ENERGY-EFFICIENT COMMUNICATIONS IN WIRELESS-POWERED COGNITIVE RADIO NETWORKS BASED ON GAME THEORY

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FACULTY OF ENGINEERING
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ABSTRACT

There are challenging and prevalent problems related to spectrum resources with the interference of battery-based devices in future wireless networks. To address such challenges, this thesis proposes a theoretical framework for designing and analyzing the distributed power control algorithms in modern 5G cognitive networks. Previous experiments have shown that game theory tools can be used as a suitable and efficient technique to build scalable, balanced, and energy efficient for the distributed power control schemes in order to use it practically in battery-based devices in wireless networks. In reality, the power control issue is constructed as a non-cooperative game for which the user selects its transmission energy to increase or decrease its own utility. The ratio of throughput to transmit power is defined as the utility that is used to signify the power efficiency scheme, on the other hand, the cost can be presented as the sum of the sigmoid weighting of transmit power and the square of the signal to interference ratio error that can be used to signify the signal to interference balancing scheme. This work proposes a novel utility function to derive an efficient distributed power algorithm. Moreover, this thesis proposes a pricing technique which guides users to an effective Nash Equilibrium point to encourage users to use network resources efficiently. Such frameworks are considered as general when applied on candidates of cognitive scenarios which is Cognitive Radio (CR), Cognitive Sensor Networks (CSN) and Unmanned Aerial Vehicle (UAV) because of the critical and challenging issue of interference. In order to prove the effectiveness of such algorithms, numerical solutions are used in comparison with current power control algorithms. The findings of this thesis indicate that the simulated analytical and numerical results of the proposed algorithms can achieve a substantial reduction in transmit power of users which in turn minimizes the overall

interference. Furthermore, the convergence rate of these algorithms is relatively fast which can help in guaranteeing that all users achieve their required QoS.

Keywords: Pricing, SWIPT, Power Control, Game Theory, Green Communications, 5G Networks.

KOMUNIKASI CEKAP TENAGA DALAM RANGKAIAN RADIO KOGNITIF TERKUASA WAYARLES BERASASKAN TEORI PERMAINAN

ABSTRAK

Terdapat pelbagai cabaran dan masalah berkaitan spektrum dan gangguan peranti berasaskan bateri dalam rangkain tanpa wayar masa depan. Bagi menghadapi rintangan tersebut, kajian tesis ini mencadangkan suatu rangka teori untuk merekabentuk dan menganalisa algoritma kawalan kuasa dalam rangkaian kognitif 5G yang moden. Kajian terdahulu telah menunjukkan bahawa teori permainan boleh digunakan sebagai teknik yang sesuai dan cekap untuk membina suatu pengawal kuasa yang berskala boleh ubah, seimbang, dan cekap tenaga yang praktikal untuk digunakan oleh peranti berasaskan bateri dalam rangkaian tanpa wayar. Tetapi pada hakikatnya, kawalan kuasa tersebut sebaliknya merupakan permainan tanpa sebarang kerjasama di mana pengguna memilih tenaga transmisi untuk meningkatkan atau mengurangkan penggunaan utiliti mereka sendiri. Nisbah celusan kepada kuasa terhantar ditakrifkan sebagai utiliti yang digunakan untuk menandakan skema kecekapan tenaga, sebaliknya, kos boleh diwakilkan sebagai jumlah pemberat sigmoid kuasa terhantar dan kuasa dua kepada ralat nisbah isyarat kepada hingar yang boleh digunakan untuk menandakan skim imbangan isyarat kepada gangguan. Kajian ini mencadangkan satu fungsi utiliti yang baru untuk mentakrifkan suatu algoritma kuasa teragih yang efisien. Selain itu, suatu teknik penentuan harga yang baru adalah dicadangkan yang membimbing pengguna kearah titik Nash Equilibrium yang berkesan, untuk menggalakkan pengguna menggunakan sumber rangkaian dengan lebih cekap. Rangka kerja sedemikian dianggap sebagai umum apabila diapplikasikan pada calon-calon senario kognitif seperti Radio Kognitif (CR), Rangkaian Sensor Kognitif (CSN) dan Kenderaan Udara Tanpa Penguasa (UAV) disebabkan gangguan yang kritikal dan mencabar. Untuk membuktikan keberkesanan algoritma tersebut, penyelesaian berangka digunakan sebagai perbandingan dengan algoritma kawalan kuasa sedia ada. Hasil penemuan kajian tesis ini menunjukkan bahawa keputusan analisis simulasi dan kiraan berangka bagi algoritma yang dicadangkan dapat mencapai pengurangan yang besar dalam kuasa pengguna terhantar yang seterusnya mengurangkan gangguan keseluruhan. Tambahan lagi, kadar penumpuan algoritma yang secara relatifnya lebih cepat dapat membantu menjamin semua pengguna mencapai QoS yang diperlukan.

Kata kunci: Harga, SWIPT, Kawalan Kuasa, Teori Permainan, Komunikasi Hijau, Rangkaian 5G.

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LIST OF SYMBOLS AND ABBREVIATIONS

1G	:	First Generation
2G	:	Second Generation
3G	:	Third Generation
4G	:	Fourth Generation
5G	:	Fifth Generation
B5G	:	Beyond 5G
IoT	:	Internet of Things
EE	:	Energy Efficiency
BS	:	Base Station
E2E	:	End-to-End
CR	:	Cognitive Radio
CRN	:	Cognitive Radio Network
CN	:	Cognitive Network
CS	:	Cognitive Sensor
CSN	:	Cognitive Sensor Network
UAV	:	Unmanned Aerial Vehicle
NE	:	Nash Equilibrium
QoS	:	Quality of Service
UDN	:	Ultra-Dense Network
D2D	:	Device to Device Communication
DSA	:	Dynamic Spectrum Access
PU	:	Primary User
SU	:	Secondary User
SWIPT	:	Simultaneous Wireless Information and Power Transfer

IP	:	Internet Protocol
MIMO	:	Multiple Input Multiple Output
MISO	:	Multiple Input Single Output
RMS	:	Root Mean Square
AOA	:	Angle of Arrival
AOD	:	Angle of Departure
C-RAN	:	Cloud Radio Access Network
Het-Net	:	Heterogenous Network
CoMP	:	Coordinated Multiple Point
OPEX	:	Operating Expense
CAPEX	:	Network Capital outlay
BBU	:	Base Band Unit
RRH	:	Remote Radio Head
WSN	:	Wireless Sensor Network
UE	:	User Equipment
BS	:	Base Station
MS	:	Mobile Station
LOS	:	Line of Sight
NLOS		Non-Line of Sight
RA	:	Resource Allocation
OFDMA	:	Orthogonal Frequency Division Multiple Access
NOMA	:	Non-Orthogonal Multiple Access
SC	:	Secure Communication
CJ	:	Cooperative Jamming
CSI	:	Channel State Information
EH	:	Energy Harvesting

DF	:	Decode and Forward
HCN	:	Heterogenous Cognitive Network
DL	:	Downlink
UL	:	Uplink
WN	:	Wireless Network
CSIT	:	Channel State Information at the Transmitter
ZF	:	Zero Forcing
EHE	:	Energy Harvesting Efficiency
ITE	:	Information Transmission Efficiency
RF	:	Radio Frequency
TS	:	Time Switching
PS	:	Power Splitting
AS	:	Antenna Switching
DC	:	Direct Current
SS	:	Spatial Switching
DoF	:	Degree of Freedom
SVD	:	Singular Value Decomposition
SIR	:	Signal to Interference Ratio
SINR	:	Signal to Interference Plus Noise Ratio
CGT	:	Cooperative Game Theory
NCGT	:	Non-cooperative Game Theory
NB	:	Nash Bargaining
CE	:	Correlated Equilibrium
CDMA	:	Code Division Multiple Access
LTE	:	Long Term Evaluation
RRM	:	Radio Resource Management

PC	:	Power Control
PSR	:	Packet Success Rate
BER	:	Bit Error Rate
BPSK	:	Binary Phase Shift Keying
DPSK	:	Differential Phase Shift Keying
FSK	:	Frequency Shift Keying
FSR	:	Frame Success Rate
CBS	:	Cognitive Base Station
PAP	:	Primary Access Point
MSFLA	:	Modified Shuffled Frog Leaping Algorithm
ESIA	:	Efficient Swarm Intelligent Algorithm
EF-NPGP	:	Energy Efficient Non-Cooperative Power Game with Pricing
BR	:	Best Response
GC-NPGP	:	Green Communication Non-Cooperative Power Game with Pricing
MCC	:	Mobile Cloud Computing
EH-NPGP	:	Energy Harvesting Non-Cooperative Power Game with Pricing
EE-NGPAP	:	Energy Efficiency Non-Cooperative Game Theory Power Allocation with Pricing
ITU	:	International Telecommunication Union
ATG	:	Air to Ground

CHAPTER 1: INTRODUCTION

1.1 Introduction

With rapid increased using of mobile internet supported by smart devices like smart-phones, tablets and iPad, combining with the Internet of Things (IoT) upcoming revolution. Current cellular networks couldn't stand to offer client requirements of highly data-intensive applications, such as wireless video streaming, social networking, and peer-to-peer communication on which they are keeping growing exponentially. Current cellular networks such as the first generation (1G), second-generation (2G), third-generation (3G), and fourth-generation (4G), are still far from fulfilling the rapidly increasing traffic and the high-energy efficiency (EE), as the base station (BS) is consuming a lot of power to overcome path loss, which in turn introduces interference to other users. On the other hand, the fifth-generation (5G) system was first deployed in 2020 and is supposed to offer nearly 1000 times higher wireless area capacity and will save approximately up to 90 percent of power consumption per service when compared to the current 4G network. Moreover, in 5G networks it is expected that more than 1000 Gb/s spectral capacity in congested urban environments, 10 times much battery life for connected devices, and five times reduced end-to-end (E2E) latency could be achieved (Mitra & Agrawal, 2015; Gupta & Jha, 2015).

Therefore, network architecture supposed to be one of the critical factors for next-generation revolution, especially with the sudden rise in the number of mobiles that can use high-speed data services and applications has produced an ever-increasing requirement for consistent high-speed data services. This market has led to the emergence of many techniques that can utilize the spectrum resources and mitigate interference. Cognitive radios (CR) have emerged as a favorable solution for the problem of spectrum utilization due to their ability to access and utilize the unused parts of the licensed spectrum without causing harmful interference. In addition, the cognitive sensors networks (CS) and UAVs has also emerged as another solution for the spectrum sharing, short-range and low power data transmission.

Data communications like web browsing and file downloads are error sensitive and delay-tolerant which requires a larger SIR. Increasing the SIR guarantees that the information data will be delivered to the receiver correctly and this will decrease the number of retransmissions. Therefore, the level of satisfaction achieved by each user is a continuous function of the SIR (Goodman & Mandayam, 2000). In this thesis, our focus is on the design of utility function criteria for the power control design which aims to mitigate interference during spectrum sharing by reducing the power consumed by mentioned scenarios users. Furthermore, reduction of the power consumed will lead to more extended battery power life of terminals. In a distributed power control, all users update their power level based on local information. These objectives can be achieved by representing the network using game theory. Wherein the users select transmit power level in accordance with a utility maximization criterion. In this case, the distributed power control is represented by a non-cooperative game as well as available strategy is the power strategy assigned for each user.

It has been known that game theory is considered as an efficient and useful mathematical instrument to experiment distributed power control of 5G networks. Power control algorithms resulting from the game theory approach are decentralized in which each individual user select its own transmit power from a transmit power strategy through a non-cooperative scheme. In a distribution scheme, another word non-cooperative scheme user updates their transmit power using limited local information, hence the outcome of the game is suboptimal compared with those obtained via centralized schemes. To overcome the suboptimal problem pricing approaches have been proposed. On the other hand, a distributed scheme is more scalable and is thus practically used in large and dense wireless networks. Hence, in this thesis, we will address the problem of power control game for cognitive radio networks (CR), cognitive sensors networks (CS) and unmanned aerial vehicle (UAV) which are most candidate scenarios for 5G networks.

1.2 Problem Statement

Power control systems framework has been improved over time. Particularly, game-pricing theories will increase the lifetime of batteries for users in certain scenarios which are randomly located. Green communication is essential to wisely utilize spectrum and provide efficient communications. Moreover, green communication in wireless networks necessitates new transmission techniques to enhance the overall communication performance, such as energy conservation, efficiency and throughput. Furthermore, the static spectrum allocation resulted in poor spectrum utilization which necessitates a new and smart communication paradigm to face the challenges in green wireless networks. Hence, conventional algorithms cannot handle physical layer challenges in green wireless networks.

Furthermore, the analogy between CNs and the real market give a strong motivation in adopting game/market theory as a solution to the problem of energy consumptions in CNs. Furthermore, game and market theories employed essential tools to solve the problem of energy consumptions efficiently with less computational complexity and offers fast convergence to a stable point compared to that in an ordinary and evolutionary algorithm. Pricing-based game theory; in contrast, can be adopted to achieve good network performance in terms of rate maximization without harming the PUs. Moreover, adding pricing scheme to the energy-efficient model resulted in a simple mathematical optimization problem in which the optimal solution can be easily obtained. However, the main challenge in adopting game/market theory is to show the presence and distinctiveness of the equilibrium point, i.e., Nash equilibrium (NE) in the given game model. In addition, how fast of convergence to the NE in certain scenarios, such as distributed CNs, is another challenge that must be considered when adopting game theory to solve the problem of RA. These challenges have been solved by incorporating pricing scheme and game theory together in the resource allocation model. This is because the pricing scheme can guide the wireless nodes to more stable NE point and force CRs to reduce their transmitting power to avoid any degradation in the service of CNs. Hence, by adding the pricing game theory to the energy-efficient model, the NE is guaranteed with fast convergence to a stable point.

1.3 Study Objectives

There are several challenges that must be addressed in order to implement networks of cognitive scenarios like Cognitive Radio, Cognitive Sensor and UAV Networks in the real environment. Therefore, the work of this thesis is driven by the following objectives:

1- To propose a conceptual framework for resource allocation strategies using game and pricing theories including definitions, scenarios, examples and new description to the solution of the game, that is NE.
2- To propose an appropriate utility and cost functions that have a physical meaning to improve spectrum sharing and reducing power consumption.
3- To prove the existence and uniqueness of the Nash Equilibrium for the non-cooperative power control game analytically besides a new illustration.
4- To develop iterative algorithms of power control scheme-based pricing that can converge to the Nash Equilibrium solution and present the results in numerical simulations.

1.4 Research Methodology

In modern wireless communication networks, the spectrum resources and interference should be managed efficiently to cope with the increase of users and services. In fact, each user in a wireless network represents a competitor for network resources and is trying to satisfy its own QoS requirement by choosing the best response action. These actions could involve the transmission power, transmission rate and packet size. Therefore, the action chosen by any user will affect the performance of other users. The user's QoS could be referred to as the utility or cost function where each user tries to choose the transmit power action to maximize (minimize) its utility (cost) function. However, the cognitive radio, wireless cognitive sensor and UAV networks studied in this research are assumed to consist of three basic elements; (i) Users of the network represented by cognitive radio (CR) users, cognitive sensor (CS) or sensors in UAV, (ii) An action (strategy) set that represents the network resources such as transmit power and (iii) The utility function that measures the preference of the user. Furthermore, game theory framework is proposed in this thesis to exemplify the problem of power control in the cognitive radio, cognitive sensor and UAV scenarios. The users of the network are the decision-makers (players) of the game, the transmit power represents the strategy action of the game and the user's utility function represents the utility of the game.

The power control problem is based on the game theory framework which is represented in different approaches; In the first and second approaches, we used control theory concept for SIR balancing to propose a new sigmoid function for cognitive radios and cognitive sensors to derive the power control game. We used the energy efficiency scheme to design the power control game for cognitive scenarios. A novel energy efficiency utility-price function has been proposed which represents the number of information bits that are effectively transmitted per joule of energy consumption. Also, each cognitive user seeks to increase its own utility function with some constraints similar to an optimization problem. The proposed algorithms show quick convergence and better performance compared to related works. In the last approach, we proposed an efficient power control game for UAV scenario which covered UDN fully with IoT sensors. The utility function is assigned to each sensor depending on the QoS requirement. The goal is to harvest energy efficiently from UAV which covered the area whereas no power supply is present. The local term that is introduced into the utility function of the IoT sensors is the key to the better performance of our proposed algorithm. Finally, in all approaches, this study proved the presence and distinctiveness of the Nash Equilibrium and the fast convergence of our proposed algorithms. We used the same system parameters during the comparison of our algorithms with the previous works in the literature.

1.5 Research Contributions

The contributions of this work can be classified into three distinct classes related to the objectives of this thesis: conceptual framework, formalism and algorithms. The details of the contributions can be stated as follows:

a) **Conceptual Framework:** this research proposed a conceptual framework for various wireless scenarios. Further, the thesis provides descriptions and reviews for work conducted on resource allocation in certain scenarios with the following contributions:

1) Provides a comprehensive introduction to the fundamentals of non-cooperative game theory and market theory.
2) Highlights the application of game theory in the physical layer.
3) Provides a review of recent and related studies in the literature on certain scenarios based on game and pricing theory.
4) Instead of a mathematical approach of the NE, this thesis provides a new illustration that offers a better understanding of the concept of NE.

b) **Formalisms:** in this work, new mathematical models have been developed for various scenarios of cognitive radio, cognitive sensors and UAVs networks. The mathematical model in the mentioned scenarios is combined with the concept of game and pricing theory. Moreover, the existence and uniqueness of the proposed utility functions have been verified mathematically.

c) **Algorithm:** a new and efficient power control algorithm in cognitive radio, cognitive sensors and UAVs with low computational complexity is developed.

1.6 Thesis Organization

Chapter 1 provides a brief overview of the problem statement, objectives, methodology and contributions of this thesis. The rest of this thesis is structured as follows:

Chapter 2 gives a general overview of candidate scenarios for 5G networks first, then it focuses on certain scenarios in this thesis. However, the fundamental of game pricing theory has been introduced. Also, this chapter introduces the concept of networks in use and the problem of resource allocation. The fundamentals of non-cooperative game theory and pricing are presented as well. Moreover, chapter 2 provides several definitions, scenarios and examples related to the application of game, pricing and power control theories resource allocation problem in order to achieve green communication for 5G networks.

In chapter 3, we formulate the power control scheme using an energy-efficient approach in which the objective is to increase the transmitted number of bits. A novel utility function using the pricing theory has been presented which guides cognitive radios to an efficient Nash Equilibrium. The suggested power control algorithm guides the CRs closest to the base station in order to gain their QoS prerequisite while keeping the cost as low as possible, whereas it leads the CRs farthest from the base station to gain their QoS requirement of a high cost to reduce the amount of interference. We prove the presence and uniqueness of the Nash Equilibrium of the power control game and the requirements of the selected pricing factors. Additionally, we explain the variation between the linear and power functions with the function of pricing and the impact of the weighting factor on the utility function and transmit power. The simulation results have been compared with different and recent energy-efficient power control algorithms to show the effectiveness of the suggested algorithm.

In chapter 4, a wireless cognitive sensor node (CSN) based game theory is proposed to harvest energy from the radio frequency signal that is transmitted via the primary user. In order to divide cognitive users time into three phases; spectrum sensing, energy harvest and data transmission, the time switching protocol was employed. Thus, the optimal energy harvesting phase is selected to be an effective factor in the proposed system model. Furthermore, the distributed energy harvest model is provided as a utility function through pricing based on a non-cooperative game where players increase their net utility to its maximum in a selfish manner. The price is defined as a real function of power transmission, also proving that the energy harvest game suggested in this study has a distinctive Nash Equilibrium. In addition, the best response algorithm is used to achieve a green connection amongst players. Hence, the obtained results of the proposed system model and algorithm show the superiority and effectiveness of our study, in addition to a significant reduction in power consumption when compared to related studies, and we succeeded to get the power in micro as compared to previous studies.

In chapter 5, with the help of network densification, the network coverage can be broadened as well as the throughput of the system can be improved via ultra-dense networks (UDNs). In tandem, unmanned aerial vehicle (UAV) communications, as well as networking, have recently garnered much attention because of their high agility as well as various applications. A cognitive UAV that can be employed to power the wireless nodes pertaining to the IoT ground terminal has been proposed. One UAV is included in this IoT system as the power source for the wireless nodes as well as for allocation. Quality of service (QoS) pertaining to the cognitive node has been regarded as a utility function based on pricing as well as a distributed energy harvest pertaining to a non-cooperative game that allows users to increase their net utility to its maximum. In this regard, the price has been defined as a real function pertaining to power transmission which results in pricing charge increase pertaining to the farthest cognitive sensors. In this study, the put forward energy harvest game has been proved to be in Nash Equilibrium and is also unique. We have used the energy efficiency non-cooperative game theory power allocation with pricing (EE-NGPAP) algorithm to get an efficient power control within IoT wireless nodes. Thus, based on the obtained results, the put forward energy harvest algorithm that employs a new utility function demonstrated a considerable decrease in consumption of transmitted power in terms of average power reduction, which is regarded to be apt with the 5G networks' vision.

In chapter 6, we summarize and conclude this thesis and we discuss future works and further perspectives for this area of research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Wireless networks for communication have become a crucial part of our contemporary world since they are being used extensive in several routine applications like social networking, internet banking, distance education, etc. The earlier and the present networks have become inadequate in satisfying the users of the internet because of the exponential escalation in the users of mobile internet through devices like smartphones, tablets, iPads together with the combination of IoT (Internet of Things) in the future revolution. The rapid development in wireless networks comes together with the huge development in microelectronics technology. Thus, there is a necessity to devise an innovative solution to address these issues. Considering this, the global launch of a new generation of network called the 5G network can be assumed by 2020. This new model would offer high efficiency with respect to saving of energy, increasing the life of the battery by almost 10 times, nearly 1000 times capacity and spectrum capacity of more than 1000 Gb/s compared to 4G systems (Mitra & Agrawal, 2015; Gupta & Jha, 2015). Therefore, this new cellular network is highly expected to include a ground-breaking design that satisfies the demands of the next generation. Thus, a strong candidate for 5G networks is combining the cognitive radio network with new technologies such as IoT, CSN, D2D, UAV, etc.

Cognitive radio is a crucial technology that facilitates the integration of different next generation network technologies. It is also called DSA (dynamic spectrum access) networks which uses the spectrum more effectively in an opportunistic manner without inhibiting the PUs (primary users). It works as a radio technology that can modify the parameters of the transmitter according to the changes in the environment in which it is functional (Alam et al., 2017; Claudino & Abrao, 2017). It is different from the traditional radio instruments in that a cognitive radio can provide users with cognitive ability and reconfigurability. Cognitive ability means the ability to sense and collective data from the nearby environment like information regarding bandwidth, transmission frequency, modulation and power. With this ability, SUs (secondary users) can identify the best spectrum available. In order to obtain full utilisation of the spectrum and get the best QoS (quality of service) the SWIPT-game concepts are used, which in turn provides the maximum power consumption and energy efficiency (B. Wang & Liu, 2011).

Hence, the application of the theory of game-pricing in the wireless communication network has proved to be dramatically useful in solving several problems in the communication networks (Lasaulce & Tembine, 2011; Yan Zhang & Guizani, 2011). Many resources allocation problems can be solved and utilized based on game theory in different scenarios and the problems considered include one or more wireless issues such as bandwidth allocation, rate control, power control, routing and medium access control (Allen B MacKenzie & Luiz A DaSilva, 2006). The game theory has been introduced and used in wireless communication networks and further it also has been widely applied in present networks like cognitive sensor networks, cognitive radio, UAV (unmanned aerial vehicle), etc. It is applied to solve the issues of spectrum sharing and spectrum management in CRNs (Z. Ji & Liu, 2007; F. Wang et al., 2008), and also issues such as spectrum sharing, energy efficiency and cross-tier interference (Kang et al., 2012; Ngo et al., 2012; R. C. Xie et al., 2013).

Basically, we provide in this study an overview of potential 5G candidate scenarios besides efficient topology used for next networks and we present SWIPT in more details because of this theory is very important for upcoming and beyond wireless network. Moreover, this research provides a brief description of non-cooperative game concept and defines the most important theories of non-cooperative games like power control, marketing concept and utilisation. This is followed by an example to illustrate and analyse the behaviour of decision makers in the non-cooperative game. This research is aimed at providing a thorough description of multi-cognitive network scenarios and its several applications as an efficient means to stock energy. On the basis of its design, we can say that it is a potential candidate for setting up the next generation wireless networks. In this manner, the conventional network can be used, while establishing an association between SWIPT (power transfer techniques, network architecture and game concept). An outline is provided about the different research challenges to be faced and the future course with respect to substantial research efforts. As shown in Figure 2.4, this study is the first one to provide an outline for the SWIPT based on multi-cognitive scenarios and game theory, so far as I am aware. Figure 2.1 depicts the study flow for a better comprehension.

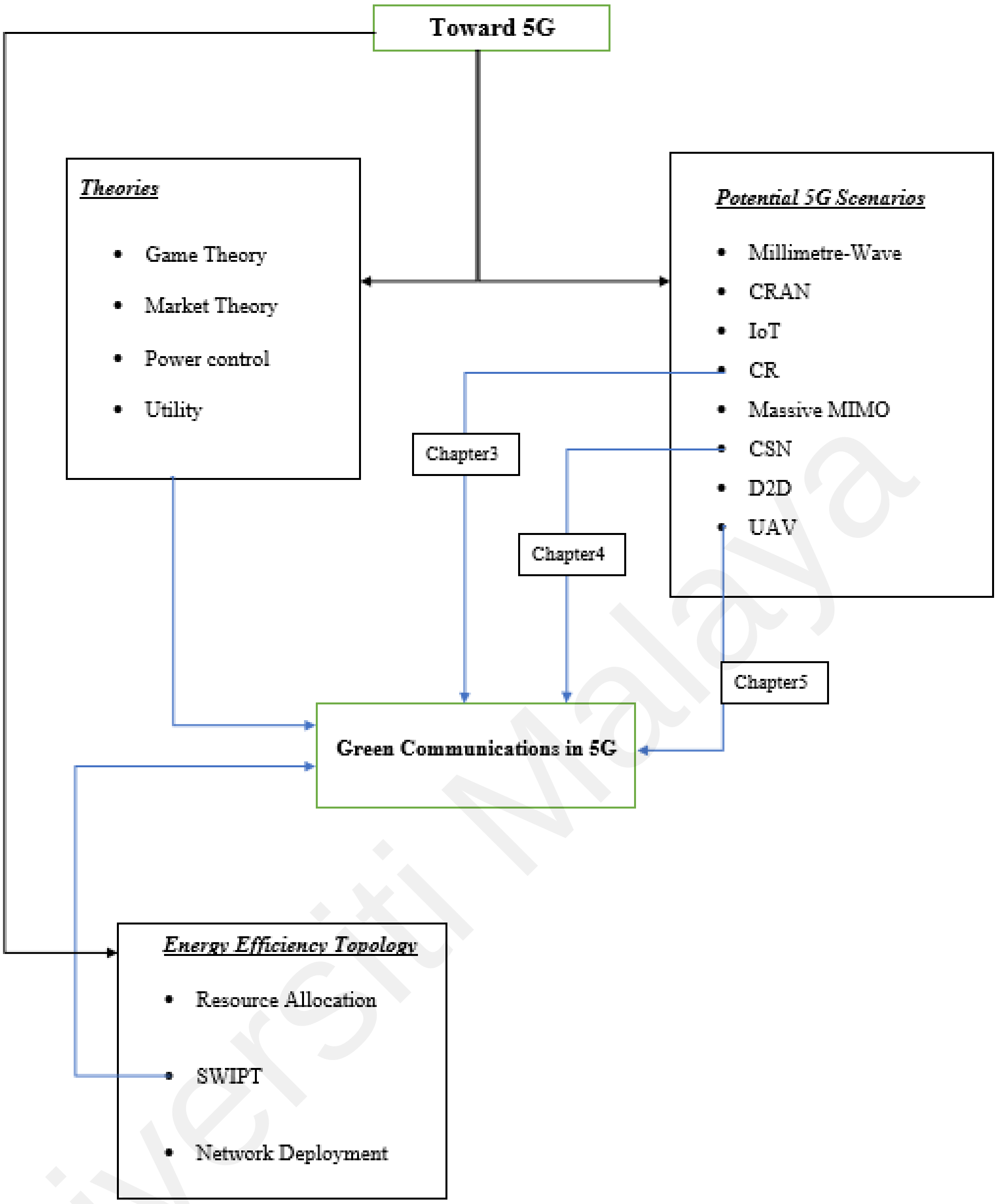

Figure 2.1: Modelling Review

2.2 Potential 5G Scenarios

Moving to 4G technology from 2G technology, the world has made a very quick transformation and evolution, specifically with respect to digital and wireless networks. The primary motivation has been the requirement for greater energy efficiency, lower latency, and high bandwidth. Thus, 4G has a true potential for mobile broadband, even though 3G technology is regarded as the first standard for mobile broadband, its actual design being for voice together with certain information and multimedia consideration, whereas the 2G technology was intended to be the first benchmark for digital voice transmission with improved coverage. The data rate has improved from 64 kbps in 2G technology to 2 Mbps in 3G technology and 50–100 Mbps in 4G technology. It is anticipated that 5G will improve the data transfer rate as well as scalability, energy efficiency and the network's connectivity. It is supposed that by 2020, there will be 50 billion devices connected to the worldwide IP network, a challenge in the present times (Mitra & Agrawal, 2015). Thus, the most significant aspects in 5G are: high reliability, high throughput, low-latency, increased scalability and energy efficiency in the mobile network (Le et al., 2016). Hence, the end-users will be able to experience efficient network connectivity (Andrews et al., 2014).

Nonetheless, the future world will be a linked society. The IoT along with intelligent, integrated sensor devices and in-home sensor systems will change the manner in which people live (S. Zhang et al., 2014; Jia et al., 2014). It also gives better energy efficiency, utilisation of spectrum, and cost-effectiveness. It provides improved scalability as well to manage the increasing number of linked devices. Provided the image of an all-communication globe in the present network, the overall technical objective is to provide an idea that achieves increase in data bulk, high latency, machine-machine communication and greater energy utilisation with high spectral efficiency (Osseiran et al., 2014). Thus, 5G and its enabling technologies are listed to provide an idea regarding the main pillars of the next generation wireless network.

2.2.1 Millimetre-Wave

To introduce the era of 5G, an innovative concept is required to keep pace with the exponential of the mobile networks. 1GHz for millimetre-waves in front of 20 MHz for current cellular systems lead to use of millimetre-waves (Heath Jr, 2013). Thus, mm-wave is one of the primary candidates for the new generation of mobile networks that ranges from (30-300) GHz with a possible gigabit per second pairing with Massive MIMO (Alkhateeb et al., 2014). A real-time measurement for mm-waves at Texas and New-York Universities was performed (Rappaport et al., 2013). Intensive propagation measurements were conducted at 38GHz and 28GHzin order to obtain insights into the path loss, RMS delay spread, AOD, and AOA (Ben-Dor et al., 2011), and building infiltration and reflection attributes for designing advanced millimetre-wave cellular systems.

From the examination of the hardware, it was found that there was no breakdown within a radius of 200 metres from the cell. Thus, the 200-metreradius indicated the size of cell in New York city which can be used for 5G wireless communication networks (Akdeniz et al., 2014). In the study of (Murdock et al., 2012), the outage probability is mentioned to be 38 GHz. The real-time measurements are conducted at the Austin Campus located in the University of Texas to procure urban measurements; the findings prove that there is no occurrence of any outage within a radius of 200 metres for path-loss threshold of 160 dB for transmitters of heights 18 and 36 metres. In short, MM-waves will be employed as the candidate technology for new generation ultra-dense networks rather than the fibre optics (Baldemair et al., 2015).

2.2.2 Cloud Radio Access Network (C-RAN)

Data traffic in mobile networks has increased substantially since the last decade. To meet this requirement (Hwang et al., 2013) Massive MIMO (Rusek et al., 2013) as well as heterogeneous networks (Het-SNets) (Hwang et al., 2013) are regarded as the two most competent techniques to accomplish this goal (Hoydis et al., 2011). The Cloud-RAN (cloud radio access network) has recently been recommended as an efficient network design that can facilitate the integration of both the technologies mentioned above in order to handle the interference together through CoMP (coordinated multiple-point process) (K. Chen & Duan, 2011; Hicham et al., 2016). Moreover, the objective is to increase the capacity of the network, improve its energy efficiency (by densifying the network), and reduce both the OPEX (operating expense, by shifting the processing of the baseband to BBU (baseband unit) pool) and the CAPEX (network capital outlay) (Chen & Duan, 2011; Rost et al., 2014). Nonetheless, there are three primary elements of Cloud-RAN: low-latency high-bandwidth optical front-haul linking, a pool of baseband units in a cloud data centre, and distributed reception/transmission points (RRHs) (Gesbert et al., 2010).

An important facet in the C-RAN is its energy efficiency consideration, since several RRHs and front-haul links have greater power consumption. Thus, past studies that investigated the energy efficiency of the wireless networks only considered the consumption of power at the BS (Dahrouj & Yu, 2010; C. Li et al., 2013). Of late, the impact of the backhaul power consumption on the cellular networks was investigated by (Tombaz et al., 2011). Consequently, Rao et al. in (Rao & Fapojuwo, 2013) explored the spectral efficiency and energy efficiency trade-off in homogeneous wireless networks when considering the backhaul power consumption. In case of a Cloud-RAN, the energy efficiency of the network will be more substantially affected by the power consumption of front-haul network. Thus, providing front-haul connections and corresponding RRHs the prospect of supporting sleep mode is crucial in decreasing the power consumption in the Cloud-RAN. It will also be sensible to employ this concept in Cloud-RAN with the help of central signal processing in the pool of BBUs. Therefore, for the new wireless networks, achieving high efficiency of energy consumption is one of the primary objectives (K. Z. Wang et al., 2016; J. Wu, 2012).

2.2.3 Internet of Things (IoT)

The IoT (Internet of Things) technology refers to the primary concept that is revising several perspectives in the domain of 5G wireless networks. IoT is the network of daily physical objects, domestic devices, buildings, vehicles, other devices, etc. Certain examples of devices that could be regarded as parts of the IoT are wearable smart watches, health monitors, washing machines, and microwave ovens. These devices can sense certain information and send it to a server located at a remote location, a process that largely takes place via the Internet (Alaba et al., 2017; F. Wang et al., 2017). Nonetheless, the server can also issue instructions remotely to control the device. The data that the server gathers is then processed in order to gain information regarding the underlying process. This information can then be used to build smart systems such as intelligent transportation systems, healthcare systems, smart cities and homes, etc. (Friess, 2013). Since there are several uses of IoT in many diverse domains, its introduction will allow connecting the Internet to a number of devices. This paradigm shift, from the notion of connected people to the notion of connected things, has led to the conjecture that by 2020, around 50 billion devices will be connected to the network (Evans, 2012). Given the sheer ability of IoT devices that are believed to be connected and the several applications that we could use them in, the IoT devices have an important role in the architecture of 5G systems and several elements of the 5G network.

2.2.4 Cognitive Radio Networks (CR)

In 1993 (Joseph Mitola, 1993), Mitola published an idealistic article that introducing different type of radio that can reconfigure itself by varying the software in order to support the required service. However, the Software Define Radio (SDR) technology failed to be as a solution for high demand on the spectrum and the underutilization of the spectrum. In (JI Mitola, 2002), Mitola puts forward a visionary concept in his PhD thesis by introducing the term “Cognitive Radio” which is simply an SDR with certain additional features. That means, CR (cognitive radio) is similar to SDR with all of its features and certain other unique features that can contribute significantly in solving the problem of spectrum underutilization (Wyglinski et al., 2009). This unique aspect that makes CR able to solve the spectrum underutilisation problem is the “Spectrum Sensing”.

After Mitola's idea in 2002, both companies and researchers communities have taken the idea of CR seriously and started and started study implemented process of CR in the reality. Specifically, CR can be described as following which is provided by (Jondral, 2005): "A cognitive radio (CR) is a software-based radio that can also interrelate with its nearby surroundings and respond accordingly by adjusting its transmission factors like modulation method, transmission power and frequency of transmission by employing an intelligent strategy with 2 main goals (Haykin, 2005): reliable communication with excellent QoS and better utilisation of the available spectrum".

It can be seen from the above given description of CR that its communication procedure is different than the typical wireless devices in primarily two ways (Haykin, 2005; Akyildiz et al., 2009; Akyildiz et al., 2006). Firstly, it has a cognitive ability which means being able to detect, find and collect data from its nearby area. This data can be local data associated with the CR node itself or global data associated with the PUs (primary users) in the neighbourhood. Another difference is that there is cognitive re-configurability, which means the ability of CR to dynamically initiate taking action upon gathering data by changing its transmission variables. Cognitive capability and cognitive re-configurability give CRs the opportunity to obtain the best available hole in the spectrum in a given band which is regarded as an essential goal of CR technology (Akyildiz et al., 2006; B. B. Wang & K. J. R. Liu, 2011). Also, to facilitate the CR operation over licensed bands, there are three main situations as below:

(i) The underlay situation: Here, both PUs and CRs operate simultaneously and try to get access of the same band.

(ii) Overlay situation: Here, CR users communicate when there is no PUs.

Interweave situation: Here, CRs must conduct spectrum sensing initially to check the spectrum hole availability and then CR nodes can only communicate over these detected holes in the spectrum (Manna et al., 2011).

2.2.5 Massive MIMO

Massive MIMO represents a growing technology that is an extension of the existing MIMO technology. This system employs arrays of antennae in which there are few hundred antennas which function as frequency slots that service tens of user devices (Ali et al., 2017; C. X. Wang et al., 2016). This technology primarily aims to obtain all the benefits of the MIMO system on a greater scale. Usually, massive MIMO is a flexible technology of the new generation 5G networks, which is robust, secure, energy efficient, and spectrum efficient (Larsson et al., 2014). Moreover, massive MIMO is based on spatial multiplexing, which in turn is based on base station that possesses channel state information, for downlink and uplink. It is challenging for the downlink. Nonetheless, it is easy for uplink, because the terminals transmit pilots. The channel response of every terminal is determined on the basis of the pilots. In standard MIMO technology, the pilot waveforms are transmitted by the BS to the terminals. Nevertheless, based on these waveforms, it is not a practicable process for massive MIMO technology, especially in high mobility situations due to these two reasons. Therefore, in comparison to the standard MIMO technology, massive MIMO now requires a large number of similar slots (Nam et al., 2012).

2.2.6 Wireless Sensor Network (WSN)

A wireless sensor network (WSN) can be described as a network of devices called nodes which are able to detect the surroundings and communicated data gathered from the observed area through wireless connections. The information is transmitted possibly through multiple hopes to a destination that uses it locally or is linked to other networks via gateway. These nodes can be moving or stationary, they may be aware about their location, also they may be homogeneous (Buratti et al., 2009).

Usually, a WSN has very small or zero infrastructure. It contains several sensor nodes (10s to 1000s) working jointly to observe an area to get data from that area. There are two kinds of WSNs: unstructured and structured. An unstructured WSN is described as one that consists of a dense network of sensor nodes. These nodes may be installed in an ad hoc way into the field. Once installed, the network is left unsupervised to perform observation and reporting tasks. Here, network maintenance activities like detecting failure and managing connectivity is difficult because of there being several nodes. In the case of a structured WSN, some or all of the sensing nodes are installed in a well-planned way. The benefit of employing a structured network is that a smaller number of nodes are required to be installed with lower network management and maintenance expenses. Here, only few nodes are required because nodes are installed at particular locations to provide more coverage compared to the unstructured network in which the ad hoc manner can have uncovered areas (Yick et al., 2008). Moreover, WSNs have high potential for several applications in situations like military surveillance and target monitoring, biomedical health monitoring, seismic sensing, unsafe environment examination and relief operations in natural disaster. In military surveillance and target monitoring, a WSN can help in invasion detection and identification. Particular instances include spatially associated and coordinated tank and troop movements. In the case of a natural disaster, the sensor nodes can monitor the environment to predict disasters before they take place. In biomedical applications, surgical implantations of sensor devices can help supervise the health of the patient. In the case of seismic sensing, ad hoc installation of sensors down the volcanic area can sense the development of earthquakes and volcanic eruptions (Farsi et al., 2019; Mohamed et al., 2018). However, to optimize traditional WSN scenario machine learning (ML) techniques can be applied to react accordingly (Kumar et al., 2019).

2.2.7 Device to Device Communications (D2D)

In conventional wireless communication systems, it is possible to communicate between UEs (user equipment) via BS (base station). Nonetheless, the UEs may be in the range where direct communication is possible. This means that there is a possibility of communication between UEs without the interference of the base station. This sort of communication causes improvement in the spectral efficiency and energy efficiency, reduced delay and enhanced throughput. D2D communication plays a significant role in attending to the users' needs. D2D considers the integration of ad hoc and centralised networks. By harnessing the ad hoc network (Cheng et al., 2012; Ejaz et al., 2011), we can use D2D communication along with other technologies like IoT, cognitive radio, and cooperative communication, to improve the use of the spectral efficiency. By employing a centralised network, D2D communication enables the overall enhancement of the performance of the network, provided the control of the operator (Gandotra et al., 2017). With wireless networks being based on D2D communication, sharing of information with several users is possible if sharing zones and local caching are deployed. This supports distributive network management. Moreover, the data can be relayed using D2D communication. Also, D2D communication was termed by the METIS research project as a key facilitator for various 5G services (Sedidi & Kumar, 2016).

2.2.8 Unmanned Aerial Vehicle (UAV)

Unmanned aerial vehicles (UAVs), also generally called remotely piloted aircraft or drones, have several applications in the past certain decades. Traditionally, UAVs have been mainly employed for military purposes, the major one being deployment in enemy territory to decreases pilot losses. With continuous device miniaturisation and cost reduction, now small UAVs are more easily available to the public. Thus, several new applications in the public and industrial domains have emerged with typical instances being detection of forest fires, weather monitoring, emergency search and rescue operations, cargo transport, relay of information, traffic control and others (Li et al., 2019). UAVs can be generally classified into two types, rotary wing and fixed wing, each of them with their own weaknesses and strengths. For instance, fixed wing UAVs generally have heavy payload and high speed but they must maintain stable forward motion to remain in the air and hence they are not suitable for immobile applications such as close examination. On the contrary, rotary wing UAVs like the quadcopter while having limited payload and mobility can move in all the directions and stay motionless in the air. Therefore, which UAV to use is dependent on the application (Mohammad Mozaffari et al., 2019).

At the same time, UAVs networking and communications have started attracting more and more attention recently because of their high agility and several applications. Integrating UAVs with the UDNs (ultra-dense networks) can attain substantial benefits by fully utilising their potential (Zeng et al., 2016). UAVs can be quickly deployed to serve users of wireless networks without being obstructed by geographical constraints in comparison to the conventional global infrastructure. For instance, they can function as flying BSs (base stations) to improve wireless coverage and increase throughput at hotspots like sport stadiums or campuses or in areas where cellular infrastructure is not available. They can also function as mobile or flying relays in the regions where communication occurs among separate users without direct communication links that are reliable. Moreover, UAVs can achieve efficient relocation in response to the mobility of the users. By dynamically regulating the locations of UAVs, we can establish almost LOS (line of sight) communication links in most situations, thus substantially enhancing the system performance (H. C. Wang et al., 2018).

2.3 Energy-Efficient Topology

Notwithstanding the fact that studies by information experts on energy-efficient communications system date to more than 20 years, it has grown more during the past decade (Fehske et al., 2011; Auer et al., 2011). The present trend of radio access methods deals with the capability of handling explosion of traffic and the incessantly increasing demands on the capacity of the network (Buzzi et al., 2016; Wu et al., 2015), as well as the realisation of the significance of EE (energy efficiency) within cellular networks (Hu & Qian, 2014a). For real systems, spectrally efficient methods are proved to be not necessarily efficient in energy consumption. Moreover, there can be a trade-off between SE and EE or between EE and other parameters (Y. Chen et al., 2011), like EE-deployment expense, EE-delay, and EE-QoS (Hu & Qian, 2014b).

Nonetheless, increasing capacity of the network a thousand-fold (Hwang et al., 2013) can be achieved by huge antennas, several small cells, and considerably broader bandwidth in mm-wave bands. Nevertheless, lowering energy usage at the same time is still very difficult (Buzzi et al., 2016; C. L et al., 2014; Zappone & Jorswieck, 2017). Thus, a 5G wireless network is required to concurrently have substantial EE and SE improvements. It is anticipated that by the year 2020, there will be more than 50 billion devices in the network (Ericsson, 2011), i.e. for each person more than 6 devices, including both the machine and human communications. The idea is to design a connected world with sensors, cars, drones, medical devices and wearable devices (Hwang et al., 2013) for cellular networks in the future. As shown in Figure 2.2, majority of the useful strategies for improving energy consumption of the cellular networks can be classified as follows:

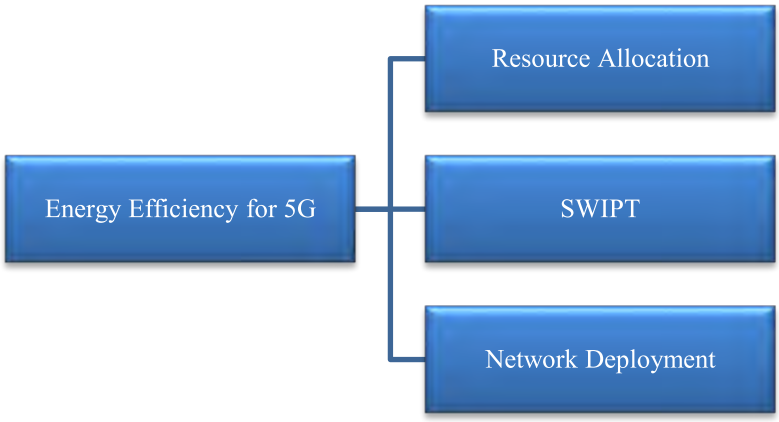

Figure 2.2: Energy Efficiency Topology

2.3.1 Resource Allocation

The functioning of majority of the systems has always been dependent on resources like power, bandwidth and spectrum, which are the backbone of the cellular communication networks (Yousafzai et al., 2017). As these resources are usually non-ubiquitous, factors like design, and methods employed to assign the limited resources are required to be measured when creating different wireless communication systems so as to maintain uninterrupted operations and gain maximum benefits. For all such networks, RA (resource allocation), which addresses this need, has become a crucial aspect. In fact, it has been a very active research subject for various traditional wireless communication systems such as the wireless networks based on OFDMA (orthogonal frequency division multiple access) (Awoyemi et al., 2016).

Nonetheless, the preliminary step to improve the wireless communication system's energy efficiency is to assign the spectral resources in a way that energy efficiency, rather than only the throughput, is also amplified. This strategy achieved large amount of energy efficiency benefits; yet, consequently there is a fair amount of throughput reduction (Alessio Zappone & Jorswieck, 2015). A wireless system's spectral resources are generally optimised in order to increase the data rate or the throughput of the system. Instead, with the popularity of the energy efficiency rising as a chief measure to evaluate the 5G performance, a shift in tendency followed, in which the wireless communication models that were throughput-based started becoming energy-efficiency-based. Here, to obtain maximum energy efficiency, both the spectral resources and power transmission were distributed. This approach provided huge benefits with respect to energy efficiency when evaluated against conventional resource allocation methods with a fair amount of reduction in throughput (Zappone & Jorswieck, 2017). A research in (H. Zhang et al., 2017) investigated the allocation of power resources in a small heterogeneous cell network as well as energy-efficient wireless backhaul bandwidth allotment. It demonstrated that there is a unique optimal worldwide energy efficiency solution, which offers an iterative technique to achieve this optimum efficiency. The research in (H. Zhang et al., 2018) investigated the power resources in the NOMA 2-way relay wireless networks and SC (secure communication) assignment by employing an eavesdropper, with and without CJ (cooperative jamming).

2.3.2 SWIPT

Gathering energy from the surroundings and converting it into electrical energy is becoming an attractive possibility for functioning of the wireless communication networks. In fact, although this approach does not directly reduce the amount of energy needed to operate the system, it makes it viable for clean and renewable sources to operate wireless networks (Mumford, 2016). With respect to wireless communications, two main types of energy harvesting have emerged so far: Environmental and Radio Frequency (Hassan et al., 2013; Ulukus et al., 2015; Lu et al., 2015; Visser & Vullers, 2013). Moreover, radio-frequency energy harvesting offers an interesting possibility, which helps in reducing the randomness related to a wireless power source. The idea involves integrating wireless power transmission and energy harvesting techniques. Consequently, it is possible to share energy among the nodes of the network (L. Liu et al., 2013), which in turn extends the life of the nodes when there is low energy (Gurakan et al., 2013; Chia et al., 2014). This strategy can even be extended by superimposing energy signals on standard communication signals, which causes the so-called "simultaneous wireless power and information transfer" (SWIPT) (Huang & Larsson, 2013; Ng et al., 2013).

2.3.2.1 Overview

Recently, it has been demonstrated that wind and solar energy harvesting can be utilised to run communication systems (Hassan et al., 2013; Ulukus et al., 2015). The stress should be on the way in which this method does not improve directly the energy efficiency of the system, since the amount of energy needed to run the system is not decreased. Nonetheless, it is still appealing since it makes it feasible for clean and renewable sources of energy to operate wireless networks, thus providing an energy stream that is practically unlimited, while lowering CO2 emissions. Nonetheless, we can also collect energy over the air from the radio signals (Lu et al., 2015). This strategy enables the nodes in the network to utilise wireless power transmission methods to share energy with each other, with the objective of recharging the nodes with low battery wirelessly (Gurakan et al., 2013; Ng et al., 2013; Zappone & Jorswieck, 2017). Nevertheless, the goal of the present and upcoming cellular communications network is to provide higher data speeds, high protection and global communication with consistent QoS (quality of service).

However, the simultaneous transmission of energy and information is not achievable in reality, since the operation of energy harvesting conducted in the domain of radio frequency obliterates the information part. To achieve SWIPT, there is a strategy in which the inward signal must be split in two different portions. Here, the first portion includes energy harvesting portion and another portion is the decrypted information. SWIPT process offers greater energy efficiency since it has the capability to utilise the harvested energy again for more subsequent transmission (Krikidis et al., 2014a). It enables the optimisation of EE problem for the power transmission (SWIPT) MIMO networks and concurrent transmission of information with statistical CSI (channel state information) feedback. Provided the subsequent transmission of the energy harvesting node, the potential ability that is produced by the transmitted energy is computed in the system ability (Sun et al., 2014). Apart from the fact that the findings of the harvesting reveal the superiority of the proposed schemes on EE, the EE system can be improved further (Sun et al., 2014). The SWIPT network and its use in wireless cooperative networks was also explored in (Chu et al., 2015), in which the signals transmitted from each starting point were used to operate the EH (energy harvesting) relay. Nonetheless, the use of SWIPT is considered in cooperative clustered WSNs (wireless sensor networks) (Guo et al., 2015; Yang et al., 2016). In (Ng & Schober, 2015), the technique for resource allocation was also devised for the wireless transmission of renewable green energy and protected information to mobile users within the distributed antenna communication networks. Moreover, the SWIPT (simultaneous wireless information and power transfer) was also carried out for heterogeneous wireless communication networks (Akbar et al., 2016; Dong et al., 2016). Table 2.1 shows the main techniques of SWIPT.

Table 2.1: Critical Review of SWIPT

References	Methods/Techniques/Approaches	Descriptions	Strengths and Weaknesses
(Sun et al., 2014)	Given the energy harvesting node's further transmission, the potential capacity that is generated by the transferred energy is accounted for in the SWIPT-MIMO system capacity.	Examined the EE optimisation for MIMO SWIPT system using the covariance CSI feedback.	Results reveal the proposed schemes on EE's superiority. One can easily extend the work to the case of multiple energy harvesting (EH) receivers as well as to the increase in the amount of EH receivers.
(Chu et al., 2015)	The relay makes use of a power splitting (PS) scheme in harvesting the energy that is sent from each source, which it then makes use to send the transmissions to the destinations.	The application of the SWIPT to the wireless cooperative networks has been examined, where the signals sent from each source were used to power the EH relay.	Compared to a scheme that uses a uniform PS ratio, the proposed scheme consistently attains a higher total transmission rate.
(Guo et al., 2015)	The authors formulated a distributed iteration algorithm that is used for power allocation, relay selection, and power splitting.	SWIPT is applied to cooperative clustered WSNs. Here, the energy-constrained relay nodes harvest energy and simultaneously offer benefits to the surrounding RF signal.	Compared to current algorithms that do not have energy harvesting or energy efficiency maximisation, the proposed iterative algorithm is capable of achieving more remaining energy and higher energy efficiency.
(G. Huang et al., 2015)	The authors suggested a power allocation (PA) and joint time-switching (TS) optimisation algorithm to attain the maximum end-to-end achievable rate.	The joint TS and PA optimisation problem was examined for the multicarrier decode-and-forward (DF) relay network as well as the TS-based relaying.	Results revealed that the joint TS and PA scheme that was proposed performed better than the scheme that has a fixed TS ratio for energy harvesting (EH).
(Ng & Schober, 2015)	The design of the resource allocation algorithm is meant to secure information and to transfer renewable green energy to mobile receivers that are found within distributed	The design of the resource allocation algorithm was examined based on the wireless delivery of both renewable green energy and secure information to	The performance of the proposed suboptimal iterative resource allocation scheme is close to the optimal scheme.

	antenna communication systems.	mobile receivers that are found in shared antenna communication systems.	
(Akbar et al., 2016)	The authors examined cell association and found that it has a significant effect on the DL's energy harvesting and the wireless powered HCNs' performance in the UL, in comparison to the DL and the UL.	It presents a tractable analytical model of K-tier HCNs with SWIPT. Here, the MUs gather energy and simultaneously decode information in the DL. Then, the energy harvested at the MU is used for transmitting information in the UL.	Increasing the BS transmit power, the small cell base station (BS) density, the energy conversion efficiency, and the time allocation factor. One cannot improve the UL performance of a random MU in HCNs with its associations to the NBS and the MRP cell.
(Dong et al., 2016)	The authors using the stochastic optimisation theory, a dynamic algorithm, which can trade average power consumption for wireless nodes (WNs') delay, is proposed to allocate the transmission power and time switching factor jointly.	A stochastic optimisation framework was presented to examine the trade-off between power-delay for the SWIPT systems.	The discrete time switching (TS) metric can achieve the same performance as the continuous TS metric by setting a large number of time-slots.
(Lee & Hong, 2016)	The authors suggested a strategy for energy-efficient resource allocation using an iterative method. They also offered a way to converge the proposed algorithm depending on nonlinear fractional programming.	The study examined the efficiency of collecting energy from radio frequency (RF) signals found in wireless networks by applying a realistic assumption for the imperfect channel state information at the transmitter (CSIT).	Attaining maximum energy efficiency while making sure that the harvested energy requirements and data rate met. Proposing an efficient algorithm that has its basis in a theoretical approach may be worthwhile and useful in developing a potential technique that can be utilised in wireless sensors that have semi-permanent power lifetimes.
(Sheng et al., 2016)	This study aims to maximise the energy harvesting efficiency (EHE) of EH FUs and the information transmission efficiency (ITE) of ID FUs by using the QoS of all users and examining their relationship.	The study examined the energy efficient beam forming design in wireless-powered two-tier MISO heterogeneous cellular networks (HCN).	Results showed that compared to zero-forcing (ZF), MBF offers better ITE and EHE. There are several avenues for extensions and future work. One aspect is the absence of CSI, which is vital in the performance of EHE and ITE. It also examined the

			extension to multi-cells using co-channel deployed Femtocells.
(Ma et al., 2016)	The main goal is to design transceiver architecture and conduct the SWIPT strategy for the remote radio heads (RRHs).	The article examined an uplink C-RAN's performance.	Simulation results revealed that the performance of the transmission is better compared to the conventional one. Large-scale remote radio heads (RRHs) led to increase of transmission power consumption.
(Yang et al., 2016)	Suggested a two-phase time-sharing protocol. During the first phase, the destination node collects energy form the source node. In the second phase, the information-bearing signal is sent through the protecting artificial noise that comes from the destination node.	The secure transmission is examined in a simultaneous wireless information and power transfer (SWIPT) system.	Multiple-antenna techniques and systems can be an interesting research direction in the future works for enhancing the security of the SWIPT system.

2.3.2.2 Taxonomy of SWIPT

From a wide critical study of more than 90 articles on SWIPT, we discovered that this method is primarily associated with five channels and networks (MISO, MIMO, Cooperative Networks, Relay Channel and Resource Allocation) as given in the Figure 2

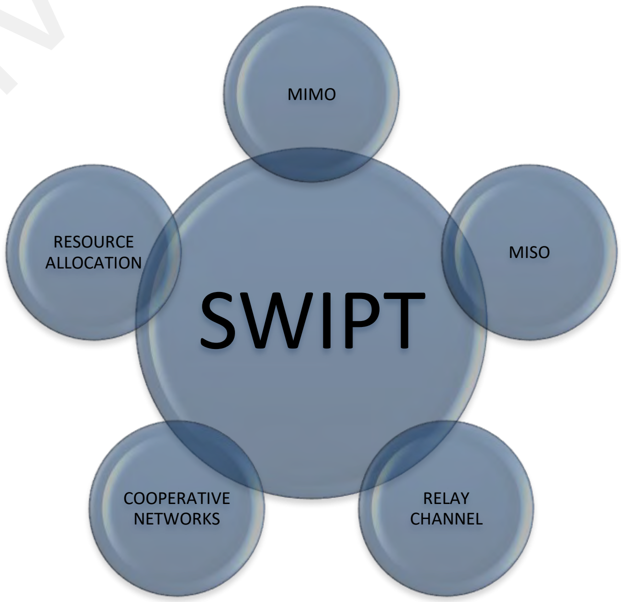

Figure 2.3: SWIPT Based Channels and Networks

The transmission power of the data-carrying signal can be boosted to enable energy transmission from the source to the destination. Nonetheless, a higher transmission power causes a huge possibility of data leakage due to the broadcasting nature of the wireless channels. Thus, in communication networks with new technologies, SWIPT will become a critical issue.

As is apparent, the literature studied is classified into five networks and channels to provide a critical examination about the various efficient methods to preserve energy in the new generation wireless networks. Together with certain performance trade-offs in SWIPT networks, some basic ideas of SWIPT are also considered. In particular, the study examines the application of SWIPT and associated technologies, including MIMO, MISO, resource allocation, relay channel and cooperative networks. Nonetheless, for different network categories, SWIPT models have been investigated.

2.3.2.3 SWIPT Techniques

Preliminary reviews on information concepts regarding SWIPT were conducted under the supposition that the same signal can transmit both energy and information without any loss, revealing an essential trade-off between transmission of information and power (Grover & Sahai, 2010). Nonetheless, it is not viable to carry out concurrent transmission of power and information in practice because the energy harvest which is performed in the domain of radio frequency impairs the information content. To achieve SWIPT, we need to split the incoming signal in two different portions: one is for energy harvesting and another is for information decryption. In the discussion that follows, the techniques that were recommended to facilitate the signal splitting in different domains (space, power, antennae, time) are described (Krikidis et al., 2014b; Ding et al., 2015). The four methods which can achieve the signal splitting into different domains will be presented (Zhou et al., 2013; R. Zhang et al., 2015).

(a) ***Time Switching (TS)***

In time switching, the recipient will switch to another time. Here, the signal is split with respect to time. Thus, the signal received at the recipient side during single slot of time is used to decrypt information or transfer power. This method can equip the recipient with a simple piece of hardware. If it utilises time switching (TS), the recipient will be required to switch between information decryption and energy harvesting with respect to time (R. Zhang & Ho, 2013). In this case, it carries out the splitting of the signal in the domain of time. Thus, the whole signal received in a single time slot is used for either information decryption or power transmission. This technique requires simple hardware at the receiving end but it also requires energy/information scheduling and precise time synchronisation (Krikidis et al., 2014a).

(b) ***Power Splitting (PS)***

The power splitting (PS) techniques implement SWIPT by partitioning the received signal into two different power level portions. The first portion is transmitted to the antennae circuit in order to harvest the energy and the other portion is carried to the baseband to decode the information. TS and PS are different in that the PS method requires a greater complexity at the recipient side and needs power splitting parameter α to be optimised. Nonetheless, it uses instantaneous SWIPT, as the single-time slot received signal applies to transmission power and information decryption (Zheng et al., 2014; Krikidis et al., 2014b; Ng et al., 2013; R. Zhang & Ho, 2013).

(c) ***Antenna Switching (AS)***

The task of the arrays of the antennas is to generate DC power to make sure that the equipment operates correctly. In this technique, the AS (antenna switching) switches each of the antenna parts for decrypting/rectifying for SWIPT implementation with respect to the antennas. In AS method, receivers are differentiated into two portions, where one is used for harvesting energy and the other for decrypting information. The requirement of this method is that there must be optimisation for each communication frame. The goal is to determine the optimal allotment of the antenna components (Krikidis et al., 2014a; Krikidis et al., 2014b). Nonetheless, provided a MIMO DF (decode-and-forward) relay channel, in which the harvested energy is utilised by the relay node to transmit the incoming signal again, the problem of optimisation was represented as a knapsack problem and then it was solved by using dynamic programming in (Krikidis et al., 2014a).

(d) ***Spatial Switching (SS)***

We can make use of the SS (spatial switching) method in MIMO systems and then we are able to achieve SWIPT implementation in the domain of space by using multiple DoFs (degrees of freedom) of the interference channel (Timotheou & Krikidis, 2013). Provided the SVD (singular value decomposition) of the MIMO channel, it transforms the communication channel into corresponding Eigen channels which are able to transfer either information or energy. At the output of every Eigen channel, a switch sends the output to either the conventional decoding circuit or the correcting circuit. The allocation of the Eigen channel and power allotment in different Eigen channels is regarded as a tricky problem of nonlinear combinatorial optimisation. (Timotheou & Krikidis, 2013) recommended an optimal polynomial complexity technique for the distinctive case of having infinite maximum power in each Eigen channel (Krikidis et al., 2014b).

2.3.3 Network Deployment

The modelling of standard network deployments is carried out in such a manner that it will spread out the coverage and increase throughput. We can achieve substantial energy savings by re-designing the traditional networks and considering the energy efficiency in the coverage region. In this domain of study, the trend of dense networks is popular. In fact, a couple of robust candidate technologies for 5G networks have been developed in this trend, which are massive MIMO system (Larsson et al., 2014) and heterogeneous networks (Andrews, 2013). Here, the former densifies the number of installed antennas, while the latter densifies the number of infrastructure nodes. It has been confirmed by several studies that the densification of network is an energy-efficient approach, since it reduces the ‘physical and/or electrical’ expanses between the communicating nodes, thus enabling higher data speed without additional energy consumption (Soh et al., 2013; Björnson et al., 2016). Moreover, on/switch-off techniques, base station (BS) switch, as well as antenna muting methods to adapt to the traffic situations are effective in further reduction of energy consumption (Niu et al., 2010; Oh et al., 2013).

2.4 Game-Pricing Theory

In this section, we will give the problem redesign and will present the game-pricing model by describing the utility function-based marketing concept to compute the power transferred by every user. Initially, the game theory was a mathematical tool utilised for economics, business and political studies. It helps figure out situations wherein decision-makers work together in a complex environment as per a set of rules. Several different kinds of games exist which can be used to represent the analysed condition, for instance, cooperative or non-cooperative games, potential games, and repeated games. In the situations considered in this research, the formal game concept for power control is defined as actions, players and utility functions.

The essential concept of the game theory is the way in which a decision from a player impacts the decision-making of all the other ones and also the way in which a state of equilibrium can be attained, satisfying majority of the players. A renowned contributor in the domain is John Nash after whom the Nash Equilibrium is named. The concept confirms that a state of equilibrium can be attained where all of the decisions are fixed, and represent the best likely situation for the players. Nonetheless, CR system needs to carry out complex adaptation and learn dynamically from the surroundings. This scenario makes the process of learning very complex in comparison to the situation found in economics. The game theory is also used in other communication fields such as routing, congestion control, topology control, trust management and power control. Our interests lie in its utilisation for power control since it can be regarded as a game with set number of players where each has to try to optimise their extent of power. There are several characteristics that make this issue suitable for a cognitive game model:

(i) The payoff of the players is a function of transmission power level and the SIR (signal to noise and interference ratio). The SIR of the players is a function of his own transmission power as well as the transmission powers of the remaining players in the cell.
(ii) When a player raises power level, it will raise its own SIR and reduce it for other users.
(iii) For an unchanging SIR, the players have a preference for lower levels of power. It implies that the players want to preserve power and increase the battery life whenever possible.
(iv) For an unchanging power level, players have a preference for higher SIR. It means that the players wish to have the best possible channel characteristics for a specific amount of power consumption.

There are several ways to handle these issues like adding restriction to power use by levying expenses from the user. This can be done by adding a cost factor to the function of payoff to add impartiality to the network; another concept is to model the situation as repeated game. In this research, we devise the problem of resource assignment with respect to cognitive scenarios to represent the requirements of PUs and SUs, also take into consideration the main uplink of one cognitive user where transmitters send signals to several SUs, while the primary base station receives the desired signal from a main transmitter and interference from each of the cognitive transmitters. To solve the predicament of resource assignment, we present a utility function that fulfils the criteria to maximise capacity for SUs and safety of the PUs. In particular, we define a function of payoff that corresponds to the SIR constraint and a price function that indicates the outage probability constraint. The utility function is described as:

$$utility\ function = payoff\ function - price\ function$$

2.4.1 Game Theory

Game theory has become a significant statistical tool to investigate the problem of allocation of resources in decentralised wireless networks. This is due to the fact that the game theory is confirmed to be a potent decision-making process which is able to provide exceptional performance for cognitive players and nodes as compared to the traditional optimisation concept (Allen B MacKenzie & Luiz A DaSilva, 2006; Tragos et al., 2013). The stimulus behind the adoption of the game concept in CNs can be summed up as given below:

(i) In CNs, there are two kinds of users, also known as decision makers with conflicting interest, working together with one another independently attempting to get into the same spectrum band. It adds certain impediments in assessing the resource allocation problem in CNs. On the contrary, the game theory seems to be one of the most appealing tools for discarding these impediments since it is chiefly used to represent situations where the act of one player affects that of the other players.

A common solution in the game theory like the Nash Equilibrium proves to be another benefit in representation of the resource allocation problem.

2.4.1.1 Game Theory Basic Concept

Initially, the game theory was introduced by Neumann J. Von and O. Morgenstern in the year 1947 (Von Neumann & Morgenstern, 1947). It is a set of statistical tools whose goal is to understand, evaluate and model the correlation between the decision makers. This theory has been widely used in fields like microeconomics, and only recently it has been broadly acknowledged as a potent tool to represent resource allocation problem in CRNs. Moreover, according to the studies conducted by (Neel, 2006; Allen B MacKenzie & Luiz A DaSilva, 2006; Scutari et al., 2010; Srivastava et al., 2005), the term game and game theory can formally be defined according to the following definitions:

Definition 2.1: "*Game*": A game is a representation of the interactive decision issues among decision makers.

Definition 2.2: "*Game theory*": Game theory is an area of applied mathematics that can be used to study scenarios in which the actions of many decision makers, also known as players, are at odds. In mathematical terms, a game can be described as per Equation (2.1) (Von Neumann & Morgenstern, 2007; Allen B MacKenzie & Luiz A DaSilva, 2006).

$$\Phi = \langle N, \{A_i\}, \{u_i\} \rangle \tag{2.1}$$

Where N represents a finite group of decision makers (players); A represents the Cartesian product of the action sets for each player; and u_i represents the payoff/utility/objective functions of players n, which represents function of the action selected by player $n(a_n^{ction})$ and the actions selected by all the players in the game barring that of player $n(a_{-n}^{ction})$. Put differently, the utility function for a particular player assigns a value for every potential outcome in the game wherein a greater number means that the outcome is more favoured in comparison to other outcomes.

Furthermore, the game theory can be categorised into two primary strategies cooperative game theory (CGT) and non-cooperative game theory (NCGT). Table 2.2 provides a summary of the primary attributes of both the strategies.

Table 2.2: Summary of Main Branches of Game Theory

Type	Description	Example	Common Solution Point
NCGT	In case of *NCGT*, players are self-centred and aim to increase their own objective functions.	Strategic Game	NE (Nash equilibrium) is an important notion used to determine NCGT outcome.
CGT	In case of *CGT*, decision makers are permitted to assist each other on a combined strategy (called cooperative behaviour) aiming to increase the overall network utility.	Bargaining Game	NB (Nash bargaining) is a key to an NB game which is based on Nash axiom constraints (Nash Jr, 1950).

In addition, the approaches used in NCGT can be classified into two types: pure approach and mixed approach. Table 2.3 provides a brief comparison of these strategies in game theory.

Table 2.3: Players Strategies in A Non-Cooperative Game

Strategy Model	Description	Type of Equilibrium
Pure strategy game	A standard or strategic game is regarded as the basic representation in game theory. In this case, the players are supposed to be carrying out just the deterministic strategies (known as pure strategies).	Nash equilibrium (NE)/correlated equilibrium (CE)
Mixed strategy game	In a game of mixed strategy, the players' actions are determined by probability distributions.	Mixed strategy Nash equilibrium

In the subsequent sections, the notion of NCGT is discussed by providing definitions, instances, and assessments about the standard solution when a game is used. Thus, the concerned readers can understand better the idea of the game theory and its uses in the resource allocation problem in the CNs.

2.4.1.2 Non-Cooperative Game Theory

The growth in the number of mobile users, applications and services in present and future cellular communication networks requires new analytical models that are able to face the various technological challenges. Consequently, recently, the game theory has been put forward as an effective statistical tool to design the new cellular communication networks. It is among the best techniques for the integration of decision-making procedures and rules into the new generation wireless communication nodes so that they can function efficiently and fulfil user requirements and provide them the best QoS (quality of service) (Han et al., 2012). The power control issue in wireless networks is among the most general game theory applications. The problem in the architecture of uplink cellular networks is how to enable users to control their transmission power during use of a shared spectrum, in the presence of the interference produced by the other users of the spectrum. Scholars and engineers of wireless networks have been able to represent the power control issue in a wireless network through the non-cooperative game theory. There is a competitive scenario among all the players in the NCG, where every action of the player (selection of approach) has an effect (negative or positive) on the utility (for instance, gain or preference) of other players. Similarly, in the regulation of power in a cellular network, all the users are in a competitive scenario where the transmission power level chosen by the user will affect the extent of interference of the cell and will further affect negatively or positively the transmission quality of other users. Thus, solving the issue of power control in wireless networks is like solving a non-cooperative game problem, i.e. by determining the Nash Equilibrium (Han et al., 2012). Of late, many experts have been working on the application of the game theory for solution of problems in the cellular networks, but they have to face several challenges in discovering efficient solutions. It is because of the design of the models of the game theory which do not correspond to particular engineering problems like time-based cellular channel scenario, performance problems (utilities) that rely on several communication metrics (rate of transmission, transmission power, SIR, delay) and compliance to some standards (IEEE 802.16, LTE, CDMA). Hence, it is essential to find efficient game theory models that can be employed to devise the new generation cellular communication networks (Han et al., 2012).

Nonetheless, the game theory is an extensive area of applied mathematics that describes and evaluates the conditions among the interactive decision makers. Particularly, it provides a model based on the formation of rigorous frameworks that describe scenarios of cooperation and conflicts among rational decision makers (Tadelis, 2013). In economics and decision theory, rational behaviour is described as selecting actions that increase the payoff with respect to the constraints. The game theory has been effectively used in many areas such as the functioning of makers, auctions, jury voting, business rivalry and economics. Game theory has also been useful in other disciplines such as political science, sociology and biology (Straffin, 1993). Since the 90s-decade, computer science and engineering have been included in the discipline category. In recent years, the concept of game theory has been broadly applied in telecommunications engineering especially in wireless networks resource management (Altman et al., 2006; Felegyhazi & Hubaux, 2006).

In the game theory, every player vies with others in order to optimise its own utilisation by changing strategies. The player's utility is a function that determines the players' satisfaction level. Strategic and utility-based games can be described as follows:

Definition 2.3: "In a game, utility u is the motivation of players".

The utility function for a particular player allots a number for each possible game outcome where a lower or higher number signifies the outcome being preferred (Hossain et al., 2009b).

Definition 2.4: "A strategy denoted by r is a whole contingent plan or a decision directive that defines the action selected by an agent in each distinct state of the world which is denoted by A of the world" (Hossain et al., 2009b).

A strategic form of game consists of three elements:

(1) A set of rational decision makers referred to as players
(2) A set of strategies associated with the players
(3) The utility (payoff) function received by each player which represents the objective.

A game with N players can be formulated mathematically as shown in the following definition (Gibbons, 1992):

Definition 2.5: A game Φ in normal form is given by $\Phi = \langle N, \{A_i\}, \{u_i\} \rangle$, where:

(1) $N = \{1,2,3, \ldots, n\}$ is a finite set of players
(2) $\{A_i\}$ is the strategy (action) set for player i, where $A_i = A_1 \times A_2 \times A_3 \ldots \times A_n$ is the product of the sets of strategies available to each player
(3) $\{u_i\} = \{u_1, u_2, u_3, \ldots u_n\}$ is the set of the utility functions for player i. In the strategy profile, supposing that $a \in A$, we let $a_i \in A_i$ denote player $i's$ action and a_{-i} denote the actions of the other $i - 1$ players.

Game can be classified based on their application which is cooperative and non-cooperative game:

Cooperative game in which the players can communicate among each other to make enforceable contracts and non-cooperative game as defined before in which players cannot communicate among themselves and are unable to make enforceable contracts. The non-cooperative game is the only choice if the information is strictly limited to local information (Hossain et al., 2009a). If the players make only a single decision, then the game is termed static game. Alternatively, if the players make several decisions, the game is termed as dynamic game. The game is called a repeated game if the players make one decision but plays the game multiple times.

The most significant concepts in the game theory are the dominant strategy, Pareto optimality, non-cooperative game and Nash Equilibrium (Fudenberg & Tirole, 1991). *Non-cooperative game* theory (NCGT) is a category of game theory where rational decision makers decide independently. Thus, it examines the decision makers' behaviour in any scenario where each decision maker's optimal selection depends on his prediction of the others' choices. In short, decision makers in NCGT aim to better their objective in a selfish way.

Definition 2.6: "A non-cooperative game is a game where players are not able to make binding contracts other than those already embedded in the game. Thus, it does not fall into the category where players do not oblige but it is a game where any obligation is self-enforcing" (Hossain et al., 2009a).

Definition 2.7: "Dominant strategies: A dominant strategy is one in which a player earns a larger payoff irrespective of what others may do. Thus, a dominant strategy is always superior to other strategies as it disregards the actions of other players. In case a player has a strategy that is dominant, then he/she will always maintain equilibrium. Moreover, if there is one dominant strategy, then all the others are dominated" (Hossain et al., 2009a).

Definition 2.8: "Dominated strategies: A dominated strategy is one in which a player earns a smaller payoff irrespective of what others may do. Thus, in case of a dominated strategy, it is ever better to use any other strategy, irrespective of the actions of the opponents. A dominated strategy is always played in equilibrium" (Hossain et al., 2009a).

Definition 2.9: A Nash Equilibrium of a game $\Phi = \langle N, \{A_i\}, \{u_i\} \rangle$ is a profile $a^* \in A$ of strategies with the property that for every player $i \in N$

$$u_i(a^*_{-i}, a^*_i) \geq u_i(a^*_{-i}, a_i) \qquad \text{for all } i = 1,2,3, \dots, N \qquad (2.2)$$

Where $a^*_{-i} = [a^*_1, a^*_2, \dots, a^*_{i-1}, a^*_{i+1}, \dots, a^*_n]$

The Nash Equilibrium is a steady point where none of the users has any reward when he/she changes the strategy. An effective way to get to this equilibrium point is to obtain the players' best action. In the game theory, the player's best action is a strategy which generates the best outcome taking the strategies of other players for granted (Fudenberg & Tirole, 1991).

Definition 2.10: A set of strategies $(a_1, a_2, a_3, \dots, a_n)$ is Pareto optimal if and only if there exist no other set of strategies $(b_1, b_2, b_3, \dots, b_n)$such that

$$u_i(b) \geq u_i(a) \qquad \text{for all } i = 1,2,3, \dots, N \qquad (2.3)$$

In the Pareto optimal solution, the players can not in any way improve their current utility (payoff) through a different strategy choice without reducing others payoffs.

To demonstrate the above descriptions and ideas, the instance of a typical 2 player game called the prisoner's dilemma is worth taking into consideration. Hence, the prisoner dilemma model is the famous game that has been analysed by game theory to explain the behaviours of players (Geckil & Anderson, 2016). The prisoner's dilemma model can be explained as follows:

The police in a joint crime arrested two partners and separated them into different rooms. The police offer each of them the same deal to confess to the crime or remain silent. The punishment that each receives is dependent not only on his or her decision but also on the decision of his or her partner. The possible outcomes of this model are as follows:

(1) If one of the partners confesses to the crime while the other remains silent, the confessor will be set free (i.e., payoff of 0) and the other partner will get a maximum sentence (i.e., payoff of -9) because the information provided by the confessor is used to incriminate him or her.
(2) If both partners confess to the crime then each gets a reduced sentence (i.e., payoff of -6) but neither is set free.
(3) If neither partner confesses to the crime then each gets the minimum sentence (i.e., payoff of -1).

In this game, the group of players includes 2 players (called the prisoners) $n = 2$, and thus $N = \{1,2\}$. Every player has a fixed set of permitted strategies (signifying that this game is finite) represented by space $A_1 = A_2 = \{Confess, Remain\ Silent\}$.

Table 2.4: Bi-Matrix Form of Prisoner Dilemma Game

Player1	**Player2**	
	Confess	**Remain Silent**
Confess	(-6, -6)	(0, -9)
Remain Silent	(-9, 0)	(-1, -1)

The prisoner's dilemma game can be explained mathematically as follows:

(i) Two partners represent the set of players in a game $N = \{1,2\}$.
(ii) The strategy sets of the game are: (Confess, Confess), (Confess, Remain Silent), (Remain Silent, Confess), (Remain Silent, Remain Silent).

(iii) The outcome/payoffs of the game can be: (-6, -6), (0, -9), (-9, 0), (-1, -1), which depend on the chosen pairs of strategies.

The prisoner's dilemma game can be denoted as a bi-matrix as given in Table 2.4, where player 1 acts as the row player and player 2 acts as a column player. This game's solution can be found easily. Player 1 believes that the best decision to make is to confess. Likewise, player 2 also believes that the best action for him/her is to confess to whatsoever chosen by player 1. The solution to this game is the strategy pair (Confess, Confess) and it is referred to as the Nash Equilibrium solution where none of the players can one-sidedly get better outcome/payoffs. The Nash equilibrium outcome of the prisoner's dilemma game (-6, -6) is not the Pareto optimality of the game because there is another outcome (-1, -1) that is better for the payers. The Pareto optimality outcome (1, -1) can be obtained by allowing the two partners to cooperate then they would choose the (Remain Silent, Remain Silent) strategy.

2.4.2 Market Theory

The game theory concepts as described in the previous section emphasise the following fact: the game theory offers mathematical tools to examine the situation in which the rational decision makers interact with one another. On the basis of this fact, this theory can also be used for an actual supermarket setting to investigate how individuals collaborate and negotiate with one another as sellers and buyers in the supermarket domain. The game theory application in the supermarket setting is extremely appealing in the domain of CN due to the following primary reasons:

(i) PUs go into the supermarket with the idle band as a product for sale in order to increase their returns.

(ii) In contrast, CNs go into the supermarket in search of a product, that is, the spectrum holes for purchase to carry out a transmission in conjunction with their partner.

Therefore, the game theory is a decent candidate that is applicable to the supermarket of the spectrum commodity to examine the interaction between sellers and buyers. However, the concept of supermarket theory which includes pricing theory and auction theory are introduced. Further, the relevance of supermarket theory to game theory will be heighted as well:

Pricing Theory was initially introduced and accepted in the economics domain. In the area of the problem of resource allocation, spectrum market strategies and pricing theory are some of the most significant tools because of the reasons that follow: (i) For NCGT, pricing can provide an economical NE by directing selfish players to a more cost-effective operating point (Saraydar, Mandayam, & Goodman, 2002). (ii) For cooperative game theory (CGT), pricing can provide an improved negotiation environment and impartial distribution of the resources in order that the spectrum's seller/buyers i.e., PUs/CRs are pleased. (iii) Lastly, pricing functions as a punishment system for those buyers that produce some interference to PUs and further interference to the spectrum's owner can be well controlled. Thus, the pricing strategy can be defined as given below:

Definition 2.11: The function for pricing is defined as the price that CRs must reimburse to Pus in terms of the degradation of performance that may occur in the PU networks. Nonetheless, in a certain situation, e.g., centralised setup, the pricing function can be used for the following reasons: (i) Price is provided to PU as a reimbursement of purchasing spectrum from the spectrum owner by the CRs or (ii) Pricing system can be applied to manage the produced interference to the PUs.

Auction Theory is very useful in the area of economics to determine certain parameters, for instance, the value of the product which has uncertain costs (Klemperer, 1999). Recently, it has been used to solve problems related to resource allocation in cellular networks. The common auction scene can have the following constituents (Y.

Zhang et al., 2013; Y. Zhang et al., 2012): (i) bidders, (ii) a seller, (iii) an auctioneer and (iv) the commodity. Table 2.5 shows a mapping between fundamental components of the auction theory and the CN entities.

Table 2.5: Mapping of Auction Theory Elements to CNs

Auction	Comments	Elements of CN
Bidders	Bidders are buyers (or auction players) who vie with one another by asking the product's price in the spectrum market to procure the available product.	CR nodes act as buyers. They vie with one another to procure some resource for transmission purpose.
Seller	Sellers are radio resource owners (or auction players) who, in some situations, vie with one another to get more buyers to increase their returns by submission of a (***bid***) suggesting the bidding price for the demanded product (Y. Zhang, Lee, Niyato, & Wang, 2013).	PU acts as the seller that possesses the license to utilise the idle spectrum.
Auctioneer	A mediator between bidders and sellers who regulates the process of the auction.	The auctioneer can also act as a seller.
Commodity	The commodity (or auction commodity) represents the product traded between sellers and buyers.	For instance, the commodities are empty subcarriers.

2.4.3 Power Control in Modern Wireless Networks

In networks for wireless communication, RRM (radio resource management) is recommended to support system QoS and allocate the vacant spectrum resource among the users in an efficient manner. Several RRM components are working together to improve the QoS of users such as admission control, transmission power control, rate allocation, handoffs channel assignment and adaptive bean forming. Power control (PC) is among the most essential methods in RRM and contributes significantly in efficient resource allocation with respect to wireless communication networks. Power control comes with several features in wireless communication networks (Chiang et al., 2008):

(i) **Interference management:** PC method moderates the interference to boost the capacity of the system by ensuring efficient reuse of the spectrum and a satisfactory user experience.
(ii) **Energy management:** PC preserves energy to increase battery life in wireless stations and networks.
(iii) **Connectivity management:** PC can maintain at least a small amount of the incoming signal in order to make sure that the terminal remains connected.

In wireless communication networks, power control (PC) is categorised based on transmission directions as follows: uplink power control where transmission direction is from MS (mobile stations) to BS (base stations) and downlink power control where the transmission direction is from BS to MS. The challenges in uplink power control are the limited transmit power in battery-based mobiles, low computational capability of mobiles and the near/far field effects.

Power control is also classified based on the uses of information as centralized or distributed. In centralized power control, the centralized controller like base station uses information such as path gain to calculate and select suitable actions for all mobile users. Alternatively, in the distributed PC, users use only local data to choose their actions. Every user belonging to the distributed wireless communication network uses just the local data and it is unaware about the other users' channel conditions. Users function selfishly to increase their own utilisation in a distributive way.

Nonetheless, non-cooperative power control is used in wireless networks with two user priority levels:

(i) Primary users (PUs) in cognitive networks are the high priority users to access the available channels and guarantee their own QoS because of their ownership property of the licensed spectrum.

(ii) Cognitive Users (CUs) or secondary users (SUs) are the low priority access users in the network because only unused parts of spectrum can be assigned to them and for this reason QoS should be not guaranteed and can be adjustable.

Hence, extravagant use of transmit power by low priority users will cause undesirable harmful interference to the QoS of high priority users during spectrum sharing. Therefore, a strict power control algorithm should be run in low priority cognitive user's devices to protect other users and utilize the spectrum efficiently. However, researchers and engineers' designers in networking area take into consideration the high priority of users who own the licensed spectrum (Primary users) in which their QoS should be guaranteed forever.

In power control, the QoS can be guaranteed for users by specifying a particular value of the SIR referred to as the target SIR, whereby users should achieve the same as this target or higher. On the other hand, the QoS of low priority users such as a secondary user can be slightly varied below the target SIR depending on the status of the system, a forced decrease in low priority users SIR is due to the increase of interference and the decreasing QoS of high priority users.

2.4.4 Utility Function

2.4.4.1 Overview

The power control game has been used in several works based on utility and pricing functions. (MacKenzie & Wicker, 2001) provide stimuli for applying the game theory to investigate communication networks especially the power control concept. (Ji & Huang, 1998; Goodman & Mandayam, 2000; Meshkati et al., 2007) presented power control technique as a non-cooperative game where users select their transmission powers with the aim to maximise their utilities where utility is the ratio of throughput and transmission power. (Goodman & Mandayam, 2001) presented a network assisted power control strategy which aims to enhance overall system utility. The function of pricing has been presented in (Saraydar et al., 2001) as well as (Saraydar et al., 2002) to achieve a more effective solution for power control game. Similar strategies are presented in (Xiao et al., 2003) as well as (Sung & Wong, 2003) with distinct utility function models. (Feng et al., 2004) examined a joint user-centric and network-centric power control. (Meshkati et al., 2006) presented a power control concept related to multi-carrier CDMA networks. (Ghasemi et al., 2006) presented a novel pricing function for PC in wireless communication networks which is based on the linear SINR (signal to interference and noise ratio) rather than power. A summary and more information on game theory strategies for allocation of idle resources in wireless communication networks have been proposed by (Meshkati et al., 2007).

2.4.4.2 Concept

The selection of the utility function is considerably crucial when the game theory is used to solve issues such as resource allocation and power control in cellular communication networks. There are many types of data whereas the signal must able to support like voice and video conference and calling same current mobile applications in real time are examples of delay sensitive and error tolerant services while web browsing and file downloading in non-real time are examples of delay tolerant services and are error sensitive. Hence, in wireless data networks, the SIR influences the probability of transmission errors. When γ is very high, the probability of transmission errors approaches zero and the utility function rises to a constant value, whereas when γ is very low, the probability of transmission errors increases and the utility function is near zero. Therefore, the utility function for wireless data networks could be characterized as a concave function.

The distributed power control algorithms used in wireless voice systems are not appropriate for use in wireless data systems. This is mainly because of the distinguishing aspect between the utility function in data service and voice service systems. A lot of literature has proposed different utility functions to solve the power control and resource allocation problems depending on the main concern of their work. In the theory proposed by (Goodman & Mandayam, 2000), energy efficiency was the primary concern of the utility function, and it is defined as the number of information bits that can be successfully transmitted for every joule of energy consumed. As recommended by (Saraydar et al., 2002; Meshkati et al., 2006), an energy efficient utility function was also applied. This utility function has a dependency on the transmission power and the Signal to Interference Ratio (SIR) of a given terminal. To transmit data successfully at a low bit error rate, the SIR level has to be high at the output of the receiver. Attaining a high SIR level necessitates mobile terminals to disburse a high-level of energy, which eventually leads to low battery life. Throughput is defined as the net number of information bits that can undergo transmission without any error per unit time. The utility function can be defined as the ratio between the throughput and user transmission power in this case, which is expressed as:

$$u_i = \frac{LT_i}{Mp_i} \tag{2.4}$$

Where p_i is the transmission power of user i, and L and M are the transmission bits and the length of packets, respectively. The throughput $T_i$here can be expressed as:

$$T_i = R_i f(\gamma_i) \tag{2.5}$$

Where γ_i and R_i and are the SIR and the transmission rate for the user i, respectively, while $f(\gamma_i)$ is the efficiency function representing the packet success rate (PSR). The efficiency function is dependent on data transmission that involves coding, modulation, and packet size. The following expression shows the modulation scheme dependent efficiency function:

$$f(\gamma_i) = (1 - P_e)^M \tag{2.6}$$

Where P_e represents the bit error rate (BER) of terminal i. Table 2.6 shows the BER as a function of different modulation schemes:

Table 2.6: The BER as a Function of Various Modulation Schemes

Modulation Scheme	**BER**
Binary phase shift keying BPSK	$Q(\sqrt{2\gamma})$
Differential phase shift keying DPSK	$\frac{1}{2}e^{-\gamma}$
Coherent frequency shift keying FSK	$Q(\sqrt{\gamma})$
Non-coherent frequency shift keying FSK	$\frac{1}{2}e^{-\gamma}$

Further, the energy efficient utility function for non-coherent FSK is expressed as:

$$u_i = \frac{L}{M}\frac{(1 - e^{-\gamma_i/2})^M}{p_i} \tag{2.7}$$

(Saraydar et al., 2002) also introduced the pricing function to improve the Nash Equilibrium as a function of power transmission:

$$c_i(p_i) = cp_i \tag{2.8}$$

Where c is the pricing factor. The utility function with pricing is expressed as:

$$u_i = \frac{L}{M}\frac{(1 - e^{-\gamma_i/2})^M}{p_i} - cp_i \tag{2.9}$$

To ensure no error correction and perfect error detection, the Frame Success Rate (FSR) can be expressed as $P_c = (1 - P_e)^M$, wherein all modulation schemes, P_e reduces monotonically with the SIR. As a result, P_c is regarded as a monotonically increasing function of the SIR. When $p = 0$ for all modulation schemes, the best strategy for the receiver is to guess for every bit, which results in $P_c = 2^{-M}$ and thereby leads to infinite utility (Saraydar et al., 2002). The probability behaviour of correct reception is closely followed by the efficiency function $f(\gamma_i)$ and the FSR, while producing $P_c = 0$ at $p = 0$ (Saraydar et al., 2002).

In the research conducted by (Alpcan et al., 2002; Gunturi & Paganini, 2003), the key objective of a utility function was to optimise the spectral efficiency. The utility function was defined as a logarithmic concave function of the user's Signal to Interference Ratio (SIR) expressed as:

$$u_i = Blog(1 + \gamma_i) - cp_i \tag{2.10}$$

Where γ_i is the SIR of user i, B is the communication bandwidth, and c_i is the pricing factor of user i. The term $c_i p_i$ represents the linear pricing of the user's transmission power.

The utility function of the user was defined by (Xiao et al., 2003) as a sigmoid function of the user's SIR. The pricing function was further defined as a linear function of the user's transmit power. Additionally, the net utility function was defined as the difference between the sigmoid function and the pricing function, and was expressed as:

$$NU_i = u_i(\gamma_i) - c_i p_i \tag{2.11}$$

Where $u_i(\gamma_i)$ is the sigmoid function and c_i is the pricing factor. The efficiency function that is suggested in this work was a sigmoid function that was expressed as:

$$f(\gamma_i) = \frac{1}{1 - e^{a - \gamma_i}} \tag{2.12}$$

Where a is the sigmoid parameter.

2.5 Toward Green Communications in 5G

The purpose of this research is to offer green transmission vision for prospective 5G scenarios. Figure 2.4 demonstrate typical wireless scenario combined with the wireless RF signal. Moreover, there are two parts that the wireless link signal can be divided into: the first one is related to information, and the second one is involved in the power transfer. However, radio frequency could not be used for both of them simultaneously (Lee & Hong, 2016). In order to achieve green wireless transmission, recommended performing techniques were applied in combination with the algorithms and theories, and the wireless signals were then used for information and transfer of power as depicted in Figure 2.1 in the Introduction section. In this study, the suggested techniques in relation to green communications have also been used besides the maths approach for various kinds of wireless cellular networks such as: UAV, C-RAN, CS, CR,and D2D.

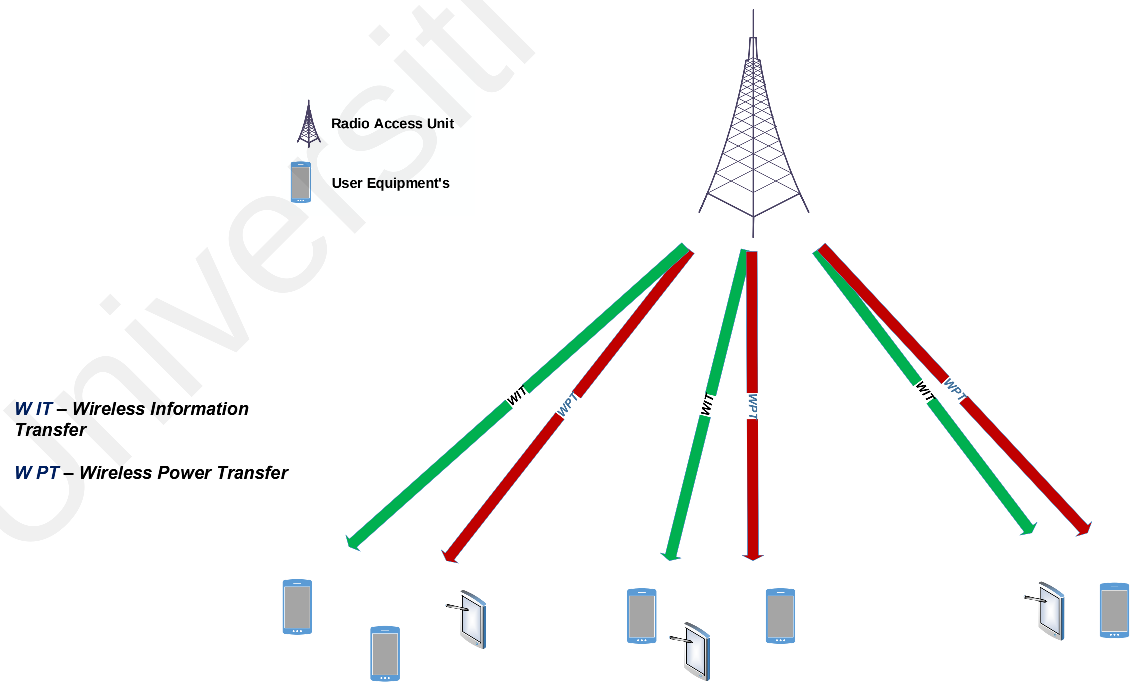

Figure 2.4: Wireless Network Clarify WIT & WPT

2.6 Summary

Based on the SWIPT-Game theories, a review of the energy efficiency optimisation for prospective candidate scenarios of 5G wireless networks has been provided in this research. The 5G networks are remarkably different and powerful than the previous wireless networks. The SWIPT techniques and game theory were discussed to identify the compatible channels, with the objective of improving network energy efficiency. On the basis of energy efficient criteria, the future networks will need to be deployed. Furthermore, the need is to be able to collect clean energy from the environment and use the available energy efficiently through energy efficient resource allocation or other similar techniques.

CHAPTER 3: GREEN COMMUNICATION FOR COGNITIVE RADIO NETWORKS BASED ON GAME AND UTILITY-PRICING THEORIES

3.1 Introduction

Going from 2G to 4G technologies, there has been an extremely fast evolution and progress of technologies particularly with respect to the computer networks and wireless networks. The primary force for this occurrence has been the demand for better energy efficiency, lower latency, and bandwidth. Thus, 4G is truly mobile broadband, even though the first standard for mobile broadband is considered to be the 3G technology. The 3G technology was originally designed for voice transmission, for the transmission of data and multimedia, certain specific considerations were taken, whereas 2G was considered as the foremost digital voice transmission having a better range of coverage. An improvement has been seen in the rate of data transmission in 2G ranging from 64 kbps to 2 Mbps in 3G while 4G has 50–100 Mbps. It is supposed that the 5G networks will enhance the speed of data transfer along with the connectivity, efficacy of the energy and measurement of the network. It is expected that 50 billion devices will be linked to the worldwide IP network by the year 2020, that is a daring task (Mitra & Agrawal, 2015; Mukhlif et al., 2018b; 2018c). Thus, the below given are the most crucial components for describing 5G: high reliability, high throughput, energy efficiency, increased scalability and low latency (Le et al., 2016). Hence, users will be able to experience seamless network connectivity (Andrews et al., 2014). Therefore, this upcoming technology in the wireless networks domain is highly likely to incorporate a ground-breaking architecture that fulfils the demands of the next-generation networks. Consequently, Cognitive Radio Network (CRN) is one of the most significant contenders for 5G network.

Nonetheless, CRN as an emerging technology has the potential to issue underutilization of the spectrum the current wireless networks face. The basic standard of CRN use boosts up flexibility and effectiveness in the use of spectrum by permitting the unauthorized (secondary) consumers to use the resources possessed by the authorized (primary) consumers resourcefully. Along with several performance challenges and design in carrying out the CRN, and a peaceful coexistence between the primary and the secondary users is one of the most difficult challenges (Luitel & Moh, 2018).

The imbalanced and self-managed nature of CRN creates quite complicated resource management issues such as the regulation of power. Wireless devices with mental capacity are smart and calculated decision-makers who function according to their self-concern. Secondary users struggle with one another to increase their utilization whereas primary users levy charges from secondary users for the consumption of resources like the power to increase their profits. Thus, pricing is an important factor with respect to the interaction between the primary users and secondary users. In CRNs, secondary users are price payers, they perform tactically taking into consideration the cost and the rivalry they come across while primary users are generating the price by utilizing the imperceptible indicator to assign resources and increase their returns (Yu et al., 2010). The effective handling of the resources is necessary for wireless networks generally having limited radio spectrum, an undependable channel of propagation and user movement. A significant element of the management of radio resources is the power control (Xiao et al., 2003).

In CR devices, an effective technique is needed in order to decrease the interference produced along with the sharing of spectrum for controlling power. The inevitability of signal-to-interference ratio (SIR) is stabilized by power control and it also enhances battery life for CR devices. The primary conception of the game and economic theory has recently been implemented to fix the issue of power control in wireless networks using various methods, where the preference of facility is not independent of the utility function. Development of a utility function is a significant element on a particular part of game theory approach that has an influential effect, and the consequences of this approach are nontrivial (Hossain et al., 2009). Different procedures are developed as a power control method considering price and utility functions. Few researches have recommended utility based on the pricing and utility functions, so the users try to increase the utility in a selfish way. Here, the utility function characteristics could be quasi-concave and selecting an optimum point in the proximity of the practical variable range of the utility function, with maximum and minimum power can be affected by the behavior of other users. The efficiency of energy is recognized as a particular instance of utility function wherein it impacts physically; that is, the bits number magnificently obtained per joule of energy used. Each user adjusts the transmission power to attain the requisite SIR which is indirectly described in the utility function; rather it is dependent on the function for asserted efficiency (Al-Gumaei et al., 2015).

3.1.1 Contributions

This study is chiefly concerned with the effect of energy harvesting on the QoS (Quality of Service). Moreover, wireless networks services pricing has emerged as a useful device for the management of radio resources due to its capability to guide behavior of the users towards an additional effective operational idea. Purposely, a system for power control is presented in the CRN. The primary objective of the power control techniques in the CRN is to increase the utilization of spectrum by permitting multiple CRs to share the authorized users. When the spectrum is shared, each of the CR terminals should be functioning within the limit of interference temperature to maintain primary user QoS and the CRN. To achieve this objective, certain experts emphasize to improve power control techniques in the less preference unrestricted network (CR) and ignore high priority network interaction (primary user). Here, the power control technique development is the same as that applied in the wireless networks without affecting the CRN structure. Thus, we use the model of utility to represent the satisfaction (QoS) a user receives by using the resources. We work on the problem of power control for one CR cell in a wireless network having N users where every user attempt to increase his individual efficacy. Whereas a Nash Equilibrium is possessed resultantly by the non-cooperative power control game it is ineffective. Thus, the pricing function is employed to enhance the effectiveness of the technique. Further, we demonstrate that there is equilibrium in the pricing based non-cooperative power control game and it is Pareto superior in comparison to the game equilibrium which has no pricing. Nonetheless, the pricing-based game is still not able to reach a socially acceptable power solution. The key contributions of this work are summarized below:

1. We presented a utility function of utility containing a weighted exponential of the ratio of the required SIR and the expected signal, as well as pricing function containing a power function for power transmission of the CRs.
2. The pricing and utility functions are instrumental in enabling each CR to select its transmission power efficiency. The nearest CRs is directed to the base station to attain its QoS requisites at minimum price while from the base station, it directs the most distant CRs to attain the essential QoS at a higher price to moderate the intervention.
3. It was confirmed that the presence and uniqueness of the NE of the green communication model and the criteria of the chosen pricing parameters.
4. Instead of a mathematical approach to the NE, this work provides a new illustration that offers a better understanding of the concept of NE.
5. We consider the non-cooperative game as the problem and utilize the best response technique to reach NE, the recommended efficient non-cooperative energy harvest technique can be actually applied in a disseminated manner without the need for any additional information.

3.2 System Model & Game Formulation

In this study, a single cell Cognitive Radio Networks having a cognitive base station (CBS) and one primary access point (PAP) are given in Figure 3.1 based on the case of the uplink power control. N CRs partaking of the commons licensed spectrum are connected with one primary user, and a code division multiple access (CDMA) method is applied by them to use the conventional spectrum for their transmission. It is supposed that all CRs are fixed and dispersed along with the cell's coverage area. We denote the transmission power as p_i of ith cognitive user and the channel link gain as h_i between the ith cognitive user and CBS.

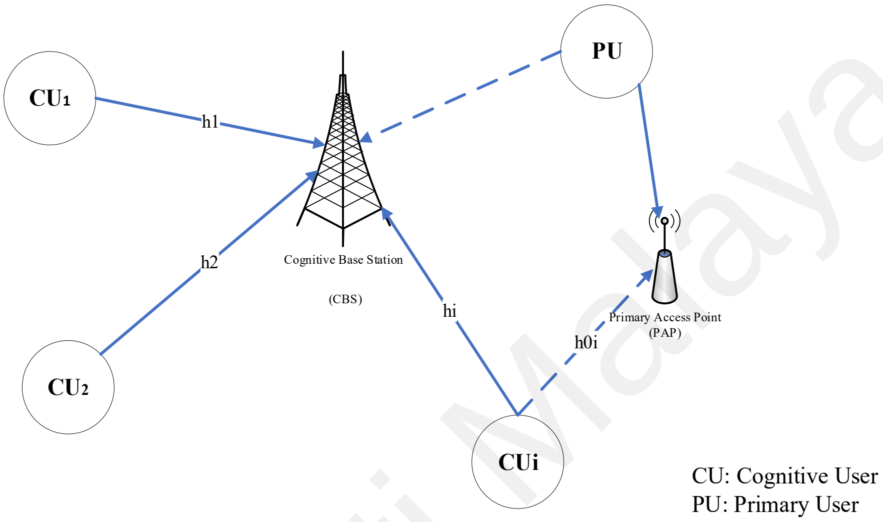

Figure 3.1: Cognitive Radio Network System Model

A generalized SIR formula in the single cell CRN of ith CR can be written as:

$$\gamma_i(p_i) = \frac{Gp_ih_i}{\sum_{j\neq i}^{N} p_ih_j + \sigma_i^2} \geq \quad \Gamma_i \quad {,i=1,2,,3,\ldots,n} \tag{3.1}$$

Where G represents the spread spectrum system's processing gain, Γ_i represents the threshold SIR and σ_i^2 represents the Gaussian noise power. The total amount of interference along with the noise in the denominator of Equation (3.1) is represented by $I_i(\boldsymbol{p}_{-i})$, and thus Equation (3.1) is expressed with user transmission power function and the other user's transmission power as follows:

$$\gamma_i(p_i, \boldsymbol{p}_{-i}) = \frac{Gp_ih_i}{I_i(\boldsymbol{p}_{-i})} = \frac{Gp_ih_i}{\sum_{j\neq i}^{N} p_jh_j + \sigma_i^2} \tag{3.2}$$

The interference based on the transmission of power by the users excepting the ith user is represented by the subscript $-i$.

The main goal of the system is to increase its benefit by permitting several CRs to let other users use their own spectrum. The inadequate production of the authorized users or the limit of temperature interference limits the increase in the benefit (Hossain et al., 2009).

The CRs generate the overall interference power that must be below a specified limit which is known as interference temperature limit and it is expressed as below:

$$\sum_{i=1}^{N} p_i h_{0i} \leq I_{TL} \tag{3.3}$$

Where h_{0i} represents channel benefit obtained by cognitive radio i transmission to the primary system's access point and I_{TL} represents the limit of the interference temperature.

3.2.1 Non-Cooperative Power Control Game with Pricing

Game theory concepts and microeconomics are employed to describe QoS of the users concerning utility function rather than SIR (Hossain et al., 2009). Generally speaking, the model of energy harvesting game consists of three components: (i) CRs (end users) that correspond to the decision-makers or the players of the game, (ii) power strategy which corresponds to the action space or strategy of the game and (iii) user preferences (utilization function). Every player performs its function is to increase utility selfishly in the network. The NPGP (non-cooperative green communication) game model is presented based on the following formula:

$$\Phi = [N, \{P_i\}, \{U_i(.)\}] \tag{3.4}$$

Where $\mathrm{N} = \{1,2, \ldots, \mathrm{N}\}$ represents the player's set of index CRs, $P_i = [0, P_i^{max}]$ denotes the users' power transmission procedure set i, and P_i^{max} represents the users' optimal power i. The function of utility belonging to the user i is termed as $U_i(.)$, wherein every user belonging to the network aims to increase its efficacy in a self-centered way. To decrease consumption of power the CRs to reach the prerequisite SIR and moderate intervention in the network, the utility function of energy game harvests in Equation (3.4) should regard the subsequent characteristics as given by (Allen B. MacKenzie & Luiz A. DaSilva, 2006):

i. The utility function of CRs delivers power as SIR. The CR SIR is a function of CRs transmission as well as that of the other users.
ii. When there is an increase in the power used by the CR, it will also increase the SIR of that user, though it will reduce SIR of other CRs.
iii. To predefine SIR, the CR chooses to use low power for extended battery life and decrease interference.
iv. In lieu of a predefined power, the CR chooses to have greater SIR to get good channel condition.

Like any wireless network, in a CRN, every CR sends its data over the medium of air through the various systems of access. Subsequently, all the signals share air as a medium; every CR signal can be viewed as interference for the signals of the other users. Besides this interference, the fainting background and multipath noise distort the signal as it is transmitted between the source and the destination. The SIR's denominator in Equation (3.1) corresponds to the signal's characteristics. Moreover, CR users are devices that are usually battery-operated, and thus the power used for transmission is another significant factor for them. Hence, transmission power and SIR are the most significant factors that are used to express the model, which in turn determines the satisfaction of the user of the network (Shah et al., 1998).

Information sent to the destination from the source in CR and wireless data networks is represented by packets or frames of length M bits, having $L < M$ bits of information with a data at the rate of R bits/sec. In the received data, the system identifies the errors and the erroneous data are retransferred, obtained throughput T can be demonstrated as:

$$T = Rf(\gamma) \tag{3.5}$$

Where $f(\gamma)$ represents the transmission efficiency function. This function $f(\gamma)$ must be based on the SIR obtained through the channel, and its value ranges from 0 to 1 (i.e., $f(\gamma) \in [0,1]$). Moreover, the transmitted power is $p_i$if users i transmit the power, consequently, the function of utility of user i can be written as the information bits accurately received as per joule of energy used as stated by (Goodman & Mandayam, 2000):

$$U_i(p_i, \boldsymbol{p}_{-i}) = \frac{LRf(\gamma_i)}{Mp_i} \tag{3.6}$$

Non-cooperative power control caused the Nash Equilibrium, and it is inefficient since it does not take into consideration the cost it enforces on supplementary nodes by producing the interference. Thus, the pricing idea was employed to inspire users to utilize the network resources more effectively. The usual representation of the pricing-based non-cooperative power control game is given below:

$$\Phi^c = [N, \{P_i\}, \{U_i^c(.)\}] \tag{3.7}$$

Where $U_i^c(.)$ represents the function of utility using pricing that is written as:

$$U_i^c(p_i, \boldsymbol{p}_{-i}) = U_i(p_i, \boldsymbol{p}_{-1}) - C_i(p_i, \boldsymbol{p}_{-1}) \tag{3.8}$$

Many works pondered upon the power control problem by providing different pricing and utility functions. Hence, selected works to be compared with are EH-NPGP (Al-Gumaei et al., 2015), R-NPGP (Xie et al., 2014), NPG-ESIA (Kuo et al., 2013) and NPG-MSFLIA (X. D. Zhang et al., 2012).

3.2.2 Proposed Green-Game Model

We present a new utility function that depends on a novel sigmoid effective function as well as a function of power transmitting, power pricing function of the users. An efficient sigmoid function has been introduced as the fractional with exponential ratio power multiply tuning factor (z) all power to target SIR as shown:

$$f_i(\gamma_i) = \frac{1}{(1 + exp\ (1 - z\ sir_i))^{r_i}} \tag{3.9}$$

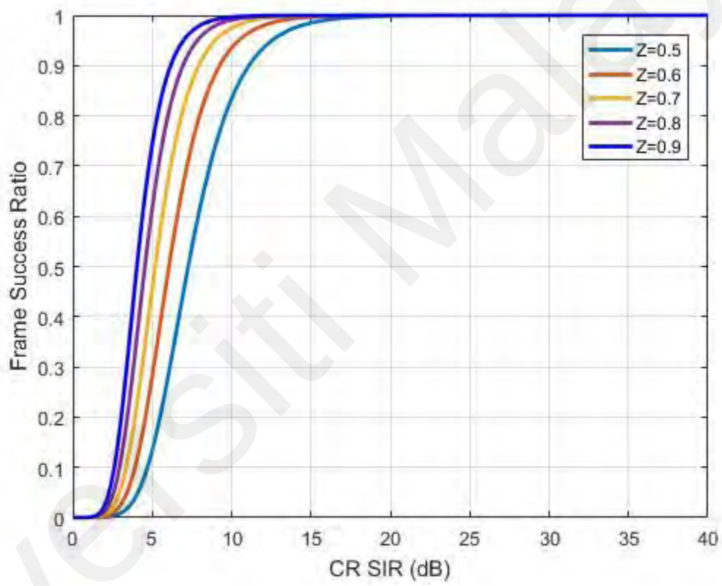

Figure 3.2: Optimal Efficiency Function with Different z Values

Where z is the tuning factor where its change will change the response of the efficiency function proposed, as shown in Figure 3.2. With this ability in controlling response, the proposed function will be more efficient than others which are compared with as shown in Figure 3.3 hence, we called it an optimum function because of we could use it to control efficiency response as well controlling the utility function value as shown in Figure 3.4. Nonetheless, our recommended sigmoidal function is more efficient compared to others since it is simpler and more effective to handle only a single equation and regulate the efficiency function response. The above efficiency functions are compared in Figure 3.3. As per Equation (3.6), the function of utility of the i^{th} CR is expressed as:

$$U_i = \frac{LR}{Mp_i} \frac{1}{(1 + exp\ (1 - z\ sir_i))^{r_i}} \ \frac{bps}{joule} \tag{3.10}$$

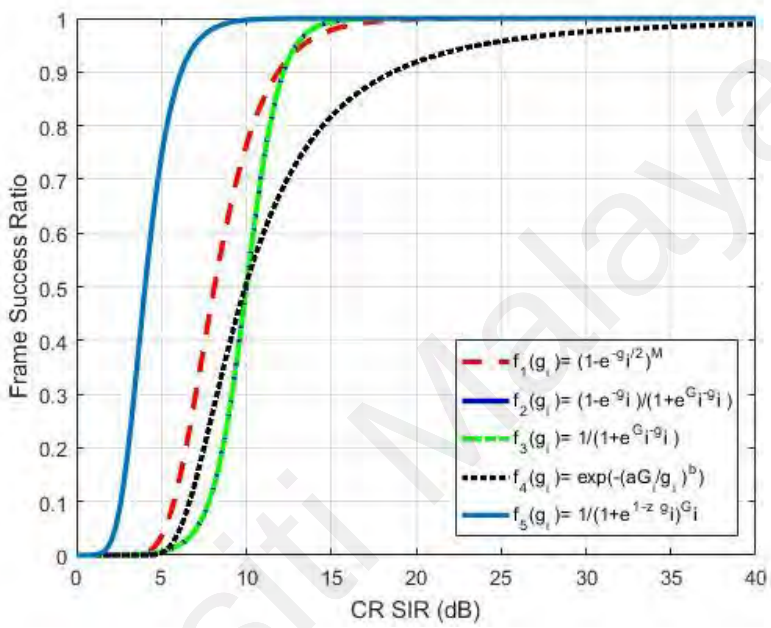

Figure 3.3: Proposed Efficiency Function (f_5) Compared to Functions in *(Al-Gumaei et al., 2015)*, *(Xie et al., 2014)*, *(Kuo et al., 2013)* and *(X. D. Zhang et al., 2012)*

The utility function is given in Equation (3.10) corresponds to balance between the life of battery and throughput, and it is especially suitable for applications in which power saving is crucial as compared to get a better throughput like green cognitive radio (Meshkati et al., 2006). We assume that the defined SIR value is determined for the cognitive radio. The adjustment of the suggested function of utility can be made by applying the factor for tuning (z). The user's maximum power transmission would be altered according to the optimal function of utility. Figure 3.4 displays the curves of the recommended utility function regarding transmission power for various z values, which are presented in Figure 3.5. It reflects how the factor of tuning can make the recommended utility function more effective as compared to the other methods found in the literature. It can be proved that there is an increase in the utilization and the transmission power reduces by diminishing parameter z value, therefore, it will reduce the system of the target SIR. The main system relays the z factor to CRN to tune the target SIR, based on the interference amount. A lower value of z is transmitted by the main system, as the interference amount almost touches the limit of the interference temperature.

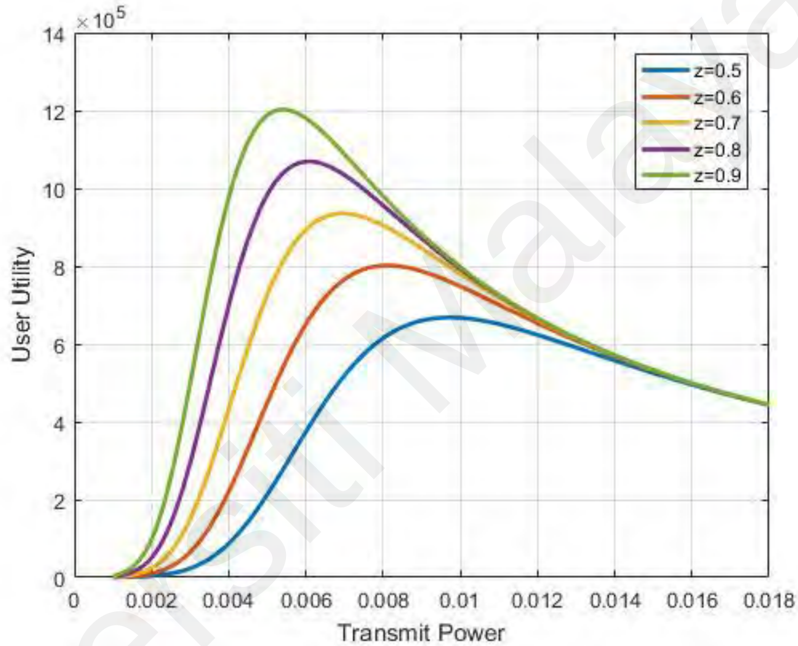

Figure 3.4: Utility Function for User as a Power Transmission Function for Fixed Interference and Different Tuning Value of z Factor

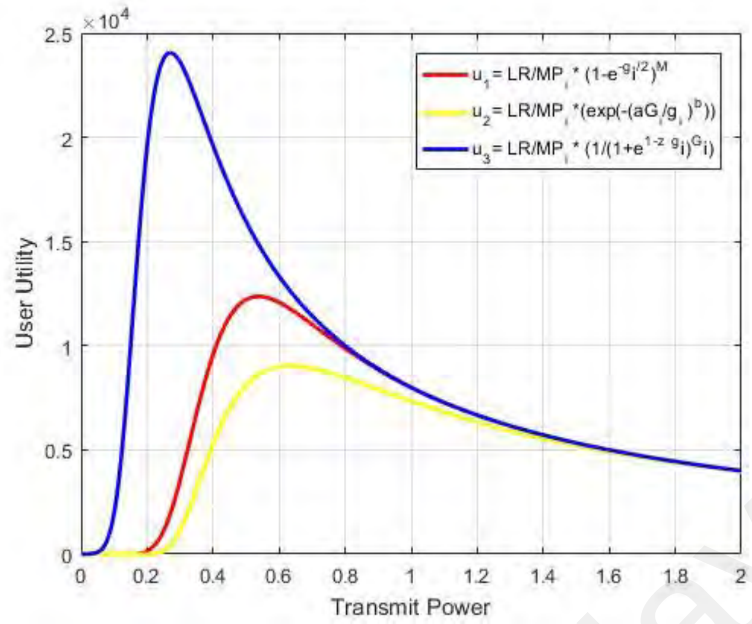

Figure 3.5: Proposed Utility u3 Compared to u1 (Goodman & Mandayam, 2000) and u2 *(Al-Gumaei et al., 2015)*

Moreover, we present a new structure for pricing to improve the system's efficiency of the system by promoting CRs to utilize the system's resources effectively. This design contributes by applying a higher cost for users who are farthest from the base station and use more power. Thus, we present an exponential power function of the transmission power rather than the conventional linear pricing. Figure 3.6 displays an instance of the disparity among the power pricing and the linear pricing methods. We supposed that the power transmitted by different users ranges from minimum to maximum limit for power strategy [0,1], and a numeric calculation is made for the price functions. It can be seen that the pricing obtained by using the power function is lesser than that of the linear pricing CRs function using low transmission power and who are closer to the network while it is higher for the farthest CRs which use high power.

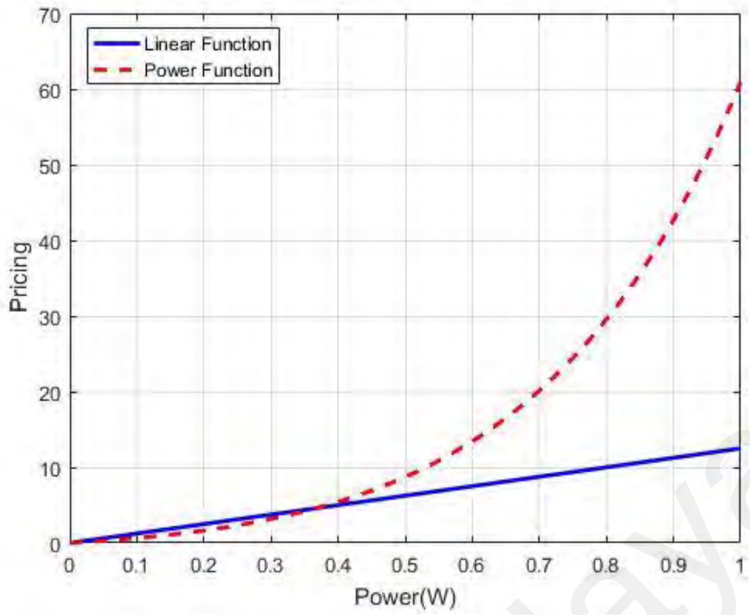

Figure 3.6: Comparison of Linear and Power Function Pricing

Hence, the suggested pricing function is stated as:

$$C_i(p_i, \boldsymbol{p_{-i}}) = c\, p_i\, exp(p_i\, \alpha) \tag{3.11}$$

Where c and α represent the pricing factor. Therefore, the pricing-based utility function is written as:

$$U_i^C(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i} \frac{1}{(1 + exp\ (1 - z\ sir_i))^{r_i}} - c\, p_i\, exp(p_i\, \alpha) \tag{3.12}$$

Thus, green non-cooperative power control with pricing is the recommended in the game and described as:

$$GC - NPGP : \max_{pi \in Pi} U_i^C(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i} \frac{1}{(1 + exp(1 - z\ sir_i))^{r_i}} - c\, p_i\, exp(p_i\, \alpha) \tag{3.13}$$

The benefit of a function of pricing is its capability to direct CRs towards Nash Equilibrium mark effectively. It is accomplished by enhancing pricing of the most distant users, utilizing greater power transmission to communicate. Also, the function of pricing decreased the pricing used to the closest CRs who utilize lower power transmission to communicate. Every CR performs a search to increase its financial gains by regulating its power transmission distribution. Likely, the power control game causes Nash Equilibrium, and it signifies the composed power of all CRs such as not a single CR can raise the advantage by altering its power transmission. To formulate the technique used in the game of non-cooperative power control, we employ a power control method wherein every CR tries to maximize its net utilization $U_i^C(p_i, \boldsymbol{p_{-i}})$. For the optimisation of power, the maximization can be attained at a level where the partial derivative of $U_i^C(p_i, \boldsymbol{p_{-i}})$ corresponding to power p_i is equal to zero.

3.3 Nash Equilibrium In GC-NPGP

In this portion, a mathematical representation associated with the uniqueness and existence is given bellow (J. O. Neel et al., 2004):

Definition 3.1: Nash equilibrium in the GC-NPGP method can be described as the power vector, e.g. $P_i = [p_i, \ldots., p_i]$, in which no participant can enhance the utility function, $U_i(p_i, p_{-i})$, by independently changing its own strategy outline, i.e..,p_i. In mathematical terms, Nash equilibrium is presented as follows:

$$U_i(p_i, \boldsymbol{p_{-i}}) \geq U_j(p_i, \boldsymbol{p_{-i}}), \qquad \forall\, p_i \in \widehat{P_i}, \;\; \forall\, i \in N \tag{3.14}$$

3.3.1 Nash Equilibrium Existence

The Nash equilibrium in the recommended method provides a consistent and predictable outcome where several CRs with opposing interests participate and get to a point where no participant can request to adjust its own strategy outline. To confirm NE's existence, the below theorem is proposed:

***Theorem 3.1*:** The Nash equilibrium is present in GC-NPGP= $[N, \{P_i\}, \{U_i(.)\}]$, if it fulfils the following criteria $\forall\, i \in N$:

The profile action strategy (i.e.,p_i) is a compact, convex and nonempty subset.

The function of utility $U_i(p_i, \boldsymbol{p_{-i}})$ is a concave and continuous function over strategy set of the players.

Proof: It can be obtained by proving that both the criteria provided in ***Theorem 3.1*** are satisfied by GC-NPGP. It is corroborated by the following evidence:

As every CR user uses a strategy outline well-defined by optimal and minimal power as given in Equation (3.10), the first condition is promptly satisfied.

For proving that the second criterion is also satisfied, the given utility function based on variable pricing must be shown to be concave in p_i,$\forall\ i \in N$.

Definition 3.2: According to (Saraydar et al., 2002) Super Modular ***definition 5***, The utility function $U_i(p_i, \boldsymbol{p_{-i}})$ characterised by the convex set $\widehat{\boldsymbol{P}_i}$ is concave in P_i only in case, the surplus function's second derivative is greater than 0 (Pang et al., 2010; Saraydar et al., 2002).

To show this condition is true, the following set of Equations: $\frac{\partial^2 u_i^p}{\partial^2 p_i^c} > 0$, must be solved $\forall\ i$. Hence, the following Lemma must be satisfied.

Lemma 3.1: The utility function based on pricing provided in Equation (3.12) is concave in p_i,$\forall\ i \in N$.

Considering that both the criteria are given in **Theorem 3.1** are satisfied, the recommended GC-NPGP is a concave n-player game having one or more NE in it.

3.3.2 Nash Equilibrium Uniqueness

The strategy outline of the players carries the recommender concave and continuous utility function. Therefore, NE is present in GC-NPGP. Nonetheless, a question may arise at this juncture naturally: Is the existence of the NE unique? The uniqueness of NE can be examined as follows:

Definition 3.3: An alternative NE definition is the best response strategy which can be defined as per the following:

$$BR(\boldsymbol{p}_{-\boldsymbol{i}}) = \left\{p_i^c \in \hat{P}_i : u_i^c(p_i^c, \boldsymbol{p}_{-\boldsymbol{i}}^{\boldsymbol{c}}) \geq u_i^c(\vec{p}_i^c, \boldsymbol{p}_{-i}^c), \quad \forall\, \vec{p}_i^c \in \hat{P}_i\right\} \tag{3.15}$$

Also, the best strategy for response is a set including just a single maximum point that increases the objective function, which is mathematically formulated as follows:

$$p_{i= arg \max_{p_i \in P_i} U_i^c(p_i, \boldsymbol{p}_{-\boldsymbol{i}}))} \tag{3.16}$$

Furthermore, the second derivative has been proven to be greater than zero, which means that the maximum point is the optimal unique point.

Theorem 3.2: The NE of the GC-NPGP game is $[N, \{P_i\}, \{U_i(.)\}]$ which is unique.

Proof: The main feature of the uniqueness of NE is to prove that a typical function is the best strategy for response. For the recommended game, GC-NPGP = $[N, \{P_i\}, \{U_i(.)\}]$, which is the best response given by the i^{th} user with respect to others' power strategy.

To prove the uniqueness of NE, the function for the most suitable response must be a regular function and must also possess the following characteristics (Yates, 1995):

i. Positivity: $BR(\boldsymbol{p}_{-i}) > 0$.
ii. Monotonicity: given $\boldsymbol{p} \geq \hat{\boldsymbol{p}}$, then $BR(\boldsymbol{p}_{-i}) \geq BR(\tilde{\boldsymbol{p}}_{-i})$.

iii. Scalability: given, for all $\varepsilon > 1$, then $\varepsilon BR(\boldsymbol{p}_{-i}) > BR(\varepsilon \boldsymbol{p}_{-i})$.

Moreover, it has been confirmed in (Koskie & Gajic, 2005) that if a fixed point from Equation (3.13) fulfils the characteristics as mentioned earlier, then the $BR(P_{-i})$ proceeds towards a fixed point. Thus, according to (Koskie & Gajic, 2005), a fixed point in Equation (3.13) meets the positivity, monotonicity and scalability under the specific circumstances mentioned in theorem 3.1.

In conclusion, a standard function must be used as the best response strategy function. Thus, the non-cooperative power control system recommended by us has only a single unique NE solution which satisfies the evidence of the distinctiveness of the Nash Equilibrium.

3.4 GC-NPGP Algorithm

We propose an iterative best response technique to control all users' transmission powers to achieve the required SIR for all CRs and ensure NE opportunistically with available information of SIR.

Nonetheless, we assume that every CR updates its transmission power at time instances $t_i = \{t_{i1}, t_{i2}, \dots.\}$, where $t_{ik} < t_{i(k+1)}$, and we suppose the power strategy set of the ith CR is $P_i = [P_i^{min}, P_i^{max}]$. We fix an infinitesimally small quantity ε where ($\varepsilon > 0$) and the recommended technique is given in Equation (3.13) produces a sequence of powers as given below:

GC-NPGP

I. Initialize transmit power vector $p = [p_1^0, p_2^0, p_3^0, \dots, p_N^0]$ randomly at time t_0

II. For all $i \in N$ at time instant t_k;

    a) Update $\gamma_i(t_k)$ using Equation (3.1)

b) Consider the best response of power strategy $r_i(t_k)$;

Based on $r_i(t_k) = arg \max_{p_i \in P_i} u_i^C \ (p_i, \boldsymbol{p_{-i}}(t_{k-1}))$

c) Allocate the transmit power as $p_i(t_k) = \min\ (r_i(t_k), p_i^{max})$

III. If $\|p(t_k) - p(t_{k-1})\| \leq \varepsilon$; stop iteration and state Nash equilibrium as $p(t_k)$

IV. Else;

$k = k + 1$ and refer to step II

V. End

Where $r_i(t_k)$ is the set of the most suitable transmission powers for ith CR which is obtained by applying objective function with constraint in best response technique at time instant k concerning the interference vector $p_{-i}(t_{k-1})$. It is noteworthy that the ith CR optimises the overall utilization over the power strategy domain of the GC-NPGP. The presented technique determines the transmission power of the ith CR by choosing the smallest power among all probabilities suggested by the method. The technique will solve separately the maximum of every CRs objective. The flowchart of the recommended technique is given in Figure 3.7. Moreover, the proposed algorithm is based on power allocation using pricing function. Hence, the computational complexity is directly depending on the number of users and the available channels which resulted in $O(\log(N))$.

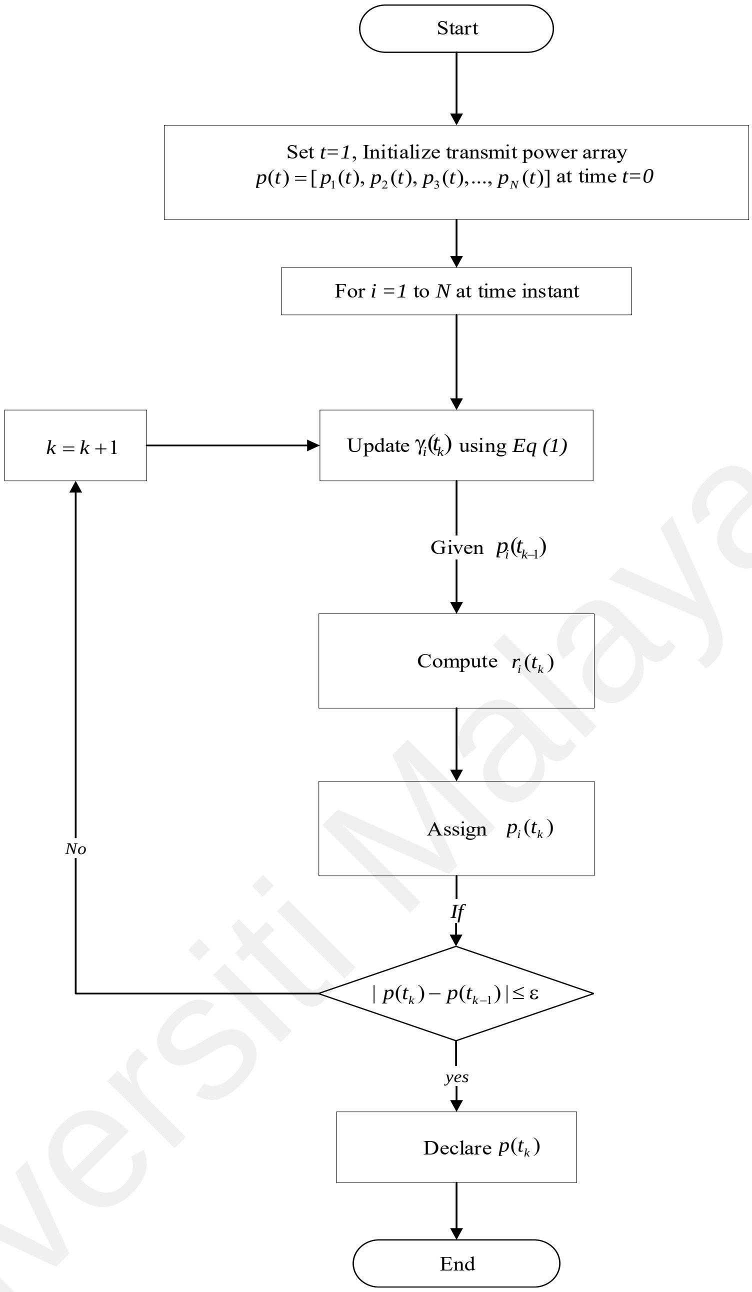

Figure 3.7: Proposed Algorithm Flowchart

3.5 Numerical Results & Discussion

This section evaluates the functioning of the recommended power control game based best response method by us against the EH-NPGP (Al-Gumaei et al., 2015), R-NPGP (Xie et al., 2014), NPG-ESIA (Kuo et al., 2013), NPG-MSFLIA (X. D. Zhang et al., 2012). The same numerical calculations were employed to achieve the Nash Equilibrium solution utilities functions to reap the benefits of the recommended function of utility.

The stable system variables applied in the experiment are enumerated in the below-given Table 3.1.

Table 3.1: System Parameters

Parameter	Value
Number of players	7
Overall number of bits per frame, M	80
Total counts of information bits for each frame, L	64
Spread Spectrum processing gain, G	70
Data rate, R	10 kbps
AWGN power at receiver, $\boldsymbol{\sigma^2}$	1e-14 Watts
Maximum power constraint, $\boldsymbol{P_i^{max}}$	1 Watts
Target SIR, Γ_i	9
Pricing factors, $\boldsymbol{c}$ **&** $\boldsymbol{\alpha}$	1e4, 2.5
Tuning factor, $\boldsymbol{z}$	0.5-0.9

We regard a model for the system depends on a sole cell CRS (cognitive radio system) using a predefined packet size and without coding to forward error correction. In case of the all-purpose efficacy of function described, the SIR equilibrium is determined by resolving the formula $f(\gamma)\gamma - f(\gamma) = 0$ that ensures optimal utilization of $\gamma^* = 12.4$. The quantity of γ^* is the actual target SIR that each of the CRs attain to maximize the efficiency of their particular utility function. The feasibility condition for γ^*, for the cognitive radio system, is given by the subsequent tied up the amount of users (Yates, 1995):

$$N \leq 1 + \left(\frac{G}{\gamma^*}\right) = 7 \ CR\ terminals \tag{3.17}$$

As per Equation (3.17), we suppose that the system has at the most 7 CRs and, their distance from the base station is $d = [368, 490, 580, 630, 720, 810, 950]\ m$.

In this study, we employ an uncomplicated propagation model wherein the entire route achievements determine the functions having path loss exponent (denoted by β), of the gap between the CBS (cognitive base station) and cognitive radio i and cognitive base station (CBS) and is given as follows:

$$h_i = \frac{K}{d_i^{\beta}} \tag{3.18}$$

Where the distance between base station and the ith user is represented by d_i, the path loss exponent is represented by β, assumed to be 2 and generally from 2 to 6, and $K = 0.097$ is a persistent. This K value is chosen to form a transmission power of 1W for a CR terminal functioning at 950m from CBS in the system having 7 CRs and each one of them operating with γ^*. Nonetheless, the current experiment shows all the cognitive users begin with preliminary power $p_i^{(0)} = 2.22 * 10^{-16}\ w$ and $\varepsilon = 10^{-18}$.

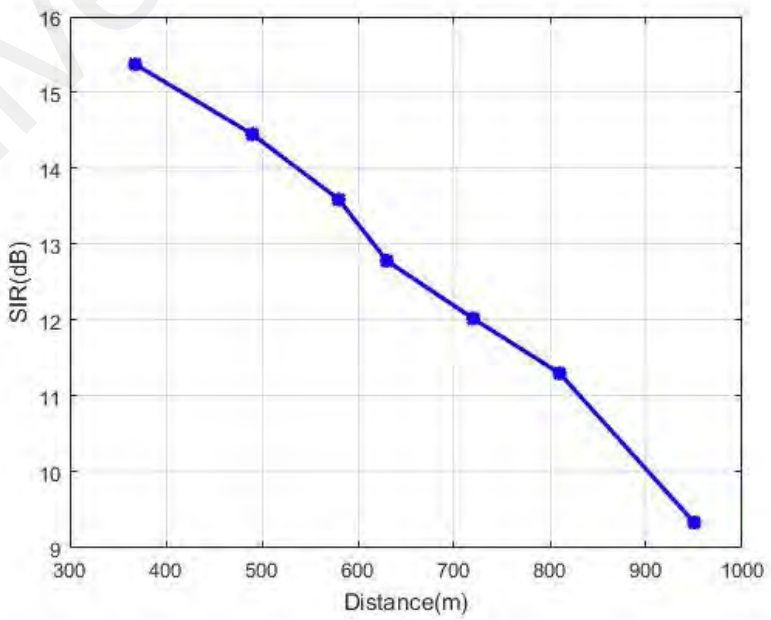

Figure 3.8: SIR Vs. Distance for Each User

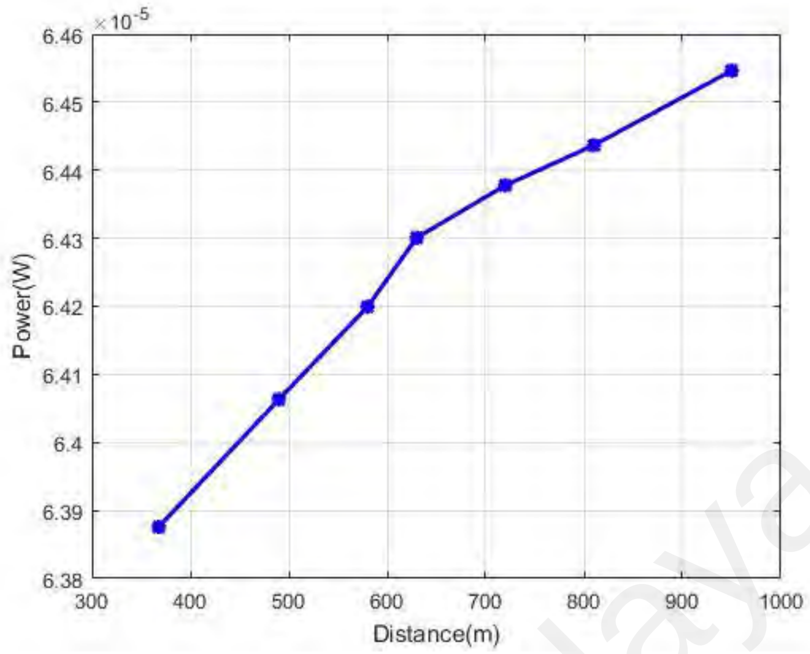

Figure 3.9: Power Vs. Distance for Each User

The outcomes of SIR at Nash Equilibrium are described in Figure 3.8. CR obtains these outcomes in accordance with the remoteness between the base station and every CR. All the users of CRs retain their SIR more than the required value ($\mathrm{r}_i = 9$) and SIR value is reduced by enhancing the distance for each of the cognitive users. The Figure 3.8 curve of SIR demonstrates that our recommended technique GC-NPGP is more effective when there are the highest SIR values as compared to the other techniques. The highest powers are utilized by the farthermost CRs and signify the interference source, and thus our recommended technique used a greater cost to the most distant users. Figure 3.9 demonstrates the graph of transmission power (in Watts) against the distance of CR from the base station for the suggested method in which the transmission power increases steadily when the distance of the user is increased. Here, it is apparent that the curve of the transmission power of the recommended GC-NPGP is increasing steadily.

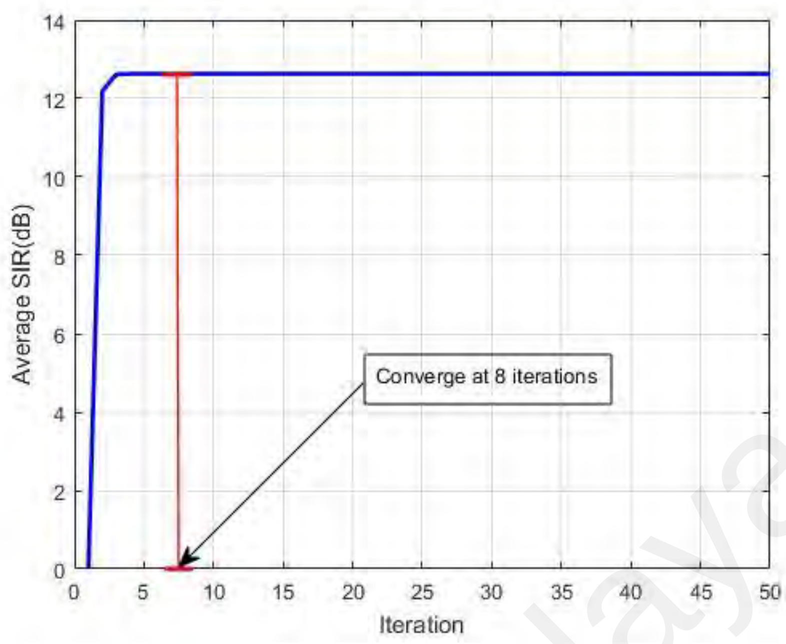

Figure 3.10: Convergence of Average SIR in the Proposed Algorithm

Table 3.2 demonstrates the CR users' SIR in the last part of the network algorithm experiment. The table demonstrates that the GC-NPGP technique along with the suggested price function attain the highest SIR value in comparison to the other methods found in the literature. The SIR of the 2 most recent CR users is smaller due to application of higher cost. Thus, it can meet a better point of equilibrium by limiting the least SIR needed for terminals with poor channel conditions.

Table 3.2: Final SIR of CR Users

CR user	Final SIR of NPG-MSFLIA (X. D. Zhang et al., 2012)	Final SIR of NPG-ESIA (Kuo et al., 2013)	Final SIR of R-NPGP (Xie et al., 2014)	Final SIR of EF-NPGP (Al-Gumaei et al., 2015)	Final SIR of Proposed GC-NPGP
1	12.41	12.42	12.42	12.69	15.33
2	12.4	12.43	12.43	12.69	14.41
3	12.4	12.43	12.43	12.69	13.56
4	12.39	12.43	12.43	12.69	12.76
5	12.37	12.42	12.42	12.68	12.00
6	12.33	12.4	12.4	12.66	11.28
7	12.26	12.3	12.3	12.4	9.32

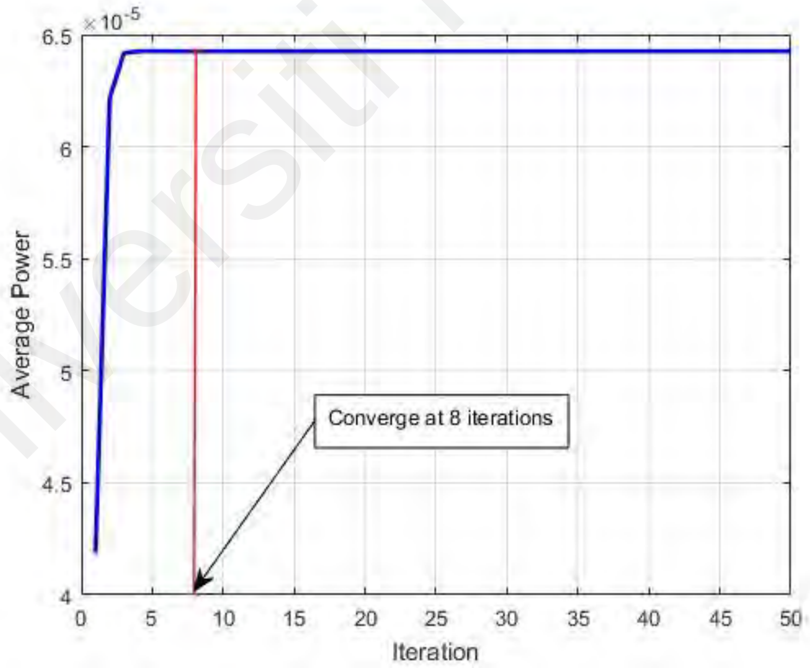

Figure 3.11: Convergence of Average Power in the Proposed Algorithm

Additionally, we examine the average SIR and average power in comparison to the other methods to find out their convergence speed and decrease in the average power. In this experiment, the iteration time is shown on the horizontal axis that is required to achieve the Nash Equilibrium, while the average power and average SIR are shown on the vertical axis. It is displayed in Table 3.2 that almost all methods obtain the similar average SIR without any noteworthy variances but there is a difference in the convergence speed for every method. It is observed that our recommended GC-NPGP method can achieve Nash Equilibrium with just 8 iterations as displayed in Figure 3.10, while for NPG-MSFLA, NPGP-ESIA, R-NPGP, and EF-NPGP, it requires 333, 360, 323 and 133 iterations, respectively. Alternatively, Figure 3.11 displays the curve of average transmission power obtained by the recommended algorithm. Figure 3.11 reflects that the usage of average power of the recommended GC-NPGP method has a considerable decrease compared to other methods and that is the most important thing in implementing potential 5G wireless networks. We succeeded in decreasing the transmission power from Watt to micro-Watt as can be seen in Figure 3.11. The outcome attained from Figure 3.11 signifies interference's extent gauged at the main system from the suggested GC-NPGP is considered the least against other algorithms; this attribute of the suggested GC-NPGP algorithm makes it apt for maximizing the sharing of spectrum, and guarantees QoS in either systems. The convergence speed of the recommended algorithm is apparent from Figure 3.11, in which it can be seen that the recommended GC-NPGP method has the highest convergence speed compared to other methods as given in Table 3.3, shows power consumption average (in Watts) and the required iterations of all the methods.

Table 3.3: Average Power and NE Convergence Comparison

Algorithm	Average Power (W)	Number of Iterations
NPG-MSFLA (X. D. Zhang et al., 2012)	0.2321	333
NPGP-ESIA (Kuo et al., 2013)	0.2319	360
R-NPGP (Xie et al., 2014)	0.2287	323
EF-NPGP (Al-Gumaei et al., 2015)	0.1926	133
GC-NPGP	6.4257e-05	8

3.6 Summary

We have proposed a non-cooperative green communication technique in CRNs within wireless networks. The CR users' QoS represent an effective utilization through pricing and energy harvesting coefficient. By presenting utility functions and new price as an effective non-cooperative green transmission game is created and Nash Equilibrium's uniqueness and its existence are confirmed mathematically. In this work, statistical outcomes suggest that the non-cooperative green transmission technique has two very important specifications such as lower power consumption and faster convergence speed simultaneously in comparison with the other methods found in the reviewed literature. Moreover, most of the nearby CR users in the method recommended by us can get better SIR than that of the other methods. The higher cost is only utilized to the most distant users that signify a more significant source of unwanted interference. The presented method provides better performance, wherein the CRN can share the additional licensed bands by staying under the limits of the interference temperature. The considerable decrease in the power consumption of the recommended method proves to be of the highest importance for application in cognitive radio in the 5G network domain. Further, we will consider an adaptation of the method to choose the best pricing values parameters

c_{best} and α_{best} , at the base station, these parameters can be employed to obtain a considerable improvement to be used in networks beyond the 5G technology.

CHAPTER 4: ENERGY HARVESTING TECHNIQUE FOR EFFICIENT WIRELESS COGNITIVE SENSOR NETWORKS BASED ON SWIPT GAME THEORY

4.1 Introduction

In the future, humans will witness a linked community. The Internet of Things (IoT), as well as smart, assimilated systems with built-in sensors, C-RAN and in-house sensing networks, would transform the manner in which individuals' lives are spent (S. Zhang et al., 2014; Mukhlif et al., 2018b). Furthermore, it enhances energy efficacy, cost and spectrum usage. It also delivers improved scalability for dealing with the increasing number of linked devices. Considering the idea of a connected ecosystem in recent networks, the general technical objective is to present an idea which would bolster high energy with spectral efficacy (Osseiran et al., 2014). A wireless sensor network (WSN) comprises multiple sensor nodes that have drawn significant attention and uses of late. For instance, for comprehending our environment better and turning it into niftier state, a type of media for connecting the cyber space with the actual world ought to be devised. Hence, the idea of Internet of Thing (IoT) has emerged and the universal WSNs have emerged as a key type of fundamental technology to bolster IoT. Wireless networks not only find applications in Mobile Cloud Computing (MCC) but also in the healthcare sector, wherein physiological activities and actions of humans can be monitored continuously, with the help of wearable implantable biosensors (Lin & Wang, 2017). Moreover, applications of WSN have become common even in unlicensed industrial, medical and scientific bands, which are quickly becoming overcrowded each day as these bands allow sharing information with other wireless applications (Luitel & Moh, 2018). The licensed bands are not utilized efficiently, thereby causing a grave imbalance in the usage of radio spectrum. Due to this, the available spectrum not only needs to be used efficiently but also there is a need to effectively manage spectrum when developing wireless applications, and in this regard, the concept pertaining to Cognitive Radio (CR) was introduced (J. Mitola & Maguire, 1999). CR can be employed to use the available licensed spectrum. This can be done by reconfiguring its features and by exploiting its cognitive capabilities, which allows unlicensed secondary users (SUs) to utilize part of the licensed frequency range that have been underutilized and will not make interference to the activities pertaining to the licensed primary users (PUs) (Arjoune & Kaabouch, 2019). A wireless cognitive sensor network (CSN) can be defined as a WSN that possesses CR capabilities. Moreover, with regards to the opportunistic use pertaining to the licensed spectrum, the unlicensed band can be used by SUs without disrupting communication amongst PUs. Hence, CSN entails the basic attributes of CR networks.

However, from the perspective of wireless infrastructure, two key kinds of energy harvesting have surfaced: radio frequency and environmental (Lu et al., 2015; Mukhlif et al., 2018c). Moreover, radio-frequency of energy harvesting presents captivating prospects, which aid in reducing the chances occurring in the wireless power-source. The idea encompasses mingling energy harvesting linked to wireless power transmission methods. Such technique facilitates sharing of energy between network nodes (Liu et al., 2013), which in turn extends nodes lifetime when the energy of battery is low (Gurakan et al., 2013; Chia et al., 2014). Energy signals are superimposed within other signals of regular communication which allows such approach to the next level, which in turn allows for 'simultaneous wireless information and power transfer (SWIPT)' (Huang & Larsson, 2013; Ng et al., 2013).

An effective power control algorithm is required in CSNs to reduce interference from CSNs during spectrum sharing. Additionally, are required for power controls to preserve the desired signal-to-noise ratio (SIR) besides extending CSN device lifetime. However, theories of game and economic have been published as an alternative to the issues of energy control in wireless data networks, as the choice of service depends on the functionality of the tool. The issue in game theory is to design utility functions where it has a physical connotation and the result of the game is not important (Hossain et al., 2009). Energy control algorithms can be developed in many ways in terms of instrument performance and price. According to some researchers, utilities are the difference between price and utility functions, hence consumers generally tend to upgrade these tools in a selfish way. In such a scenario, the utility function should be half and the optimum point within the practical parameters, such as maximum and minimum power, is also selected, which also depends on the behavior of the other user. The utility function of this type is related to energy efficiency, as it has a physical meaning related to the information it receives successfully and can be calculated with respect to bits per joule of energy cost. To obtain the required SIR in the network all users adjust the transmission power, which is not demarcated clearly in the utility function but relies on the effectiveness of function expectation (Al-Gumaei et al., 2015).

4.1.1 Contributions

In this research work, distinct form the existing algorithms, we assess the power allocation issue pertaining to distributed Cognitive Sensors (CSs) in SWIPT, which include multiple coexisting sensors set at the same frequency band within a communication system. Our main interest lies in a non-cooperative method, since the future distributed multiple cognitive sensors system could be faced with certain implementation challenges, wherein these sensors may fail to cooperate. Thus, autonomous distributed power allocation techniques need to be considered, which are associated with a key benefit of avoiding energy consumption usually seen in centralized policies that need substantial information exchange amongst sensors. In such case, the primary aim would be to ensure a predefined SIR requirement pertaining to targeted sensors, while at the same time, keeping power consumption to minimum for every sensor with effective optimization of transmission power allocation.

The key contributions of this work are stated below:

1. We introduce a utility function that includes a targeted SIR-weighted exponent and the required signal as well as the pricing function that includes a power function pertaining to CSs transmit power. Some of the key features with regards to the put forward energy harvesting scheme are as follows:
    a) It allows conserving the needed QoS pertaining to all CSs' efficiency with considerable decrease in Signal to Noise Ratio.
    b) Practically applied the algorithm in a distributive manner and does not even need additional information.
    c) Considerable reduction as well as power allocation enhancement for all CSs.
    d) Nash Equilibrium Quick convergence.
2. The novelty pertaining to the put forward scheme can describe how energy harvesting time can be selected in order to balance the energy renewal as well as energy consumption in CS.
3. The transmission time pertaining to cognitive users can be segmented into three parts: energy harvesting phase, spectrum sensing phase as well as data transmission phase in order to reply the time switching (TS).
4. The pricing and utility functions are important in order to allow selecting transmitting power efficiency by each CS. It also allows guiding the closest CSs towards the base station so that QoS requirement could be addressed cost-effectively, while it is also easy guiding CSs away from the base station that allows addressing Quality of Service (QoS) prerequisites along with highly expenses in order to reduce collisions.
5. Evaluation is done for the problem pertaining to non-cooperative power control challenge for the existing sensors by taking into account pricing. Also, apart from showing the existence as well as uniqueness of the put forward game model, also Nash Equilibrium is achieved in games of a non-cooperative feature.

6. Instead of mathematical approach of NE, this study provides a new illustration that offers a better understanding to the concept of NE.
7. An iterative power allocation algorithm is developed that allows fast convergence and is associated with low computational complexity. For the EH-NPGP model, this allows determining the Nash equilibrium solutions, which could be initiated from any initial feasible points. The put forward algorithm also guarantees the system's distributed nature.
8. Numerical results support the superiority of the put forward model versus the previous ones. It has been demonstrated that the put forward scheme not only ensures the desired SIR requirement but also allows distributing the minimized power to every cognitive sensor (CS).

4.2 System Model & Problem Formulation

This chapter offers a green transmission pertaining to the next-generation 5G via Wireless Cognitive Sensor Networks (CSN) scenario. Figure 4.1 presents CSN scenario where there is one Primary User (PU) as well as N Cognitive Users (CUs). The wireless link signal represents the SWIPT system that can be segmented into two components: the first one refers to the information while the second one refers to transferring of power since we cannot simultaneously apply radio frequency mutually (Lee & Hong, 2016). The secondary users (cognitive users) possess sensor nodes that can perform spectrum sensing. We have assumed the ability for each cognitive sensor user to harvest energy and is geared with an energy storage device, then denote $N = \{1,2, \dots, N\}$ defining the set of cognitive sensors (CSs).

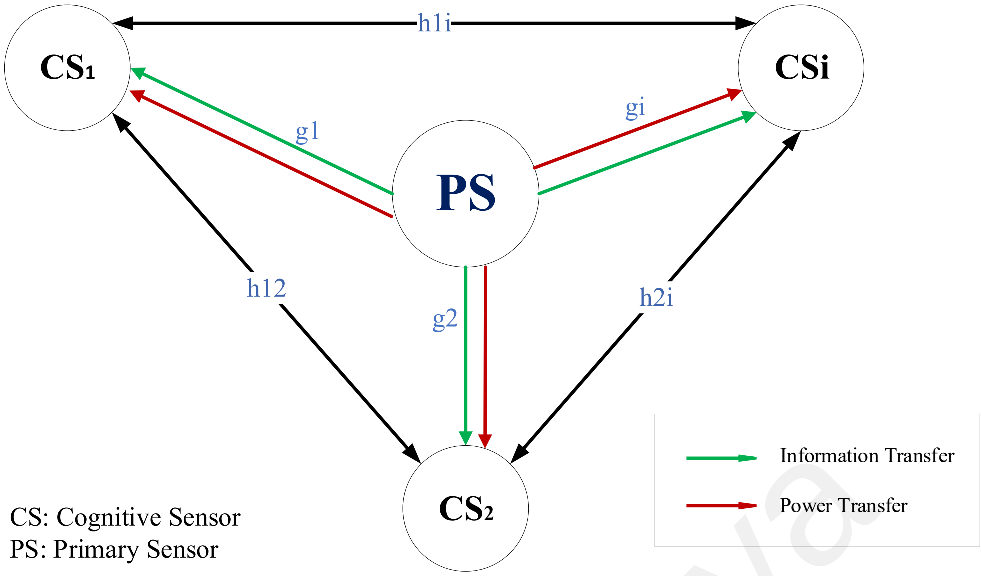

Figure 4.1: System Model

The primary user (PU) operates in the licensed band, while the band is shared with the secondary users (Zhao et al., 2018). Two modes are available for the PU: idle mode and data transmission mode, as presented in Figure 4.2a. It was taken into consideration the total of transmission state period as well as its adjacent idle state duration that can be defined as an analytical interval T since the PU state constantly tends to switch from the transmission mode into the idle mode. We also assume that the PU will not maintain a single state for longer periods of time, i.e. identical to the real state.

Data Transmission	Idle

(a) Primary Sensor

Spectrum Sensing $(1-\alpha)\,T$	Energy Harvesting $\beta\,\alpha\,T$	Data Transmission $(1-\beta)\,\alpha\,T$

(b) Secondary Sensor

Figure 4.2: Stages of i^{th} Cognitive Users in T

When PU is in the data transmission mode, it is considered as a radio frequency (RF) energy provider, while in this mode, the energy can also be harvested by cognitive users (CUs) from the PU. However, during the time T, CU possesses three states: energy harvesting phase, spectrum sensing phase and data transmission phase. Amongst these states, α that is defined as the coefficient of spectrum sensing time is divided by T into non-sensing phase and sensing phase, as presented in Figure 4.2b β can be defined as the fraction of energy harvesting time coefficient. As denoted that first period $(1-\alpha)T$, cognitive sensors in the PU state collect results in a cooperative manner. Thus, in this study, the coefficient α is assumed to be fixed, while the power consumption P_α is considered to be a constant value.

Moreover, in the first duration $(1-\alpha)T$, the PU spectrum usage information is sensed by the cognitive sensors (CSs), thereby allowing collecting sensing results in a cooperative manner. In this study, the coefficient α is assumed to be fixed, while the power consumption P_α is considered to be a constant value. Then, when the PU assumes the transmission mode, energy can be harvested by the cognitive user from the PU, wherein it is regarded that the CS does not possess its own dedicated power supply, completely relies on the radio frequency (RF) energy harvesting and all CSs function in the half-duplex mode. Therefore, these are not able to transmit data as well as harvest energy simultaneously in this duration $\alpha\beta T$. Thus, the harvested energy pertaining to CSi during the duration $\alpha\beta T$ can be represented as:

$$E_i = \eta * \alpha\beta T * P_s * h \tag{4.1}$$

Here, η signifies the energy harvesting efficiency, considering that the energy E_i will be utilized completely for spectrum sensing and the next data transmission. It is considered that the transmission power pertaining to CSi is so small that it allows effective utilization of the harvested energy. During the rest time $(1-\beta_i)\alpha T$, data will be transmitted by CSi to other CSs or PU by employing the harvested energy.

$$\beta_i = \frac{\alpha\, p_i + p_{ses}\,(1-\alpha)}{\alpha\, p_i + \alpha\,\eta\, P_s\, |h|^2} \tag{4.2}$$

During the sensing period $P_\alpha(1-\alpha)T$, the transmission power of CSi can be calculated by determining the energy consumption, which can be represented as:

$$p_i = \frac{E_i - p_{ses}(1-\alpha)T}{\alpha(1-\beta)T}$$

$$= \frac{1}{1-\beta_i} * \left(\eta * \beta_i * P_s * h - \frac{1-\alpha}{\alpha} * p_{ses}\right) \tag{4.3}$$

It is considered that the cognitive sensors have been deployed around the PU, while the interference generated by other cognitive sensors considerably exceeds that from the PU. Therefore, the SIR of a specific cognitive sensor is measured via the effect of transmission power p_i as well as energy harvest factor β_i pertaining to other CSs. Thus, the SIR pertaining to the ith CS can be expressed as:

$$\gamma_i(p_i) = \frac{p_i h_i}{\sum_{j\neq i}^{N} p_i h_j + \sigma_i^2} \geq \quad \Gamma_i \quad {}_{,i=1,2,,3,\ldots,n} \tag{4.4}$$

Here, h represents the channel gain amongst cognitive sensors, and p_i signifies the transmitted power pertaining to cognitive sensor CSi, j based on Equation (4.3). In addition, the SIR is associated with the energy harvesting coefficient vector β_i based on Equation (4.2). Γ_i signifies the threshold SIR, while σ_i^2 denotes the Gaussian noise power.

By introducing pricing functions and dissimilar utility, various works focused on the issue of power control. (Saraydar et al., 2002) put forward the utility function as:

$$\text{NPNG}: \ U_i^c(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i}(1 - e^{-\gamma_i/2})^M - C_1 p_i \tag{4.5}$$

Here, C_1 represents the positive pricing factor. With regards to Equation (4.5), (X. D. Zhang et al., 2012) employed the same utility function as (Saraydar et al., 2002). They put forward a new pricing function in which establishing of the non-cooperative power control game (NPG) is done by employing the modified Shuffled Frog Leaping Algorithm (MSFLA), as shown below:

$$\text{NPG} - \text{MSFLA}: \ U_i^c(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i}(1 - e^{-\gamma_i/2})^M - C_2\, e^{p_i} - C_3(\gamma_i - \Gamma_i) \tag{4.6}$$

Here, positive pricing factors are representing in C_2 and C_3. However, the efficiency function that was employed by (X. D. Zhang et al., 2012; Saraydar et al., 2002) is the same applied to non-coherent (FSK) scheme. So, can be represented efficiency function as below:

$$f_1(\gamma_i) = (1 - e^{-\gamma_i/2})^M \tag{4.7}$$

Based on the sigmoid function (Kuo et al., 2013), put forward a utility function as well as proposed a newly designed pricing function, in which establishing the non-cooperative power game with pricing (NPGP) by employing the efficient swarm intelligent algorithm (ESIA) as shown below:

$$\text{NPGP} - \text{ESIA}: \ U_i^c(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i}\frac{1 + e^{-\gamma_i}}{1 + e^{\Gamma_i - \gamma_i}} - \alpha e^{\beta((\gamma_i/\Gamma_i)-1)}\frac{p_i}{p^{th}} \tag{4.8}$$

Here, positive pricing factors are represented in α and β, p^{th} represents the average interference power that could be measured via mean value of p_i^{th} : $p^{th} = (p_1^{th} + p_2^{th} + \cdots + p_i^{th})/N$, while the sigmoid efficiency can be represented as:

$$f_2(\gamma_i) = \frac{1 - e^{-\gamma_i}}{1 + e^{\Gamma_i - \gamma_i}} \tag{4.9}$$

With regards to the fair power control game, (Xie et al., 2014) put forward the utility function by considering the simplified sigmoid function as utilized in (Kuo et al., 2013), a new non-linear pricing function is introduced by establishing NPGP employing a sliding model which is known as R-NPGP:

$$R - NPGP : \ U_i^c(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i} \frac{1}{1 + e^{\Gamma_i - \gamma_i}} - \mu\lambda_i \frac{p_i}{p^{th}} \tag{4.10}$$

Here, λ_i denotes another pricing factor, also μ represents a positive pricing factor that changes with CRs with regards to their generated conditions, while the efficiency function can be represented:

$$f_3(\gamma_i) = \frac{1}{1 + e^{\Gamma_i - \gamma_i}} \tag{4.11}$$

With regards to (Saraydar et al., 2002), an energy efficient Game-Pricing model (EF-NPGP) was put forward by (Al-Gumaei et al., 2015) as shown below:

$$EF - NPGP : \max_{pi \in Pi} U_i^C(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i} \exp\left(-\left(\frac{a\Gamma_i}{\gamma_i}\right)^b\right) - cp_i^\alpha \tag{4.12}$$

Here, a and b symbolise non-negative weighting factors, while c and α represent the pricing factors. The expression of sigmoid efficiency function can be done as a ratio of target SIR, while the required signal can be expressed as:

$$f_4(\gamma_i) = \exp\left(-\left(\frac{a\ \Gamma_i}{\gamma_i}\right)^b\right) \tag{4.13}$$

However, with regards to a new function of sigmoidal efficiency we put forward novel utility function as well as a power function pertaining to transmit function of user's power pricing. Also, sigmoid efficiency has been introduced as a fraction along with exponential ratio power multiply tuning factor (z) with all power to allow targeting SIR as represented below:

$$f_5(\gamma_i) = \frac{1}{(1 + exp\ (1 - z\ sir_i))^{\Gamma_i}} \tag{4.14}$$

Where z is the tuning factor where its change will change the response of the efficiency function proposed, with this ability in controlling response the proposed function will be more efficient than others which is compared with as shown in Figure 4.3. Hence, we called it an optimum function because of we could use it to control efficiency response as well controlling the utility function value. However, using of our proposed sigmoidal function will be more efficient than others because it will be easier and more efficient to deal with one equation to control the response of the efficiency function than using more equations. With regards to Equation (4.16), the utility function pertaining to the i^{th} CS can be expressed as:

$$U_i = \frac{LR}{M(p_i + pses)} \frac{1}{(1 + exp\ (1 - z\ sir_i))^{\Gamma_i}} \ \frac{bit}{joule} \tag{4.15}$$

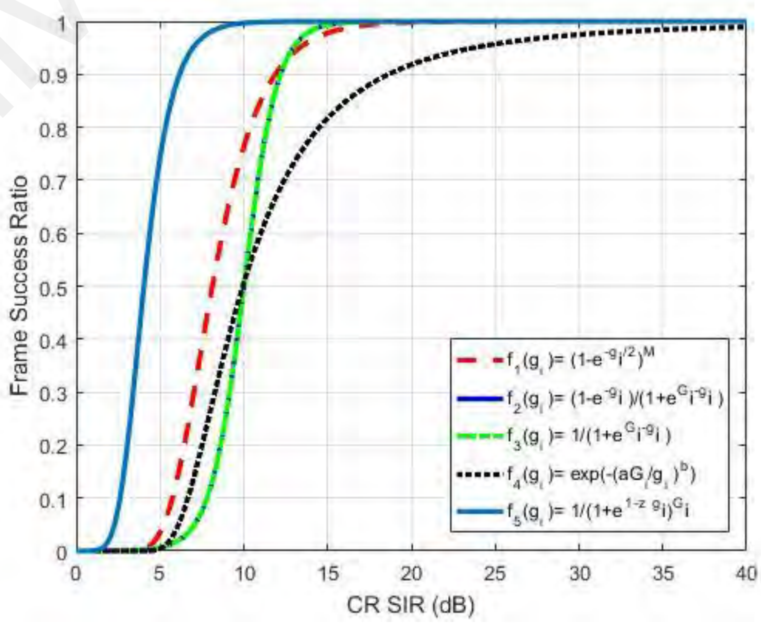

Figure 4.3: Efficiency Function Comparison

The utility function pertaining to Equation (4.15) signifies the trade-off between the throughput as well as battery life. Especially, it is suitable for applications in which it is crucial to save power rather than attaining a high throughput like green CR (Meshkati et al., 2006). At cognitive radio system, we consider a fixed value of target SIR. Tuning of the put forward utility function can be done by employing the tuning factor (z). Based on the utility function maxima, optimal transmit power of the user can be varied. Figure 4.4 presents how the put forward utility can be made more efficient by tuning factor versus others in the literature. The value of the parameter z is decreased and results in increase in utility and decrease in the transmitting power, but this also results in decrease in target of SIR pertaining to the system. Also, primary system can transmit the tuning factor z with the help of cognitive networks for adjusting the targeted SIR based on interference. When the sum of interference is about to reach the limit of interference temperature, a lower value of z is sent by the primary system.

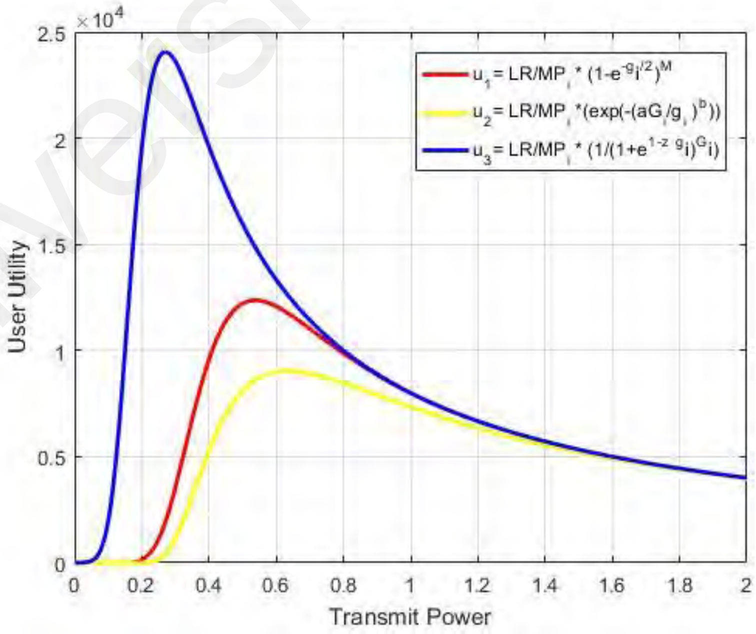

Figure 4.4: Proposed Utility u3 as Compared to u1(Goodman & Mandayam, 2000) and u2 *(Al-Gumaei et al., 2015)*

4.2.1 Game Theoretic Framework Formulation

The game theory basically includes three key components that can be numerically denoted as $G = [M, A, U]$, where $M = \{1,2, \dots, M\}$ signifies the finite of decision makers, $A = A_1 \times A_2 \times \dots \times A_M$ characterise the space of action that is accessible to every CSs and $U: A \rightarrow R$ denotes the utility function. Thus, the description pertaining to non-cooperative energy harvest game model could be given as follows:

Definition: The non-cooperative power energy harvest game problem pertaining to CSNs defined as EH-NPGP can be represented as $\mathrm{EH-NPGP} = [N, \{P_i\}, \{U_i(.)\}]$, where $\mathrm{N} =$ represents players set CSs, P_i^{max} characterises the maximum transmission power of users *i* and $P_i = [0, P_i^{max}]$ denotes the transmissions power strategy set of users i. Utility function pertaining to user i can be signified as $U_i(.)$, wherein every network user looks for ways to increase its own utility in a selfish way, which is selected to guarantee good QoS for CSs. Mathematically, User-related utility functions is represented by the number of received in terms of per joule of the energy consumption (Goodman & Mandayam, 2000):

$$U_i(p_i, \boldsymbol{p}_{-i}) = \frac{LRf(\gamma_i)}{Mp_i} \tag{4.16}$$

Here, transmitters send information to receivers in CR networks and wireless data in a frames or packets of length M bits, which include $L < M$ information bits in the form of a data rate with R (bits/sec), wherein $f(\gamma)$ denoted the efficiency function. Furthermore, $f(\gamma)$ needs to rely on the achieved SIR over the channel, whose value could range from (0-1) (i.e. $f(\gamma) \in [0,1]$). Moreover, power p_i denotes the transmitted power by the user i.

Thus, the put forward energy harvest pertaining to the game with pricing can be represented as:

$$EH - NPGP : \max_{pi \in Pi} U_i^C(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{M(p_i + pses)} \frac{1}{(1 + exp(1 - z\, sir_i))^{r_i}} - c\, p_i\, exp(p_i\, \alpha) \quad (4.17)$$

Where c and α are the pricing factors.

4.2.2 Pricing Function: Setting and Formulation

With regards to self-organized network like CSN, users could behave in a selfish manner with the intention to maximize their own objective function, which can be achieved by increasing their own power. Pricing mechanism is a popular technique employed in order to manage the selfishness in CSNs. The results of Nash Equilibrium due to power control of non-cooperative is deemed ineffective since it overlooks the cost imposed on other terminals via the generated interfering signals. Thus, the pricing concept is introduced to motivate users regarding effective utilization of the network resource. General expressions related to NPGP can be stated as below:

$$\Phi^c = [N, \{P_i\}, \{U_i^c(.)\}] \quad (4.18)$$

Here, $U_i^c(.)$ represents the utility function based on pricing, which could be expressed as:

$$U_i^c(p_i, \boldsymbol{p}_{-i}) = U_i(p_i, \boldsymbol{p}_{-1}) - C_i(p_i, \boldsymbol{p}_{-1}) \quad (4.19)$$

Subsequently, this article employs the pricing technique in order to encourage cognitive sensors to efficiently utilize network resources like power and punish users that produce higher interference to PUs or behave in a selfish manner. Moreover, the pricing function could be described as follows:

Definition: The pricing function-based non-cooperative power game can be defined by EH-NPGP, which also represents the level of punishment for a player who produces certain amount of interference to PUs. Mathematically, the put forward pricing function can be given as:

$$C_i(p_i, \boldsymbol{p_{-i}}) = c\, p_i\, exp(p_i\, \alpha) \tag{4.20}$$

Thus, modelling of the utility function with pricing could be done as:

$$U_i^C(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{M(p_i + pses)} \frac{1}{(1 + exp\,(1 - z\, sir_i))^{r_i}} - c\;\, p_i\, exp(p_i\, \alpha) \tag{4.21}$$

Here, $(U_i^C(p_i, \boldsymbol{p}_{-i}))$ defines the net utility function or the surplus function pertaining to every CSs, which could be described by the gap exists among the payment function and its utility function.

Proposed design contributes towards applying for the farther users a higher cost that employ high power like those who are farthest from the base station. Thus, an exponential power function pertaining to the power transmission that has been introduced in place of the classical linear pricing. Figure 4.5 demonstrates an instance defining an existing gap among the linear and the power pricing features. So, it’s considered that the power transmitted by the user differs between the maximum and minimum power strategy [0,1], while numerical computation is applied to the price functions. It has been demonstrated that there is a lower power function pricing versus the linear function pricing pertaining to CSs who employ low transmitting power for those the closest distance, while a high pricing cost will be associated with the CSs who employ high transmitting power for the farthest distance.

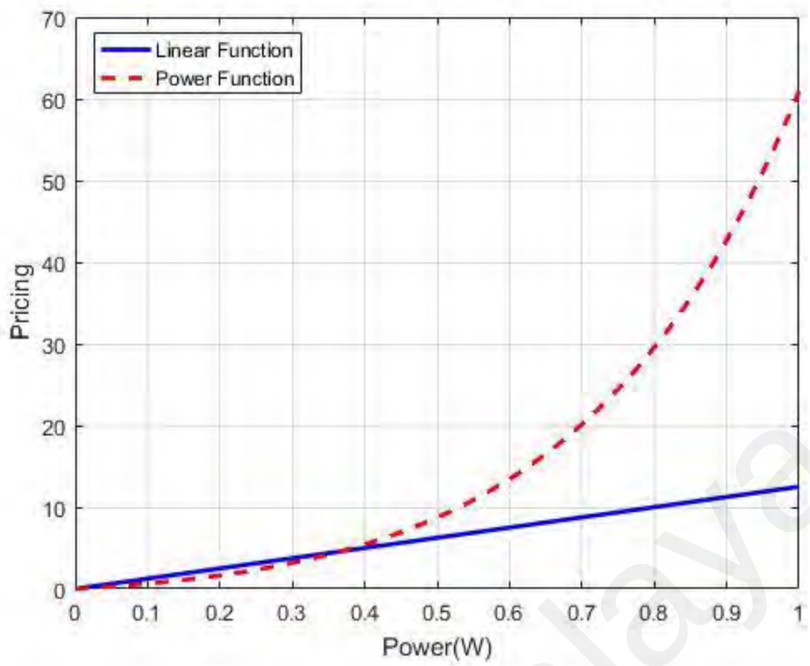

Figure 4.5: Comparing Linear and Power Function Pricing

4.3 Nash Equilibrium in EH-NPGP

This section provides a mathematical description associated with the existence as well as uniqueness pertaining to NE (J. O. Neel ., 2004):

Definition 3.1: In EH-NPGP, describing Nash Equilibrium as a power vector, e.g. $P_i = [p_i, \dots, p_i]$, wherein none of the player can enhance its utility function, $U_i(p_i, p_{-i})$; by modifying its own strategy profile unilaterally, i.e.., p_i. Numerically, the Nash Equilibrium could be represented as:

$$U_i(p_i, \boldsymbol{p}_{-i}) \geq U_j(p_i, \boldsymbol{p}_{-i}), \qquad \forall\, p_i \in \widehat{P}_{i,} \quad \forall\, i \in N \tag{4.22}$$

4.3.1 NE Existence

The Nash Equilibrium pertaining to EH-NPGP provides a predictable, stable result for a game in which there are several CSs possessing conflicting interests and then reaches a point wherein there are no requests by the CS player to modify its own strategy profile. The following theorem needs to be presented in order to validate the existence of the NE:

Theorem 3.1 (B. B. Wang et al., 2010) (Abdul-Ghafoor et al., 2013)**:** The Nash Equilibrium is considered to exist in EH-NPGP= $[N, \{P_i\}, \{U_i(.)\}]$, if the following conditions $\forall\ i \in N$ are satisfied:

The action strategy profile (i.e. p_i) is deemed as a nonempty, compact and convex subset.

The utility function $U_i(p_i, \boldsymbol{p}_{-i})$ is deemed as a concave and continuous function over the players' strategy set.

Proof: This could be accomplished by meeting both conditions that are provided in **Theorem 3.1** in EH-NPGP by demonstrating the following evidence:

The first condition is readily satisfied since every CS user possesses a strategy profile defined by the minimum power as well as maximum power as expressed in Equation (4.15).

In order to confirm the second condition is satisfied as well, it needs to be proved for a provided price-based utility function is concave in p_i,$\forall\ i \in N$.

Definition 3.2: According to (Saraydar et al., 2002) Super Modular ***definition 5***, The utility function $U_i(p_i, \boldsymbol{p}_{-i})$ characterised by the convex set $\widehat{\boldsymbol{P}_i}$ is concave in P_i only in case the surplus function's second derivative is greater than 0 (Pang et al., 2010; Saraydar et al., 2002).

To show this condition is true, the following set of equations: $\frac{\partial^2 u_i^p}{\partial^2 p_i^c} > 0$, must be solved $\forall\ i$. Thus, the Lemma needs to be satisfied in the following.

Lemma 3.1: The priced-based utility function that is provided in Equation (4.22) is deemed concave in p_i,$\forall\, i \in N$.

Assuming that the two conditions mentioned in **Theorem 3.1** have been met, then EH-NPGP is deemed concave in-player game, which requires one NE built into game.

4.3.2 NE Uniqueness

With regards to the strategy profile of the players, the put forward utility function is continuous and concave. Thus, NE was found to exist in EH-NPGP. However, at this point, a question may arise regarding the uniqueness of the existing NE? The uniqueness pertaining to the NE can be tested as:

Definition 3.3: The best response strategy pertains to NE's alternative definition that can be described as:

$$BR(\boldsymbol{p}_{-i}) = \{p_i^c \ \in \hat{P}_i : u_i^c(p_i^c, \boldsymbol{p}_{-i}^c) \geq u_i^c(\vec{p}_i^c, \boldsymbol{p}_{-i}^c), \qquad \forall\, \vec{p}_i^c \in \hat{P}_i\} \tag{4.23}$$

Furthermore, the best response strategy can be defined as a set that includes just one ideal point that allow maximizing the targeted function, which is computationally defined as:

$$p_{i= arg \max_{p_i \in P_i} U_i^c(p_i, \boldsymbol{p}_{-i}))} \tag{4.24}$$

Moreover, it was shown that the second derivative is greater than zero, which suggests that the maximum point can be deemed as the optimal unique point.

Theorem 3.2: The NE is unique for the non-cooperative game EH-NPGP = $[N, \{P_i\}, \{U_i(.)\}]$.

Proof: The main feature pertaining to NE's uniqueness is aimed at showing that the best response function can be regarded as a standard function. For the put forward game

EH-NPGP = $[N, \{P_i\}, \{U_i(.)\}]$, the best response pertaining to the i^{th} user is given by the power strategy pertaining to others.

In order to prove that NE is distinctive, a standard function should be existing as the best response function as well as the subsequent properties also need to be confirmed (Yates, 1995):

i. For Positivity: $BR(\boldsymbol{p}_{-i}) > 0$.
ii. For Monotonicity: $\boldsymbol{p} \geq \widehat{\boldsymbol{p}}$, and then $BR(\boldsymbol{p}_{-i}) \geq BR(\widetilde{\boldsymbol{p}}_{-i})$.
iii. For Scalability: $\varepsilon > 1$ for all, and then $\varepsilon BR(\boldsymbol{p}_{-i}) > BR(\varepsilon \boldsymbol{p}_{-i})$.

Through the power strategy space provided in Equation (4.15) as well as by **Theorem 3.1,** the first two characteristics can be verified with ease. Thus, the scalability characteristic was found to be satisfactory.

In conclusion, the best response strategy function was found to be a standard. Thus, non-cooperative power control model was put forward to include just one unique Nash Equilibrium solution, which also proves the distinctiveness of the Nash Equilibrium.

4.4 EH-NPGP Algorithm

This section presents an iterative based best response algorithm scheme that control all transmission powers and guarantees the required SIR among all CSNs. Also, it ensures Nash equilibrium opportunistically with available SIR information.

However, we suppose that each CSN updates it's transmit power at time instances $t_i = \{t_{i1}, t_{i2}, \ldots.\}$, where $t_{ik} < t_{i(k+1)}$, and as an assumption that the strategy set of power of the ith CSN is $P_i = [P_i^{min}, P_i^{max}]$. We set an infinity small quantity ε where ($\varepsilon > 0$) and by considering the proposed algorithm as given Equation (4.17) generates powers sequence as follows:

EH-NPGP

I. Initialize vector of transmit power $p = [p_1^0, p_2^0, p_3^0, \dots, p_N^0]$ randomly at time t_0, besides other parameters including: σ^2, P_i^{max}, Γ_i, Pricing factors, c & α and Tuning factor, z.

II. Iteration Step:

For all $i \in N$ when time instant t_k;

a) Update $\beta_i(t_k)$ By Equation (4.2)
b) Update $p_i(t_k)$ By Equation (4.3)
c) Update $\gamma_i(t_k)$ By Equation (4.4)
d) Given $p_i(t_{k-1})$, consider the best response of power strategy $r_i(t_k)$ from BR algorithm based on $r_i(t_k) = arg \max_{p_i \in P_i} u_i^C\ (p_i, \boldsymbol{p}_{-\boldsymbol{i}}(t_{k-1}))$
e) Assign the transmit power as $p_i(t_k) = \min\ (r_i(t_k), p_i^{max})$

III. Convergence Step:

If $\|p(t_k) - p(t_{k-1})\| \le \varepsilon$, declare Nash equilibrium and stop iteration as $p(t_k)$; otherwise: $k = k + 1$ & go to step II

IV. End

In which $r_i(t_k)$ is used as the representative of the collection of the best transmit powers that correspond to the ith CSN. This can be obtained when the objective function is applied with BR algorithm during time instant k. This is performed as a response to the interference vector $p_{-i}(t_{k-1})$. One should remember that the ith CSN is responsible for the optimisation of the net utility given the power strategy space for the EH-NPGP. The algorithm that was formulated can be used to determine the ith CSN's transmit power by choosing the less values of power given all the possibilities, which is set by the algorithm. The algorithm can then be used to separately solve the maximum for every CSNs objective. Figure 4.6 illustrates the flowchart of the proposed algorithm:

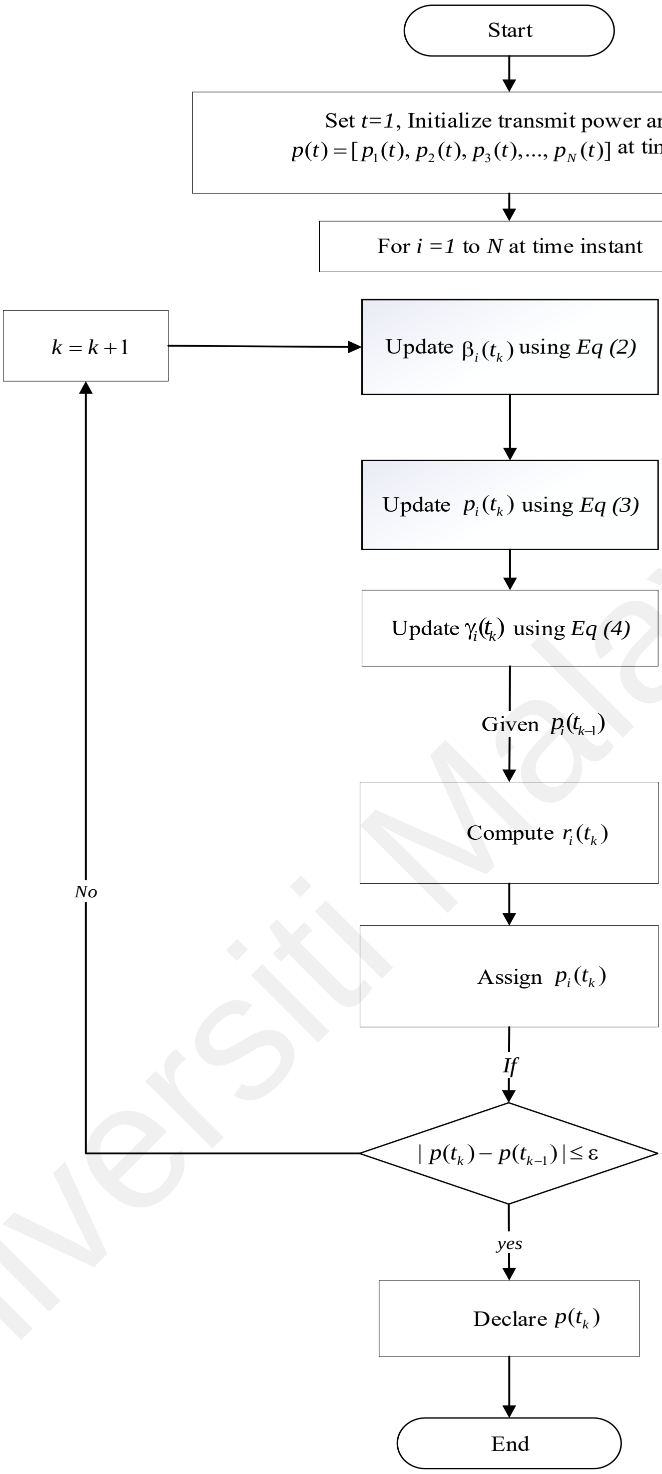

Figure 4.6: Proposed Algorithm Illustration

4.5 Results & Discussion

Defining in this section CSN scenario and simulations setting. Moreover, it has also verified the NE convergence for both SIR and power. Moreover, there is a similarity of the suggested power algorithm with the algorithm given in NPG-MSFLIA (X. D. Zhang et al., 2012), R-NPGP (Xie et al., 2014), NPG-ESIA (Kuo et al., 2013), and EH-NPGP

(Al-Gumaei et al., 2015) as a way of showing the superiority of the suggested power algorithm.

Furthermore, the utility functions utilized during the comparisons are presented in Equations (4.6), (4.8), (4.10) and (4.12). In order to attain the utility functions' Nash Equilibrium solution as a way to introduce the benefits of the proposed utility function, same numerical computation was implemented. Table 4.1 lists down constant system parameters utilized in simulation.

Table 4.1: System Parameters

Parameter	**Value**
Players Number	7
M	80
L	64
G	70
R	10 kbps
σ^2	4e-8 Watts
Maximum power constraint, P_i^{max}	1 Watts
$Pses$	10e-2 Watt
Efficiency η	0.5
Target SIR, r_i	10
Pricing factors, c & α	1e4, 2.5
Tuning factor, z	0.9

As experimented, there are no more than 7 CSs in the structure, also the distance from the base station presented as $d = [368, 490, 580, 630, 720, 810, 950]\ m$.

A simple propagation model utilized in this study that uses path gains as deterministic functions, β is represent path loss exponent. The formula below can then be used to compute the cognitive base station (CBS) given the distance between the cognitive users i:

$$h_i = \frac{K}{d_i^{\beta}} \tag{4.25}$$

In this formula, d_i represents the gap between the base station and ith user, β represents the path loss exponent that normally has a value of 2 which is usually between (2&6), while K is a constant which is equal to (0.097), the chosen of this value is to set a transmit power of 1W when a CSN works at 950m from CBS in a system that has 7 CSs which all work with γ^*. For the simulation of this study, the sensor users begin with initial power $p_i^{(0)} = 2.22 * 10^{-11}\ w$ for all algorithms and $\varepsilon = 10^{-5}$.

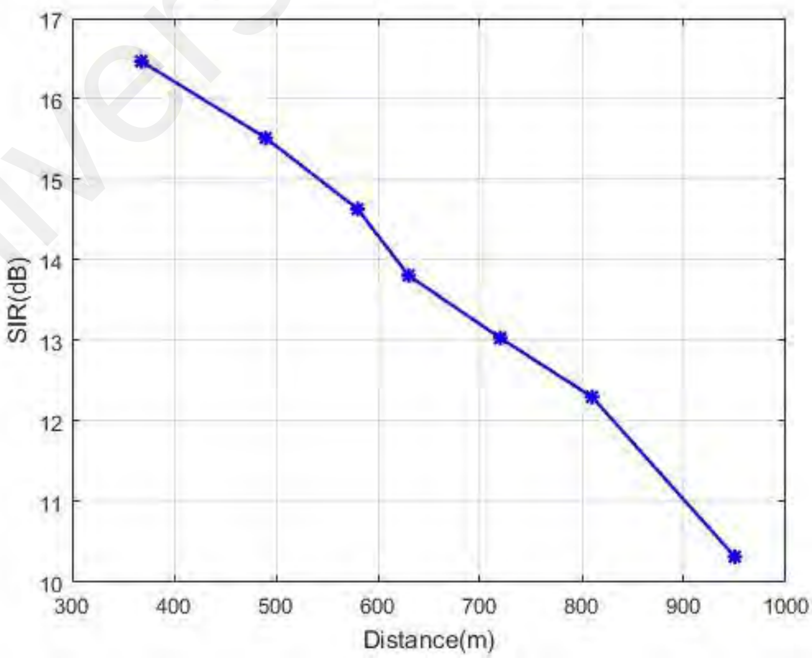

Figure 4.7: SIR Vs. Distance for Each User

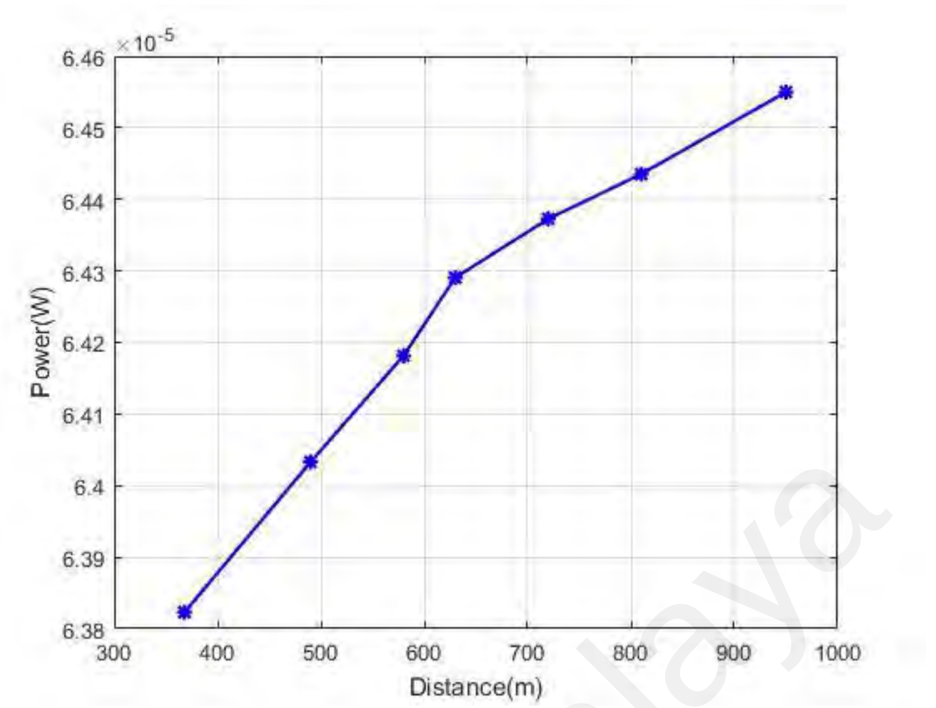

Figure 4.8: Power Vs. Distance for Each User

Figure 4.7 illustrates the findings of SIR at Nash Equilibrium. These results were obtained by CS based on the gap among each base station and CS. All CS users keep the value of their SIR higher than the target value ($\Gamma_i = 10$). One can decrease the SIR value by lengthening the gap for all algorithms. Among all algorithms, the differences values of SIR revealed that the proposed algorithm EH-NPGP has more efficiency where the SIR values are highest compared to the compared algorithms. The outmost CSs have highest power consumption and they are representative of the origin of interference. The proposed algorithm is designed and implemented to charge farthest sensors higher cost. Figure 4.8 demonstrates the curves power transmitted in Watts with distance between base station and the CS for all algorithms. In such cases, power transmission experiences a gradual increase when the distance of the user is increased. One may observe that the suggested EH-NPGP has the lowest power transmission curve compared to the compared algorithms in literature which are; NPG-MSFLIA, R-NPGP, NPGP-ESIA, and EF-NPGP.

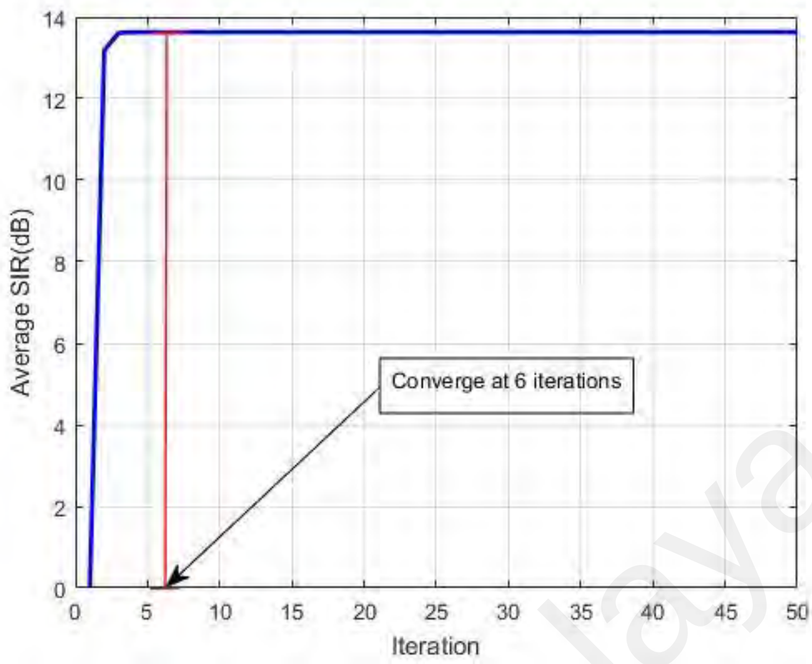

Figure 4.9: Proposed Algorithm Convergence of Average SIR

SIR of CSN users of the network algorithm simulation is shown in Table 4.2. Further, demonstrating in the table the EH-NPGP with proposed price function achieving high SIR value as compared to other algorithms compare with. Seen in the last two cognitive sensors SIR is smaller because of applied higher cost. So, achieving a better equilibrium it can be.

Table 4.2: CSN Final SIR

Users	Final SIR of NPG-MSFLIA (X. D. Zhang et al., 2012)	Final SIR of NPG-ESIA (Kuo et al., 2013)	Final SIR of R-NPGP (Xie et al., 2014)	Final SIR of EF-NPGP (Al-Gumaei et al., 2015)	Final SIR of Proposed EH-NPGP
1	12.41	12.42	12.42	12.69	16.47
2	12.4	12.43	12.43	12.69	15.51
3	12.4	12.43	12.43	12.69	14.63
4	12.39	12.43	12.43	12.69	13.80
5	12.37	12.42	12.42	12.68	13.03
6	12.33	12.4	12.4	12.66	12.30
7	12.26	12.3	12.3	12.4	10.31

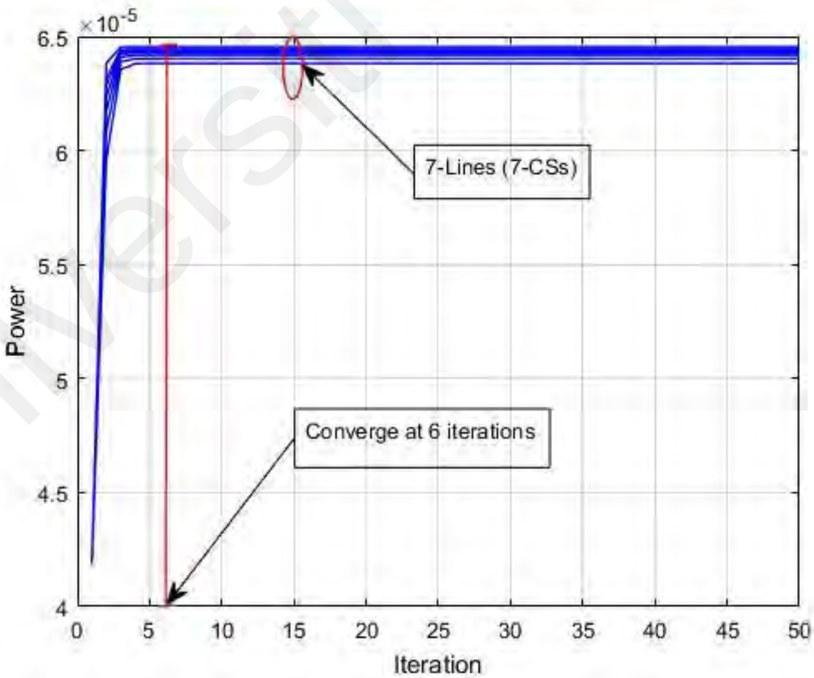

Figure 4.10: Convergence of the Proposed Power Algorithm

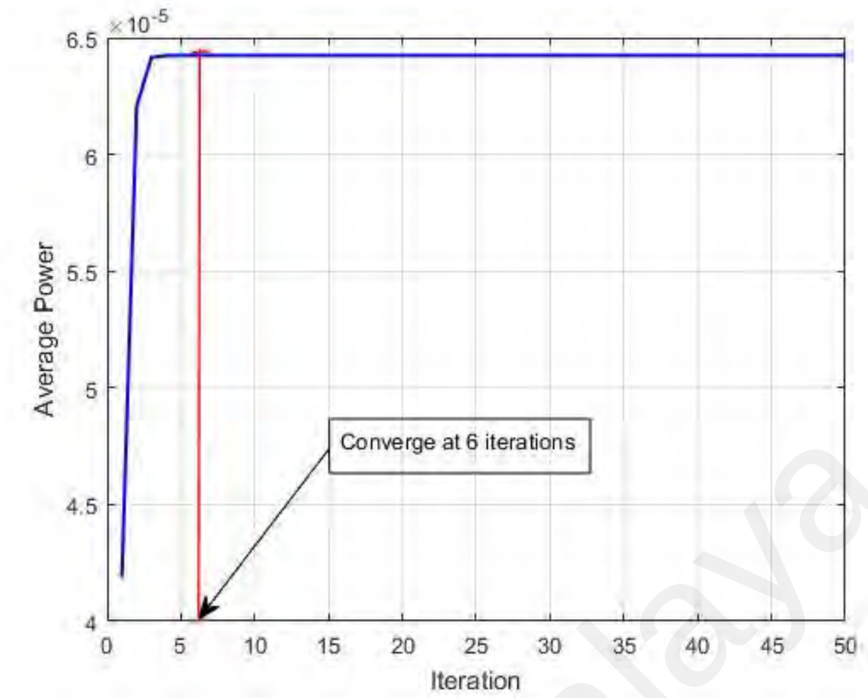

Figure 4.11: Convergence of Average Power in the Proposed Algorithm

However, Figure 4.10 has demonstrated the proposed algorithm convergence. Figure 4.10 has therefore proven that the allocated power in the network with 7 cognitive sensors performs better since it has faster convergence. It only needs (6) iterations to converge, compared with (333, 323, 360 & 133) for NPG-MSFLA, R-NPGP, NPGP-ESIA, and EF-NPGP, respectively. Moreover, average SIR and average power were tested and compared with the method of algorithms comparison to determine the reduction of average power and the convergence speed of algorithms. In this test, the iteration time needed to obtain the Nash Equilibrium is represented by horizontal axis while the average power and average SIR are represented by the vertical axis. Table 4.2 demonstrates that all algorithms were able to achieve approximately the same average SIR value without any considerable differences. However, they have unequal speeds of convergence. The algorithm proposed in this study was determined to be able to obtain the Nash Equilibrium after 6 iterations. This is illustrated in Figure 4.9. On the other hand, NPG-MSFLA, NPGP-ESIA, R-NPGP and EF-NPGP need 333, 360, 323 and 133 iterations, respectively. Figure 4.11 demonstrates the average transmit power curve obtained by the suggested algorithm. Figure 4.11 demonstrates that the suggested EH-NPGP algorithm has significantly reduced average power consumption compared with other algorithms. This is necessary in building promising 5G wireless networks. The study was able to successfully lower the transmitted power from Watt to micro-Watt, as illustrated in Figure 4.11. The outcomes presented in Figure 4.11 are indicators of the amount of interference that is observed at primary system based on the proposed EH-NPGP, given that it is the lowest compared to all the compared algorithms in the literature. Thus, the proposed EH-NPGP algorithm characteristic of renders it the best option for the maximization of QoS guarantees and spectrum sharing in both systems. Figure 4.11 demonstrating clearly the speed convergence of the suggested algorithm, which indicates that the suggested EH-NPGP is faster as compared with other algorithms, as observed in Table 4.3. This can also be attributed to the values of average power in Watt and the numbers of repetitions for all algorithms in comparison to algorithms in the literature.

Table 4.3: Comparison of Average Power and NE Convergence

Algorithm	Average Power (W)	Iterations
NPG-MSFLA (X. D. Zhang et al., 2012)	0.2321	333
NPGP-ESIA (Kuo et al., 2013)	0.2319	360
R-NPGP (Xie et al., 2014)	0.2287	323
EF-NPGP (Al-Gumaei et al., 2015)	0.1926	133
EH-NPGP	6.4241e-05	6

4.6 Summary

This study determined the best way to use the energy harvest time for maximizing the radio frequency energy efficiency. The study proposed a novel EH-NPGP algorithm that is built on non-cooperative game pricing theory. The suggested algorithm has a convergence that has been verified by simulation. There is also mathematical proof for the presence and distinctiveness of the NE. One of the most apparent benefits of the suggested energy harvesting algorithm is its ability to quickly converge to the NE compared to previous works. The suggested algorithm is therefore more appropriate for a functional distribution application. Furthermore, pricing is a vital component of CSNs for avoiding cheating behavior among players. Thus, one can achieve better performance for both primary and secondary CSN users. Furthermore, for the future work we recommended the researchers to consider proposed algorithm and mathematical model for another scenarios and techniques to get more enhance system and harvest more energy to achieve the green scenario for wireless networks in the nearest future 5G and beyond.

CHAPTER 5: IOT EFFICIENT POWER CONTROL IN COGNITIVE RADIO UAV SCENARIO: A GAME THEORETICAL PERSPECTIVE

5.1 Introduction

Rapid advancement in mobile internet has also brought in serious challenges pertaining to the design of mobile wireless networks, particularly when offering ultra-high data rate as well as very low time delay. As per a recent International Telecommunication Union (ITU) report, there will be an increase by 10000 times in wireless data traffic by 2020 compared to 2010 (Mukhlif et al., 2018b). The ultra-dense network (UDN) technique is regarded suitable to meet the needs pertaining to explosive data traffic (Bhushan et al., 2014). With the help of flexible deployment as well as deployment of massive small cell base stations (SBSs) with low transmit power, the network coverage can be broadened effectively as well as the overall throughput can be improved (Kamel et al., 2016). Majority of the current studies on UDNs concentrate on performance enhancement of terrestrial heterogeneous cellular networks by managing different parameters such as the coexistence of resource allocation, energy efficient frequency reuse in heterogeneous small cell networks, Wi-Fi and heterogeneous ultra-dense scenarios user association, amongst others (Samarakoon et al., 2016; Su et al., 2016).

Furthermore, UAV communications as well as networking have gained much popularity recently because of their high agility as well as their use in many applications. When UAVs are introduced into UDNs, significant gains can be achieved by completely exploiting their potential (Zeng et al., 2016). Rapid deployment of UAVs to serve wireless users can be achieved without being impacted by geographical constraints compared to the traditional terrestrial infrastructure. It could also be used as flying base stations (BSs) to improve wireless coverage as well as enhance throughput at hotspots like sport stadium and campuses or in areas that do not have cellular infrastructure. They could also behave as flying relays in regions where the separated users do not possess reliable direct communication links. Thus, UAVs can be incorporated to achieve efficient relocation with regards to user's mobility. Almost line of sight (LOS) communication links can be established in most situations by adjusting the locations of UAVs dynamically. Thus, this allows considerable improvement in the performance of the system. Therefore, UAVs could also carry an energy source or at times act as an energy source for charging wireless nodes in order to extend the network lifetime. Some of the usual applications are internet of things (IoT) and wireless sensor networks, wherein wired charging is not available (H. C. Wang et al., 2018).

In tandem, The Internet of Things plays a leading role in wireless networks as well as in the next generation of mobile communications and now works in a variety of everyday life services. With recent advances in IoT implementation, transmit data has become more intense and the volume of information interchange has increased significantly. Hence, it is necessary to equip communication technologies with higher bandwidth, higher speeds, less arrival times and less energy consumption to ensure successful implementation of the internet (Majeed et al., 2018). However, applications and developments of IoT technologies need to also handle unprecedented as well as severe challenges due wireless devices energy limitation. An urgent issue is how to implement sustainable energy to smart devices connected in IoT, which is the main hindrance in IoT development. Thus, wireless power transfer (WPT) technology is considered for sustainable energy supply to be an appropriate solution to provide sustainable energy and can efficiently resolve the bottleneck associated with the limited energy issue in IoT (Hui et al., 2014). More wireless devices in the nearest future will be used WPT technology to reduce immoderate dependency on batteries. Further, wireless power transfer is widely used in smart wireless, implanted medical, smart homes devices and electric vehicle etc. UAV allows dynamic movement of the IoT devices, data gathering, transmitting services and also powering IoT devices in comparison to conventional wireless networks (Lien et al., 2011; Z. Zhang et al., 2019). The UAV assisted WPT are not only improving the performance of IoT-UDNs by dynamically adjusting the power source, high UAV navigation in the proposed scenario can provide comprehensive power for wireless devices in large distribution areas faster and more flexible (B. Liu et al., 2019; Mukhlif et al., 2018a).

5.1.1 Contributions

In this research work, the UAV assisted IoT wireless powered that has been studied and the resource allocation of IoT system has been solved. With regards to the non-cooperative game theory, the issue of resource allocation between UAV nodes and wireless IoT is investigated. In this proposed system, the IoT nodes harvest energy from hovering drones. Drones act as a floating power source to supply wireless nodes using wireless power transmission. Game theory based on the proposed model for the problem of resource allocation between drones and wireless nodes is presented and Nash equilibrium is obtained for the proposed model based on the game theory approach. By accounting for the Nash Equilibrium, optimal allocation is made by UAV based on its energy sources to facilitate the transmission of wireless power. Key contributions of this research are summarized below:

1. IoT wireless power is provided with the help of UAVs including one UAV and wireless node density. IoT nodes attempt to harvest wireless energy from drones based on wireless power transmission technology. The harvested energy is employed by wireless nodes to transmit information.
2. The resource allocation issue existing between wireless nodes and UAV could be formulated in terms of a non-cooperative power control game. In the proposed game, the drone controls its source perfectly for energy transfer and the wireless node controls its source perfectly for transmitting information.
3. For the coexisting ultra IoT ground sensors, assessment of the issue pertaining to non-cooperative power control game theoretic is done.

4. Obtaining of the Nash Equilibrium with regards to the non-cooperative power control game is done. Also, the existence, as well as uniqueness pertaining to the put forward game to its Nash, has been established.
5. An iterative power control algorithm is developed that fits well with the UAV scenario as well as its trajectories.
6. The simulation results support the superiority pertaining to the put forward algorithm.

5.2 System Model and Game Theoretic Formulation

UAVs offer unparalleled benefits because of their inherent mobility compared to the conventional terrestrial infrastructures which are in fixed location. With UAV support it will bring major changes and development to UDNs. Figure 5.1 demonstrates the support provided by UAV in energy transfer when it functions as mobile energy sources. Moreover, in order to charge wireless nodes for extended lifetime of the network, UAVs could carry an energy source or at times become that source of energy. Some of the common applications are wireless IoT and sensor networks, when wired charging is not available.

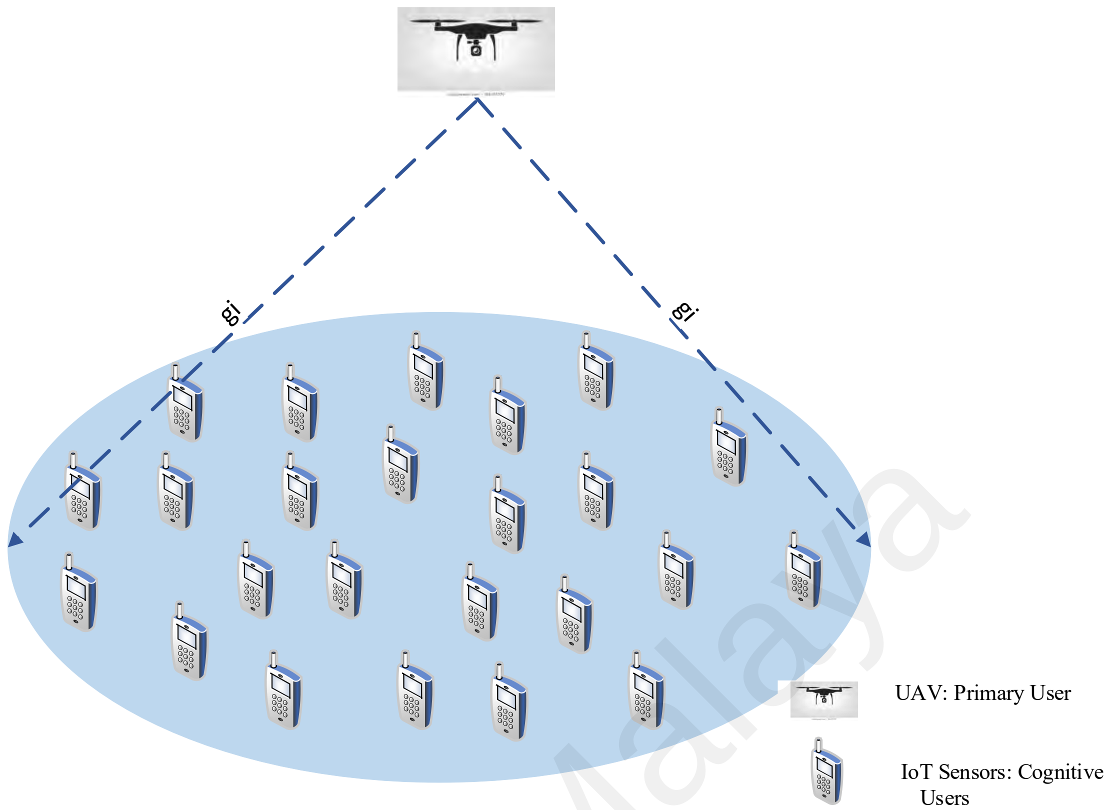

Figure 5.1: System Model of UAV Supported IoT Energy Transfer

Moreover, UDNs usually include massive spatially distributed wireless nodes, like device-to-device (D2D) communications, machine-to-machine (M2M) communications as well as sensor nodes. For these networks, the challenge is to minimize energy consuming as well as extending the network lifetime, as currently batteries remains the primary source of energy. If batteries for massive nodes requires constant recharging or replaced regularly, it can be costly as well as inconvenient (H. C. Wang et al., 2018). It is envisioned that the UAV can hover around the wireless nodes to transfer power wirelessly to the nodes as well as to transmit information. we aimed to determine the optimal way to allocate resources for wireless power transmission and information transfer to the Internet of Things that offers the system. In our advanced systems, IoT nodes sending information to UAV and its need energy form it. UAV or drone act as a moving source for charging wireless nodes. Drones can also collect all information from wireless nodes.

In this study, wireless nodes were distributed at locations located in the IoT environment and assumed to be charged by UAVs.

We consider the general characteristics of UAV based wireless communication, the general communication model consists of UAV-drones and ground IoT nodes. For three-dimension (3D) location, within the completion time T and trajectory design UAVs location is denoted as $q(t) = [x(t), y(t), H(t)]^T \in R^3$ at time t. It is presumed that the final and initial time pertaining to UAVs location conforms to $t^{(0)} = 0,\ t^{(N)} = T$. By introducing the elemental time slot length δ_t, the horizon time T is divided into M time slots, this mean $T = M\delta_t$. The selection of elemental time slot length is done to ensure that the location of UAVs and ground nodes could be assumed as constants within each slot. Or else, UAV's 3D location in time slot m could be expressed as:

$$q[m] = [x(m), y(m), H(m)]^T, \qquad m = 1,2, \dots, M \tag{5.1}$$

For trajectory design, we consider three fundamentals of the trajectory of UAV including trajectory location $\{q[m]\}_{m=1}^{M}$, speed $\{v[m]\}_{m=1}^{M}$ and acceleration $\{a_{cc}[m]\}_{m=1}^{M}$. For the fixed altitude of UAV at H the trajectory location of UAV in the mth time slot can simply as the horizontal location $q[m] = [x[m], y[m]]^T, m = 1, \dots, M$ where M is the final time slot at the end of trajectory.

The trajectory of UAV in a typical time slot is defined as:

$$q[m+1] = q[m] + v[m]\delta_t + 0.5a_{cc}[m]\delta_t^2, m = 0,1,2, \dots, M \tag{5.2}$$

$$v[m+1] = v[m] + a_{cc}[m]\delta_t, m = 0,1,2, \dots, M \tag{5.3}$$

For a constant of velocity ($a_{cc}[m] = 0$) and allowable maximum velocity of the UAV (V_{max}), the trajectory constraints of the UAV are as:

$$\|q[m+1] - q[m]\| \leq V_{max}\delta_t, \qquad m = 0,1,2,\dots,M \tag{5.4}$$

Here, $q[0] = [x[0], y[0]]^T$ represents the UAV's initial horizontal location.

In channel model, a difference exists in air to ground (ATG) channel and the ground channel because of line of sight (LoS) higher chance propagation through 3D location (Bor-Yaliniz et al., 2016). In such conditions, the impact cast by the environment on LoS occurrence becomes even more important. However, the effects of propagation blockage (Al-Hourani et al., 2014a) like building blockage still exist for the complete channel models. Due to this, for ATG channels, large scale Rayleigh, as well as free space fading models is considered to be optimum.

With regards to an arbitrary elemental time-slot, the distance between the ith ground nodes and the UAV located at (x, y, H) can be represented as:

$$R_i = \sqrt{d_i^2 + H^2} \tag{5.5}$$

Here, $d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}$ denotes the horizontal distance existing between the ith ground nodes and the UAV and x_i, y_i signifies the location pertaining to the ith ground nodes. The simple distance pathloss that exists between the ith ground nodes and the UAV could be signified as (Mozaffari et al., 2016):

$$L(R_i) = 10log\left(\frac{4\pi f_c R_i}{c}\right)^{\alpha} \tag{5.6}$$

Where $\alpha > 2$ is the path loss exponent, c is the speed of light (m/s), f_c is carrier frequency (Hz). On the other hand, the probability of LoS is given by (Al-Hourani et al., 2014b):

$$P_{LoS} = \frac{1}{1 + a\ \exp\left(-b(\arctan\left(\frac{H}{d_i}\right) - a)\right)} \tag{5.7}$$

Where a, b are constants. Thus, one has $P_{NLoS} = 1 - P_{LoS}$.

Then the total path loss expression from UAV to ith ground nodes is as:

$$PL(R_i) = L(R_i) + \eta_{LoS} P_{LoS} + \eta_{NLoS} P_{NLoS} \tag{5.8}$$

Where η_{LoS} and η_{NLoS} are average additional losses for LoS and NLoS respectively.

Assuming Los dominated in free space path loss model (Xu et al., 2018). For time slot t, the channel gain in the free space model is defined as:

$$g_i(t) = \beta_0 \, \rho^2 \, R_i^{-\alpha}(t) \tag{5.9}$$

Where g_i is the channel power gain from UAV to ground IoT, $R_i(t) = \sqrt{(x - x_i)^2 + (y - y_i)^2 + H^2}$ is the distance between UAV and ground IoT nodes, ρ Reduction Factor, α is the Pathloss exponent, β_0 is the Channel power gain at the reference distance (Nguyen et al., 2018).

By using the required energy from the drones, the information is passed by the wireless node to the drone. When a wireless contract derives its energy from drones, they can use the acquired energy to transfer information and generate revenue from the information transfer process. Because IoT nodes are in the same class that carry information in the same channel, there is overlap between IoT nodes in protected areas. At this point, the SIR can be employed to signify the revenue based on the information transmission, which can also be presented as power level pertaining to information transmission:

$$\gamma_i(p_i) = \frac{p_i(t) \, g_i(t)}{\sum_{j \neq i}^{N} p_i(t) \, g_j(t) + \sigma_i^2 \, (t)} \geq \quad \Gamma_i \quad {}_{,i=1,2,,3,\ldots,n} \tag{5.10}$$

Here, Γ_i denotes the threshold SIR and σ_i^2 signifies the Gaussian noise power. Representation of the sum of interference by considering the noise as the denominator of Equation (5.10) could be done as $I_i(\boldsymbol{p}_{-i})$, and thus Equation (5.11) could be presented in the form of a function of user transmission power as well as the transmission power pertaining to other users:

$$\gamma_i(p_i, \boldsymbol{p}_{-i}) = \frac{p_i(t)\, g_i(t)}{I_i(\boldsymbol{p}_{-i})} = \frac{p_i(t)\, g_i(t)}{\sum_{j\neq i}^{N} p_j(t)\, g_j(t) + \sigma_i^2(t)} \tag{5.11}$$

The subscript $-i$ represents the interference that is dependent on the power transmitted by all users excepting the ith node.

The total interference power generated by the Cognitive IoTs must be below a given limit which is known as interference temperature limit and it is expressed as below:

$$\sum_{i=1}^{N} p_i g_{0i} \leq I_{TL} \tag{5.12}$$

Mathematically, the expression of non-cooperative game theoretic power allocation strategy pertaining to spectrum sharing could be done as an issue with regards to decreasing the power consumption for each node subject in order to predefine the requirements for SIR to identify the target as well as to establish a maximum interference tolerant limit pertaining to the communication system. Assuming that IoT nodes pertaining to the system behave as greedy and selfish in order to increase their own utilities, exploiting of the non-cooperative game theory is done in order to effectively model the interactions between various nodes in terms of a Nash game. Thus, analytically, the existence of the Nash equilibrium as well as its uniqueness is verified successfully. Ultimately, we have put forward an iterative power allocation algorithm that possesses low computational complexity and it has been established that quick convergence plays the game amongst various nodes. However, the key aim of this work pertains to decreasing the power consumption applicable to each node along with the optimization of transmission power allocation, which has been seen to be limited by a predefined SIR requirement pertaining to target identification as well as a maximum interference tolerant limit associated with the communication system. Thus, the game theory is regarded as an appropriate mathematical tool that also accounts for player's rational as well as self-interested behavior. In particular, the IoT nodes that behave like players compete amongst each other and then select a strategy space pertaining to transmission power in order to achieve a payoff, which can also be presented by their utility functions.

In the non-cooperative power allocation game, the features pertaining to the players interaction can be strategically presented as:

$$\Phi = [N, \{P_i\}, \{U_i(.)\}] \tag{5.13}$$

Here, $\mathrm{N} = \{1,2, \ldots, \mathrm{N}\}$ denotes the player's index set of IoT nodes, wherein the key aim of each player would be to increase its utility by selecting a suitable action to transmit power. $P_i = [0, P_i^{max}]$ represents the users' transmission power strategy pertaining to set i, while P_i^{max} denotes the maximum transmission power i of the users. The utility function pertaining to user i can be defined as $U_i(.)$, where each user associated with the network tries to maximize in a selfish manner its utility. When applying the non-cooperative game theory, it is crucial to choose an ideal utility function. Mathematically, the utility function representing the user i can be expressed as the received number pertaining to information bits in the form of per joule of the consumed energy (Goodman & Mandayam, 2000):

$$U_i(p_i, \boldsymbol{p}_{-i}) = \frac{LRf(\gamma_i)}{Mp_i} \tag{5.14}$$

Here, in cognitive networks, information is sent by transmitters to receivers as well as wireless data as frames or packets pertaining to length M bits. This involves $L < M$ information bits as a data rate along with R bits/sec, in which $f(\gamma)$ denotes the efficiency function with regards to the transmission. The efficiency function $f(\gamma)$ has been seen to depend on the achieved SIR in the channel, wherein the value lies in the range from 0 to

1 (i.e. $f(\gamma) \in [0,1]$). Furthermore, power p_i represents the power that has been transmitted by the user i.

Moreover, a novel utility function has been put forward by accounting for power function besides a new sigmoid efficiency function with regards to pricing function for the user's transmit power. Furthermore, we introduce a sigmoid efficiency function in the form of a fraction by considering an exponential ratio power multiplied by tuning factor (z) along with the entire power in order to target SIR as expressed below:

$$f(\gamma_i) = \frac{1}{(1 + exp\ (1 - z\ sir_i))^{r_i}} \tag{5.15}$$

Where z is the tuning factor where its change will change the response of the efficiency function proposed. With regards to Equation (5.14), the utility function pertaining to the i^{th} cognitive nodes can be expressed as:

$$U_i = \frac{LR}{Mp_i} \frac{1}{(1 + exp\ (1 - z\ sir_i))^{r_i}}\ \frac{bit}{joule} \tag{5.16}$$

The Nash Equilibrium as a result of non-cooperative power control is not deemed to be efficient as it fails to account for the cost that it enforces on other nodes via the generated interference. Therefore, the pricing idea was introduced to motivate users to efficiently use resources associated with the network. A general representation pertaining to pricing-based non-cooperative power control game can be expressed as follows:

$$\Phi^c = [N, \{P_i\}, \{U_i^c(.)\}c] \tag{5.17}$$

Here, $U_i^c(.)$ denotes the utility function employing pricing and is expressed as:

$$U_i^c(p_i, \boldsymbol{p}_{-i}) = U_i(p_i, \boldsymbol{p}_{-1}) - C_i(p_i, \boldsymbol{p}_{-1}) \tag{5.18}$$

Subsequently, this article employs the pricing technique in order to encourage cognitive sensors to efficiently utilize network resources like power and punish users that produce higher interference to PUs or behave in a selfish manner. Therefore, the pricing-based utility function can be written as:

$$U_i^C(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i} \frac{1}{(1 + exp\ (1 - z\ sir_i))^{r_i}} - c\ p_i\ exp(p_i\ \alpha) \tag{5.19}$$

Where c and α represent the pricing factor. Thus, in the game of the recommended green non-cooperative power control with pricing is written as:

$$\begin{aligned} EE - NGPAP : \max_{pi \in Pi} U_i^C(p_i, \boldsymbol{p}_{-i}) = \frac{LR}{Mp_i} \frac{1}{(1 + exp(1 - z\ sir_i))^{r_i}} \\ - c\ p_i\ exp(p_i\ \alpha) \end{aligned} \tag{5.20}$$

5.3 Existence and Uniqueness of Nash Equilibrium

With regards to non-cooperative power control game, the ith Cognitive Sensor (CS) boosts its utility by selecting an appropriate strategy based on the strategy set $P_i = [0, P_i^{max}]$.

In non-cooperative power control game, there exists a Nash Equilibrium when all $i = 1,2, \dots, n$ comply with the two conditions given below (Al-Gumaei et al., 2015; Topkis, 1998):

The action set P_i can be defined as non-empty, compact and convex subset pertaining to certain Euclidean R^N.

The utility function $U_i^C(p_i, \boldsymbol{p_{-i}})$ can be defined as continuous pertaining to **p** and $\left(\partial^2 U_i^C / \partial p_i \partial p_j\right) \geq 0 \quad \forall j \neq i \in N$.

For each Cognitive IoT sensor in our game, the transmit power space strategy can be described with the help of maximum and minimum powers and the value pertaining to the powers lie between such values. Thus, the first condition pertaining to action set P_i can be satisfied.

In order to demonstrate quasi-concave characteristics of the cognitive IoT sensor utility function in p_i, obtaining of the second derivative with regards to $U_i^C(p_i, \boldsymbol{p_{-i}})$ could be done with p_i:

$$\frac{\partial U_i^C}{\partial p_i} = \frac{LR}{Mp_i^2}\left(\gamma_i \frac{\partial f(\gamma_i)}{\partial \gamma_i} - f(\gamma_i)\right) - ce^{\alpha p} - cp\alpha e^{\alpha p} \tag{5.21}$$

$$\begin{aligned} \frac{\partial^2 U_i^C}{\partial p_i \partial p_j} &= \frac{LR}{Mp_i^2}\left(\frac{\partial \gamma_i}{\partial p_j}\frac{\partial f(\gamma_i)}{\partial \gamma_i} + \gamma_i \frac{\partial \gamma_i}{\partial p_j}\frac{\partial^2 f(\gamma_i)}{\partial \gamma_i^2} - \frac{\partial \gamma_i}{\partial p_j}\frac{\partial f(\gamma_i)}{\partial \gamma_i}\right) \\ &= \frac{LR}{Mp_i^2}(\gamma_i \frac{\partial \gamma_i}{\partial p_j}\frac{\partial^2 f(\gamma_i)}{\partial \gamma_i^2}) \end{aligned} \tag{5.22}$$

Since the first order derivative pertaining to γ_i with regards to p_j can be expressed as:

$\left(\partial\, \gamma_i / \partial p_j\right) = -\left(h_i h_j p_i / \sum_{j \neq i} h_j p_j + \sigma^2\right) < 0$, so we need the second order derivative of our efficiency function with respect to γ_i be $\partial^2 f(\gamma_i) /\, \partial \gamma_i^2 \leq 0$.

$$\begin{aligned} \frac{\partial f(\gamma_i)}{\partial \gamma_i} &= \frac{\partial \left(\frac{1}{(1+e^{(1-z\gamma_i)})^{\Gamma_i}}\right)}{\partial \gamma_i} \\ &= \frac{z\,\Gamma_i\, e^{-z\gamma_i}}{(1+e^{1-z\gamma_i})^{\Gamma_i}\,(1+e^{1-z\gamma_i})} \end{aligned} \tag{5.23}$$

$$\frac{\partial^2 f(\gamma_i)}{\partial \gamma_i^2} = \frac{\Gamma_i^2\, z^2\, (1+e^{1-z\gamma_i})^2}{(1+e^{1-z\gamma_i})^{\Gamma_i}\,(1+e^{1-z\gamma_i})^2} - \frac{\Gamma_i\, z^2\, e^{1-z\gamma_i}}{(1+e^{1-z\gamma_i})^{\Gamma_i}\,(1+e^{1-z\gamma_i})} + \frac{\Gamma_i\, z^2\, (1+e^{1-z\gamma_i})^2}{(1+e^{1-z\gamma_i})^{\Gamma_i}\,(1+e^{1-z\gamma_i})^2} \tag{5.24}$$

Is simplified to:

$$\frac{\partial^2 f(\gamma_i)}{\partial \gamma_i^2} = -\frac{\Gamma_i z^2 e^{1-z\gamma_i}}{\left(1+e^{1-z\gamma_i}\right)^{\Gamma_i}\,(1+e^{1-z\gamma_i})}\left(1-\frac{e^{1-z\gamma_i}\,(\Gamma_i-1)}{(1+e^{1-z\gamma_i})^2}\right) \tag{5.25}$$

Due to:

$$\frac{e^{1-z\gamma_i}\,(\Gamma_i-1)}{(1+e^{1-z\gamma_i})^2} < 1 \tag{5.26}$$

As per Equation (5.26), the second condition can be satisfied by cautiously choosing the pricing factors. Thus, the put forward power control game was seen to possess a unique Nash Equilibrium solution.

5.4 Proposed EE-NGPAP Algorithm

In this chapter, development of a distributed iterative power allocation algorithm is done in order to measure the Nash Equilibrium point pertaining to the put forward model beginning from any initial feasible point. Execution of the proposed algorithm strategy is done by considering each cognitive node at every time step in a distributed way in order to determine the Nash Equilibrium point pertaining to the put forward model, i.e. optimal transmission power achieved SIR value is determined by each node. Because of this, EE-NGPAP is deemed to be apt for this model in which each IoT node needs just the transmit strategies pertaining to all the other nodes with no information on the system. Therefore, the iteration power allocation along with pricing algorithm can be defined as a completely distributed process whose pseudo-code may be summarized by considering the existence of unique Nash Equilibrium with the put forward model.

However, we suppose that each cognitive node updates it's transmit power at time instances $t_i = \{t_{i1}, t_{i2}, \ldots.\}$, where $t_{ik} < t_{i(k+1)}$, and we assume the strategy set of power of the ith IoT node is $P_i = [P_i^{min}, P_i^{max}]$. We set an infinity small quantity ε where ($\varepsilon >$ 0) and by considering the proposed algorithm as given Equation (5.20) generates sequence of powers as follows:

EE-NGPAP

I. Initialize transmit power vector $p = [p_1^0, p_2^0, p_3^0, \ldots, p_N^0]$ randomly at time t_0, besides other parameters including: $H, \alpha, \rho, \beta_0, V$, σ^2, P_i^{max}, Γ_i, Pricing factors (c & n) and Tuning factor (z).

II. Outer Iteration

III. Initialize UAV's Trajectory

IV. Inner Iteration:

For all $i \in N$ at time instant t_k;

a) Update $g_i(t_k)$ using Equation (5.9)
b) Update $\gamma_i(t_k)$ using Equation (5.10)
c) Given $p_i(t_{k-1})$, consider the best response of power strategy $r_i(t_k)$ based on $r_i(t_k) = arg \max_{p_i \in P_i} u_i^C (p_i, \boldsymbol{p_{-i}}(t_{k-1}))$
d) Assign the transmit power as $p_i(t_k) = \min(r_i(t_k), p_i^{max})$

V. Convergence Step:

If $\|p(t_k) - p(t_{k-1})\| \leq \varepsilon$, stop iteration and declare Nash equilibrium as $p(t_k)$;

Else: $k = k + 1$ and go to step IV

VI. Exit Inner Iteration (BR Iteration)

VII. Exit Outer Iteration (UAV's Trajectory Iteration)

VIII. End

Where $r_i(t_k)$ is used as the representative of the collection of the best transmit powers that correspond to the ith IoT nodes. This can be obtained when the objective function is applied with EE-NGPAP algorithm during time instant k.

5.5 Simulation Results & Discussion

In this segment, the proposed game is simulated in order to achieve the best harvesting for energy as well as efficient resource allocation pertaining to the IoT nodes on the ground based on UAV as an energy source. To develop the simulation environment, MATLAB software has been employed. Moreover, a series of experiments is conducted in order to assess the put forward algorithm's performance pertaining to an energy harvesting in $1{,}000 \times 1{,}000\ m^2$ area, in which random distribution of the 20×20 IoT nodes is done, while the maximum distance between UAV and nodes were 50 and 100 m. Such low power nodes could be regarded as sensor nodes containing much important information for the transmission. However, these nodes are regarded to lack any fixed energy source. Unless specified, the associated system parameters have been set as presented in Table 5.1.

Table 5.1: System Parameters

Comments	Parameter	Value
Total number of bits per frame	M	80
Number of information bits of each frame	L	64
Data rate	R	10 kbps
AWGN power at receiver	σ^2	1e-16 Watts
Maximum power constraint	P_i^{max}	2 Watts
Target SIR	Γ_i	9
Pricing factors	c & n	1e4, 2.5
Tuning factor	z	0.5-0.9
The altitude of the UAV	H	(50, 100) m
Maximum Flight Speed	V	50 m/s
Channel power gain at the reference distance	β_0	-30 dB
Reduction factor	ρ	0.3820
Pathless exponent	α	3

In this scenario, the trajectory employed can be regarded as spiral trajectory along with distributed IoT sensor nodes demonstrating system model as presented in Figure 5.2, wherein the default nodes are colored as blue. However, drones need to transfer power to wireless nodes based on contract requirements and maximize profits during power transfers. As the game continuous, drones need to increase their power level to transmit wireless power to meet the requirements of wireless contracts and increase their profitability. Moreover, implementation of energy harvesting technology is done under spiral trajectory along with put forward power control game to satisfy energy requirements pertaining to the nodes.

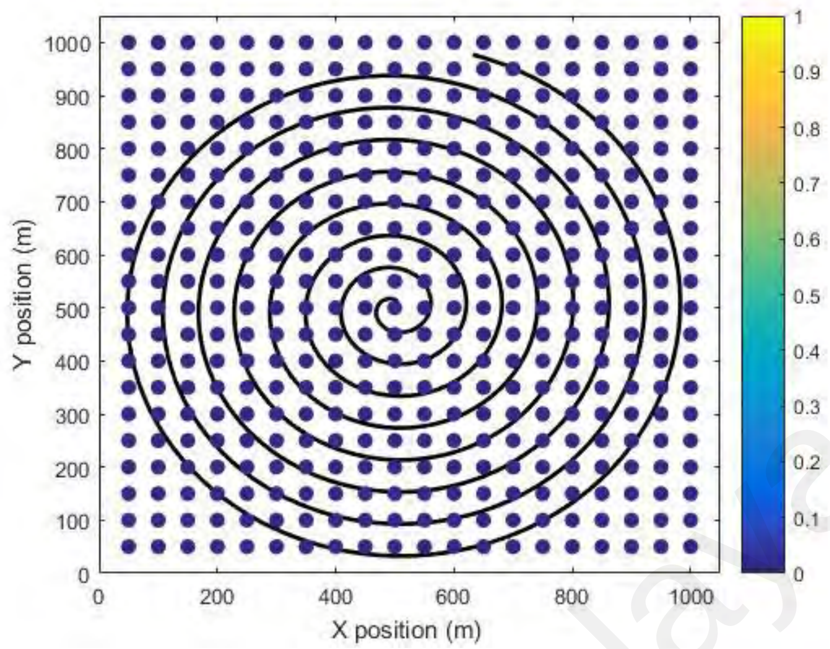

Figure 5.2: UAV Scenario Based Dense IoT Sensors

Without loss of generality, the maximum flight speed is assumed to be fixed with $50\ m/s$. Considering in our algorithm two types of results shown in Figures 5.3 with 50m height and Figure 5.4 with 100m height, results with applying the effect of game theory which is in sub-figures of (b, d and f) within Figures 5.(3&4) and results without game theory effects which is in sub-figures of (a, c and e) within Figures 5.(3&4) for both cases in order to compare between results and showing the positive effect of applying multi-decision mathematical approach which is familiar used in many scientific areas. Also, we are performing multi average flying time with fixed hovering speed, these average flying times are in seconds for $350s$ for Figures of (a &b), $450s$ for Figures of (c&d) and 550 for Figures of (e & f) all of these sub-figures within Figures 5.3&5.4.

With the 50 meters height besides multi average flying time (ft.) in which $ft = 350\ s$ as in Figure 5.3(b), $ft = 450\ s$ as in Figure 5.3(d) and $ft = 550\ s$ as in Figure 5.3(f) and applying Nash Equilibrium between players which is represented in our algorithm as an IoT nodes, the discount factor affects the optimal policies for wireless nodes which is shown in Figure 5.3(b, d and f) and Figure 5.4(b, d and f). As time goes on, the drones will increase the price of the transferred unit as the higher the transmission time, the higher the cost of transporting the drone. Because the power conversion efficiency is low for wireless power transmission and long distance for wireless power transmission, drones must have more power to transmit wireless power. All of these factors will lead to a significant increase in the cost of power transmission. UAVs will then increase the price of transmitted power units when required time to transmit wireless power is large. In Figures 5.3 & 5.4 (b, d and f) with game the optimal solutions for the IoT nodes are given as compared to Figures 5.3 & 5.4 without game (a, c and e). We have considered that all nodes that fall within the same category are standard and uniform to provide simple simulations for the users. From Figure 5.3 & 5.4 with game We have found that drones will increase the energy sent to transfer information to make more profit, even as energy unit prices are transferred over time by increasing hover time. Based on Figure 5.3(f) and Figure 5.4(f) We can see that IoT contracts are getting more and more power over time as drones increase the level of wireless power delivery by increasing average flight time to meet more wireless contract requirements. Also, the IoT node harvesting more energy and it will be there more energy to transfer information.

Without Game ***With Game***

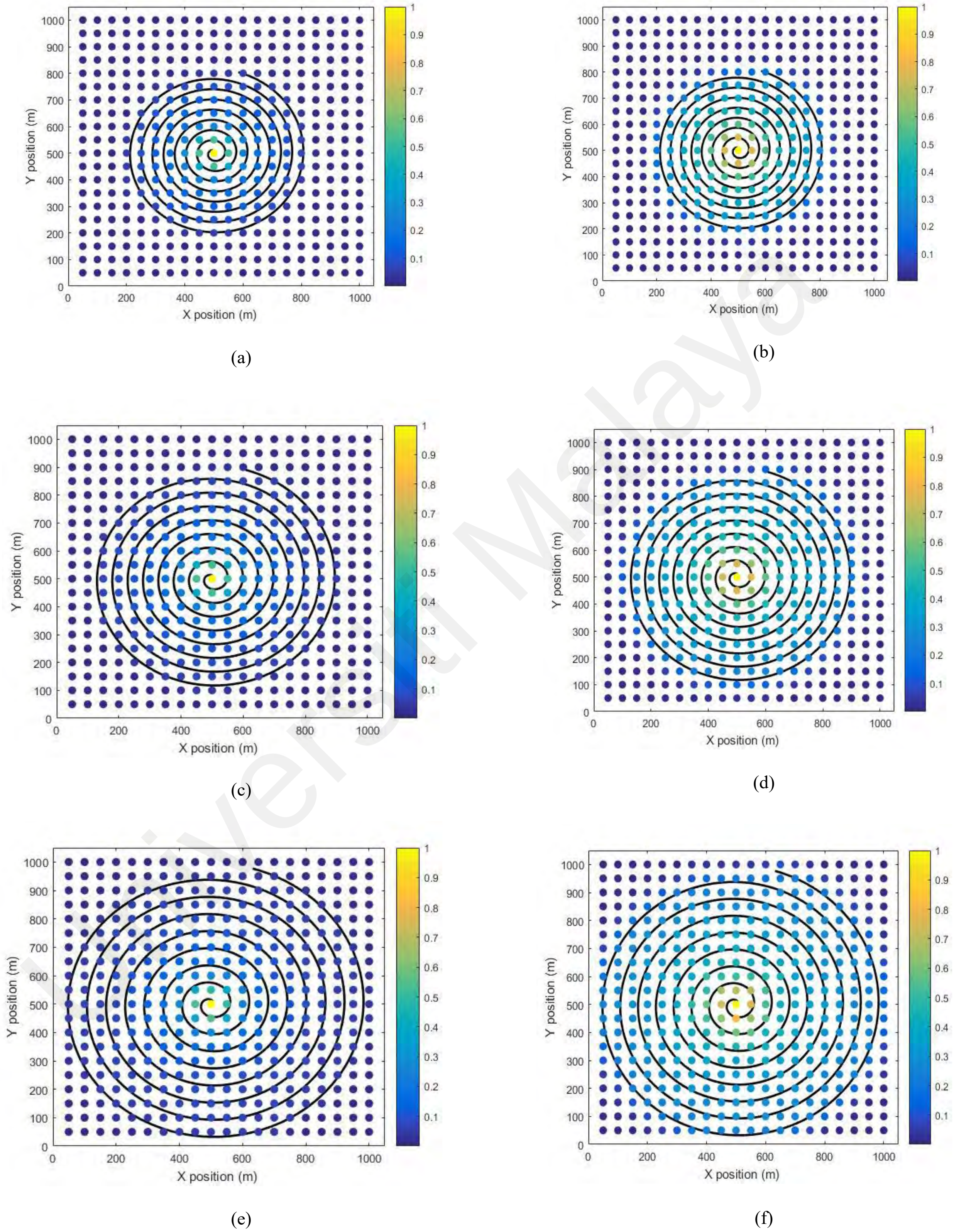

Figure 5.3: With & Without Game for UAV with Different Flying Time for H=50m

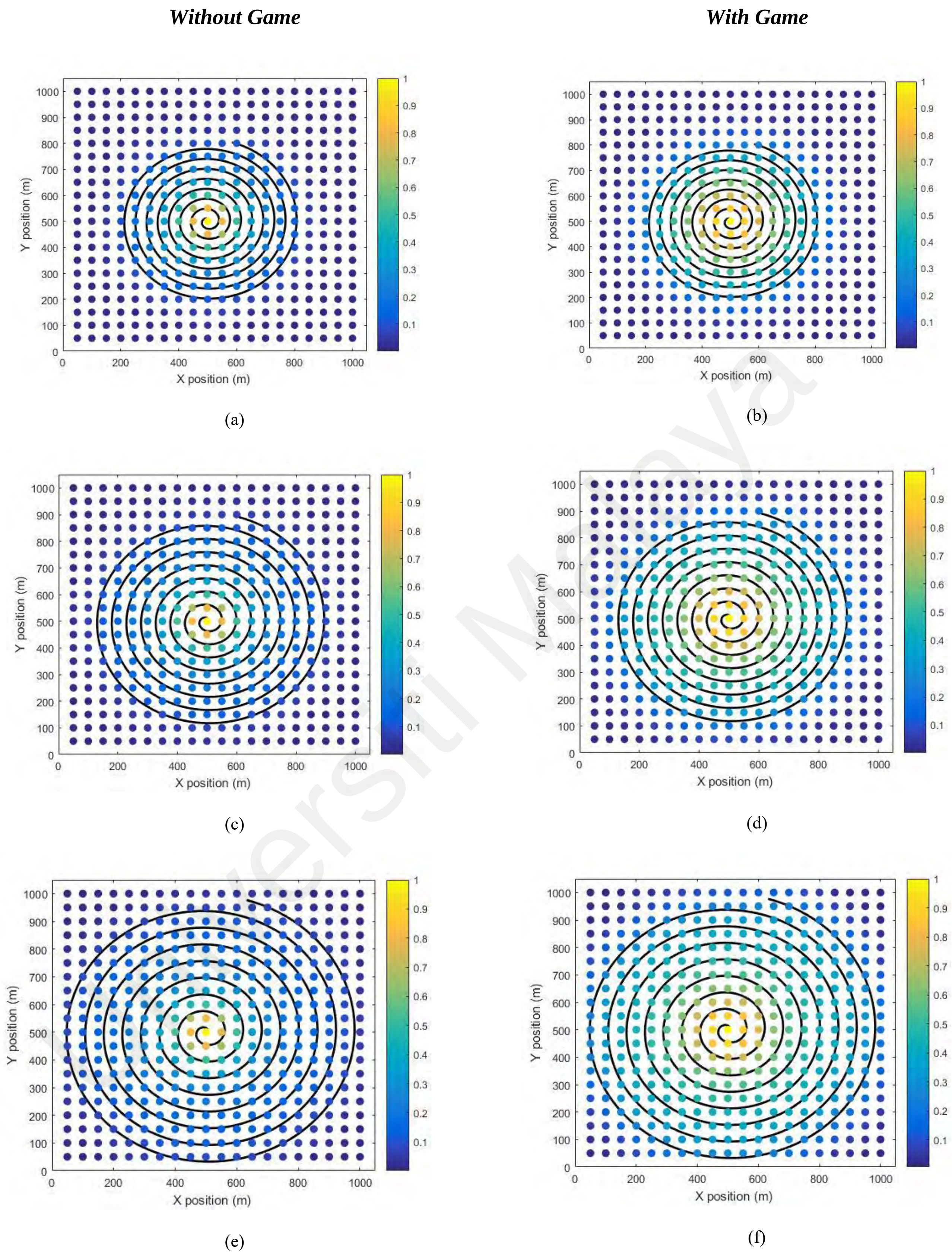

Figure 5.4: With & Without Game for UAV with Different Flying Time for H=100m

5.6 Summary

In this research work, the resource allocation issue pertaining to cognitive UAV networks has been assessed in which a UAV that acts as an energy source offers energy to numerous energy harvesting IoT sensors apart from transmission of information. An efficient non-cooperative green transmission game is developed by introducing the new energy harvesting function apart from the price and utility functions, which also mathematically confirm the uniqueness and existence of Nash Equilibrium. Based on the simulation results, the non-cooperative power control algorithm in this research work has been seen to possess better power saving properties. Also, the put forward scheme provides an enhanced performance, wherein the IoT sensor players are allowed to share extra licensed band within the interference temperature limits. The considerable reduction pertaining to the transmit power with regards to the put forward energy harvest algorithm provides the highest preference in order to apply it in cognitive radio to meet the needs of future 5G networks. For future work, further evaluation is needed for the scenario wherein UAV behaves as a mobile energy provider. Also, how could UAV trajectory effect on the energy transfer need to be study more. Finally, the way to make a connection between UAV and machine learning one of the hot topics for this scenario which is supposed be researched especially for 5G and B5G.

CHAPTER 6: CONCLUSION AND FUTURE DIRECTION

This chapter summarized and concludes the thesis followed by the discussion on future work and challenges could this work lead to it.

6.1 Conclusion

The main objective of this research is to present the solution of the problem concerning control of power in the modern cognitive radio, wireless sensor network and UAVs scenarios developed on the framework of game theory. In particular, the research focuses on the design of distributed power control algorithms that can reduce power consumed, mitigate interference and achieve the required QoS in the desired wireless systems. To achieve this, the previous concepts of power control based on the control theory perspective that has been applied in cellular networks were studied and reviewed.

Furthermore, the transition of the implementation of QoS from cellular to wireless data networks have been briefly reviewed. Microeconomics and game theory's concepts have been employed to represent the QoS of users appropriately in data networks. The QoS in data communication systems has been represented using utility function rather than SIR which describes the satisfaction of users. This has led us to the use of a utility function that reduces the power consumption of user's terminals.

In chapter 3: we have designed a power control game for cognitive radio network based on energy efficient utility function. Here, we have proposed a novel utility function via pricing to formulate the non-cooperative power control game. In this algorithm, we have obtained higher SIR for CR users closer to the base station, while the pricing is strictly fixed for the users who embody the basis of interference. The suggested algorithm simply requires only local information to maximize the net utility-price of each CR.

Improved power saving and fast convergence has been obtained as compared with the recent cited works in literature.

In chapter 4: we researched how to use the energy harvest time through it's a factor to achieve the maximize of the radio frequency energy efficiency in wireless cognitive sensor network (CSN). Non-cooperative game pricing theory laid the foundation of the proposed novel algorithm EH-NPGP. Simulation confirmed the convergence of the suggested algorithm and the uniqueness and presence of NE were numerically ascertained. The significant benefits of the recommended energy harvesting algorithm are the speedy convergence to the NE as compared to previous works. Therefore, the suggested algorithm is practically more appropriate for distribution application. Moreover, pricing is an essential technique in CSNs to prevent cheating behavior of the players. Thus, better performance for both primary and secondary users within CSN can be achieved.

In chapter 5: the resource allocation issue about cognitive UAV networks has been assessed in which a UAV that acts as an energy source offers energy to numerous energy harvesting IoT sensors apart from the transmission of information. An efficient non-cooperative green transmission game is developed by introducing the new energy harvesting function apart from the price and utility functions, which also mathematically confirm the uniqueness and existence of Nash Equilibrium. Based on the simulation results, the current study examines the non-cooperative power control algorithm to possess better power saving properties. Also, the put forward scheme provides an enhanced performance, wherein the additional licensed band within limits of interference temperature are shared by the IoT sensor players. The decrease considerable pertains to the power transmission with regards to the put forward energy harvest algorithm provides the highest preference for its application in cognitive radio to meet the needs of future 5G networks. For future work, further evaluation is needed for the scenario wherein UAV behaves as a mobile energy provider. Also, how could UAV trajectory effect on the energy transfer need to be study more. Finally, the way to make a connection between UAV and machine learning one of the hot topics for this scenario which is supposed be researched especially for 5G and B5G.

In conclusion, all the proposed objectives of this work have been achieved. However, we tackle several performances issues in cognitive radio, wireless cognitive sensor network and UAVs. It is anticipated to enable wireless networks to manage the various problems that it may come across in the future by enhancing its productivity. For example, wireless networks are capable of performing more efficiently using a higher level of network energy throughput. The effective wireless networks support the over-load from networks of cellular or assist in realizing the version of Internet of Things (IoT). The (IoT) vision is predicted to result in very severe problems concerning scalability, as a considerable number of objects are intended to obtain a green communication with transformation of higher data rate simultaneously.

6.2 Future Direction

Game and pricing theories are demonstrated as useful tools to examine Resource Allocation issues in 5G wireless networks. Nevertheless, to achieve the potential of efficient communications in 5G and B5G networks, some roadblocks are immediately required to be discussed as follows:

6.2.1 Dense Deployment

With the quick increase number of users of electronic device, re-designed wireless networks have become significantly vital as it fulfils the requirements. Thus, the thick placement is a primary research task in the age of 5G, which necessitates considerably various aspects to maximize the performance of the current networks. Hence, this field of study has grown much attention towards the general design of 5G wireless networks other than the Cognitive Radio Network (CR), Wireless Sensor Networks (WSN) and Unmanned Ariel Vehicle (UAV) design.

6.2.2 Green Game

The recent research in the field of green technology wireless networks has developed a great interest and has become significantly crucial to examine energy efficiency (EE) of the networks. Thus, much effort is required to put in this vital area of study. Game and pricing theories play important roles in designing green RA in modern wireless networks. By employing game theory and pricing game theory, transmission can be avoided by sensor and cognitive nodes in specific spectrum that primary users often use. Moreover, the application of intelligent pricing game theory can attain a green spectrum market, where cognitive nodes and sensors integrate an extensive variation of activities that include careful rent out of the available spectrum by notifying the renting policies to the other users.

6.2.3 Massive MIMO For SWIPT

The extensive use of MIMO can acquire the two distinctive advantages to SWIPT networks. On the one side, extra reaped energy can be produced using supplementary antennas at the point of the receiver as consequences to transmit the broadcast nature of wireless. On the other side, manipulation of additional transmission antennas for beamforming can be employed noticeably to enhance the efficacy of energy transmission and information. The concept of using the large MIMO is to increase the installed numbers of antennas. The huge MIMO carries small antennas in hundreds, served with less expensive amplifiers and circuitry, replaced the traditional arrays with some antennas that are served with massive and costly hardware.

6.2.4 Cooperative Game Theory in Distributed Radio Networks

Cooperative game theory performs a pivotal role in examining the challenges concerning Resource Allocation in the context of distribution, where communication of the players is taken place with one another to decide how to play the game and how to distribute the resources effectively. Bargaining game and coalitional game are the two primary topics that Cooperative game theory contains. Furthermore, effective Resource Allocation in a disseminated situation can be attained, taking coalitional game theory that denotes other avenues for the potential forthcoming research work.

6.2.5 Efficient Spreading

Though the expense of UAV is decreasing, yet installing a massive number of UAVs is still very expensive. It is important to have effective deployment, but it is also demanding as enormous several UAVs are linked and interfered. To render more effective services to the user, the number, allocation and UAVs stored energy should be measured to contribute to the strategy of the power control.

6.2.6 Interference Management

Keeping in view UDNs that large numbers of the users function in co-channel scenario, a co-channel scenario, thoughtful interference indeed determines the achievement of densification. While the UAV topology assisted UDN variation quickly interference will result in more complicated in a vibrant setting. Less complicated and high- working production methods of inference management are anticipated.

6.2.7 Pricing Mechanism

The current study employed the pricing mechanism to PHY layer merely to upgrade NE convergence. The pricing mechanism can be used for more developed situations like multi-hop UAVs to investigate the joint channel issue and distribution of router for enhancing UAVs performance by serving effective services of communication with the spectrum owner.

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