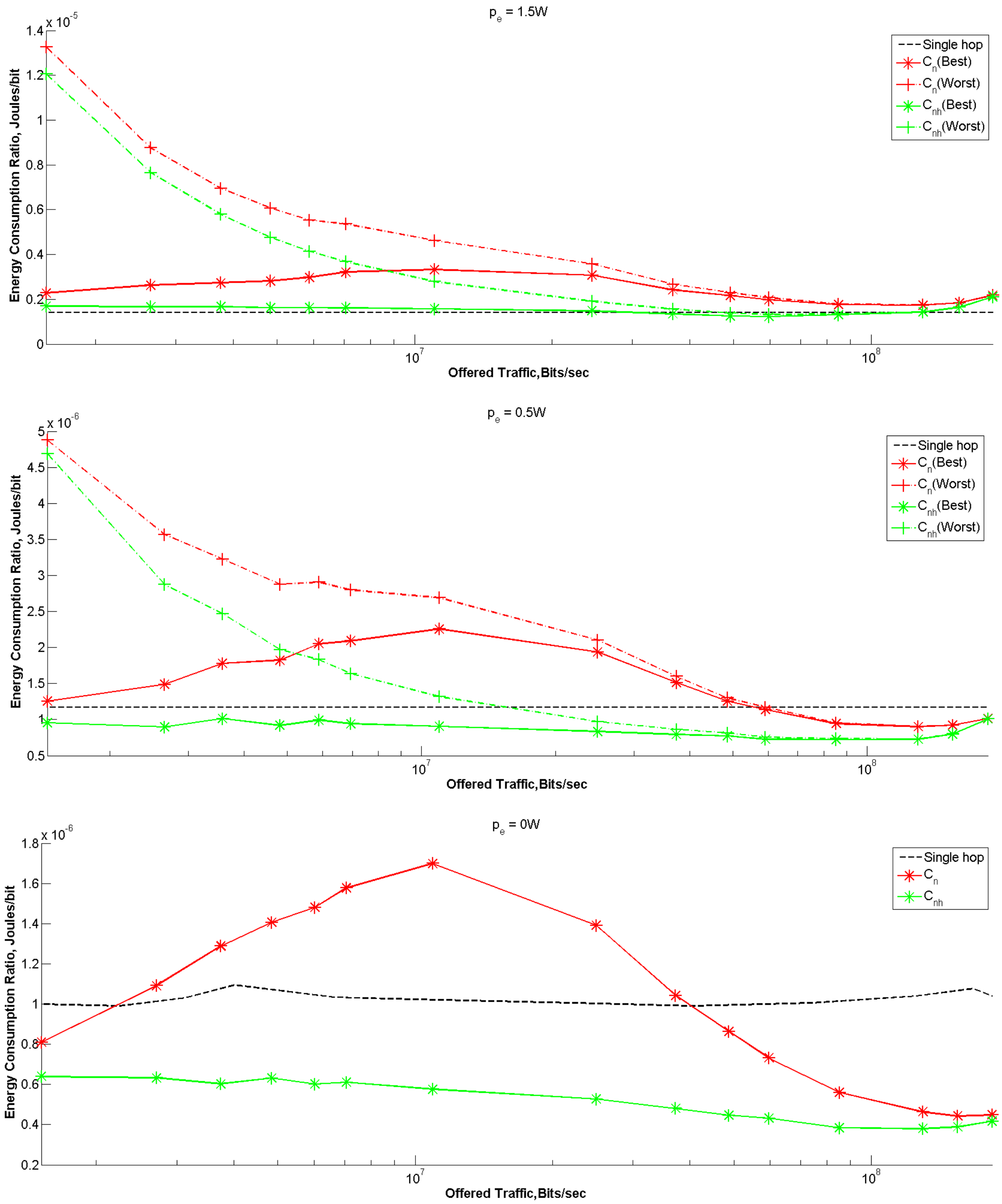


Figure 5-13: Energy Efficiency of clustered network against various offered traffic and p_e.

Figure 5-13 shows that the energy efficiency or ECR of dual hop clustered network is susceptible to intra-cluster interference as high interference causes the uplink channel capacity to degrade which increases the end to end delay. The high end to end delay in turn means that the cluster members and its respective cluster heads have to be in transmitting mode for a longer period thus increasing overall energy consumed. This is evident as a energy efficiency of C_n*(best)* becomes progressively worse and that C_{nh}*(best)* has a higher energy efficiency than C_n*(best)*. The result also shows that in general energy efficiency of clustered network with energy saving scheme becomes more energy efficient at higher offered traffic levels. This is due to the power consumption model given in 5.13 and 5.14 which does not vary in accordance to the number of connected cluster members at a given time.

Based on the results when p_e = 0W and p_e = 0.5W, the energy efficiency of a dual hop clustered network has the potential to be more energy efficient than a direct single hop transmission provided that the energy consumed by cluster heads during idle and receive mode cluster heads are turned off when there are no uplink transmissions to be relayed and that the interference is minimised.

In order to understand and quantify how a highly efficient energy saving scheme and channel allocation scheme can increase the energy efficiency of a dual hop clustered network, ERG given in (5.6) is used and the result is presented in Figure 5-14.

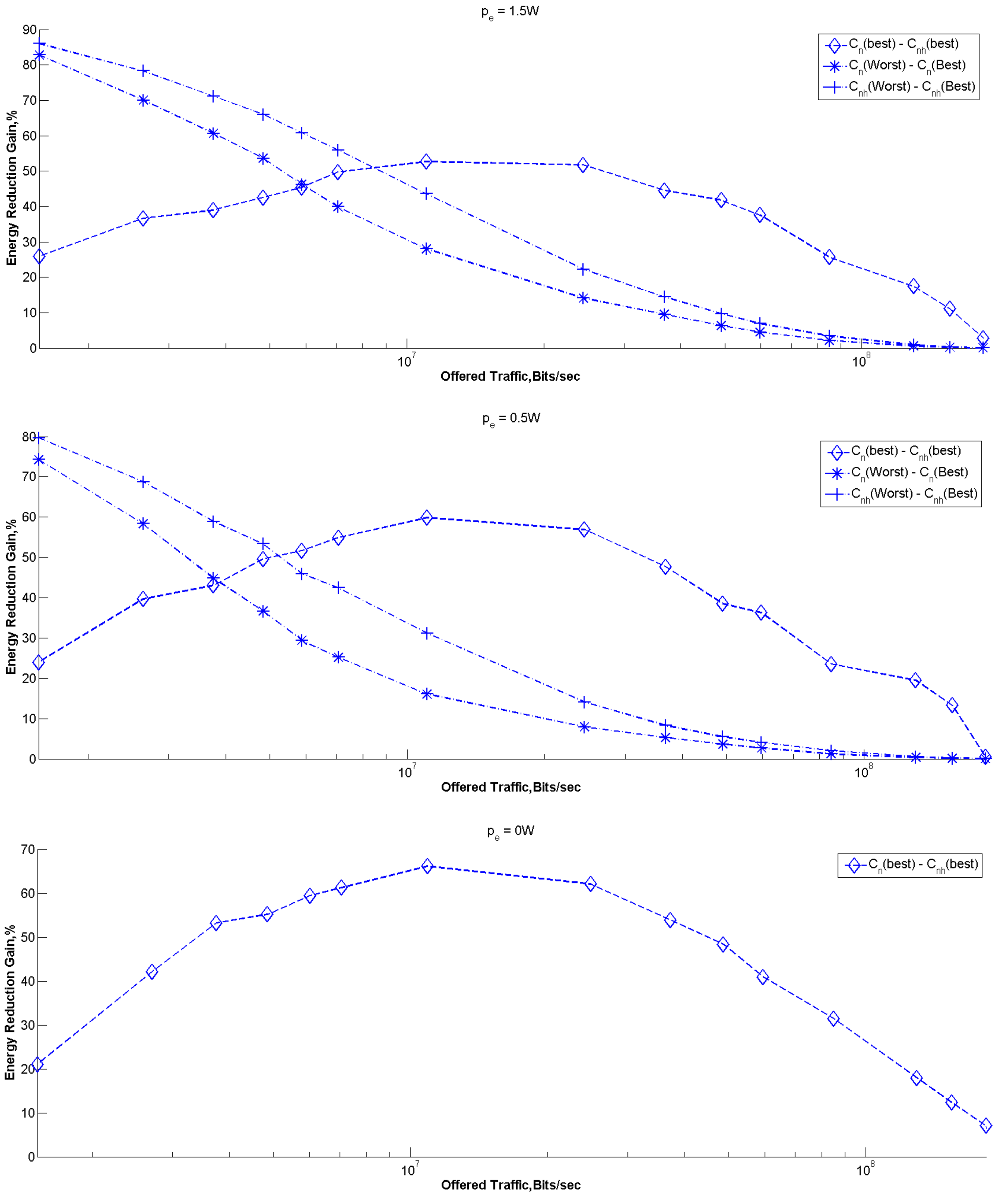


Figure 5-14: Energy reduction that can be gained via energy saving scheme and interference reduction in dual hop clustered networks for various offered traffic and p_e.

The result of ERG illustrate that the energy efficiency of clustered network can theoretically be improved by more than 80% when an energy saving scheme is applied in a clustered network with the random channel assignment scheme denoted as C_n*(Worst)*-C_n*(best)* and highest SINR channel assignment scheme denoted as C_{nh}*(worst)*-C_{nh}*(best)*. The efficiency progressively reduces to zero at higher offered traffic loads as more files has to be relayed thus clustered heads have to remain on for longer periods of time. Under a real world scenario, the energy saving scheme cannot obtain this figure as it would require perfect anticipation of cluster heads to be turned on to serve its cluster members. A delay in the rate of cluster heads turning on would result in a data loss and thus reduce the throughput or would require the respective cluster member to transmit to neighbouring cluster heads that is in idle mode or to HBS directly which would increase the transmission power by the node due to greater transmission distance. Comparing the ERG of C_n*(best)* and C_{nh}*(best)* indicates that reducing end to end delay through efficient channel allocation can improve the energy efficiency of the network by more than 50%. Just as in under power energy saving scheme the efficiency gradually diminishes with increase in offered traffic as more nodes are in transmission and the number of available channel becomes the dominating factor which limits the throughput.

Temporary Interruption of File Transmissions

In order to reduce intra-cluster dropping, a hand shaking-like protocol was implemented as shown in section 5.4.5. However, dropping can still persist due to neighbouring cluster uplink transmissions, as shown in Figure 5-10 and Figure 5-11, the clustered network uplink suffers from dropping more so than blocking. Consider that there is an ongoing uplink transmission from node *am* to cluster head *ah* as shown in Figure 5-15. The ongoing uplink transmission will be ‘hidden’ from cluster head *bh* as in order to prevent the channel being under utilise cluster heads will only respond to RTS from its respective cluster members. Therefore cluster head *bh* will allow *bm* to occupy the same as *am* and cause the transmission to drop.

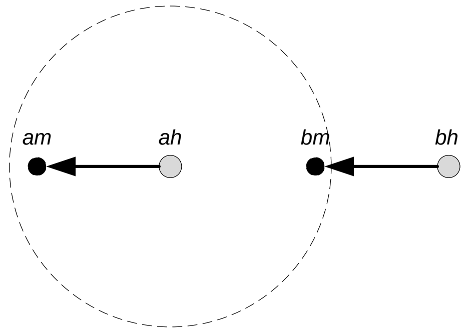


Figure 5-15: Scenario in which uplink transmission in a cluster can be dropped; circle indicates the transmission range of the node at its centre

In [103] and [102] it was suggested that dropping should not exceed 0.5% and is considered more annoying than blocking. Since a file based transfer was adopted rather than calls, the transmission can be interrupted in the event of the interference at the cluster heads exceed $SINR_{threshold}$. The transmission will re-continue once the interference drops below $SINR_{threshold}$. During the interruption of file transmission, the cluster heads will reserve the particular channel such that no nodes in the same cluster is allowed to transmit on to the channel and cause the interrupted transmission being blocked. Although the temporary interruption of the file transmission process may not increase the end-to end throughput, it can stop the occurrence of dropping and thus minimise data loss. Throughout the remainder of the thesis, the file interruption process which is summarised in the flow chart as shown in Figure 5-16 was adopted, therefore dropping is no longer an issue.

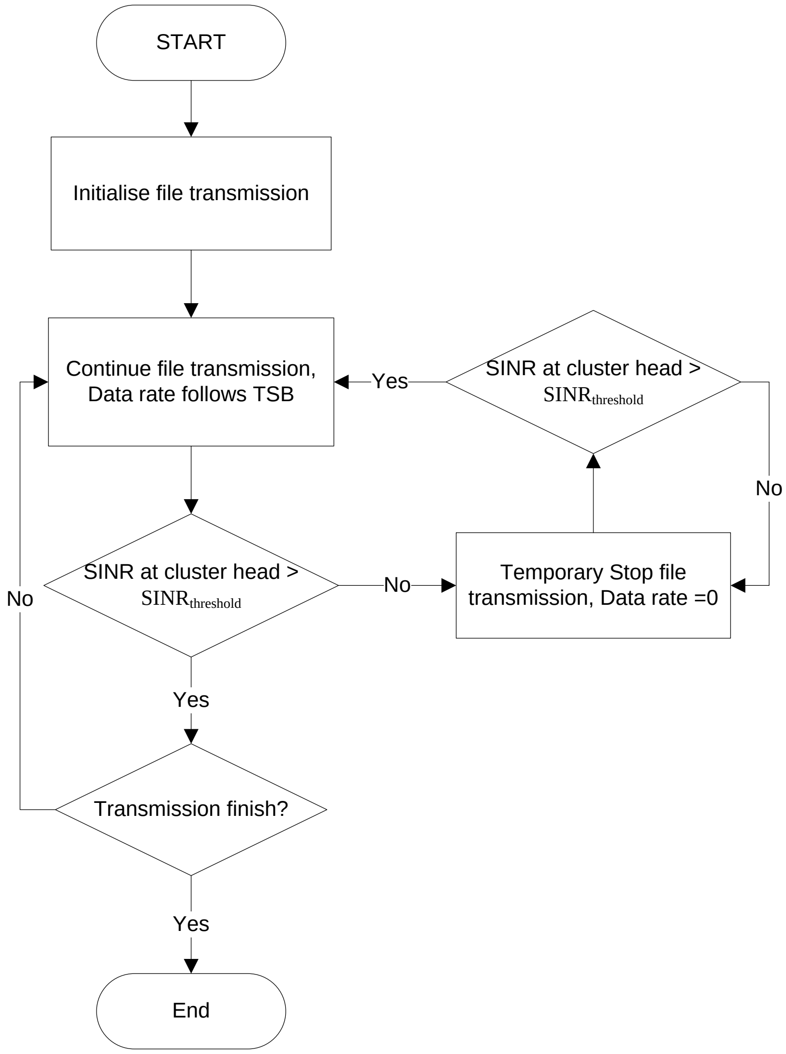


Figure 5-16: Flow chart on the interruption of file transmission

5.5.3 Uplink and backhaul channel allocations

To understand how the proportioned allocation of available channels Q between the uplink Q_u and backhaul Q_b affects the performance and energy consumption of clustered network, a Monte Carlo simulations was performed by varying the ratio of Q_u and Q_b with the energy model under the best case scenario i.e. cluster heads are turned off when they are not relaying files to the HBS and p_e=1.5W.

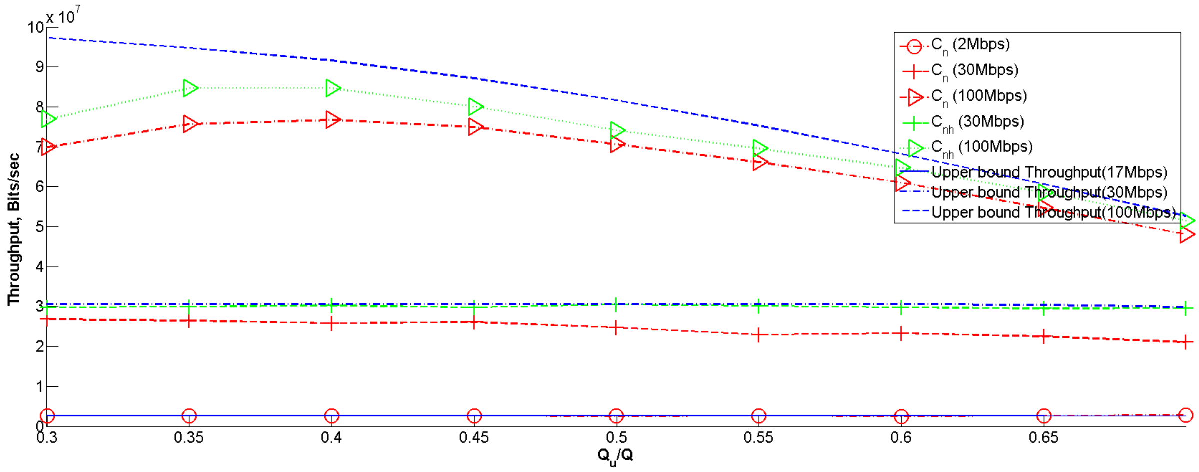


Figure 5-17: Throughput of dual hop clustered networks with varying uplinks to backhaul channels allocation (with p_e=1.5W).

Figure 5-17 illustrates that the throughput at an offered traffic level of 2Mb/s is identical to the upper bound performance predicted in (5.8) as it does not suffer from any channel contention and dropping throughout Q_u/Q. As mentioned earlier, the throughput of C_n is impaired by mainly the bottleneck on the backhaul segment as can be seen when more channels are allocated to the uplink Q_u the throughput deteriorates. However, at an offered traffic level of 100Mb/s, the blocking as shown in Figure 5-18 due to inadequate Q_u causes deterioration in the throughput and the dual hop clustered network performance is optimised when 60% of the channels are allocated to Q_b.

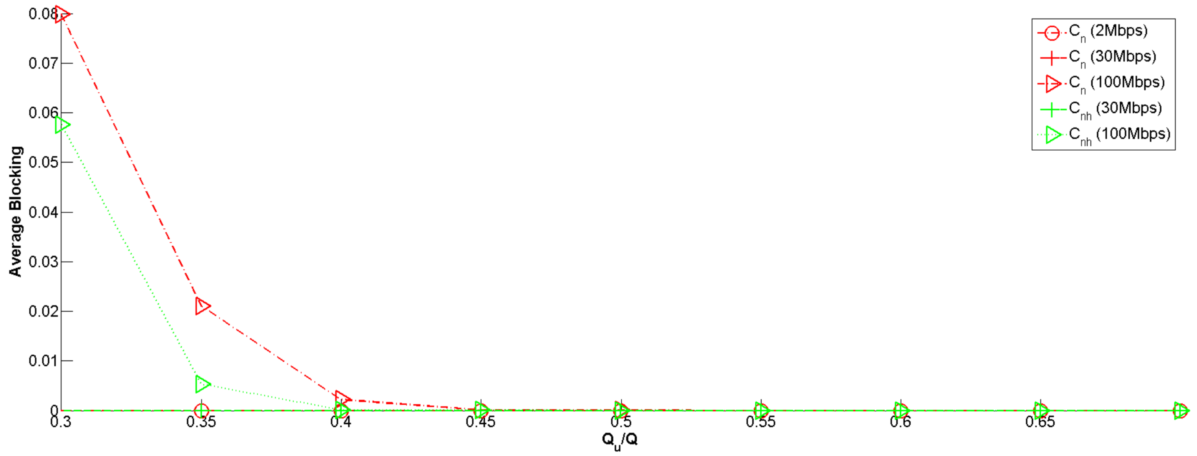


Figure 5-18: The blocking probability on the uplink of clustered networks with varying uplinks to backhaul channels allocation (with p_e=1.5W).

The energy efficiency of C_n at different uplink to backhaul channel ratios as shown in Figure 5-19 mirrors its delay performance as given in Figure 5-20. Although in general the throughput decreases with increase in Q_u /Q, at an offered traffic of 30Mb/s for C_{nh}, the network becomes more energy efficient with having more channels allocated to the uplink. This reduces the channel contentions and dropping which in turn means nodes are in transmission mode for a shorter duration hence consume less energy. When a transmission is blocked, it is assumed that the node is turned off. The architecture appears to be most energy efficient when Q_u /Q is between 0.4 to 0.50.

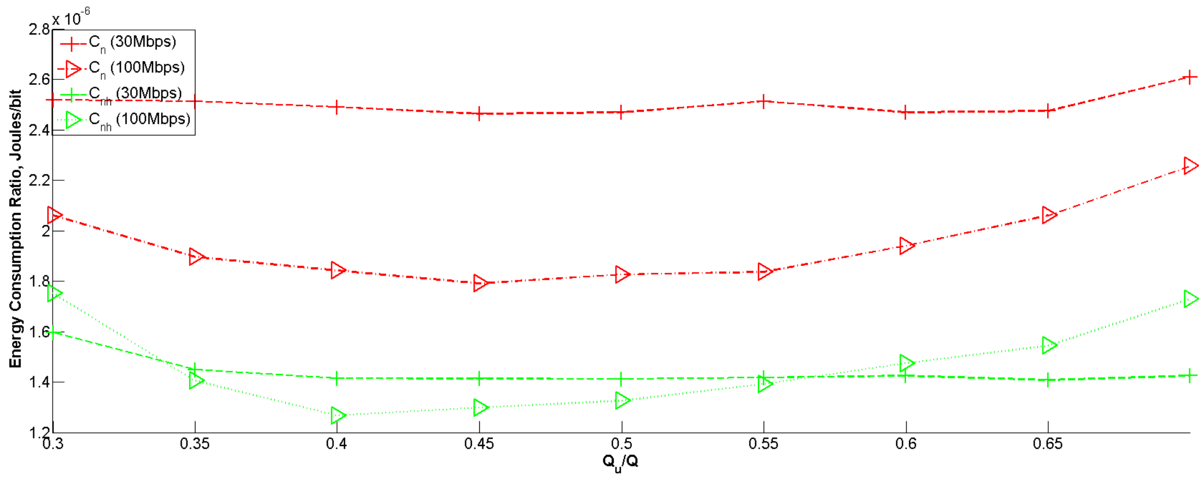


Figure 5-19: Energy Efficiency of clustered networks against various uplinks to backhaul channels allocation (with p_e=1.5W).

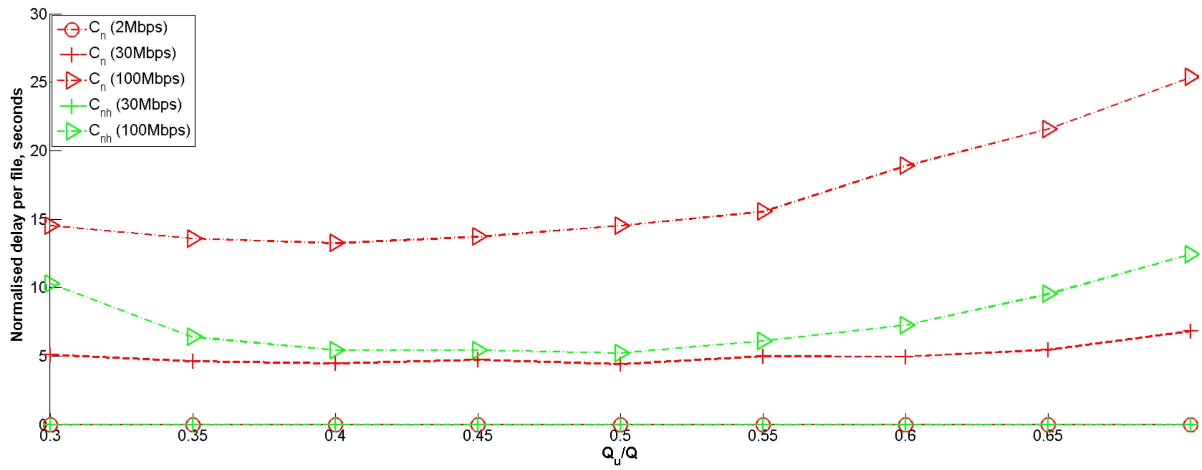


Figure 5-20: The average normalised end to end delay per file for various uplinks to backhaul channels allocation (with p_e=1.5W).

5.5.4 Energy Efficiency for Various Numbers of Clusters

As demonstrated in the results from an earlier chapter, the transmission range *r* in which cluster heads announce their existence affects the number of clusters formed in the network. Figure 5-21, illustrates the energy efficiency of dual hop clustered network ranges from 2 to 13 by varying transmission range *r* for the cluster scheme sumRSSI with p_e = 0.5W and Q_u = Qb = 20.

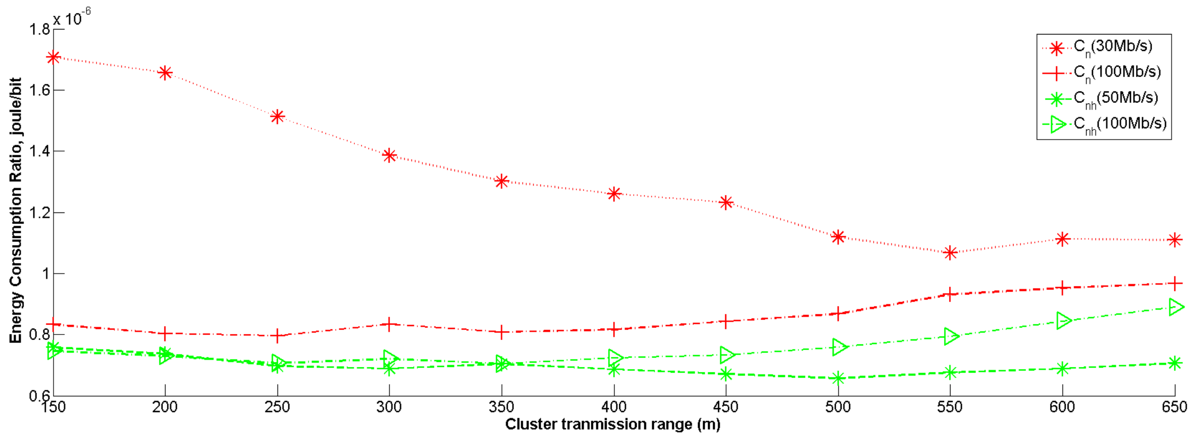


Figure 5-21: Energy efficiency of a dual hop clustered network for various number of clusters (with p_e=0.5W).

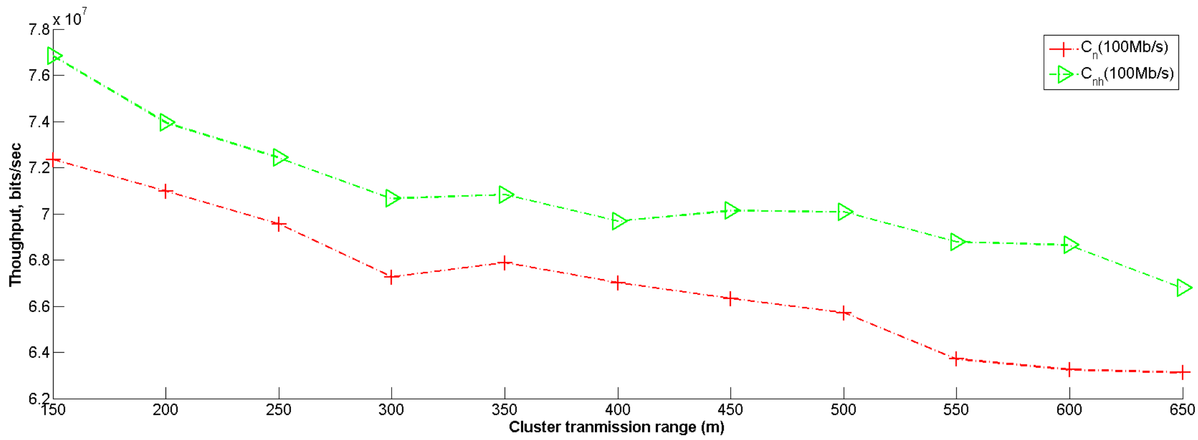


Figure 5-22: The throughput of dual hop clustered network under high uplink channel contentions for various number of clusters (with p_e=0.5W).

In the analysis presented in chapter 4, it is suggested that the upper bound cluster transmission range should be around *l/3* in order to minimise dropping/interruption of file transmissions. This claim is supported by the findings in this chapter as is demonstrated in Figure 5-22 in which the relatively high offered traffic causes the throughput to drop as the number of cluster decreases. However based on the result shown Figure 5-21, the numbers of clusters affects the energy efficiency dual hop clustered network in different ways depending upon the offered traffic. At relatively low channel contention on the uplink such as that when C_n and C_{nh} is at an offered traffic of 30Mb/s and 50Mb/s respectively, the clustered network is most energy efficient when the cluster transmission range is the order of 0.5 to 0.55 of network area which corresponds to 4 to 5 clusters.

For a high offered traffic level e.g. at 100Mb/s, the energy efficiency of the dual hop clustered network is at an optimum when there are around 6 to 9 clusters for a network area of 1000m × 1000m. The discrepancy between the optimum numbers of clusters for the high and low offered traffic is due to the channel contention amongst transmitting nodes. At high offered traffic where there are more concurrent uplink transmissions, the shortage of uplink channel $Q_{u,}$ requires the channel to be re-use more regularly by nodes in the network. The main limitation for channel re-use factor is the interference induced by neighbouring cluster uplink transmissions. Fewer clusters mean greater radiated transmission power by cluster members thus increasing the global interference which negatively affects the channel capacity and causes a greater transmission delay. The addition of delay coupled with the high total power consumption by cluster members due to large transmission link length of resulted in the energy efficiency to decrease with fewer clusters.

The result for low channel contention amongst clusters is in line with the analysis provided by [21] which suggested an optimum number of cluster lies around 3 to 5[3]. [21] employs a time division multiple access (TDMA) MAC protocol and that each cluster communicate using direct spectrum spread sequence (DSSS) and assumes few overlapping transmissions such that the channel capacity remains unaffected. Therefore, the transmission duration of uplink transmission in LEACH is dependent only on the number of nodes in the cluster. This explains the similar results obtained for the optimum number of clusters since the relatively low probability of

[3] These figures apply to a network an area of 100m × 100m. Based on [21] mathematical analysis, a similar performance is expected for network area of 1000m × 1000m provided that the transmission distance to HBS scales by the same amount.

transmission in C_n(30Mb/s) and the low interference experienced by the uplink transmissions in C_{nh}(50Mb/s) enabled it to transmit at the highest channel capacity with minimum additional delay. Having too many clusters in these scenarios degrade the energy efficiency as cluster heads consumed more power but its presence in large number yields no benefits in terms of improving delay or throughput.

5.6 Conclusion

In order to understand how the energy efficiency of channel constrained dual hop clustered network can be optimised, this chapter have presented an in depth simulation study on performance with variable offered traffic load, partitioning of the channel from uplink to backhaul and different cluster sizes. Unlike that of LEACH which was designed for sensor networks in which the main concern is the energy consumption where as the research presented in this thesis focuses in high traffic data in which a balance is needed between the throughput, delay and energy consumption. In order to quantify energy efficiency, Joules/bit otherwise known as ECR (energy consumption ratio) metric was a chosen as it provides an insight how much energy is transferred for one bit of information.

The simulation results illustrate that, assuming the inter-arrival time of transmissions follow a Poisson traffic model; reducing dropping and the end to end transmission delay can provide significant improvement in the global energy efficiency of a clustered network as it would reduce the amount of time for nodes to be in transmitting mode and the time required for cluster heads to receive and relay the files. The uplink delay can be reduced through an appropriate channel assignment scheme or having well distributed and compact clusters as minimises the radiating interference to neighbouring clusters.

The dual hop clustered networks can potentially be more energy efficient than single hop if the transmission power Pt_{xi} i.e. the amount of power needed to drive power amplifier to produce a specific radiated power Pd_{xi} dominates the total consumed power of devices coupled with end to end delay minimisation. The efficiency can be further optimised by allowing cluster heads to be in sleep mode when it is not needed to relay files and by splitting the total channel Q_u /Q =0.4.

Based on the results presented, the number of cluster heads that should be turned off will depend on the amount of traffic load. The general trend is that the lower the offer traffic level, fewer clusters are needed in order to maintain certain QOS. A predictive energy saving technique can be applied to cluster heads such as that proposed by [101] in which under low traffic loads, some cluster heads are forced into sleep mode and will ‘wake up’ based on its prediction regarding the future traffic load on a certain time of the day. Under such condition, a higher ‘order’ cluster heads that have dynamic coverage area can be elected such that under low traffic load only these cluster heads remained on and increase its coverage area to serve neighbouring clusters. The selection of higher order cluster heads will need to be chosen carefully in order to reduce interference hence delay caused by overlapping clusters.

Chapter 6 Application of Reinforcement Learning to a Dual Hop Clustered Network

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6.1 Introduction

Reducing energy consumption of a radio network without severely affecting the QOS of the system has been one of the key challenges faced by radio network designers. Techniques that are actively forcing access points or base stations into a lower power mode (known as sleep or doze mode) and 'cell zooming' which dynamically adjust the coverage area of a base station [68] have to consider and ideally predict the offered traffic load which fluctuates throughout the day [104]. In chapter 5, it was shown that when the inter-arrival time follows that of a Poisson traffic model, the energy efficiency of dual hop clustered network can also be improved by reducing the end to end delay of a dual hop clustered network which can be achieved through an efficient channel assignment scheme such as where transmission occurs on the least interfered channel [103]. The implementation of such a scheme has its drawback as it requires users to sense and analyse all the available channels which is a time consuming process [55].

The cognitive radio concept was introduced as a means of increasing channel utilisation by improving the spatial re-use factor through radio nodes sensing and analysing its environment and intelligently deciding on an action such that can optimise its communication link without severely affecting the global QOS [85]. An intelligent action and decision making process in the context of optimising the channel assignment problem has been a continuous area of research. Biologically inspired techniques such as those proposed by [105]and [106] employ a neural network while [107] uses genetic algorithm to find the optimum solution for a channel assignment problem in cellular network. However these approaches require a central coordinator to analyse all the channels before channels allocation can be made to an individual base station or cell.

A fully distributed reinforcement learning channel assignment scheme which reduces the rate of channel blocking and dropping probability was shown to be possible by Jiang in [55], [56] and [57]. Reinforcement learning enables an individual cognitive radio user to decide on a course of future actions based upon its past historical information which it has learnt and interacted through trial and error. The downside of the distributed reinforcement learning technique proposed by Jiang requires a lengthy period for the system to converge to an optimal point.

The aim of this chapter is to analyse the application of the reinforcement learning process to the uplink channel assignment in dual hop clustered network. The implementation will enable the cluster members to intelligently transmit onto channels that have low probability of temporary file interruption, thus reducing the end to end delay compared to the random channel assignment scheme. Therefore the amount of time that the nodes in the network have to be in active mode i.e. transmission, reception or idle mode can be minimised, which reduces the network energy consumption and increases their energy efficiency in Joule/Bit. A novel means of improving the learning efficiency of the reinforcement learning for channel assignment via a localised algorithm approach [108] will be introduced. The localised algorithm differs from a fully distributed and centralised approach as it requires nodes to interact with some of its immediate neighbours to achieve the desired global objective.

The overview of the application of fully distributed reinforcement learning uplink channel assignment scheme is introduced. Under the same section, a method in which the learning rate of reinforcement learning can be improved called a localised reinforcement learning scheme is presented. In section 6.3, to mitigate the backhaul channel constraint of the dual hop clustered network, a directional antenna is applied to the HBS in which the benefits in terms of reducing the energy consumption of the network is analysed. Analysis and discussions of the results through simulation obtained by applying reinforcement learning on the uplink channel assignment is presented in section 6.4 and a chapter conclusion is drawn in section 6.5.

6.2 Reinforcement Learning in Channel Assignment

The lack of optimisation of uplink channel allocation between cluster members exhibited by the random channel assignment scheme increases the rate of dropping or temporary file interruption therefore limiting the end to end throughput of the system. The high rate of channel contention amongst cluster members on the uplink also result in high energy consumption of the system as more nodes have to be in an active mode i.e. in transmission, reception or idle.

In reinforcement learning, each agent interacts with the unpredictable environment by choosing a particular action. A reward will be awarded to the agent, as a feedback to inform the agent of the consequences on the environment of choosing a particular action. The goal of the agent in reinforcement learning is to perform actions to maximise its long term reward [45]. The application of reinforcement learning in a multi-channel scenario is particularly attractive due to its ability to be fully distributed. Therefore this improves the scalability of the network as well as potentially reducing the complexity compared to a centralised approach.

6.2.1 Distributed Reinforcement Learning Channel Assignment Scheme

The challenge in a fully distributed reinforcement learning channel assignment scheme is to develop a strategy or policy π such that each agent or cluster member transmits on to a preferred channel so as to reduce its own rate of blocking and dropping or temporary file interruption probability. As shown by Jiang in [55], [56] and [57], such a policy can be made possible by mapping the memory (weight values) obtained through trial- and error interactions on random channels. In other words each cluster member will obtain the knowledge of their successful transmission rate on each uplink channel based on the previous transmission experience. Once the probability of success on one or more channels is above a predefined weight threshold, cluster members will begin to transmit on to the preferred channel set.

For the application of distributed reinforcement learning to a dual hop clustered network for uplink channel assignment; consider a network with n_{cm} cluster members, n_{ch} cluster heads and Q_u uplink channels. Each cluster member will accumulate a reward termed weight W associated with each channel. Therefore the weight W_{iq} for the *i-th* cluster member and *q-th* uplink channel can be summarised as follows

$$W = \{W_{iq}\}, i \in \{1, n_{cm}\}, q \in \{1, Q_u\} \qquad 6.1$$

Each cluster member needs to have enough experience by interacting with the dynamic wireless environment such that it is able make a decision using the accumulated weight given in (6.1). The accumulation process of W is called exploration stage, a period in which the cluster members explore Q_u with each channel having an equal probability of transmission (random channel assignment scheme). During this stage, with each successful or failed transmission, the cluster members update W on each channel through a linear value function given as

$$W_{t+1} = W_t + R_f \qquad 6.2$$

R_f is the reward[4] factor on each transmission result at time t such that the future weight ($t+1$) on each channel is adjusted. For every successful initial transmission made between cluster member with its respective cluster head on to *q-th* channel, the cluster member will give a reward of R_f =1 for the particular channel. However, if a connection was not possible due to the channel being occupied or a transmission being temporarily interrupted due to the SINR dropping below the required threshold, then a punishment will be applied with R_f = -1.

[4] The reward notation in used in this chapter is R_f rather than R as to differentiate the reward notation used in applying Reinforcement Learning for electing cluster heads as given in previous chapter.

The exploration process described above will continue until each cluster member finds a set of preferred channels. A channel will be classified as a preferred channel if its W on a particular cluster member is equal to or greater than the weight threshold (W_{thr}). Ideally, the period of exploration in reinforcement learning has to be long enough such that the performance of the system has converged to an optimum solution. Jiang in [55] empirically found that the best performance is achieved when the preferred channel is set to 5% of the total Q_u and with the weight threshold set to 5. Once a preferred channel set has been found, the cluster member will begin the exploitation stage in which transmission and sensing will only take place on a random preferred channel set. The flow chart of distributed reinforcement learning channel assignment scheme for an uplink communication between cluster member *xi* and cluster head *xr* is given in Figure 6-1.

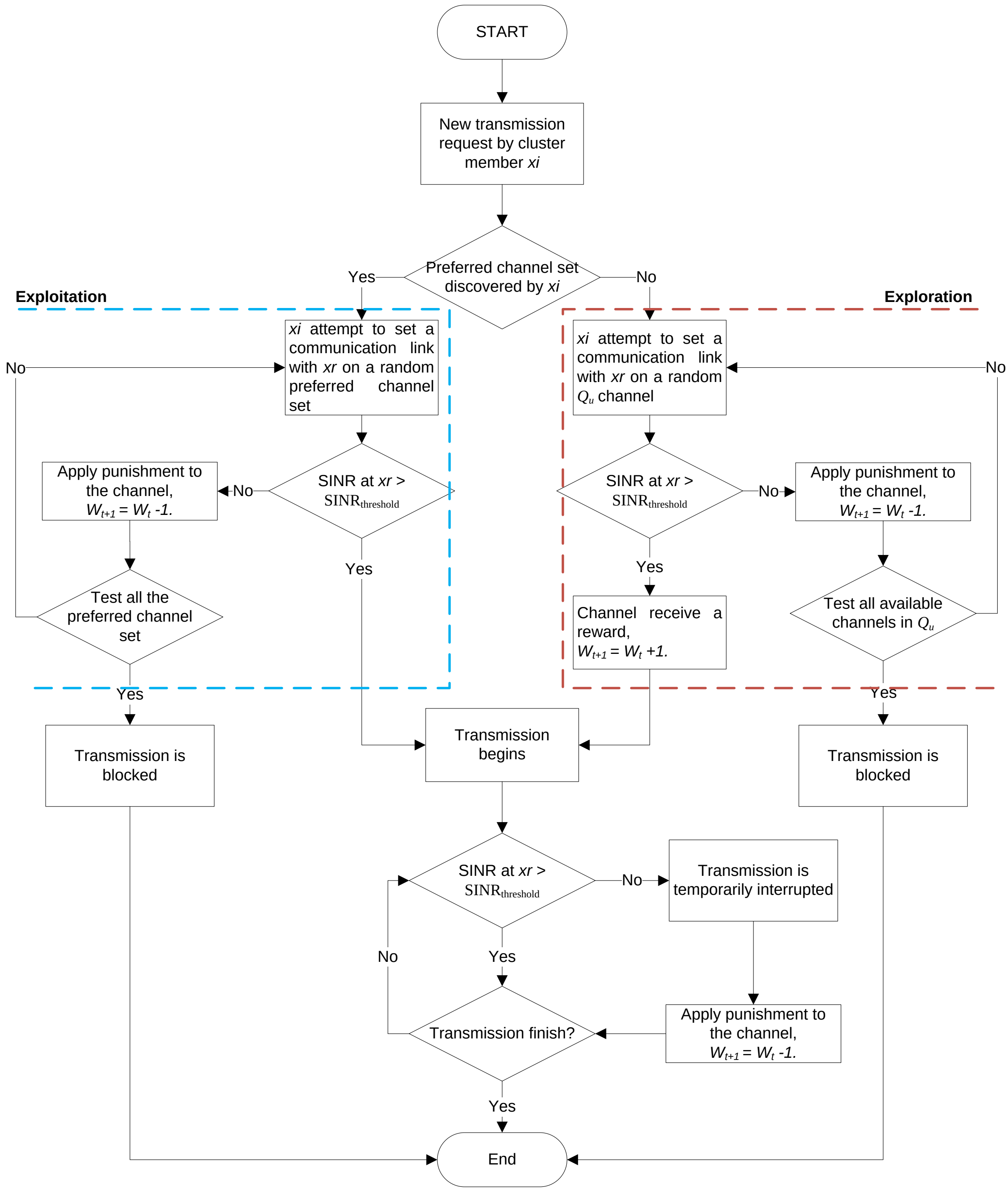

Figure 6-1: Flow chart of channel access with distributed Reinforcement Learning

6.2.2 Localised Reinforcement Learning Channel Assignment Scheme

One of the main challenges in applying machine learning for a channel assignment scheme is that the nature of the radio network environment can be very dynamic and rapidly changing such that the learning algorithms may not detect any pattern such that an optimal policy or actions can be achieved. In a clustered network environment; the incoming or outgoing of nodes, the implementation of a dynamic cluster coverage radius to optimise the energy efficiency or false detection of un-intended signals can result in an out of date database for the learning engine. Therefore, in a dual hop clustered network it is crucial for the learning rate of reinforcement learning to be as efficient and as fast as possible such that it can efficiently assign channels to improve the end to end throughput and energy efficiency of the network.

The learning rate of machine learning can potentially be improved through centralised administration to analyse the knowledge database and channel assignment on the uplink of cluster members. However, such implementation will require excessive control signals for the central coordinator to inform to the cluster member on the state of the channel as well as reducing the scalability of the network. An alternative to fully centralised or distributed techniques was proposed by the sensor network community in [108] known as a localised algorithm. A localised algorithm is defined by a network in which nodes only exchange information with a few number of its immediate neighbours so as to optimise the global objective.

Another issue associated with the fully distributed reinforcement learning channel assignment scheme as described in 6.2.1 is the inherent ‘unfairness’ due to the fixed predefined preferred channel set. This causes the uplink transmission for nodes or cluster heads located in a highly dense local area (high number of cluster members within its transmission range proximity) to have a much higher rate of blocking and dropping or temporary interruption file transmissions due higher received interference compared to the cluster heads located in sparsely populated area. A dynamic preferred channel set should be able to adapt to the local area density. In a high densely populated local area, nodes in this region should have a greater number of preferred channels set allowing for a greater flexibility on channel selection therefore minimising channel contention and interference amongst its neighbours. Nodes located in a sparse area should have a lower preferred channel set as it does not need as many to have an improvement on QOS.

The localised reinforcement learning channel scheme for a clustered network environment can be achieved having the knowledge on the rate of successful transmission on each uplink channel and the decision on which channel to transmit being decided by the cluster heads. This differs from the fully distributed scheme in which each cluster member has its own knowledge database. Consider a network of n_{ch} cluster heads, each cluster head will accumulate a reward termed weight *W* associated with each channel therefore the weight on *c-th* cluster heads can be summarised as follows

$$W = \{W_{cq}\}, c \in \{1, n_{ch}\}, q \in \{1, Q_u\} \tag{6.3}$$

On the one hands, having the learning engine at the receiver is beneficial as a channel which satisfies the *SINR* perceived by the transmitter may not held true at the receiver. The concurrent uplink transmissions by transmitters to the same receiver enable the systems to learn the success rate of several channels simultaneously. This increases the rate of learning and the transmitters can begin exploiting at an earlier stage (time domain) compared to a fully distributed scheme. On the other hand, the receiver needs to inform and update the transmitter on the weight *W* database and therefore requires additional control signals.

The following describes the step by step actions in which a localised reinforcement learning scheme with a dynamic preferred channel set can be achieved for an uplink channel assignment in a clustered network.

Step 1: Exploration of uplink channel environment: From each successful new transmission request by the cluster member on the *q-th* channel, the learning engine at the cluster head will update *W* using the value function given in (6.2)by giving an award of R_f =1 for the particular channel. Unlike the scheme given in section 6.2.1, no punishment will be applied to the channel that does not satisfy the required *SINR*, since it will require additional information transfer between cluster members to its respective cluster heads on the unsuccessful uplink channels. However a punishment of R_f = -1 will be applied to a particular uplink channel if on ongoing file transmission is temporarily interrupted due to the received interference at cluster heads failing to meet the $SINR_{threshold}$.

Step 2: Exploitation of uplink channel environment: The exploitation in localised reinforcement learning is executed by cluster members when any of the uplink channel weighs (W) exceed the weight threshold W_{thr}. A channel which has its weight above the weight threshold ($W_{cq} \geq W_{thr}$) is classified as a preferred channel. Upon entering the exploitation stage, the cluster members will first attempt to transmit onto a random preferred channel, if all the preferred channels are occupied then it will revert to the exploration stage (Step 1) and transmit on to a random non-preferred channel. Allowing the system to explore when there is insufficient preferred channels set enable clusters with large number of cluster members to have a higher number of preferred channel set than those with fewer cluster members.

The flow chart of the localised reinforcement learning channel assignment scheme for an uplink communication between cluster member *xi* and cluster head *xr* is given in Figure 6-2.Note that in step 2, the cluster members require the knowledge database of W to be available at its respective cluster heads such that the exploitation stage in step 2 can occur. The update of W at a cluster member can take place at the beginning of a new transmission request as shown in Figure 6-3a called a 'Force Weight Update '. The method however requires the cluster members to first send an RTS on to a random uplink channel to inform the cluster heads of an intention to transmit. The cluster will acknowledge the request by sending an update of W to which the cluster members will re-send RTS on to a channel based on the updated W. The main downside of this scheme is that it increases the overhead (time) from the cluster head initial request for transmission to the time in which file transmissions actually take place.

Alternatively, the weight update of an uplink channel can be sent together with a CTS frame when the cluster member requests transmission to its respective cluster heads as shown in Figure 6-3b. Although this scheme eliminates the unnecessary overhead time compared to the Force Weight Update, there will be a delay on the knowledge database W becomes available at the cluster members compared to its respective cluster heads. Thus the scheme is known as 'Delay Weight Update'. For each new transmission request at time *t*, the cluster members will decide on the channel selection based upon W_{t-1} which it was informed by its respective cluster heads based upon previous transmission request.

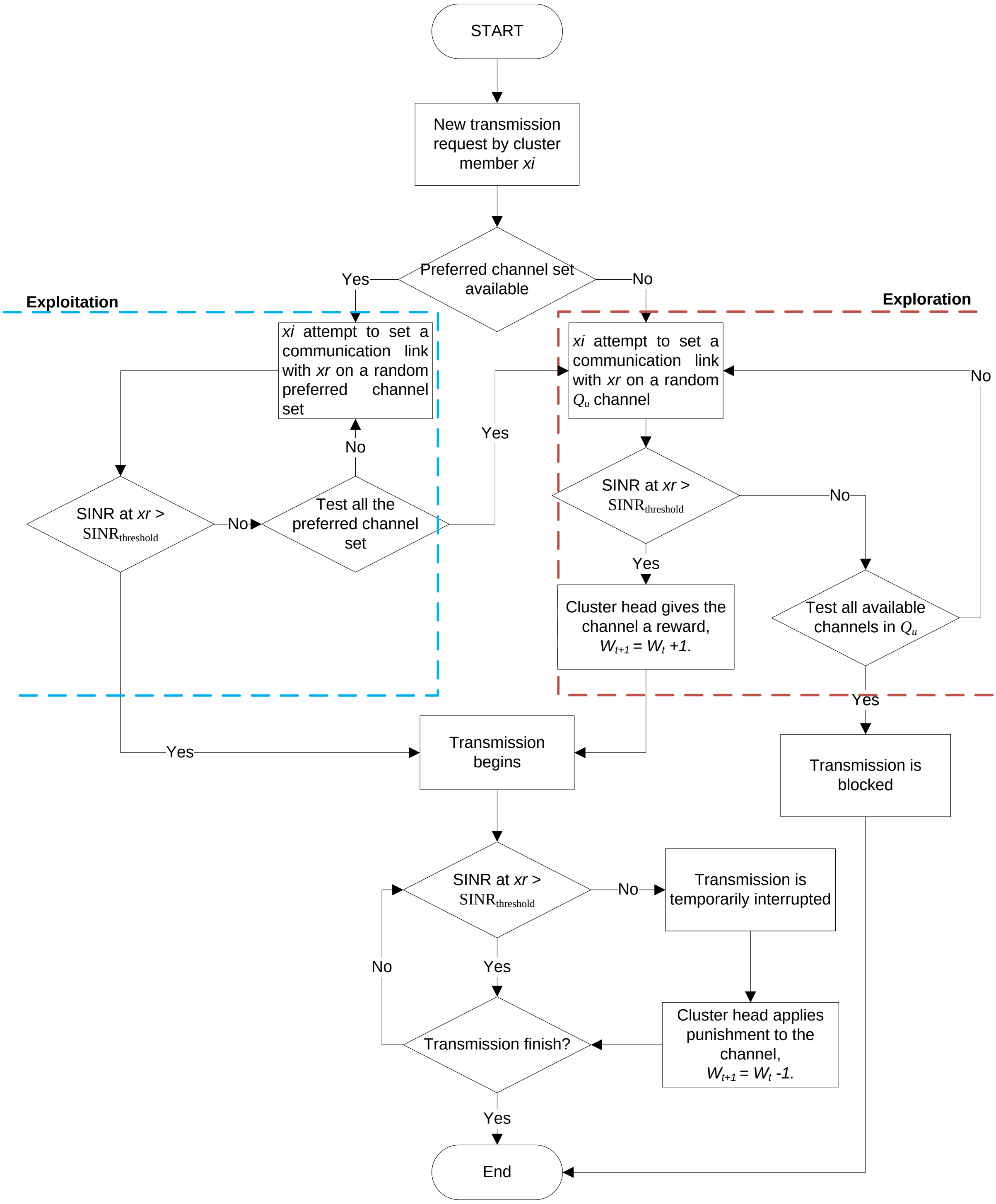

Figure 6-2: Flow chart of channel access with localised Reinforcement Learning.

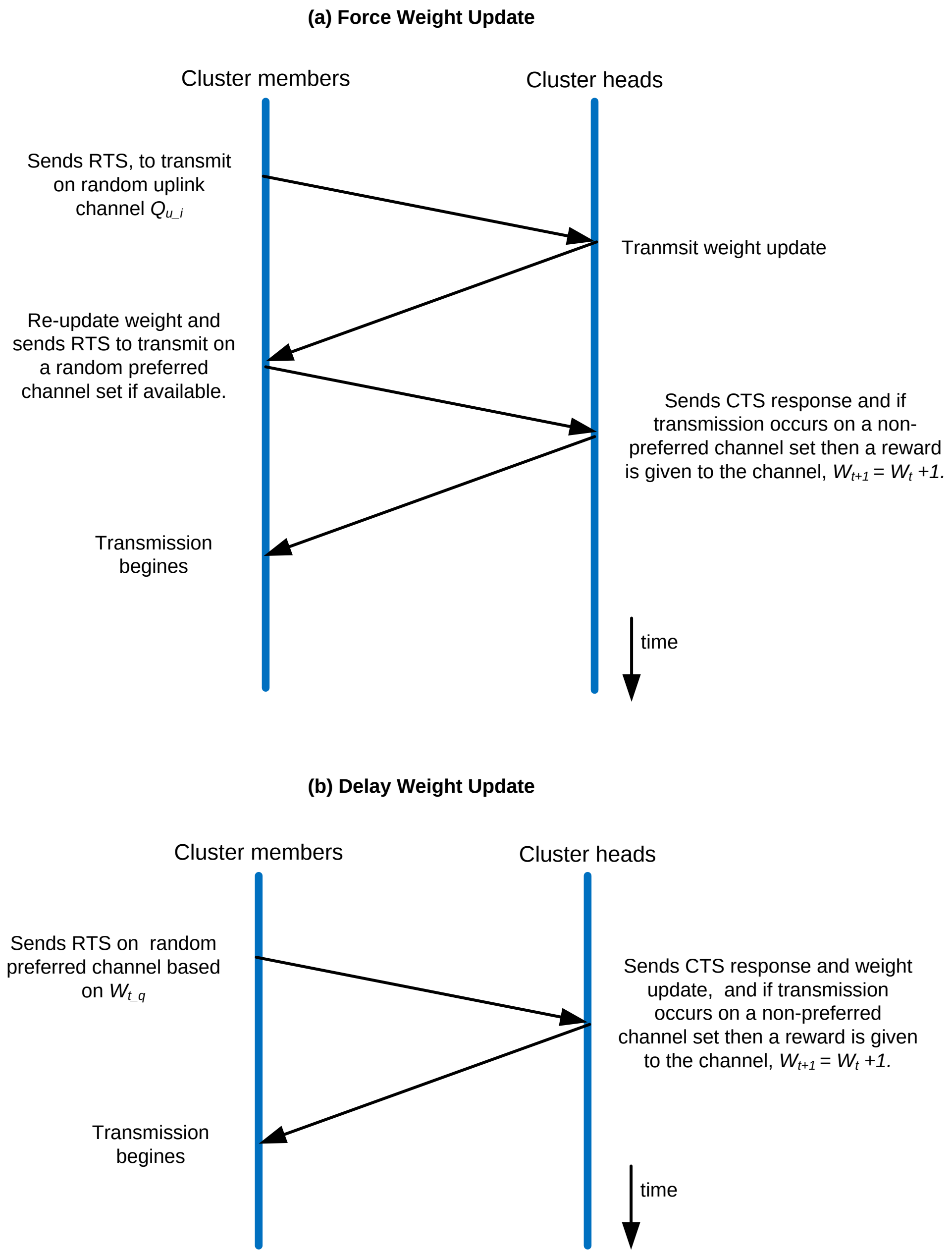

Figure 6-3: Updating weight Schemes.

6.3 Directional Antenna Application in a Dual hop Clustered Network

As shown in the results presented in chapter 5, the end-to-end throughput performance of dual hop clustered network is constrained by the high relaying burden on the cluster head. It is important that the backhaul is dimensioned appropriately otherwise some transmissions which are successfully transmitted over the access network will be delayed due to the limited resources (channels) available at the cluster heads. The level of resources can be increased by improving the spatial reuse which can be achieved by applying a directional antenna at the HBS. This approach has been adopted by the FP7 BuNGee project, with a dual hop architecture, albeit with a set of nodes that are less ad hoc in nature. The directional antenna at the HBS is based on [64] whose radiation pattern is shown in Figure 6-4.

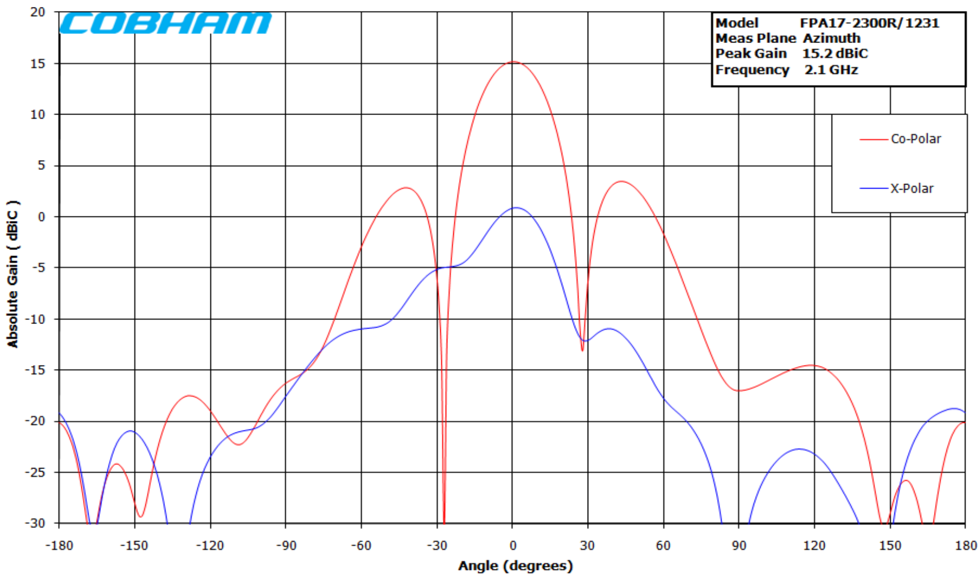

Figure 6-4: Antenna radiation pattern designed by COBHAM (directly reproduced from [64])

A 12 beam directional antenna is deployed over at the HBS with 30 degrees separation on each main lobe so as to provide a high capacity backhaul link to the cluster heads as shown in Figure 6-5. In the network modelling, only the co-polar gains were considered and the possibility of dual polarisations of such architecture were not exploited. Figure 6-6 illustrates that the throughput of a dual hop clustered network with a 12-beams directional antenna at HBS and that Q_u and Q_b are split equally from Q_T i.e. Q_u = Q_b = 20. The result shows that the network performance is no longer constrained by Q_b and is near identical to the total throughput received at cluster heads.

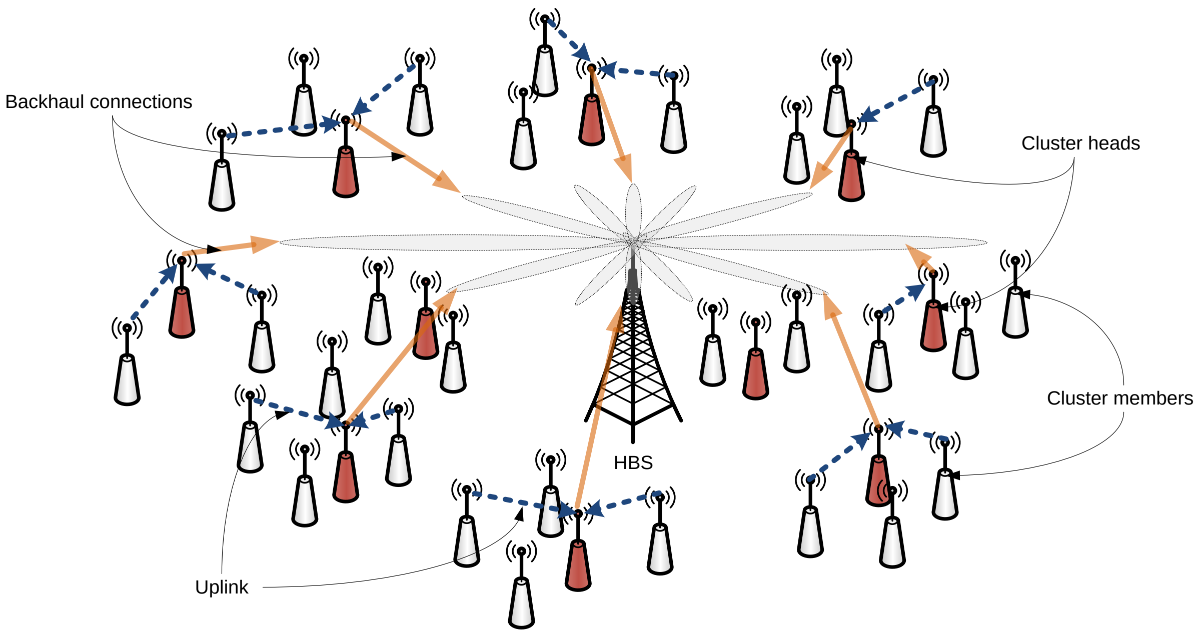

Figure 6-5: Network architecture with 12 beam directional antennas deployed at HBS

The application of directional antennas also helps to reduce the total energy consumption of the network. Figure 6-7 illustrates the breakdown of the energy consumption $E_t(Best)$ p_e=0.5 of the dual hop clustered network with 13 cluster heads and 87 cluster members. A significant portion of the total energy consumption in a dual hop clustered network without directional antennas is consumed by the cluster heads. At an offered traffic of greater than 30Mb/s, the total energy consumption of cluster heads saturate as they are required to constantly be in transmission and reception mode. The cluster heads also require a much higher transmission power Pt_{xi} in order to produce the desired radiated power than cluster members as transmission link length to a HBS is significantly greater as well as being in transmission and reception mode for a much longer duration. The additional receiver gain provided by the directional antenna at HBS enables the cluster heads to significantly reduce radiated power whilst still maintaining the desired QOS. The total energy consumed by network can be reduced by 70% and the energy consumed by the cluster members out strips the cluster heads at an offered traffic greater than 30Mb/s.

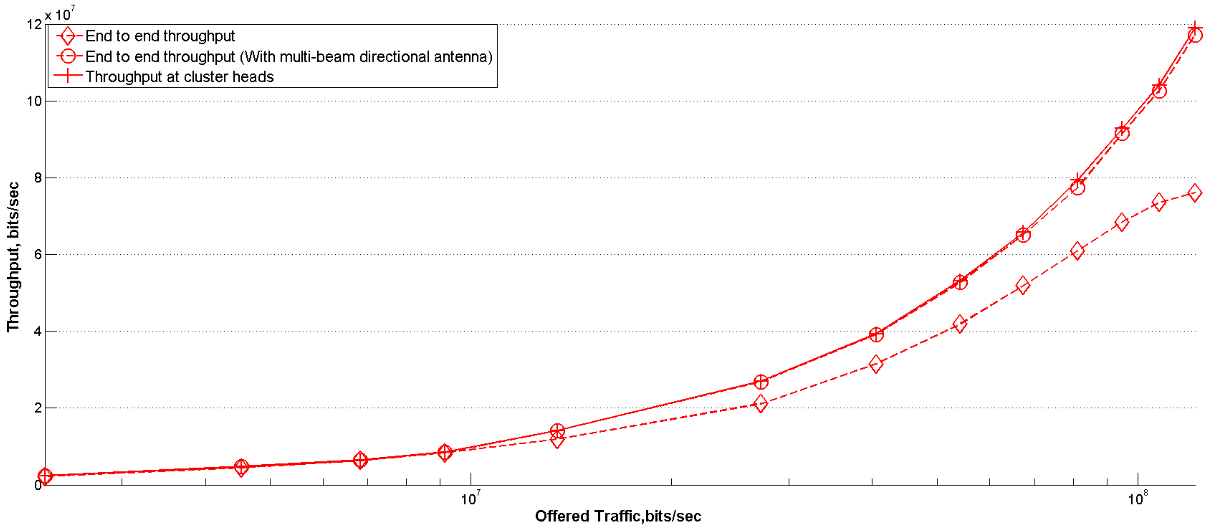

Figure 6-6: Dual hop clustered network throughput performance with and without a directional antenna at the HBS

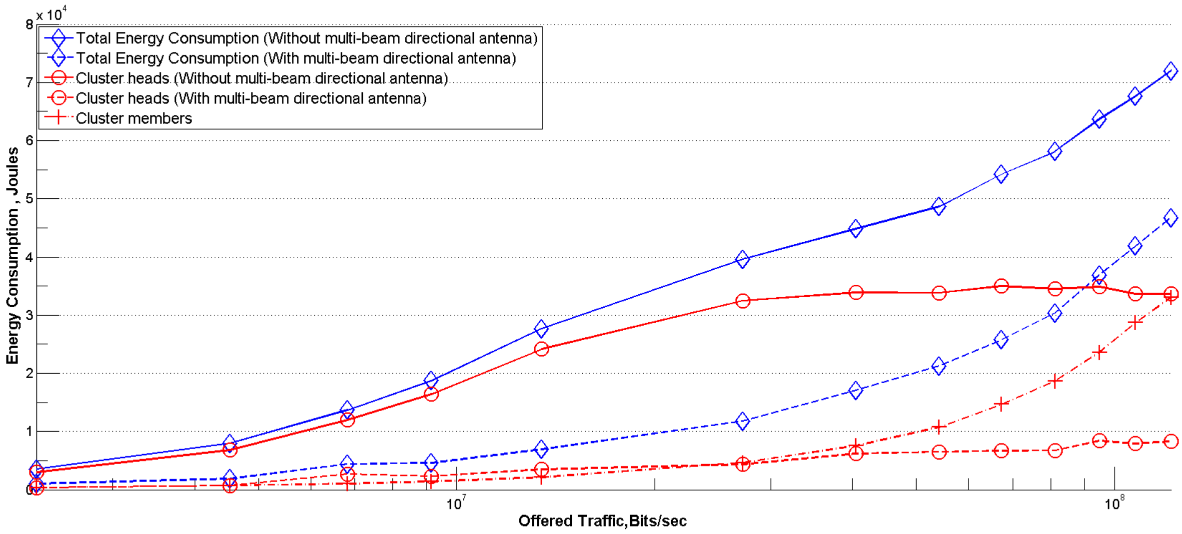

Figure 6-7: The breakdown of the total energy consumed by the network at various offered traffic.

6.4 Reinforcement Learning Channel Assignment Scheme Performance

The same system model presented in chapters 5 were used together with the 12-beams directional antenna applied at the HBS and $Q_u = Q_b = 20$. Since the system is no longer constrained by the backhaul due to an increase in the channel re-use factor of Q_b, the reinforcement learning channel assignment scheme is applied to the channel selection on the uplink. Nodes in the network were randomly distributed with the placement of nodes varied at 100 randomised sites. The distribution of cluster heads and cluster members were generated using the sumRSSI clustering protocol with transmission range *r* set at 200m. In this chapter, only the best case energy model $E_t(Best)$ scenario is considered i.e. power is only consumed when the nodes in the network are transmitting or receiving files, otherwise they are assumed to be off or in a sleep mode.

For the results presented in this chapter; the fully distributed Reinforcement learning scheme is denoted by *RL* whilst the localised learning with Force Weight Update and Delay Weight Update is abbreviated to *ARLF* and *ARLD* respectively. On all the reinforcement learning schemes presented in this chapter, the weight threshold W_{thr} in which a channel is classified as a preferred channel is set to 5. All the results presented for the system applying reinforcement learning schemes were measured when all the cluster members have found the preferred uplink channel set.

Figure 6-8 shows the average end to end delay for the dual hop clustered network against offered traffic for the various channel assignment schemes. The reinforcement learning channel assignment schemes are able to able to intelligently assign the uplink channel to cluster members based on each *q-th* channel historical rate of success. Unlike the minimum SINR scheme, the reinforcement learning scheme does not optimise the channel selection based on the received interference. At offered traffic level less than 30Mb/s, the rate of blocking and/or temporary halting file transmissions during the exploration stage rate are negligibly small such that the reinforcement learning engine is unable to distinguish the good and bad channel selections therefore there is no improvement in the end to end delay against the random channel assignment. The delay in which the cluster heads update the knowledge database *W* in *ARLD* causes imperfect channel selection which leads to a greater rate of temporary file interruptions and it is therefore experiences up to 10% and 27% greater end to end delay compared to *RL* and *ARLF*.

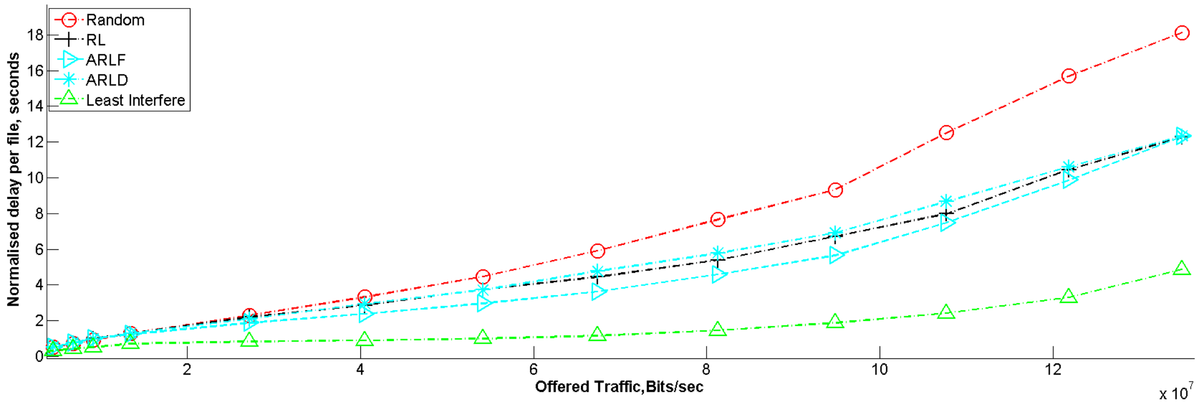

Figure 6-8: The average normalised delay per file for various channel assignment schemes

Although the average cluster members end to end delay performance of the fully *RL* distributed scheme is comparable to the localised schemes *ARLF* and *ARLD*, the result shown in Figure 6-9 illustrates that the dynamic preferred channel set incorporated with the localised schemes can improve the variation in cluster members uplink delay by 45% compared to *RL*. This indicates that the localised schemes are 'fairer', unlike *RL* which can inadvertently give a priority to certain set of cluster members on the chance to capitalise a certain channel set to reduce its blocking and temporary file transmission interactions, whilst causing other cluster members to have higher uplink channel contentions.

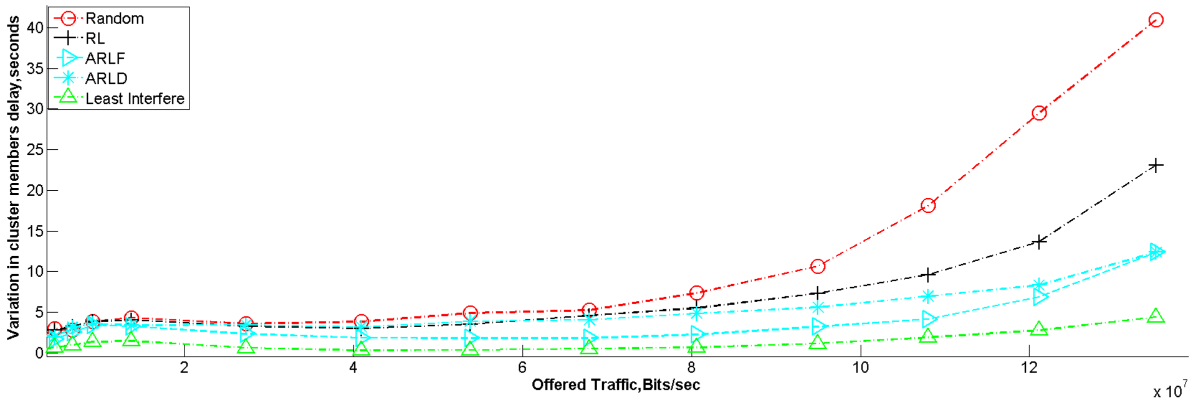

Figure 6-9: The variance of delay for the various channel assignment schemes.

Figure 6-10 to Figure 6-13 show the average individual cluster member's end to end delay represented by circles for the various channel assignment schemes for a given geographical distribution of cluster members and cluster heads elected using sumRSSI. The larger the circles, the higher the end to end delay. For each figure, each cluster members end to end delays were averaged after a duration of t_e=1000 at an offered traffic of 120Mb/s. The figures for the cluster members applying the reinforcement learning channel assignment schemes are accompanied by the size of its preferred channel set. As can be seen in Figure 6-12 and Figure 6-13, the variations in the circles sizes for the localised reinforcement learning schemes are less pronounced compared to the fully distributed *RL* scheme shown in Figure 6-11. This is due to the fact that the localised schemes enable its cluster member to re-enter exploration despite already having obtain a preferred channels since the channel is being occupied by other cluster member uplink transmissions. This creates a more dynamic distribution of the preferred channel set between each cluster and reduces the variations in uplink transmission delay between cluster members.

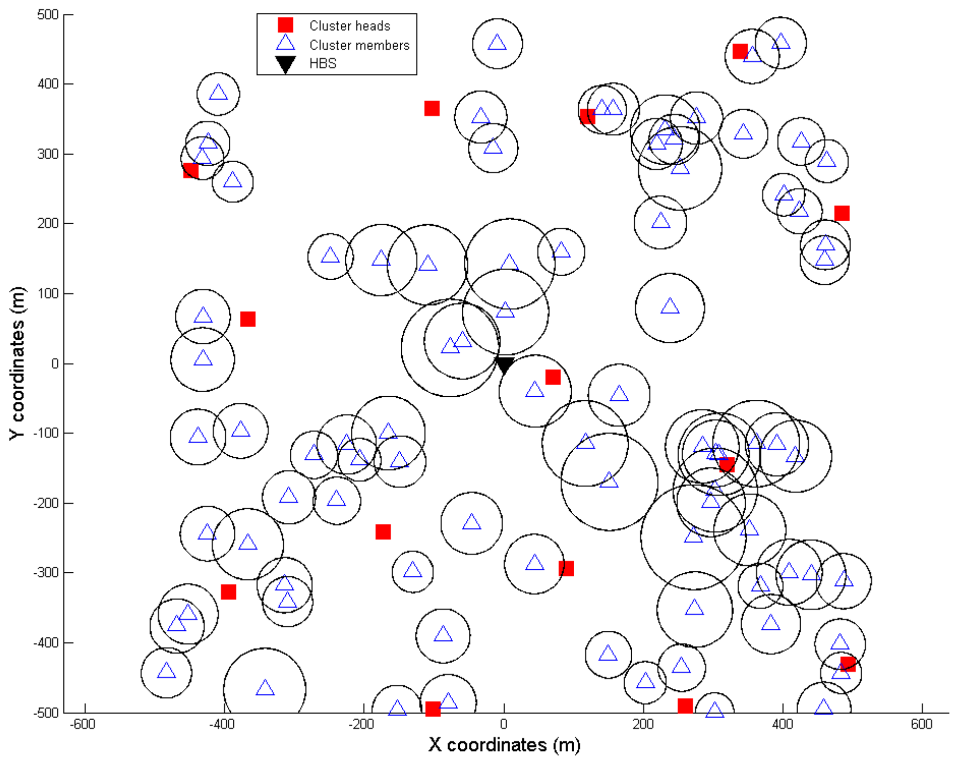

Figure 6-10: Snapshot of cluster members end to end delays applying Random channel assignment scheme

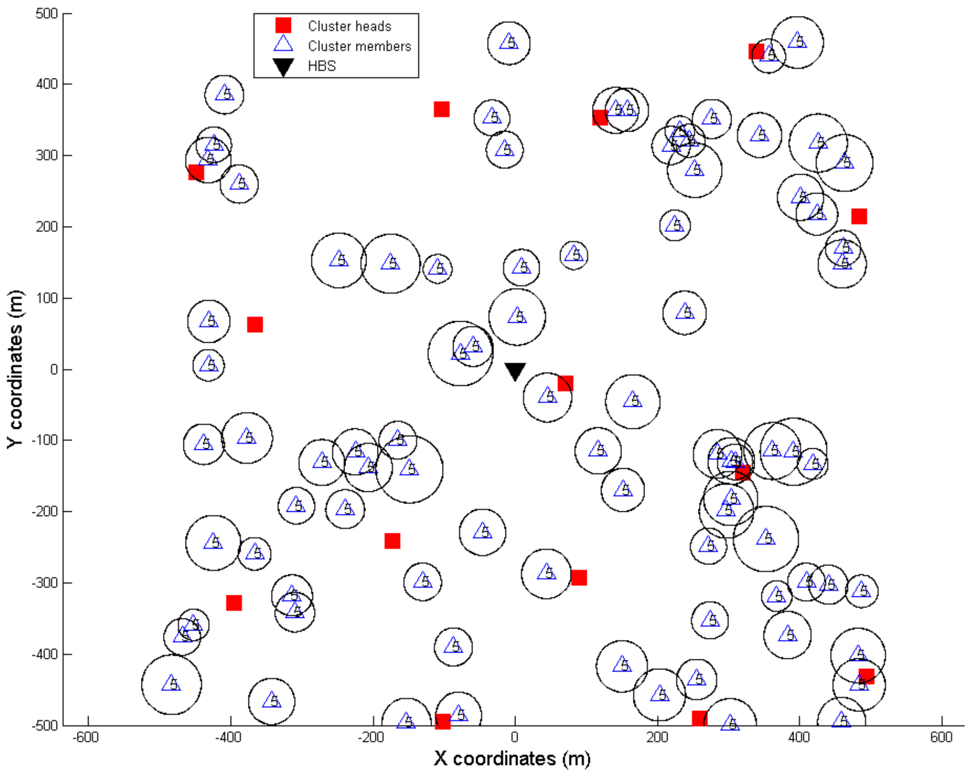

Figure 6-11: Snapshot of cluster members end to end delays applying RL channel assignment scheme.

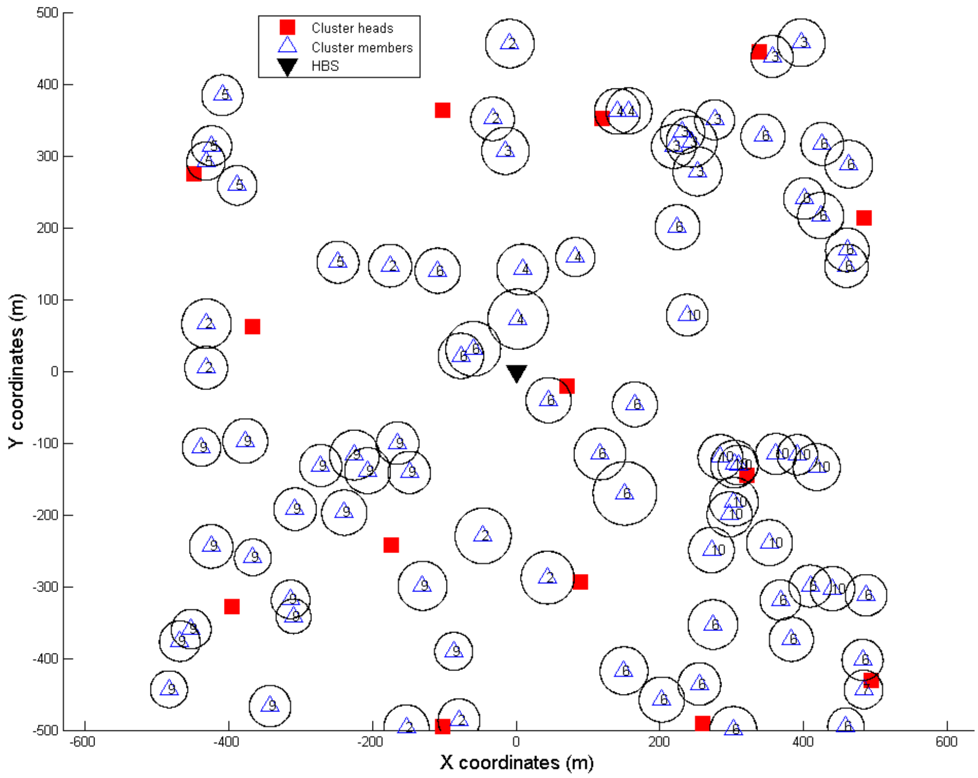

Figure 6-12: Snapshot of cluster members end to end delays applying ARLF channel assignment scheme.

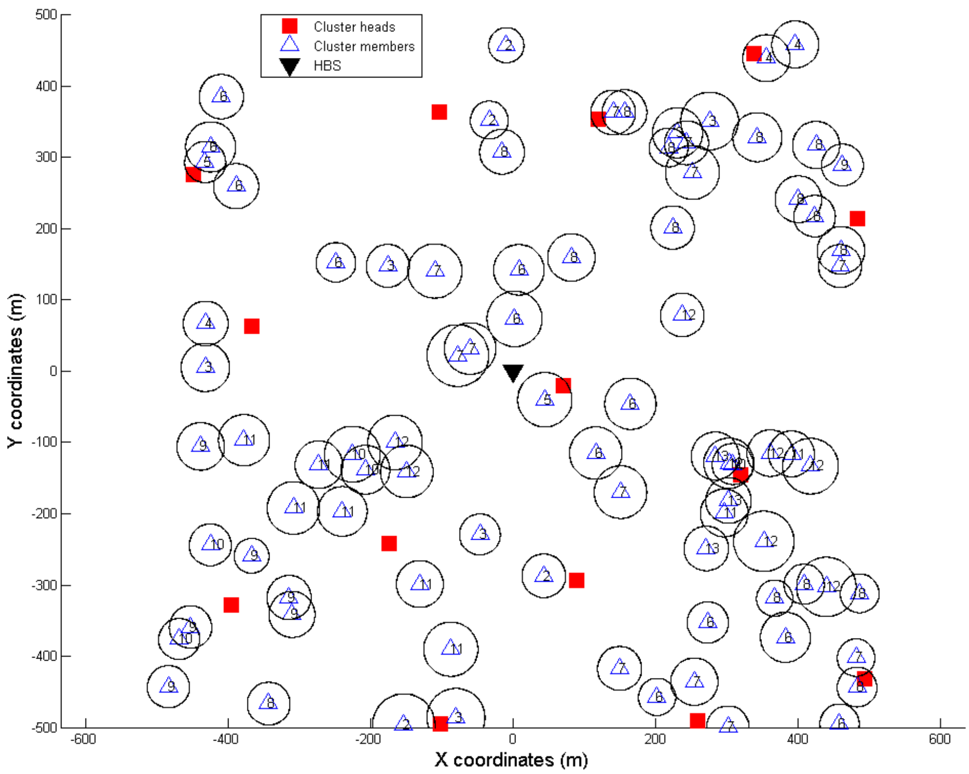

Figure 6-13: Snapshot of cluster members end to end delays applying ARLD channel assignment scheme.

Figure 6-14 shows how energy efficiency in Joules/Bit of the dual hop clustered network with a 12-beam directional antenna on the HBS for the various uplink channel assignment schemes and Figure 6-15 presents the subsequent Energy Reduction Gain (ERG) that is achieved with random uplink channel assignment for the dual hop schemes as a baseline. Just as in the delay performance, the inability of *RL* scheme to optimise the channel selection based on the received interference means that it is unable to reduce the energy consumption compared to the random uplink channel assignment scheme. At higher offered traffic levels where the rate of temporary files interruption becomes more pronounced, *ARLF* can improve the energy efficiency by almost 10% where as *ARLD* and *RL* have 8% improvement compared to the random uplink channel assignment scheme.

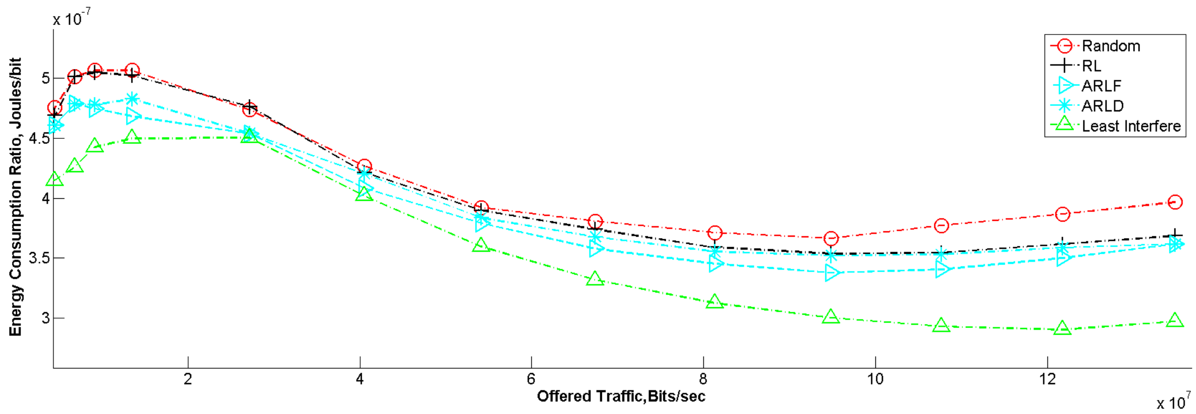

Figure 6-14: ECR of various channel assignment schemes on dual hop clustered network with directional antenna at HBS

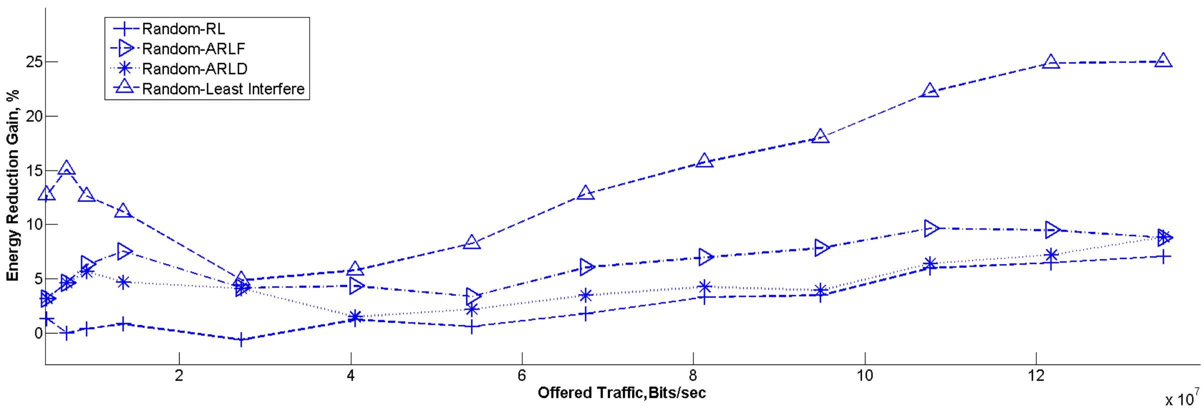

Figure 6-15: ERG achieved through intelligent channel assignment schemes on dual hop clustered network with directional antenna at HBS, with the Random scheme used as a base line

6.4.1 Learning rate

In the Reinforcement Learning scheme, the agents first need to explore the consequences of different actions in order to enable the agent to exploit actions that can provide the greatest reward [58]. The learning algorithms for channel selection need to be able to quickly adapt to the changes in radio network environment so as to not make a channel selection based upon previously perceived environment knowledge database.

Although the rate of exploitation can be made quicker by reducing the value of weight threshold W_{thr}, the system performance is not optimised due to an insufficient sample of channels success and failure. As mentioned earlier, the channel assignment scheme *RL* is optimised when W_{thr} = 5, a parameter which was also used in the localised schemes.

The rate of learning in cluster members can be analysed by measuring the number of cluster members that are able to transmit on the preferred channel set, i.e. the exploitation stage for a given weight threshold and offered traffic against the total number of network uplink transmissions.

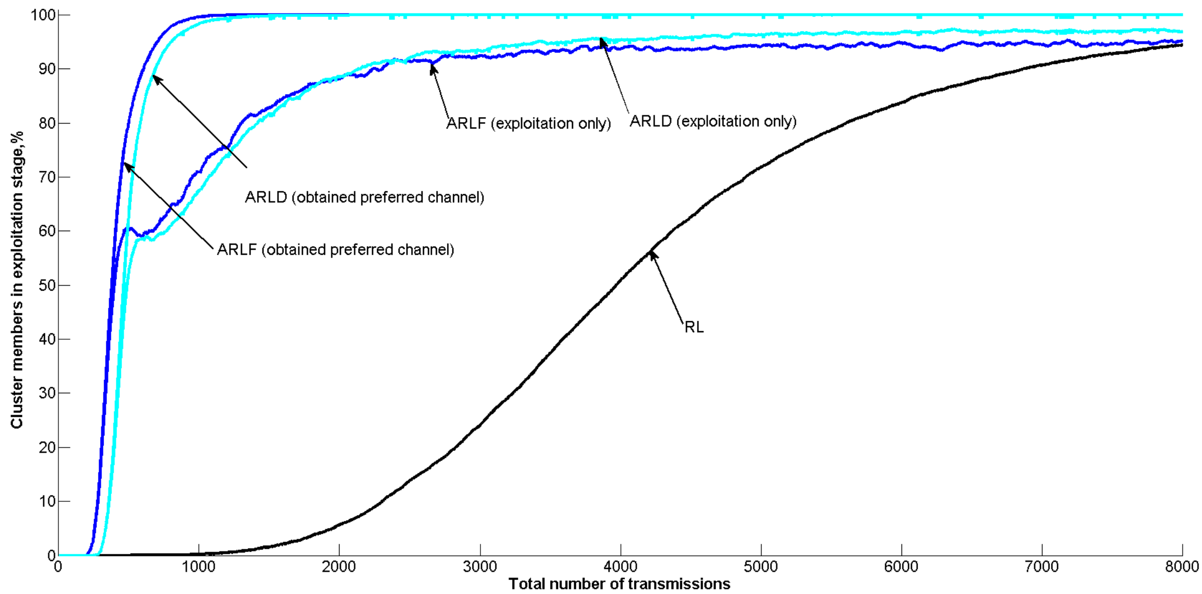

Figure 6-16: Exploitation rate of the various reinforcement learning based channel assignment schemes.

From Figure 6-16, it can be seen that more than 90% of the cluster members implementing the localised reinforcement learning schemes at an offered traffic of 100Mb/s were able to enter exploitation stage at around 2000-2500 transmissions, which is a stark improvement over the fully distributed scheme which requires a further 4000 transmissions. The localised schemes were able to achieve such performance as the learning engine is located in the cluster heads. Unlike the fully distributed scheme which requires individual cluster members to analyse its current channel selection, the cluster heads are able to simultaneously assess several uplink channels induced by its respective cluster members uplink transmissions. The result also illustrates that around 5-8% of cluster members implementing localised schemes will revert to exploration stage despite having obtained a preferred channel set. This is due to the fact that the preferred channels set are occupied by other cluster members uplink transmissions.

6.5 Conclusion

In this chapter, reinforcement learning was introduced to the uplink channels assignment problem in a dual hop clustered network as a mean of reducing delay and thus minimising the amount of time and energy for the nodes in the network to be in transmission or reception mode. The reinforcement learning schemes can exploit the spectrum perceived as a good option based upon individual channel historical information W recorded as an accumulation of rewards and punishments given to the channels. At an offered traffic level where the temporary interruption of file transmissions become very prevalent, the reinforcement learning schemes can potentially improve the energy efficiency in Joules/bit of dual hop clustered network by almost 10% and reduce the uplink delay by more than 20%. Since the rewards and punishments are given based on a channel rate of success and failure (blocking and dropping), at low offered traffic level where blocking and dropping in the network are almost non-existent, the reinforcement learning schemes are unable to select a channel that would optimise the rate of file transfer and reduce delay.

The results presented in this chapter have shown that the proposed localised reinforcement learning schemes are able to reduce the total number of transmissions for at least 50% and 90% of cluster members to exploit the preferred channel set by a factor of 3 and 2.5 respectively compared to the fully distributed scheme. This indicates that the localised schemes are able to facilitate the learning rate and reduce the amount time in which cluster members examine their environment to find the preferred channel set compared to the fully distributed scheme. The incorporation of a dynamic preferred channel set on to the localised schemes reduces the variations between cluster members uplink delay thus making the system more equal.

Chapter 7 Conclusion and Future Outlook

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7.1 Summary

This thesis has investigated suitable learning approaches to enhance the capability of self organisation in wireless networks such as ad hoc and green small cell networks in order to facilitate spatial reuse. A brief summary and conclusion of the entire thesis is presented below. More detailed and specific summaries are provided at the end of each chapter. In addition, the main findings of the research and the original contributions to the field are also highlighted in this section. Finally, further recommendations on the research are provided at the end of this chapter.

Chapter 2 delivered the essential background information related to this thesis. Self-organising networks and spatial reuse were briefly introduced to give the readers the necessary information on the issues that were worked on. The definitions of cognitive radio as well as its features were described to give readers clear ideas of cognitive radio. Existing clustering algorithms that have been proposed by ad hoc and sensor network researchers were reviewed in detail and categorised according to their objectives. Different clustering strategies and their characteristics were described. The purpose of this chapter was to determine whether improvements can be made despite numerous publications in this area and to analyse their methodology.

The simulation, modelling and evaluating techniques were described in Chapter 3. MATLAB was chosen to perform the simulations and the widely used Monte Carlo simulation technique was applied in order to obtain a more statistically accurate results. Several performance measures were introduced which were broken down into two main parts; the first part was to assess the distribution of clusters and second part was to determine the network quality and grade of service. In this chapter, the basic of queuing theory was also introduced in order to help verify and understand the network performance as shown in chapter 5 and 6.

In chapter 4, learning and competition concept are first introduced, the idea is that a node will be able to learn its geographical location through repeated sensing and whether a node which has sufficient neighbouring nodes (must be un-clustered) will win and become a cluster head. The proposed algorithm called sumRSSI is fully distributed. It is shown that by delaying the formation of clusters i.e. making nodes to repeatedly learn about their environment by sensing RSSI, the resulting cluster formation can be improved in terms of its distribution and compactness. The proposed algorithm can be modified such that nodes which have the highest number of neighbouring nodes are more likely to be elected as cluster heads known as node degree. The performance of the proposed clustering formation converges as $R_{threshold}$ grows larger. This indicates that after a certain point, any further learning and competition no longer aids the clustering formation.

Chapter 5 serves as the performance measures in order to understand the quality and grade of service on applying hierarchical architecture to ad hoc and green small cell networks via a two-hop backhauling. The energy consumption ratio (ECR) and the energy reduction gain (ERG) metrics were selected to quantify the energy efficiency of the dual hop network. The energy efficiency of the network was investigated under various load conditions and ratio of channels allocation between the first and second hop. The metrics allow us to understand how the network can achieve a balance between energy saving and maximising throughput. If the transmission power dominates the total power consumed by devices in the network, then the dual hop clustered network can be more energy efficient than a direct single hop provided that the interference is kept low.

Based on the findings of chapter 5, chapter 6 sought to optimise the performance of the network through an intelligent channel assignment scheme via reinforcement learning on the first hop to channel utilisation. The reinforcement learning enables a node to exploit the spectrum which it perceives as a good option based upon individual channel historical information. At high offered traffic where interruption of file transmissions becomes more pronounced, the reinforcement learning schemes can potentially improve the energy efficiency in Joules/bit of dual hop clustered network by almost 10%.

Also In chapter 6, the directional antennas on Hub Base Station significantly help in reducing the energy consumption of the cluster heads as well as providing high capacity link on the second hop.

7.2 Contributions and Findings

This thesis has provided an understanding of how learning can aid self organisation on infrastructureless wireless networks such as ad hoc and small green cell networks on improving its spatial reuse and optimise energy efficiency. The contributions that have been made in this line of research are as follows:

- **Reinforcement learning based approach through RSSI to form clusters**
  The novel aspect of this algorithm is that the received signal strength indication (RSSI) will be sensed by a node multiple times. Each time a node performs sensing, it will receive reward that corresponds to its perception of the environment. The accumulation of reward will be used by a node to decide the right course of action on whether to become a cluster head.

  The periodic sensing of RSSI beacon transmitted by other nodes in the network enables it to discover its geographical significance and to determine if it is the best candidate to become a cluster head. Through the repeated sensing before forming clusters, the proposed algorithm is able to reduce the average transmission distance of nodes to cluster head by up to 11% and the average degree of overlapping clusters by 23%. Unlike other clustering algorithms (whose objective is to minimise cluster overlap) such as [24], the proposed clustering algorithm does not require Node Discovery (ND) process. In chapter 4, it is also shown that only nodes that is within the transmission range (on demand beacon) of a node performing sensing needs to transmit its beacon. The amount of beacons transmitted can be reduced by a factor of 10 times and thus reducing the total energy consumption of the network during clustering process.

The node degree scheme can have a Dunn Index of less than 29% compared to the learning schemes (sumRSSI and on demand beacon), which suggests that the learning schemes produce a more compact and distributed clusters.

A Monte Carlo simulation shows that under a shadowing environment, the cluster members (on average) of the learning schemes can reduce its transmission power by up to 1.37dBW and 2dBW to achieve the same signal to noise ratio (SNR) as that of no learning and node degree, respectively.

In certain geographical layout of nodes, learning schemes are unable to provide significant improvement on the clustering performances. Therefore, in this circumstance, no learning algorithm is advantageous due to the lower overhead time for clusters formation.

The relative simplicity of the algorithm means that it is very versatile and can be applied to a low cost and low processing power devices.

- **Address the challenges of optimising energy efficiency in dual-hop hierarchical networks**

  Several researchers such as [109] and [110] have analysed the performance of dual-hop wireless communication in terms of bit error rate (BER) and outage probability. The simulation results as presented in chapter 5 differ in that it provides perspective on the energy efficiency of dual-hop hierarchical networks. As pointed out in chapter 5, by efficiently switching off cluster heads when it is not relaying data, the energy efficiency can be improved by more than 80% (upper bound limit). Interference can also effect the network energy consumption as high interference will result in greater end to end delay and therefore cluster heads have to be in transmission mode for a longer period of time. Reducing interference by efficient channel allocation i.e. assigning channel with the highest SINR can improve the network energy efficiency by more than 50% compared to a random channel assignment scheme.

- **Localised reinforcement learning**

  A localised reinforcement learning channel assignment schemes have been developed to improve the speed at which a user can begin exploiting the spectrum. The ability for user to quickly learn and enter exploitation stage is desirable in a wireless network whose topology constantly changes e.g. mobile ad hoc network. The localised reinforcement learning is achieved by having the cluster heads record a successful initial and interrupted transmission instigated by all its cluster members. The cluster heads will share the channel weights with its cluster members thereby enabling it to enter exploitation quicker compared to the fully distributed reinforcement learning.

  Unlike the fully distributed reinforcement learning [55], [56] and [57], the localised schemes do not have a fixed predetermined preferred channel size. This enables the localised schemes to have up to 45% lower variations between the performances of nodes in the network compared to the distributed reinforcement learning. Moreover, the proposed localised reinforcement learning schemes are able to significantly facilitate the learning rate as the total number of transmissions required for 90% of cluster members to exploit the preferred channel set is by a factor of 3 less compared to the fully distributed scheme.

  Coincidently, the cooperation and sharing of information between cluster heads with its cluster members to aid decision making falls into a novel paradigm proposed by [112] known as Docitive Networks.

7.3 Further Work

This section presents an overview of potential further research that is relevant to the work in this thesis.

- **Traffic load dependent cluster size**

  In chapter 4, a static clustering algorithm was presented. However, based on the findings in chapter 5, the network energy efficiency can be optimised by allowing the number of clusters to change periodically to adapt to the change on the amount of traffic load. Figure 7-1 illustrates the fluctuation on the traffic load during 24 hours period. By forecasting the traffic load on hourly basis, clustered networks can adapt accordingly to maximise the network energy efficiency. The proposed clustering algorithm presented in chapter 4 can be modified by mapping and calibrate the transmission range *r* to the desired number of clusters.

- **Analysing clustered network energy efficiency with micro-sleep**

  [105] Demonstrated that despite throughput degradation, applying micro-sleep during “silent period” to base stations in cellular networks can improve its energy efficiency in J/bit. However, the effect of micro-sleep in maximising energy efficiency of dual-hop backhauling of dual-hop clustered network is less understood. Although the cluster heads are able to reduce its energy consumption through micro-sleep, the lost in throughput could cause the network to have a lower energy efficiency in J/bit.

- **Interference mitigation via multi-dimensional reinforcement learning in heterogeneous network**

  With the rapid development of wireless communication techniques, communication architecture systems are becoming increasingly complex. Future radio systems are required to be increasingly energy efficient, owing to the high data transmission rates, limited battery capabilities on portable devices, and a trend towards 'green' radio in general. As stated in chapter 1, the green small cell networks, femtocells and mesh nodes are deployed in ad hoc manner. The unplanned nature of these networks will not only interfere with each other but also with the existing cellular networks. Multi-dimensional learning enables nodes to prioritise and learn which is worst? The interference caused by other small cell networks or the cellular base stations.

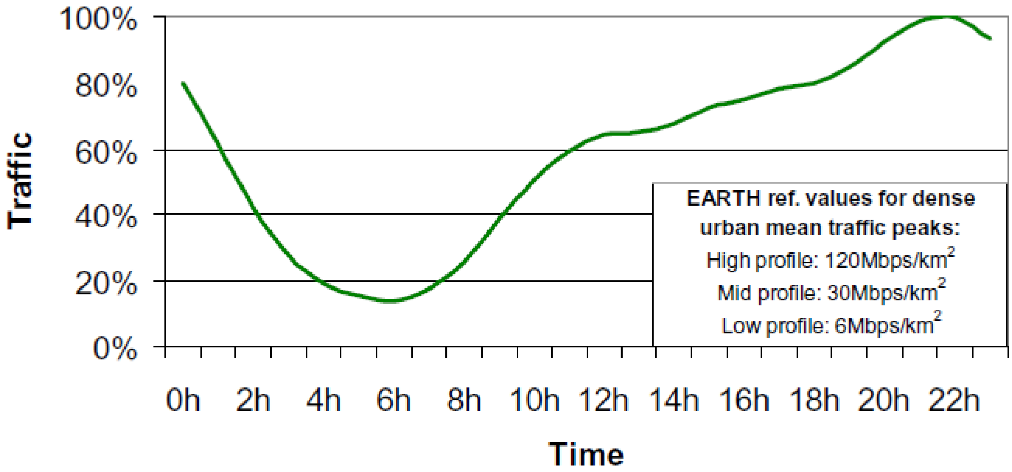

Figure 7-1: Traffic Load within 24 hours period (directly reproduced from [104])

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