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Improving the Dynamics Spectrum Allocation in Cognitive Radio Wireless Mesh Network Using Mixed Integer Non-Linear Programming

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Abstract

Cognitive radio (CR) technology has emerged as a solution to the issue of spectrum underutilization and spectrum scarcity. Cognitive radio (CR) -enable device can (detect) the unused spectrum (i.e. spectrum holes), and used them in an opportunistic manner. However for cognitive radio technology to deeply penetrate the industry or enterprises, the problem of dynamic spectrum allocation has to be effectively addressed. Hence this developed mixed integer nonlinear programming MINLP algorithm to address the problem of dynamic spectrum allocation in cognitive radio network. In the study, a mixed integer nonlinear program optimization algorithm for dynamic spectrum allocation was deployed in which objective function was the minimization of sensing power. The developed mixed integer nonlinear algorithm was implemented in a java program language. Simulation was setup and carried out with the advance Cisco packet tracer 7.0. Result from the simulation carried out show that the developed mixed integer nonlinear program algorithm outperformed the Maximal Independent Set (MIS) in term of throughput, traffic delay, resource utilization of reduction in spectrum sensing energy. The developed mixed integer nonlinear programming archived 33.15% in throughput improvement over the MIS algorithm. It reduced traffic delay by 52.91%, increased network system resource utilization by 11.52% and reduce spectrum sensing energy usage by 24.98% using the MIS as a baseline.

Keyword: Cognitive radio, Mixed integer non-linear programming, Cognitive Radio Wireless Mesh Network.

I Introduction

Cognitive radio emerged as a solution to spectrum scarcity problem [1]. The radio frequency is a limited natural resource whose usage gets higher day by day due to growing demand in wireless communication application. To operate on a specific frequency band, licenses are needed. The use of radio spectrum in each country is governed by corresponding government agencies. In conventional techniques, every user is assigned a license to operate in a certain frequency band. Most of the time, spectrum remains unused and it is difficult to find it. Spectrum utilization varies with time, frequency and geographical location and as a result this; it is not properly used [2]. Thus, to overcome the spectrum scarcity and unutilized frequency, a new communication phenomenon called cognitive radio (CR) was introduced. Cognitive radio emerged as a solution to spectrum scarcity problem [1]. The radio frequency is a limited natural resource and getting higher day by day due to growing demand in wireless communication application. To operate on a specific frequency band, licenses are needed. The use of radio spectrum in each country is governed by corresponding government agencies. In conventional techniques, every user is assigned a license to operate in a certain frequency band. Most of the time, spectrum remains unused and it is difficult to find it. Spectrum utilization varies with time, frequency and geographical location and as a result this, it is not properly used [2]. Thus to overcome the spectrum scarcity and unutilized frequency, a new communication phenomenon called cognitive radio (CR) was introduced. Cognitive radios are the radio system that automatically co-ordinate the usage of radio band. The key characteristic of cognitive radio system is to sense the electromagnetic spectrum and adapt to their operating parameters like frequency, modulation techniques and power. Cognitive radios are fully programmable wireless devices that can sense its environment and dynamically adapt to its transmission waveform, channel access method, spectrum use, and networking protocols as needed for good network and application performance. One of the applications of cognitive radio is for more efficient, flexible, and aggressive dynamic spectrum access. The communication parameter can be adjusted to the change in radio environment, topology, operating condition or user requirement. Cognitive radio is a self-aware and intelligent device which can sense the changing environment condition and can change its parameters according to changing statistical communication environment, thus resulting in efficient utilization of available resource [3] . In general term, a cognitive radio is defined as a radio that can change its transceiver parameters based on the interaction with surrounding environment[4]. In Cognitive radio paradigm, wireless users are classified into two categories based on whether they are licensed to use a particular band or not, the categories include the primary users which are the licensed band and secondary users which are the unlicensed users. Cognitive radio recognize radio spectrum that are unused by Primary User (PUs) and intelligently allocate these spectrum to Secondary User (SUs). So unused radio spectrum is called spectrum opportunity and also known as white space [5] or spectrum hole [6].Secondary Users are allowed to opportunistically use the spectrum as long as they do not cause harmful interference to active Primary Users. This opportunistic and dynamics of communication paradigm leads to higher spectrum utilization and provide Secondary Users with good source of availability and reliability because they can access any part of spectrum as long as they do not interrupt ongoing PUs transmission and also hop to a different part of the spectrum when needed. Assigning of free channels among primary users and secondary users in a specific geographical region while minimizing interference among all user is known as the spectrum allocation in cognitive radio. Conventional noises in wireless communication systems can be overcome by increasing transmit power, but it introduces interference. Therefore, in both centralized and ad hoc wireless networks, if each device only uses the minimum required transmission power, the overall system capacity can be maximized while the interference caused to other devices is minimized. In Fixed Spectrum Allocation (FSA) the spectrum resources are statistically allocated to the licensed user by government agencies or service on a long term basis. Here the unlicensed user cannot use the idle spectrum temporally to improve utilization efficiency. Dynamic spectrum allocation technique using mixed integer non-Linear Programming is a way to overcome the problem of underutilized holes or space and improve inefficiency of fixed sense spectrum holes. MINLP is abbreviation of mixed integer nonlinear programming. It refers to a mathematical programming problem, in which variables can be continuous, or discrete, containing integer and non-integer variables, and nonlinearity for the objective function and constraints. MINLP problem is an important category of optimization problems, which can be applied in various real-world problems. For example, there are a lot of applications of MINLP applied in financial, engineering design problems, chemical engineering, process operations research and management. In MINLP problems, the objective function and the constraints always include mixed integer problems (MIP), non-linear problems (NLP) and sometimes non-convex problems. Thus, MINLP problems are generally difficult to solve. However, many approaches have been developed and used to solve MINLP problems. But in this work the objective function is to minimize the spectrum sensing energy and the constraints is the limit sensing duration, number of SUs per channel, alarm of co-operative SUs per channel, flag indicating SUs sensing channel (0s and 1s). The constraint is stated as a mathematical inequality.

Spectrum assignment functionality of cognitive radio deals with how secondary users can opportunistically utilize unused license spectrum on non-interference and leasing basis at any location over the entire spectrum. System throughput is one of the key factors that significantly influence the performance of cognitive radio network (CRN).

II Literature review

They have been several research effort made to find the optimal solution to the spectrum allocation problem in wireless network using cognitive radio system. [7] developed colour sensitive graph coloring (CSGC) algorithm, in which the problem into colouring model was generalizes. By reducing the allocation problem to a variant of the graph coloring problem, it was show that the global optimization problem is NP-hard, and provides a general approximation methodology through vertex labeling.[8] developed cooperative spectrum sensing techniques using Welch's periodogram in cognitive radios. An analysis of radio spectrum deployment for detecting utilized frequency channels and isolate unoccupied parts of radio spectrum was carried out. Spectrum sensing is the basic and essential mechanisms of Cognitive Radio (CR) to find the unused spectrum. [9], [10]presented a Maximal Independent Set (MIS) spectrum allocation algorithm. Spectrum allocation algorithm using Maximal Independent Set (MIS) is aiming at the characteristic and request of the cognitive radio systems. When taking no account of the spectrum diversity, this algorithm can gave consideration to both utilization and fairness of channel allocation. [11] developed Models abstract the spectrum allocation problem into graph-colouring problem. Cognitive user's spectrum can be equivalent to graph vertex colouring problem. [12] in their work, they used Hidden Markov Models (HMMs) to model and predict the spectrum occupancy of licensed radio bands[13].In this work Spectrum allocation model was presented firstly, and then spectrum allocation methods based on Genetic Algorithm (GA), Quantum Genetic Algorithm (QGA), and Particle Swarm Optimization (PSO), were developed later. In this work presented by [14] a demand based spectrum allocation algorithm in order to match between user's demand and radio channel and that the algorithms have limitation. Zhou (2014) developed Dynamic Spectrum Allocation in cognitive mesh network using Parallel Immune Optimization; the algorithm reduces the total spectrum allocation time and to achieve higher network profits. Compared with traditional serial algorithms, the algorithm had better speedup ratio and parallel efficiency but energy dissipation during sensing period was not considered. [15] eveloped an effective dynamic spectrum access algorithm for multi-hop cognitive wireless networks. They used graph theory to perform the reasonable channel allocations.[16] developed a Dynamic Spectrum Allocation algorithm based on game theory, which jointly performs spectrum leasing and interference mitigation among SUs.

System throughput is one of the key factors that significantly influence the performance of cognitive radio network. Under idle circumstance, system throughput can be considered equal to channel capacity. Power consumption during spectrum sensing pose a very big threat in cognitive radio operation, it also shown that many research is ongoing for good allocation techniques that will address the problem of power control mechanism. The main target of this work is to maximize the theoretical system throughput of the secondary user with optimal spectrum allocation subject to transmit power of secondary user and primary user interference constraint. Good allocation schemes also need to provide fairness across devices. An optimization method is an interesting tool to model and solve the problem of spectrum allocation in cognitive radio network. Hence this work proposes the use of optimization method to address the problem of spectrum allocation and power allocation for cognitive radio mesh network using mixed non integer programming.

III Methodology

The method used herein was to develop a mixed integer non-linear programming model for cognitive radio that reduces spectrum sensing energy dissipation is energy detection method. It is non-coherent detection method that detects the PU signal based on the sensed energy **[17].** Due to simplicity and no requirement on prior knowledge of PU signal, energy detection (ED) is the most method in cognitive radio sensing**.**

The mixed integer programming was formulated to tackle the problem of deciding the SUs to use for the available spectrum. The problem of selecting the spectrum for allocation is tackled using MINLP which implemented in java program .Spectrum analysis is tackled using log-distance path loss model and adaptive modulation code (AMC) to estimate the minimum bandwidth of the SUs

Advanced Cisco packet tracer software is used to build a virtual mesh cognitive radio environment used for testing and validation of the developed spectrum allocation technique.

Cognitive mesh radio traffic is simulated within the visual basic software environment. Poisson distributions are used to model the Pus and SUs traffics. The cognitive users (PUs and SUs).transmission arrivals are taken to be Poisson distribution the cognitive radio users (PUs and SUs) transmission arrivals are taken to be Poisson distribution

IV Experimental Measurement and Data Collection

The case study cognitive radio network from when the data used for this work was collected from MTN Nigeria network operator. The MTN network is based on the CISCO RFSS network controller. The P25 channel controller of the RFSS radio system manager radio access and assignment. It gathers and records radio network traffic statistics. For the data collecting snap shots of traffic radio network traffic statistic was pulled from the traffic log of CISCO P25 RFSS radio network controller. From the network traffic snapshot, the parameter of RF environment, the performance data was extracted and tabulate as shown in table 1

Data sampling window: 3secs

No of channel radio frequency channel: 13

Channel bandwidth: 0.1MHZ

Transmission power: 15watts

Bus (slots) duration: 625secs

Table 1 Data used for setup of cognitive radio network simulation

Table 1 Network traffic statistics collection

Records #(interval 3secs)	Occupied channel	Unoccupied Channel	No of SUs	No of PUs	Average spectrum sensing duration(seconds)	Wait Queue	Active radio session
1	118	2	45	73	4.56	3	113
2	120	-	40	80	8.86	16	109
3	116	4	59	57	6.42	8	116
4	111	9	25	86	4.98	4	106
5	114	6	34	80	3.97	7	108
6	120	-	70	50	8.27	18	118
7	120	-	30	90	7.98	12	117
8	110	10	40	70	5.98	8	104
9	120	-	18	102	9.06	20	116
10	109	10	60	49	5.65	13	104

a. The Block Diagram

The components of the developed dynamic spectrum assignment algorithm for cognitive radio network is shown in figure 1

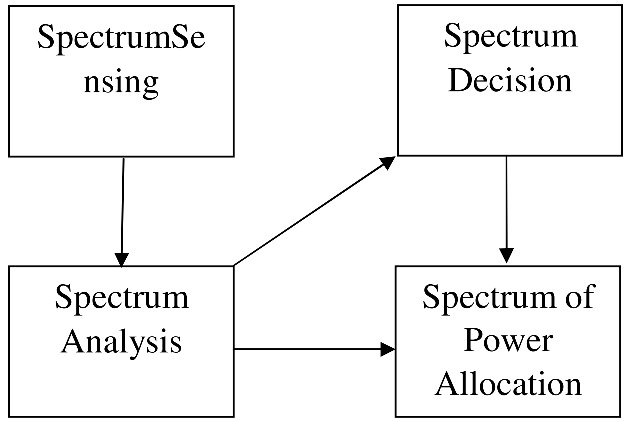

Figure 1 Block diagram of the components of the developed dynamic spectrum allocation algorithm for cognitive radio network.

V System Modeling and Analysis

The algorithm behind the components of the developed system is given in the block diagram of figure. 1. In the design of the algorithm presented in this chapter, a cognitive radio network consisting of m primary users and n secondary users was considered. Primary users hold licenses for specific spectrum and can only occupy their assigned portion of the spectrum. Secondary users do not have any licensed spectrum and opportunistically send their data by utilizing idle portions of the primary user's spectrum.

a. Assumption Made In This Research

Let the multi-hop wireless network be modeled by a directed connectivity graph $g(V, E)$, where $V = \{V1, \ldots\ldots, Vn + m$ is a finite set of modes, with $|V| = n + m$, and $(i, j) \in E$ represent a unidirectional wireless link from mode Vi to node Vj (referred to also as node i and node j, respectively, for simplicity).

Nodes from the subset $PV = \{V1, V2, \ldots\ldots, Vm\}$ are designated as primary users, and nodes from subset $SV = \{Vm + 1, \ldots\ldots, Vm + n\}$ are designated as secondary users. It is assumed that all secondary users are equipped with cognitive radios that consist of a reconfigurable transceiver and a scanner. The transceiver can tune to a set of contiguous frequency bands

$[f, f + \Delta B]$, where ΔB represents the maximum bandwidth of the cognitive radio. However, it was also assume in this work that multiple transmissions can concurrently occur in a frequency band, e.g. with different spreading codes.The available spectrum was assumed to be organized in two separate channels.

(i) A Common Control Channel (CCC) was used by all secondary users for spectrum access negotiation, and was assumed to be time slotted.

(ii) A Data Channel (DC) was used for data communication.

The data channel consists of a set of discrete mini-bands $\{f - min, f - min + 1, \ldots\ldots, f - max - 1, fmax\}$, each of bandwidth w and identified by a discrete index. For example, the interval $[fi, fi + \Delta fi]$ represents the (discrete) set of mini-bands selected by secondary usersi between fi and $fi + \Delta fi$, with bandwidth$w\Delta fi$. Here, $w\Delta fB$ denote the maximum bandwidth of the cognitive radio, where Δf_B denotes the maximum number of mini-bands, also $\Delta fi \leq \Delta f_B$ represent the constraint of maximum bandwidth of the cognitive radio.Each backlogged secondary user contends for spectrum access on the control channel fcc, where $fcc \notin$[fmin, fmax]. All secondary users exchange local information on the common control channel. Traffic flows are carried over multi-hop routes. Let the traffic demands consist of a set $S = 1, 2 \ldots S$, where $S = /S/$, of unicast session. Each session SE is characterized by a fixed source-destination node pair. The arrival rate of sessions at node I is indicated as λ_i^s(t), and $\wedge$ indicate the vector of arrival rates. Each node maintains a separate queue for each session s for which it is either a source or an intermediate relay. At time slot t, define Q_t^s (t) as the number of queued packets for sessions waiting for transmission at secondary user $i, r_{ij}^s(t)$ was defined as the transmission rate on link (i, j) for sessions during time slot t, and R as the vector of rates. For $\forall \in$ SU, the queue is updated as follows:

$$(Q_t^s(t+1) = \left[Q_i^s(t) + \sum_{k \epsilon SU, k \neq i} r_{ki}^s(t) - \sum_{l \in SU, i \neq i} r_{il}^s(t) + \lambda_i^s(t)\right]^+) \qquad (1)$$

b. Modeling of the Spectrum Sensing Component

The goal here was to sense all M primary users (i.e. all M channels) with minimum energy and sufficient accuracy such that cooperate detection probability of each channel is greater than some predicted threshold value (denoted by thQ^d and cooperate false alarm probability is smaller than another threshold (denoted by thQ^f). Since channel sensing consumes energy, an SU may not utilize all of the quiet period duration for sensing if not necessary. On the other hand, it is desirable to sense a channel with a couple of SUs instead of a single (though, it may satisfy the thresholds) in order to increase robustness. Hence, there is a trade-off between energy consumption and sensing reliability. The problem includes the assignment of SUs to channel for the sensing task together with the decision of the sensing time for the channels to be sensed by each SU.

Let$P_{m,n}^f$,$P_{m,n}^d$, $\Upsilon_{m,n}$ denote the probability of false alarm, probability of detection, SNR over channel m, respectively. It was assumed here that $P_{m,n}^f$ was fixed, then for a complex-valued phase shift keying (PSK) channel with circularly symmetric complex Gaussian noise, $P_{m,n}^d$ becomes

$$P_{m,n}^d = \cup\left(\frac{\cup^{-1}\left(P_{m,n}^f\right) - \sqrt{Tm,n\, fs\, Ym,n}}{\sqrt{2\quad m,n+1}}\right)$$

(2)

Where f_s is the sampling frequency and U is the complementary cumulative distribution of a standard Gaussian, and $T_{m,n}$ was the time spent by $SU_n$for sensing channel m.

c. Development of a Mixed Integer Non-Linear Programming Model

This model was being developed for cognitive radio mesh network to reduce the spectrum sensing energy dissipation in wireless network. Let P^s and $E^s_{m,n}$ be the power consumed during channel sensing and energy dissipated by SU_n for sensing channel m, respectively. $E^s_{m,n}$ is equal to $P^s_{\mathrm{T}m,n}$. Then, energy consumption for channel sensing (denoted by E^s) can be written as

$E^s =$
$\sum^M \quad \sum^N P^s_{\mathrm{T}m,n}$
)

Besides channel sensing, SUs also consume energy transmitting their local results to the cognitive Radio Base Station (CBS). It was assumed here that SU transmits its sensing report as a single packet regardless of the number of channels sensed, and the reporting period is long enough such that all SUs can find their packets.

Let E^{rep}_n denote the energy consumed for reporting the sensing result to CBS, which depends on the location of SU_n relative to the CBS. In addition, let S^{rep} denote the set of SUs that perform sensing in this frame that are required to report their local decision to the CBS. Then, the total energy consumption for reporting is given by

$$E^{rep} = \sum_{n \epsilon S^{rep}} E^{rep}_n$$

The optimization model for the spectrum sensing and the decision variables used for the optimization model is first defined.

Let $X_{m,n}$ = {1, if channel m is sensed by SU_n}
{0, otherwise}

Y_n = {1, if SU_n transmits sensing result to CBS}
{0, Otherwise}

From equation (3.2), for a given $P^d_{m,n}$ value the required $T_{m,n}$ can be written as :

$$\mathrm{T}_{m,n} = \left(\frac{U^{-1}\left(P^f_{m,n}\right) - U^{-1}\left(P^d_{m,n}\right)\sqrt{ZY_{m,n}+1}}{Y_{m,n}\sqrt{f_s}}\right)^2$$

(5)

In addition, let $\mathrm{T}^{min}_{m,n}$ denote the sensing time required for SU_n in order to achieve a $P^d_{m,n}$ value of 0.5. it can be calculated from (4) as

$$\mathrm{T}^{min}_{m,n} = \left(\frac{U^{-1}\left(P^f_{m,n}\right)}{Y_{m,n}\sqrt{f_s}}\right)^2$$

It assumed in this model that channel should be sensed by at least δ^{min} SUs. δ^{min} Defined the minimum number of cooperating SUs for a channel. The selection of δ^{min} is a design criterion. In order to encourage cooperation and improve robustness, a δ^{min} value greater than one is used in this design. Assuming that $P^f_{m,n} = P^f \forall_{m,n}$,

then Q^f_m is given by

$$Q^f_m = 1 - \prod_{n \epsilon S_m} (1 - P^f)$$

(3)

Since $Q^f_m \leq \mathrm{th}Q^f$, then the maximum number of cooperating SUs, denoted by δ^{max}, can be calculated as

$$\delta^{min} = \left\lfloor \frac{\log(1 - thQ^f)}{\log(1 - P^f)} \right\rfloor$$

Where Q^f false alarm probability for another threshold is In other words, δ^{max} is the maximum number of cooperating SUs that satisfy the cooperation false alarm constraint. (4)

The solution methodology applied here can also be used for the case where $P^f_{m,n}$ values differ.

The optimization problem can be written as

Optimization problem1:

$$min_{w} = \sum^{M} \sum^{N} P^{s} \mathrm{T}_{m,n} + \sum_{n=1}^{N} E_{n}^{rep} y_{n}$$

Subject to the following constraints:

$$\mathrm{T}_{m,n} \geq \mathrm{T}_{m,n}^{min} X_{m,n} \forall_{m} \epsilon M, \forall_{n} \epsilon N \quad (9)$$

$$\sum_{m=1}^{M} \mathrm{T}_{m,n} \leq T_{yn}^{s} \forall_{n} \epsilon N \quad (10)$$

$$\sum_{n=1}^{N} X_{m,n} \geq \delta^{min} \forall_{n} \epsilon M \quad (10a)$$

$$\sum_{n=1}^{N} X_{m,n} \leq \delta^{max} \forall_{n} \epsilon M \quad (10b)$$

$$\sum_{m=1}^{M} X_{m,n} \leq M y_{n} \forall_{n} \epsilon N \quad (10c)$$

$$\mathrm{th} Q^{d} - Q_{m}^{d} \leq 0 \forall_{m} \epsilon M \quad (10d)$$

$$X_{m,n} y_{n} \epsilon \{0, 1\} \forall_{m} \epsilon M, \forall_{n} \epsilon \quad (10e)$$

$$\mathrm{T}_{m,n} \geq 0 \forall_{m} \epsilon M, \forall_{n} \epsilon N \quad (10f)$$

$(10g)$

Where Q_{m}^{d} is defined as

$$Q_{m}^{d} = 1 - \prod_{n=1}^{N} \left(1 - \cup \left(\frac{\cup^{-1} (P^{f}) - \sqrt{\mathrm{T}_{m,n} f_{s} Y_{m,n}}}{\sqrt{2Y_{m,n} + 1}}\right) X_{m,n}\right) \quad (11)$$

Hence, SUs with $X_{m,n}$ value of O contribute 1 to the above multiplication, whereas with $X_{m,n}$ value of 1 contribute (1 - $P_{m,n}^{d}$).

The objective function in (8) minimizes the total energy consumption associated with sensing for frame.

Constraint (9) specified that if Sun senses channel M, the sensing duration should be at least$\mathrm{T}_{m,n}^{min}$.

Constraint (10) denoted that total time spent by an SU for sensing should be less than or equal to the sensing duration of the frame. It also forces all $\mathrm{T}_{m,n}$ value associated with SU_n to zero, if Y_n=0.

Constraint $(10a)$ requires that each channel should be sensed by at least δ^{max} SU_s.

Constraint $(10b)$ limits the number of cooperating SU_S for a channel in order to satisfy the false alarm probability threshold.

Constraints $(10c)$ force Y_n value for an SU to 1, if that SU sense any channels. The requirement for cooperative detection probability being greater than the threshold for each channel is expressed by

Constraints$(10d)$. Finally Constraints $(10e)$ and Constraints $(10f)$ specify the type of variables.

Development of an algorithm for throughput maximization in spectrum allocation in cognitive mesh

The above problem is a mixed integer Non-linear programming problem. Algorithm 1 is used to solve the problem. The algorithm is presented in a pseudo code as

Algorithm 1: For Spectrum Sensing

Require: Pd, δ^{min}, M, N, Y^{min}, T3

1: remaining Time [n] = T^3

2: S^{rep}= ∅, S^{nrep} = {SU, SU_2, … SU_N}

3: for m = 1 to M do

4: Sort SU_s in S^{rep} in descending order of $Y_{m,n}$

Index Rep be the list of indices of the sorted entries

5: Assignment No = 0, k = 1

6: While (assignment No <δ^{min}) && (k ≤ |S^{rep}|) do

7: n = index Rep [k]

8: Select Sun € S^{rep} as a candidate and calculate $T_{m,n}$
Value to achieve P^d
9: If $T_{m,n} \leq$ remaining Time [n] then
10: remaining Time [n] = remaining Time [n] – $T_{m,n}$
11: assignment No = assignment No + 1
12: end if
13: k = k + 1
14: end while
15: if assignment No $< \delta^{min}$ then
16: Sort SU_sinS^{rep} in descending order of Y_{mn} and let index Nrep be the list of indices of the sorted entries
17: k = 1
18: While assignment No $< \delta^{min}$ do
19: n = index Nrep [k]
20: Select $SU_n S^{nrep}$ as a candidate and calculate $T_{m,n}$ value to achieve Pd using equation (4)
21: If $T_{m,n} \leq$ remaining Time [n] then
22: remaining Time [n] = remaining Time [n] – $T_{m,n}$
23: assignment No = assignment No + 1, S^{rep} = S^{rep} U {SU_n}, S^{nrep} = S^{nrep}) \ {SU_n}
24: end if
25: k=k +1
26: end while
27: end if
28: end if

In the Algorithm 1, S^{rep} is set of SU_s that are going to perform sensing and transmit their reports for frames. Similarly, S^{nrep} is the set of SU_s that are not assigned to sense a channel yet. Initially, $S^{rep} = \emptyset$, $S^{nrep} = \{SU_1, SU_2, \ldots SU_N\}$. The algorithm first looks for SU_s among the ones in S^{rep} in order to save reporting energy. If enough SU_s are not found, then it moves on to S^{nrep}. SUs in S^{rep} and S^{nrep} are processed in decreasing order of $Y_{m,n}$ values for the considered channel. Each channel is sensed with δ^{min} SUs. The required P^d (probability of false detection) value is calculated with:

P^d = max $\{1 - (1 - {}_{th}Q^d)\ 1/\delta^{min},\ P^d_{min}\}$ (11)

This guarantees a minimum detection probability of P^d_{min}

T^s is the sensing direction for a frame.

T^s given by: $\underset{n}{Max}\{\sum T_{m,n}\}$

VI Simulation, Result Analysis And Discussion

The developed MINLP algorithm was implemented in the java programming language. The digital model of the case study cognitive radio network was created using the advanced Cisco packet tracer 7.0. The packet tracer is a network modeling simulation program for the design and simulation of infrastructure (wired of wireless). It has the facilities to emulate enterprise network device, protocol and algorithms. The Cisco packet tracer program has Application Programming Interface (API) support for java and C^{++} programming language. With this program codes of algorithm (such as that of the developed mixed integer non-linear programming (MINLP)) can be loaded into it workspace, enabling it to interact with the kernel of the packet tracer program. The mixed integer non-linear programming (MINLP) program interacts with the packet tracer radio network operating system object via Common Object Request Broker Architecture (CORBA).This program allows inter object communication. It allows communication between object that are written in different programming language.

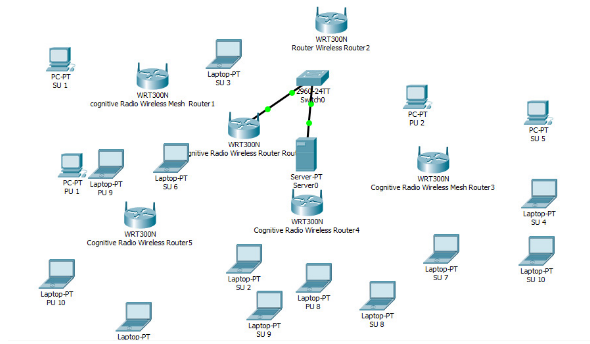

Figure 2 Cognitive Radios Mesh for evaluating the performance of developed MINLP algorithm

Figure 2 shows the case study cognitive radio mesh network created using the Cisco packet tracer software. The model consists of 5 mesh network routers and 20 mesh client (PUs and SUs). Of the 20 mesh client 10 are PUs and the other 10 are SUs. The program allows configuration of the network router radios characteristics, the parameters of the layer 2 switches and the mesh client. In the packet tracer environment the radio network parameters such as numbers of channels, transmit power, burst (slot) duration are configure able in other to properly setup the simulation. Data used for the setup and configure ration of the simulation environment is shown in Table 2. In the packet tracer network model in figure 2 cognitive radio wireless router 0 is setup as mesh controller. It has a wired connection to the base server. As the mesh controllers, it runs the spectrum allocation and de-allocation program in the network. Background program script interacts with the packet tracer radio network operating system.

The packet tracer's radio network operating system loads the mesh client access control script that runs the activations of the SUs and PUs based on Poisson distribution. This emulates the SUs requesting and yielding channels at random. The network management memory space (i.e. the Cisco packet tracer network operating system running configure ration) of the mesh controller can be accessed programmatically to view network traffic statistic logs and trace files such as buffer size, transmit power, allocated /de-allocation channel numbers of client service session, the queue size and the routing table as the simulation runs. In the simulation 60 iteration was done. Each iteration last for 60 seconds.

During each iteration, the network traffic statistics is queried programmatically from the simulation trace file in interval of three seconds (the network performance data sampling window is 3 seconds). From the simulation trace file, the network performance statistics are extracted and plotted to evaluate the performance of the developed algorithm. From the simulation trace file the performance for throughput, spectrum counts, delays, bytes transferred, spectrum sensing duration, energy usage for sensing, are extracted, tabulated and plotted. The traffic trace file extracts for 60 seconds iteration is given in source code.

The java source code for the maximal independent set (MIS) spectrum allocation algorithm for cognitive radio network is given in source code. The working of the MIS spectrum allocation algorithm is simulated using the same set of data in order to compare its performances with that of the developed algorithm. Its traffic trace file for the simulation is given in source code.

Throughput Evaluation

From the simulation trace file, the network performance statistics are extracted and plotted to evaluate the performance of the developed algorithm. From the simulation trace file the performance for throughput was also tabulated and plotted for the proposed MINLP and MIS algorithm

Table 3: Throughput realized using the developed MINLP spectrum allocation technique

Time interval(sec)	Throughput
3	2.6786
6	20.1786
9	41.9643
12	64.1071
15	74.4643
18	86.6071
21	102.3214
24	121.2500
27	128.3929
30	145.8929
33	153.3929
36	152.6786
39	153.3929
42	153.3929
45	153.0357
48	153.0357
51	153.0357
54	153.3929
57	153.3929
60	155.1786
Average	**116.0893**

The variation of throughput with time using the developed algorithm for spectrum allocation in the simulation is shown in figure 2 (the associate values are given in Table 2). From the figure it can be seen that the throughput rise (varies) with time than almost because stabilized to 153.6765kbytes/sec at about 28.5seconds. The increased and steady throughput indicates effectiveness in the algorithm. This show that the PUs and SUs activities increase as holes detection effort varies, that the algorithm kept the attained throughput at a good steady level.

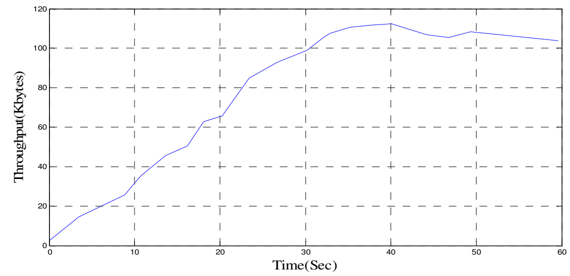

Figure 3 Variation of network throughput using the Developed MINLP algorithm for spectrum allocation

Table 4: Throughput realized using the MIS spectrum allocation technique

Time interval(sec)	Throughput
3	2.7941
6	14.5588
9	25.7353
12	35.4412
15	45.7353
18	50.4412
21	62.7941
24	65.7353
27	84.8529
30	92.7941
33	98.9706
36	105.1471
39	107.5000
42	110.7353
45	111.9118
48	112.5000
51	106.9118
54	105.4412
57	108.3824
60	103.6765
Average	**77.60295**

For the MIS algorithm the variation of throughput is shown on figure 4(the value are in table 4). Unlike in the case of the developed MINLP, the throughput rose gradually. It got to its peak value of 112.5kbytes/sec at about 39.4657 seconds than it fall to 105.147kbytes/sec at about 49.3246seconds than it gradually tappers to 102.7941kbytes at about 60seconds. This indicates that the variation in throughput with the MIS algorithm is not stable as it is with the developed MINLP algorithm. This variation is a result of algorithm not adapting properly to the increase in the opportunistic allocation and de-allocation of spectrums to secondary users. Hence its ability to co-ordinate dynamic spectrum sensing in the event of sustained random spectrum sensing by SUs result to less stable network throughput than with the case of the developed MINLP.

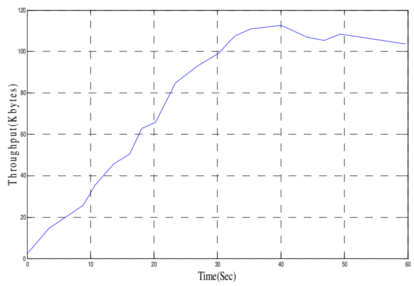

Figure 4variation of network throughput using the MIS spectrum allocation algorithm

From table 3 the average throughput with the developed algorithm is 116.0893kbytes/sec. from table 4 the average throughput with the MIS algorithm is 77.60295kbytes/sec. This shows that the developed MINLP outperform the MIS algorithm by 33.15%. it is clear by the combine plot given in figure 4 that MINLP algorithm outperforms the MIS algorithm.

Sensing Energy (Power) Evaluation

Figure 5 shows increase of sensing energy with increase in secondary user spectrum opportunistic access. As more secondary users gain radio access, the sensing energy increases.

Table 5: Spectrum sensing energy with respect to SUs using the MIS algorithm

SU	Sensing Energy(Watts)
1	15.0286
2	16.0762
3	17.4095
4	19.6952
5	21.4095
6	23.981
7	27.981
8	31.219
9	33.3143
10	34.6476
11	36.5524
12	38.0762
13	39.6
14	41.5048
15	42.9333
16	44.4571
17	45.4095
18	46.1714
19	46.9333
20	47.6952
Average	33.50476

However, the amount by which this increase also depends on the versatility of spectrum allocation algorithm. The more versatile the frequency allocation algorithms the more efficient spectrum holes are discovered thus the less in the increase of sensing energy required.

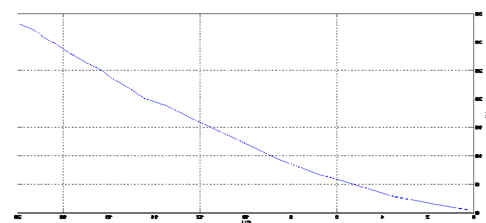

Figure 5 shows that the spectrum sensing energy (using the MIS algorithm) increases from about 15watts (i.e. the base station transmits power) to about 47.7 watts with the entrants of at least 20 SUs.

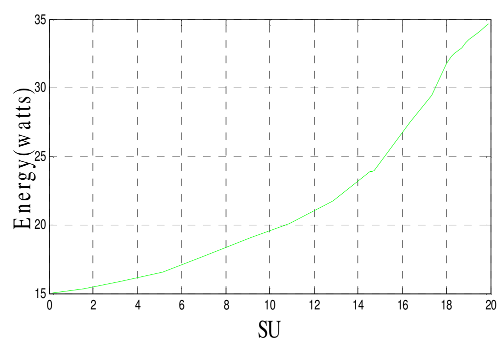

Figure 6 shows the variation of sensing energy with SUs for the case of developed MINLP algorithm. Table 6: Spectrum sensing energy with respect to SUs using the developed MINLP algorithm

SU	Sensing Energy(Watts)
1	15.0687
2	15.3187
3	15.8812
4	16.5687
5	17.6312
6	19.0687
7	20.0687
8	21.7562
9	23.8812
10	23.8812
11	23.9437
12	27.4437
13	29.4437
14	31.7562
15	32.5062
16	32.8812
17	33.3187
18	33.5062
19	34.0687
20	34.6937
Average	25.13433

The increase in the sensing energy is not as steady as that of the MIS algorithm. The energy increase from about15 watts to about 34.78 watts with entrants of at least 20 SUs. One thing this does is that the detection of spectrum holes using the developed algorithm is more efficient than using the MIS algorithm. This relate directly to the effectiveness and versatility of the spectrum allocation algorithm.

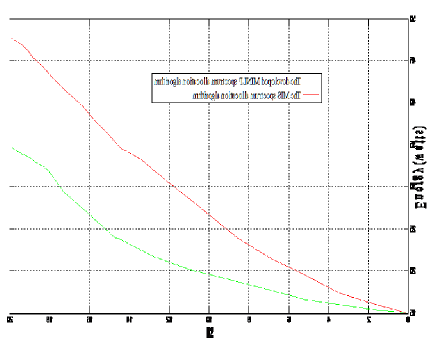

Figure 7 shows the combine plot comparing the spectrum sensing energies of the two algorithms. The figure 7 distantly shows the difference in the sensing energy requirement for the two algorithms. From table 5 and 5, the average sensing energy for the MIS algorithm and that of the MINLP algorithm are 33.50476 watts and 25.1343 watts respectively

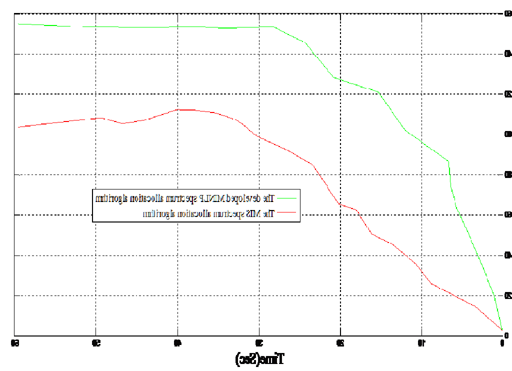

Figure 8 comparison of the variation of network throughput using the developed MINLP algorithm with the variation of throughput using MIS algorithm.

Conclusion

In conventional radio communication technology, every user is assigned a license to operate in certain frequency band. Most of the time, spectrum remain unused and it is difficult to find it. To solve this problem of underutilized frequency and thus tackle the issue of spectrum scarcity, cognitive radio was introduced. Cognitive radio is a highly promising communication technique to increase the efficient utilization of the existing radio spectrum. However one of the key challenges that have to overcome to optimally harness the power of cognitive radio is the problem of dynamic spectrum allocation. In this work the problem of dynamic spectrum allocation was tackled using mixed integer nonlinear programming (MINLP) optimization algorithm. The MINLP algorithm was designed to optimally decide, based on the spectrum sensing minimization, the secondary user SUs to assign available channel. The objective function of the optimization algorithm designed is the minimization of spectrum sensing energy. The constraints of the optimization include; sensing time limit, limit on cooperating SU for channels, flags indicating whether SU sensed a channel or not.

The MINLP algorithm was implemented in the java program language to test the performance of the developed MINLP; a digital model of a cognitive radio network environment was created using the advanced Cisco packet tracer 7.0 software. The performance of the developed algorithm was compared with that of the Maximal Independent Set (MIS) spectrum allocation algorithm for cognitive radio network.Result from simulation carried out showed the effectiveness of the developed algorithm. Comparative analysis showed that the developed MINLP algorithm outperformed the MIS algorithm. Analysis of the variation of throughput with time indicates the developed MINLP algorithm maintained the stability of throughput even with the increase in SU radio connection session. The MINLP algorithm achieved higher average throughput than the MIS algorithm. The developed algorithm in traffic throughput by a margin of 33.15%. The use of the MINLP dynamic spectrum allocation algorithm result is far less traffic delays than the MIS algorithm. It reduced the delay experienced with the MIS algorithm by about 52.91%.The developed MINLP algorithm had an effective impact in the improvement of the utility of the radio network resource. It realized a higher rate of system resource utilization over the MIS algorithm. The average utility of the network resource using the developed allocation method is 71.02%, while that of the MIS algorithm is 59.5%. This shows the MINLP algorithm achieved 11.52% improvement over the MIS algorithm in spectrum hole usage. The MINLP algorithm reduced the spectrum sensing energy usage of the MIS by 24.98%. The lower the spectrum sensing energy used by the MINLP showed that it is more versatile and a efficient than the MIS algorithm

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