ENERGY HARVESTING IN 5G NETWORKS

By

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THESIS ACCEPTANCE CERTIFICATE

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ABSTRACT

With exponentially increasing number of users and their demand regarding data rate, current 4G cellular networks need to be evolved to next Fifth Generation (5G) networks. Heterogeneous Cloud Radio Access Network (H-CRAN) is the capable architecture for future high data rate enabled, energy efficient networks.

H-CRAN differs from today's cellular system by addition of extra number of Remote Radio Heads (RRHs) within the vicinity of one Macro Base Station (MBS). This provides high data rates to users with minimized interference by centrally controlling the resource allocation. On the other hand, increased density of hardware in the area, H-CRAN also consumes more grid power of the system.

To mitigate the greater power requirements for this type of dense network, Energy Harvesting (EH) techniques are used to minimize the grid energy consumption. In EH, energy is harvested from natural sources like solar, wind etc. By maximizing the harvested energy usage instead of grid power, the system's Energy Efficiency (EE) can be improved significantly.

In this thesis, EE of an H-CRAN consisting of several Green RRHs (G-RRHs), powered by EH modules are explored. A Mixed Integer Non-Linear Programming (MINLP) problem is formulated which maximizes the EE of the system. Mesh Adaptive Direct Search (MADS) algorithm is used to optimize the problem. As a result of this optimization, efficient power and resource allocation is done and higher EE is achieved with low complexity and lower consumption of grid power.

DEDICATION

This thesis is dedicated to

MY BELOVED PARENTS, SISTERS,

HONORABLE TEACHERS AND FRIENDS

for their love, endless support and encouragement

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I am grateful to Allah Almighty who has blessed me with the strength and the passion to complete this thesis and I am thankful to Him for His mercy and benevolence, and His Prophet (PBUH) without whose consent I could not have indulged myself in this task.

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NOTATION

$\mathcal{R}, \mathcal{N}$:	Sets of GRRHs, UEs repectively.
$\mathcal{S}$:	Set of all GRRHs and MBS.
R_i, *n*, *s* :	GRRH $R_i \in \mathcal{R}$ User $n \in \mathcal{N}$, GRRH or MBS $s \in \mathcal{S}$.
x_s^n :	Binary indicator for connection mode of UEs with MBS or any GRRH R_i.
y^n :	Binary indicator user selection for connection with MBS or any GRRH R_i.
$p_M^n, p_{R_i^n}$:	Power allocated to user *n* when served by MBS or any GRRH R_i respectively.
$\Phi_M^n, \Phi_{R_i^n}$:	Channel gain when user is connected to MBS or any GRRH R_i respectively.
$\Phi_M'^n, \Phi_{R_i}'^n$:	Rayleigh Random Variable when user is connected to MBS or any GRRH R_i respectively.
ð :	Zero mean gaussian variable.
G_0, H_0 :	Antenna Gain of MBS or GRRHs respectively.
$\mathrm{d_o}$:	Antenna far field reference distance.
$d_M,\ d_{R_i}$:	Distance of User *n* from MBS and GRRH respectively.
c_s^n :	Capacity of user n while connected to MBS or any GRRH R_i
ς_{total} :	Total Transmit rate of Network
ε_{R_i} :	Maximum storage capacity of battery of GRRH R_i
$E_{R_i}^{avail}$:	The available energy at GRRH R_i at any timeslot
e_{R_i} :	The amount of energy harvested by GRRH R_i in any timeslot.
$\gamma_{R_i}(t)$:	Maximum amount of energy that an GRRH R_i can harvest in any timelslot.
P_M, P_{R_i} :	Total power consumption of MBS and GRRH R_i respectively
P_M^{max}, $P_{R_i}^{max}$:	Maximum Transmit power of MBS and GRRH R_i respectively
P_M^{static}, P_R^{static} :	Static power consumption of MBS and GRRHs respectively.
μ_M^{eff} and μ_R^{eff} :	Drain efficiency of MBS and GRRHs respectively
p_{total} :	Total Power consumption of Network

ACRONYMS

1G:	First Generation
2G:	Second Generation
3G:	Third Generation
4G:	Forth Generation
5G:	Fifth Generation
AMPS:	Advanced Mobile Phone System
BBU:	Baseband Unit
CDMA:	Code Division Multiple Access
CRAN:	Cloud Radio Access Networks
EE:	Energy Efficiency
EH:	Energy Harvesting
ESA:	Exhaustive Search Algorithm
GPS:	Generalized Pattern Search
GRRH:	Green Remote Radio Head
GSM:	Global System for Mobile Communication
HCRAN:	Heterogeneous Cloud Radio Access Networks
HetNets:	Heterogeneous Networks
IEEE:	Institute of Electrical and Electronics Engineers
IoT:	Internet of Things
IS:	Interim Standard
ITU:	International Telecommunication Union
KPI:	Key Performance Index
LTE:	Long Term Evolution
MADS:	Mesh Adaptive Direct Search
MBS:	Macro Base Station
MIMO:	Multiple Input Multiple Output

MINLP: Mixed Integer Non Linear Programming

NOMADS: Nonlinear Optimization using Mesh Adaptive Direct Search

OAA: Outer Approximation Algorithm

OFDMA: Orthogonal Frequency Domain Multiple Access

QoS: Quality of Service

RF: Radio Frequency

RRH: Remote Radio Head

SE: Spectral Efficiency

SWIPT: Simultaneous Wireless Information and Power Transfer

TACS: Total Access Communication System

TDSCDMA: Time Division - Synchronous Code Division Multiple Access

UE: User Equipment

WCDMA: Wideband Code Division Multiple Access

WiMAX: Worldwide interoperability for Microwave Access

Chapter 1

INTRODUCTION

1.1 Communication Networks - Past, Present and Future

In past few decades, a marvelous emergence of wireless communication in global market has been witnessed. Even after years of growth, number of communication devices are still progressively increasing even in some countries number of communication devices have surpassed their population due to consumers need of seamless wireless connectivity. In 1979, when Bell Labs [1, 2] proposed the concept of cellular communication systems, mobile communication systems witnessed their four generation and are steps away from their very dense, complex but very efficient and data rich 5th generation. It started from 2.4 kbps in 1G to 100 Mbps of 4G. 1000x more data rate is expected in 5G networks. The journey of cellular communication systems is depicted in Fig. 1.1.

The first-generation networks (1G) were rolled out commercially in the 1980's. 1G mainly provided only voice services and was limited in terms of low quality, very small system capacity and limited services. 1G systems lacked the digital processing and were pure analogue systems with throughput up to 2.4 kbps. Typical 1G systems included North American Advanced Mobile Phone Systems (AMPS) and British Total Access Communication Systems (TACS) [3].

1.1.1 2G and 3G Networks

In early 1990's, the second-generation (2G) mobile systems were rolled out commercially as a digital communication system. As 2G was of digital nature of the system, the system capacity and quality were improved significantly as compared to 1G. 2G also supported low data rate services along with voice services. These positive edges, made 2G systems to receive a quick market boost and were spread out globally. 2G systems are circuit switched networks with throughput up to 384 kbps. Typical examples being

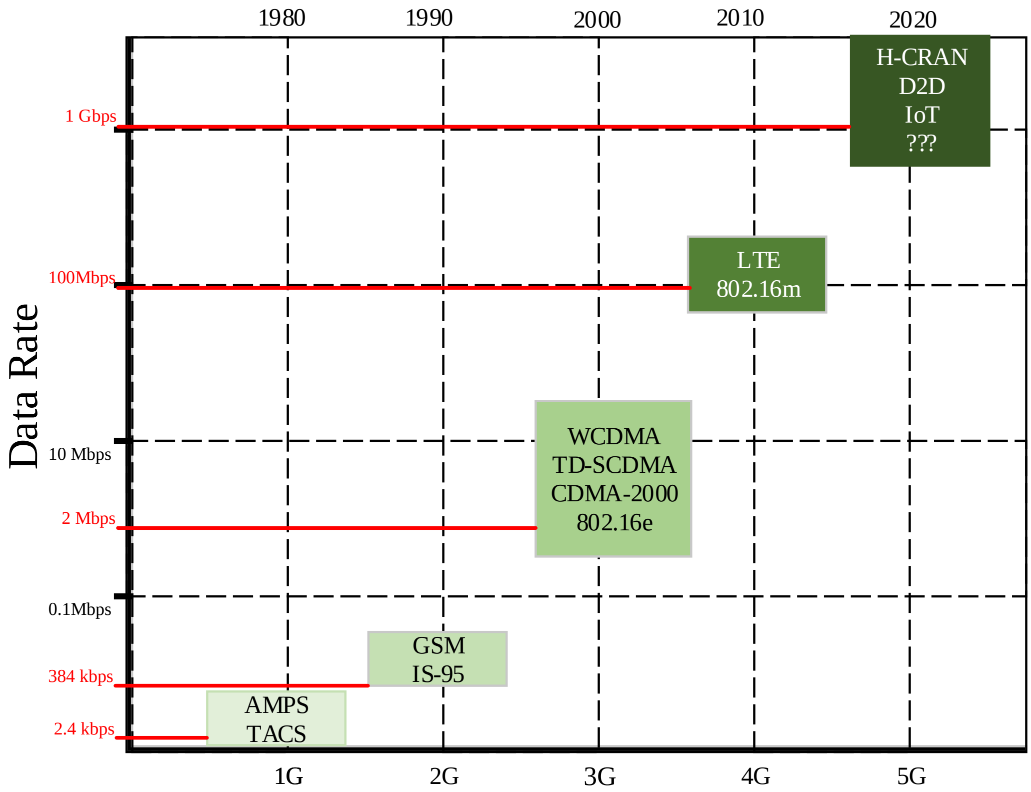

Figure 1.1: Journey of cellular networks

North American IS-95 (Interim Standard - 95) [4] and European GSM (Global System for Mobile Communication) [5].

In the 21st century, third generation mobile systems (3G) were standardized under the coordination of International Telecommunication Union (ITU) [6]. Based on Code Division Multiplexing Access (CDMA) technology, 3G supported higher data rates, system capacity and larger bandwidth. The services were more data oriented and was capable of providing seamless user experience. 3G networks are both packet switched and circuit switched digital networks with throughput up to 2Mbps. Major members of 3G standardization include Wideband CDMA (WCDMA) in Europe, CDMA2000 in North America and Time Division - Synchronous CDMA (TD-SCDMA) in China [7]. Worldwide interoperability for Microwave Access, IEEE 802.16e (WiMAX) became 4th member technology of 3G global standards family in 2007 [8].

1.1.2 4G LTE Networks

Long Term Evolution (LTE) proposed by Third Generation Partnership Project (3GPP) was initial taste of 4G networks around 2004 [9]. LTE was CDMA based digital communication system with higher data rates and IP based voice services. In 2010, 4G standards were laid down to overcome the drawbacks of 3G networks. With introduction of orthogonal frequency division multiple access OFDMA and MIMO, 4G networks provides much higher data rates than 3G [10, 11]. These networks are packet switched and both data and voice communications are Internet Protocol (IP) based. 4G LTE consists of a single radio access network node called evolved Node B (eNB). Throughput of 4G networks reaches up to 100 Mbps.

1.1.3 5G Networks

A massive research and development is observed in cellular networks and mobile internet for past decade [12, 13]. As the internet is transforming from only human users to the internet of things (IoT), there is an explosive rise in number of machine to machine modules with dense sensor networks and smart devices, loaded with multimedia-rich applications such as high definition video conferencing, online gaming and social media platforms with huge amount of data communications. It is projected that smart phones will surpass 86 percent of total mobile data traffic and 78 percent of mobile data traffic will be video by 2021 [14]. The present LTE wireless networks are far away to take such huge mobile data traffic burden, hence wireless communication is entering new fifth generation (5G) networks. In comparison with current 4G networks, 5G networks are expected to deliver energy efficient performance with approximately 1000x more wireless capacity with 90 percent savings of energy consumption. Also, with these high data rates, 5x reduced end-to-end latency and 10x higher batter life of the devices will be key characteristics of 5G networks to provide uninterrupted user experience [15, 16]. An illustration of 5G networks presented in [17] is given in Fig. 1.2.

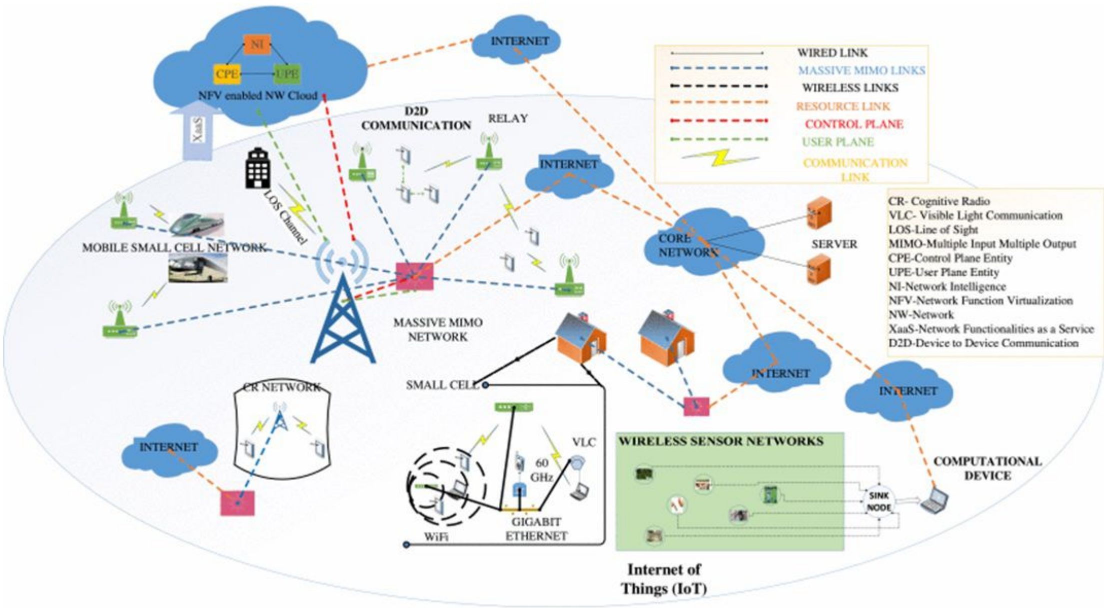

Figure 1.2: Illustration of 5G networks [17]

1.1.3.1 Cloud Radio Access Networks

To reach the goals mentioned above, topologies and architectures must be smoothly evolved from traditional simple 4G to much complex, dense and heterogeneous 5G architecture. Cloud radio access networks (C-RAN) and heterogeneous networks (Het-Nets) with ultra-small cells architecture have been considered as potential enabler of 5G networks. In C-RANs, large number of low-cost, low-power remote radio heads (RRHs) are deployed randomly in the coverage area. These RRHs are connected with baseband (BBU) pool through fronthaul links. C-RAN has an advantage over traditional networks deployment with reduced propagation distance between base station and user. Smaller distance with lesser interference allows network to achieve more system capacity with very less power consumption. Moreover, centralized baseband processing at BBU, interference can be mitigated by cooperative processing techniques. Although C-RAN is much energy and cost-efficient architecture, but its performance is degraded by fronthaul limitations and by the limit of maximum number of RRHs connected to BBU. We cannot deploy too large number of RRHs due to implementation complexity. Although C-RAN is explored extensively by search groups and implemented by industry, it is still not straightforward solution for 5G networks.

1.1.3.2 Heterogeneous Networks

To increase the system capacity in HetNets, along with one homogeneous cellular macro base station with high transmission power under laid with several low powered femto-cells, pico-cells and relay nodes collectively called small cells. Purpose of small cells is to offload traffic from macro base station hence providing higher throughput and higher edge data rates. All cells are connected to core network directly via back haul links. A key lead of HetNets is the decoupling of control plane and user plane [18]. Small cell base stations provide data only service while control channel and signaling are fully managed by macro base station. Unfortunately, the architecture of HetNets in which macro base station and under laid small cell base stations share and reuse same spectral resources, there is presence of high inter-tier interference. Although several interference mitigation techniques have been proposed in literature [19, 20], HetNets still lag to deliver the 5G demands. Inter-cell coordinated multi-point access in HetNets to reduce interference between macro base station and small cell base stations need huge amount of signaling in backhaul link hence effecting the capacity of backhaul link. Ultra-dense small cell may increase the capacity of the system but also increase the consumption of energy by the system hence reducing the energy efficiency of the system.

1.2 Heterogeneous Cloud Radio Access Networks

H-CRAN network is the hybrid of CRAN and HetNets. It acquires the cloud processing feature from CRAN and several small cells of heterogenous nature from HetNets. The CRAN in which there is also a Macro Base Station (MBS) is known as Heterogeneous Cloud Radio Access Network (H-CRAN). MBS do all the signalling directly to user equipment to improve mobility and is connected to BBU pool via back haul link. The User Equipment (UEs) can be connected to either MBS or any of RRH. UEs with high data rate demand can be served by RRH and UEs with low data rates are served by MBS. UEs can also be served by RRH, if MBS has high traffic and resources cannot be allocated to any further UE. Resource allocation is done by BBU pool hence minimizing the intra-tier interference. Hybrid nature of H-CRAN is shown in Fig. 1.3

The main contribution of this thesis is summarized below:

- A thorough literature review on history and developments in cellular communication networks, energy harvesting and its implementation in cellular networks, optimization in 5G cellular networks is presented. Presented literature review will help in formulating the proposed problem and its solution.

- An H-CRAN architecture is considered in which several green RRHs powered by harvested energy are deployed to increase the system capacity. Capacity of system is increased significantly without putting any burden on grid energy.

- User association is maximized so that most of the user can be served constrained by the QoS threshold. Admission control is considered to keep the system Key Performance Indicators (KPIs) up to the mark. If any user does not fulfil the minimum admission requirements, it will not be served.

- In practical scenario, rate of arrival of harvested energy and rate of traffic are totally random in nature and can not be known precisely a priori, so power allocation is also optimized to use the green energy efficiently.

- A less complex sub optimal algorithm MADS [21] is used to solve formulated fractional MINLP problem which gives $\epsilon - optimal$ solution and allocates the power and resources to a user very efficiently.

As the basic architecture of 5G and previous cellular networks has been discussed briefly, the organization of rest of the thesis is as chapter II with previous work done on energy harvesting and optimization in 5G networks specially in HCRAN networks are thoroughly discussed. System model, formulated problem and optimization technique is proposed in chapter 3. Simulation setup and results are discussed in chapter 4. Chapter 5 concludes this thesis along with highlights on possible future work which can be done.

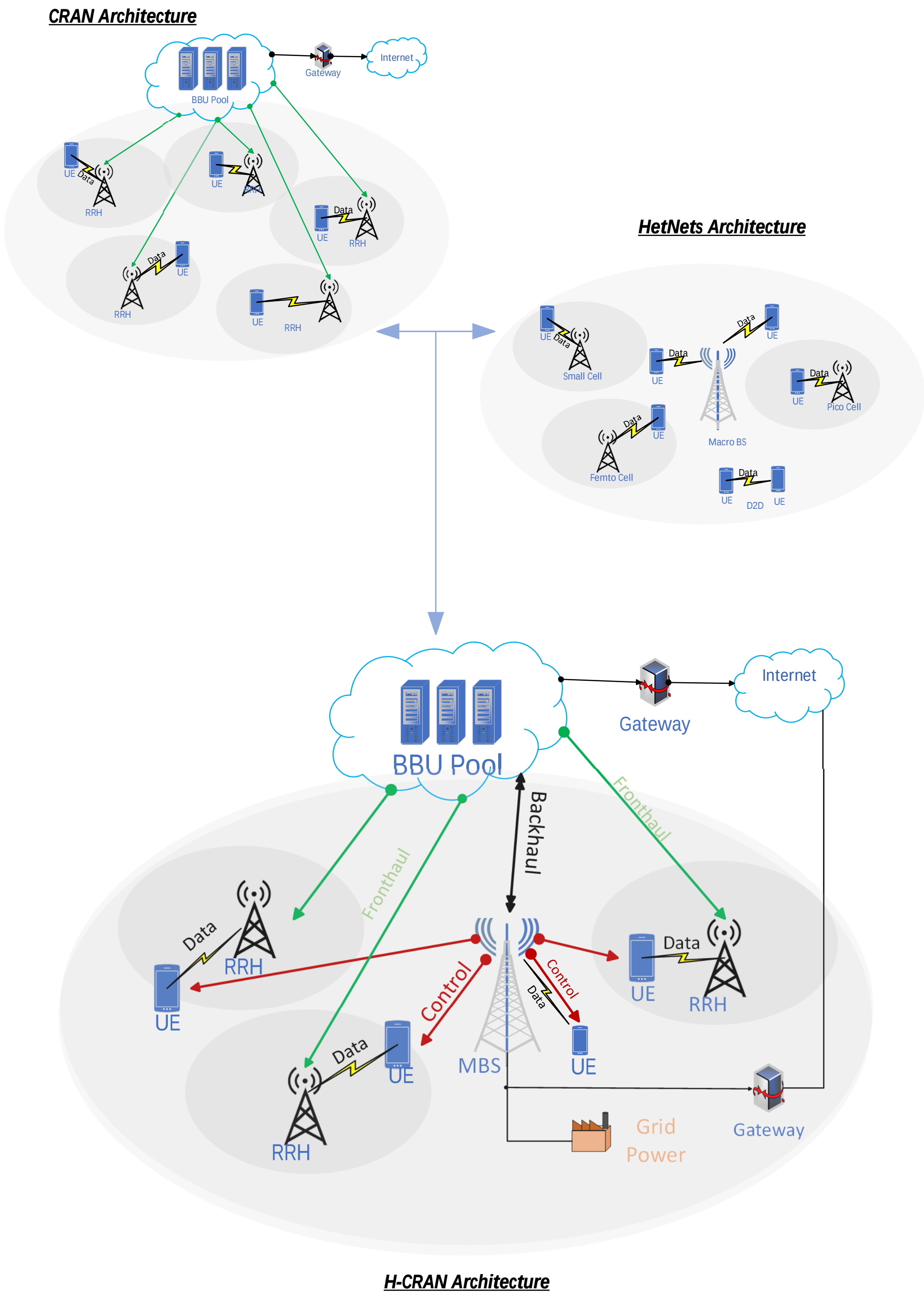

Figure 1.3: H-CRAN - As a hybrid of CRAN and HetNets Architecture

Chapter 2

LITERATURE REVIEW

2.1 Energy Harvesting

As discussed in previous chapter that 5G will be dealing with huge amount of data traffic with very dense network architectures. As a result of this processing this huge data traffic and maintaining the architecture will also result in highly increased energy consumption resulting in larger carbon footprint of the mobile communication industry. 2% of the global CO_2 emission is contributed by information and communication technology (ICT) industry. In this 2%, mobile communication contributes about 15-20% [22]. Only the operation of BSs consumes 80% of consumption of energy in mobile communication [23, 24].

To mitigate this huge energy consumption issue in 5G networks, a technique of energy harvesting is being focused by academia as well as industry. EH is the process in which energy is generated from ambient environmental sources like solar, wind etc. Fig. 2.1 shows different forms of ambient energy sources in natural environment.

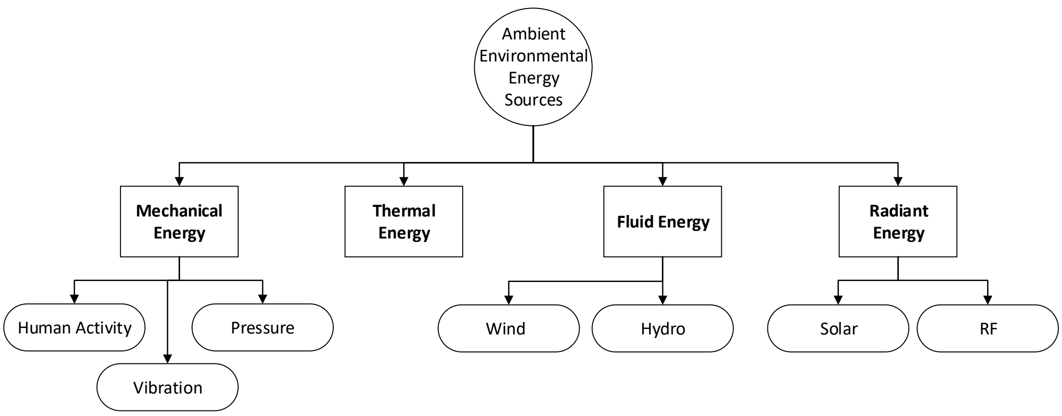

Figure 2.1: Different ambient energy sources in environment

2.1.1 Energy Harvesting Integration Techniques

Energy harvesting can be integrated with a cellular system in three main techniques, which are:

- Standalone EH
- Hybrid EH
- Simultaneous Wireless Information and Power Transfer (SWIPT)

In standalone EH, some entities of cellular system such as small cells base stations, are solely connected to EH system. These entities are totally green and self powered. In Hybrid EH integration, cellular system is both powered by grid energy and EH. In the unavailability of harvested energy system uses grid energy. In SWIPT, system gets the energy harvested from the radio frequencies through which data is being received. EH module is able to separate the data stream and energy stream from RF waves. Mostly in SWIPT, user equipment is mounted with EH modules which charges their batteries with the energy extracted from the received data signal. These three integrations are explained in Fig. 2.2.

2.1.2 Green 5G Networks

As the 5G standardization is in on-going phase, one of the most used terminology in 5G systems is ”*Green*”. Energy harvested green networks not only focus on improving the EE but also offloads the dependency of system energy on electric grid. There are several potential advantages of energy harvesting in 5G cellular networks. First from the point of view of network operator, EH can reduce the cost of energy consumption by deploying base stations powered by solar or wind energy. Base stations are the eighty percent energy consumers in cellular networks. EH enabled BSs can use solar energy for operation in daytime along with storing it in rechargeable batteries and at night time, stored energy can be utilized along with the wind energy power generation. Second from the consumer point of view, the lesser expenditure of running cellular network, lesser will be the network utilization charges for the users of that network.

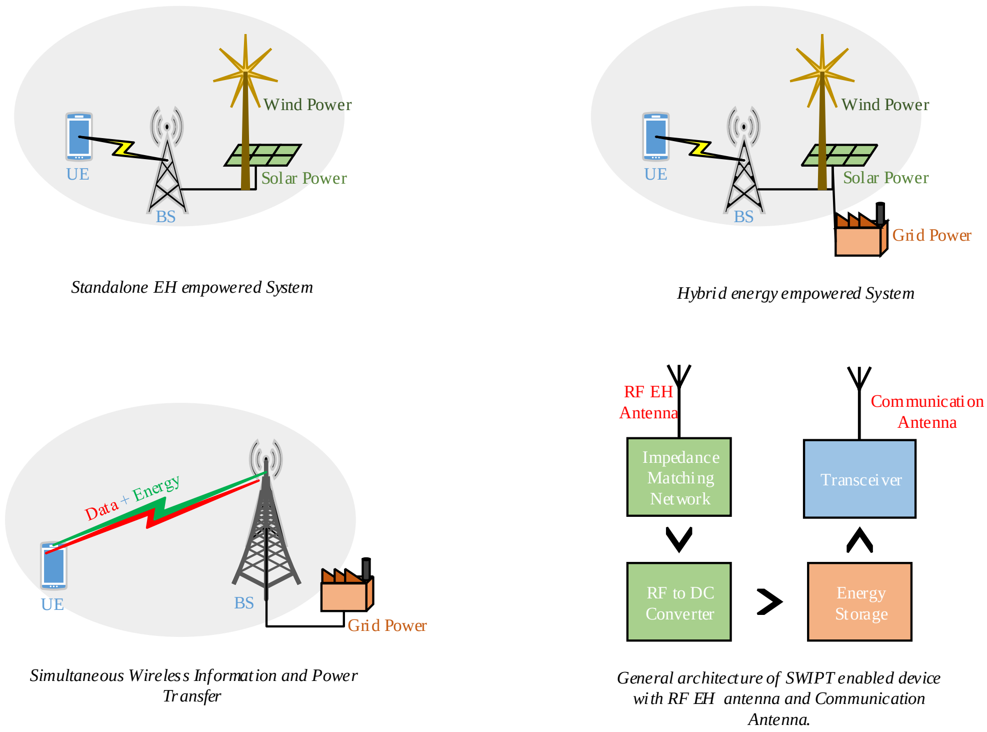

Figure 2.2: Energy harvesting integration techniques

EH also speed up the roll out of the cellular network in remote areas which lack power grid infrastructure.

2.1.3 Energy Harvesting and Industry

It is estimated that to operate an off-grid base station, approximately twelve solar panels are sufficient and even able to transfer extra harvested power to electric grid through sophisticated mechanism [25]. Industry and academia are focusing on making cellular networks greener and energy efficient. According to Pike Research statement it is predicted that more than 390 thousand green stations will be deployed from 2012 to 2020 [26]. Motorola and Sony Ericsson have considered deployment of solar powered base stations several years ago [27]. Telekom company deployed first base station which is powered by wind energy, in Eibesthal in Lower Austria [28]. NTT DoCoMo has already started environmentally friendly, disaster proof green base station empowered by wind and solar energy [29]. Illustration of base station is shown in Fig. 2.3. Hence EH can be a vital part of future 5G networks. EH not only reduces the consump-

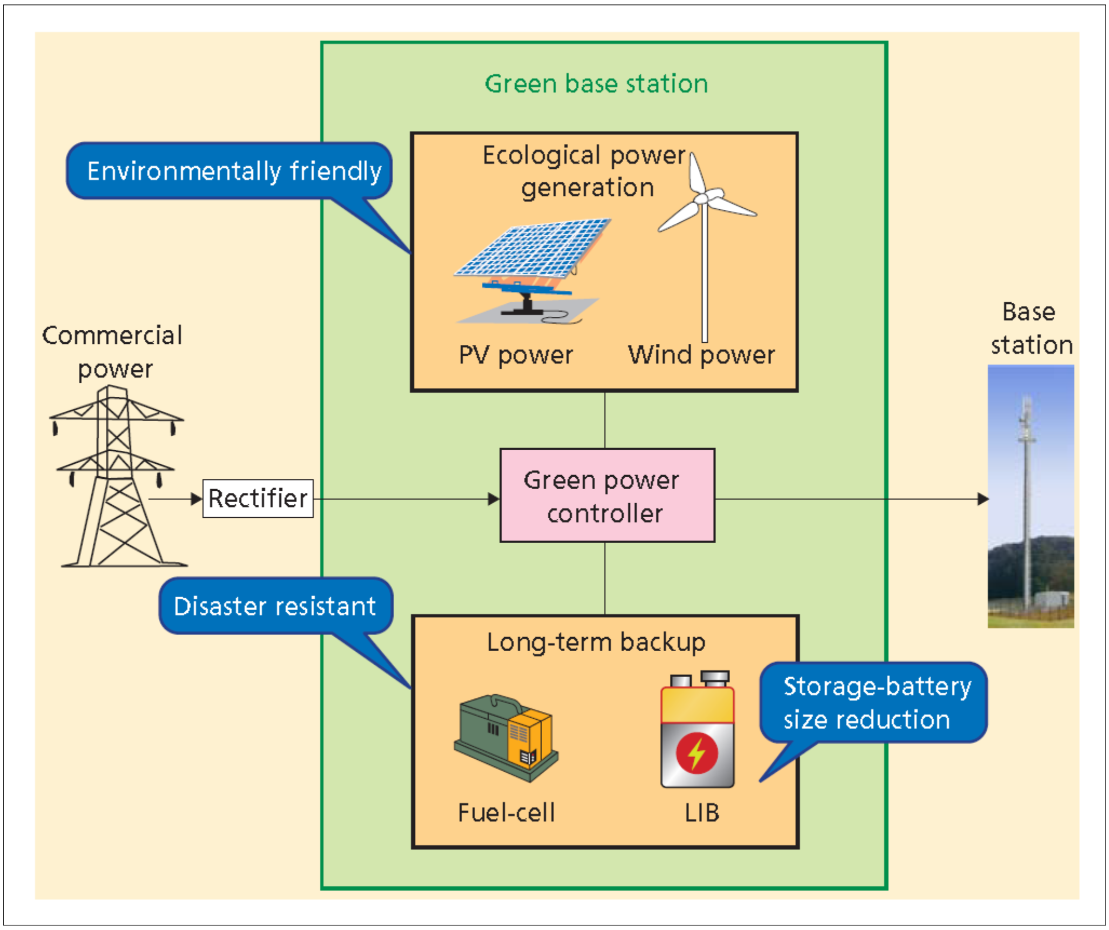

Figure 2.3: Model green base station illustration by NTT DoCoMo

tion of grid energy of the system but also helps in making the environment cleaner.

2.2 Optimization in 5G Heterogeneous Networks

The necessity for implementing green communication has been recognized by the research groups and the industrial assemblies worldwide [30], [31]. The upcoming 5G shift will be focusing on new techniques in network deployment, resource allocation, grid energy management and base stations that are smart enough in traffic offloading and efficient sleep control to maximize the EE. Studies target the improvement of EE and cost minimization of the system by minimization of transmit powers of base stations and minimization of grid energy consumption with the help of traffic shaping and EH and green energy management respectively [32]. User association, resource allocation and base station sleep control have also been focused in literature to improve the EE [20, 33].

2.2.1 Grid Energy Minimization

EH is widely implemented in 5G HetNets and is used in the form of standalone EH enabled base stations, hybrid energy enabled base stations and SWIPT. In this section, grid energy minimization with the help of EH implementation is briefly discussed.

A multi-cell cooperation scheme is discussed in [34], a cooperative sleep mode and transmission operation is proposed to confront the inter-cell interference and conserve the network energy i.e., grid energy minimization. The study also investigates the integration of hybrid energy sources in proposed system to get green multi-cell cooperation and further offload energy burden from grid system.

In [35], simultaneous data transmission and power transfer is studied. Both information and energy are transfer to information and EH receivers. An optimization problem for minimization of transmit power across the network is formulated. Problem is subjected to data reliability, information security and EH. To achieve rank-one optimal solution semi-definite relaxation technique is used.

In [36], a HetNets architecture which consist of MBSs and EH enabled small-cell base stations is considered. Due to dense nature of the system, joint optimization problem is formulated for maximization of the total system utility of both network operators and end users. Optimization problem is solved in two stages due to complexity and interference among the small cell base stations. These two phases are location update phase and small cells cooperation and association phase. Location update keeps the track of available energy and traffic load that is left in small cell base station. On the basis of this location update, an optimal user association vector is formulated with the help of two-side matching algorithm. The proposed algorithm in this study improved the system efficiency effectively.

[37] proposed a distributed delay aware and energy aware algorithm for user association in 3 tier HetNets architecture with hybrid energy. Algorithm aims to minimize the consumption of grid energy by maximizing the usage of green harvested energy. Algorithm also ensures the QoS by the average traffic delay minimization. A convex optimization problem is expressed which is constrained with traffic delay and on-gird power consumption constraints. Results shows that proposed algorithm succeeds in al-

locating the green power. It is also able to adjust the base station traffic load by efficient user association resulting in minimized traffic delay.

[38] also adopted optimization of green power allocation and user association to minimize the consumption of grid energy in HetNets. A two-dimensional optimization problem is studied in which user association is optimized in space dimension and green power allocation is optimized in time dimension. Results of simulations shows that the proposed optimal offline algorithm effectively conserve grid energy as well as reduces peak consumption of on-grid energy.

[39] studies the minimization of the grid energy consumption by jointly investigating admission control, sub-carrier assignment, power allocation and transmission time. System is hybrid energy enabled OFDMA based with battery leakage constraint. Formulated optimization problem is solved using Lyapunov optimization technique. Authors also proposed battery leakage aware algorithm with dynamic resource allocation policy to tackle the minimization problem. By using Lagrange dual theory and nonlinear fractional programming, authors further devised a bisection based iterative algorithm. Simulation results support the feasibility of the theoretical analysis of proposed algorithm.

In [40] grid energy minimization problem is optimized in OFDMA based hybrid energy powered cellular network. Formulated problem is constrained with QoS constraint. A sub-optimal online resource allocation algorithm is proposed using Lagrange dual method and stochastic optimization theory.

[41] also studies the energy minimization in hybrid energy empowered cellular network. Long term average network service cost is taken as the performance metric which include both grid power consumption and QoS achievement. Lyapunov optimization-based BS assignment and power control algorithm is proposed to optimize the formulated problem. Proposed algorithm is less complex online algorithm that make decisions only on the basis of the instantaneous information without having any information regarding channel and EH processes.

In [42] a game theoretic approach is discussed for energy cooperation in self powered small cells to minimize the grid energy. Authors proposed two algorithms in the study, one is centralized and one is decentralized. In decentralized approach, BSs with redundant harvested energy can sell their energy to energy deficit BSs. Algorithm uses matching theory to make the transaction of energy between the BSs. In second centralized approach different values of portions of energy are pre-defined. BSs are involved in double-auction bid algorithm on the basis of their bids. An optimization is carried out to minimize the usage of smart grid for transferring energy between the BSs. Authors demonstrate that second algorithm is more truthful and balanced in budget. Both algorithms reduce the renewable energy consumption considerably.

2.2.2 Capacity Maximization

[43] considered EH enabled small cell based cellular system. A sleep-awake scheduling scheme has been proposed. Along with optimized power control, proposed scheme maximizes the capacity of the cell by 25%. A near optimal heuristic polynomial-time algorithm is proposed for the formulated mixed integer programming problem. Capacity is maximized with maximum battery capacity constraint and energy causality constraint. It is proposed that keeping the small cell BSs always active may not be always good method to maximize the capacity.

System capacity of EH empowered HetNets is maximized by adaptive user association in [44]. In contrary to user association based on constant transmit power of BSs in grid powered cellular system, an adaptive user association algorithm with varying transmit powers is proposed. The proposed technique is expressed as an optimization problem which maximized the number of users that are accepted by the system and minimized the usage of radio resources at the same time. Proposed online heuristic algorithm makes the user association decision on the basis of available resources in timely manner hence reducing the user association delay.

In [45] energy harvesting is only in relay nodes through which base station communicates with edge users. Self-sustaining relay nodes harvest energy from the received signals from base stations for processing and forwarding information to the edge users. Study optimizes transmission power of BS, transmission power of relay node and the separation of energy from the received signal for EH operation and processing the signals at relay node jointly. Three separate optimization problems are formulated for capacity maximization, throughput fairness and sum power minimization. Due to limited radio resources and high inter-cell interference, formulated problems are highly non-convex. Successive convex approximation approach is applied to derive an iterative algorithm, which converts the three on-convex problems in to set of convex problems which are solved by interior-point method. Results confirm that joint optimization solutions effectively improve the network performance

[46] also considers SWIPT mode for EH in connected devices. A small cells based network overlaid with a macro cell is proposed in which resource allocation is investigated. Formulated MINLP problem is optimized using scalarization technique and is converted to convex problem by relaxation of some variables and introducing some new auxiliary variables. Results show that efficient resource allocation is done with improvement in energy harvesting rate.

2.2.3 Energy Efficiency Maximization

In [47], a non-linear in nature fractional programming problem is proposed to optimize the transmit power, consumption of grid power and sharing of energy in small cell base stations which are empower with hybrid energy sources. Optima allocation of resources is carried out using Lagrangian duality method based energy efficient algorithm. Results show that proposed algorithm efficiently controls the consumption of power to substantially improve the system EE.

[48], system's EE is maximized by controlling power allocation and energy management among the cells in heterogeneous networks with hybrid energy power. By minimizing the amount of energy consumed from the constant energy source and maximizing the transmitted data per constant energy unit, the proposed fractional programming problem maximized the system EE substantially. An optimal iterative offline algorithm is proposed to solve the problem. Simulation results depict that algorithm utilizes harvested energy more efficiently and by increasing the data transmission per unit energy improved EE is obtained.

[49] uses first harvest-then-transmit technique on user level to maximize the energy

level of the user which is expressed as ratio of system throughput to amount of harvested energy. A wireless powered communication system is considered in which a user has to harvest energy first then performs communication. A resource allocation algorithm proposed which maximizes the individual EE of the users. Proposed EE problem is non-convex problem and to solve it authors first convert the problem into its corresponding parameterized subtractive form and then efficient iterative two-layer algorithm is applied to get the optimal results. Simulation results depict that proposed algorithm yields better EE performance that conventional schemes by fairness-based nature of the algorithm.

[50] investigates the SWIPT energy harvesting technique in cloud based cellular system. In this study, an energy efficient allocatioin of resources optimization problem for uplink is considered. In order to obtain sufficient amount of energy harvested from ambient RF frequency, a ractenna is equipped with the user equipment which is able to harvest energy from six frequency bands at the same time. These six frequency bands are Wi-Fi (2.4 - 2.45 GHz), UMTS (2150 - 2200 MHz), GSM1800 (1850 - 1900 MHz), GSM900 (850 - 910 MHz), LTE (750 - 800 MHz) and DTV (550 - 600 MHz). This wide spectrum of RF frequency enables users device to harvest more energy than conventional single frequency energy harvesters. Objective of the proposed optimization problem is maximization of the energy efficiency which is constrained by the energy consumption and data rate requirements. Quantum-behaved particle swarm optimization technique is used to solve the problem with sub-optimal solution and low complexity. Results show that greater amount of energy is harvested resulting in improved EE of the system. [51] introduces massive Multiple Input Multiple Output (MIMO) technology along with EH technique in small cells to maximize the EE of the system. Capacity is maximized in HetNets based cellular system with energy efficient power allocation and admission control using a heuristic algorithm while taking energy causality constraints in to account.

2.3 Optimization in 5G HCRAN

Due to its cloud-based nature, H-CRAN as a promising candidate is also been studied in literature [18,52]. According to [18], the motivation of H-CRANs is to assimilate the cloud computing technology into HetNets so that a large-scale centralized cooperative information processing and network functionalities can be realized, and thus spectral and EE performance is considerably improved beyond existing HetNets and CRAN. In [53], CRAN architecture is considered in which several BSs are solely powered with energy harvesting. In addition to these self-operated BSs, these BSs also transmit wireless information as well as energy to the data receivers and energy receivers simultaneously. A throughput maximization problem is formulated obtain at joint beam forming design over finite time. Problem is constrained with the amount of sufficient RF charged energy of the energy receiver. The formulated convex problem is relaxed to convex problem and is upper bounded by the rank one optimal values of relaxed form of the problem.

In [54], CRAN architecture with RRHs that are solely powered with harvested energy is considered. By jointly considering the energy harvesting process and wireless channel conditions, optimization of a utility function problem is formulated. Problem decomposition method is used based on Lyapunov techniques for optimization. Decomposed problem separately optimizes the data scheduling, energy harvesting and resource allocation. An online energy efficient algorithm is proposed which ensures the stability of both energy buffers and data buffers.

[55] explores the multi-tenant network slicing in H-CRAN networks. Proposed dynamic network slicing considers tenant's priority, baseband resources QoS, interference and capacities of fronthaul and backhaul links. The upper level of sliced network manages baseband resource allocation, user association and admission control while the lower level looks after the radio resource allocation. The proposed schemes show improved network throughput and QoS performance. This work lacks the green energy integration.

[56] authors proposed a tiered framework for the design and analysis of H-CRAN with EH aided RRHs and heterogeneous internet service provider. The proposed hi-

erarchical framework works efficiently by trading energy model between the ISPs and utilizing the energy sharing model. Study also incorporated D2D communication based on available energy and traffic load status of the RRHs. Using multi time scale Markov decision processes (MMDP), a multiple time-scale energy scheduling scheme is proposed. EH rates, channel states and user association are considered while designing the proposed scheme. Results show that the proposed algorithm significantly reduces the energy consumption cost of the network.

[57], EE is maximized in H-CRAN by using online learning model to optimize the resource and power allocation backed by test bed implementation and simulation results. Approximated online learning methodology is proposed to jointly allocate resources and energy to the users. Sophisticated frequency partitioning is proposed to mitigate the interference. Results include improved EE, SE, bit error rate and data rate in the system.

[58] considers H-CRAN network in which macro BS is powered with grid energy and RRHs are powered solely with green energy. A resource allocation problem is formulated on the basis of which a new problem with maximizes the utilization of green energy, is formulated. Proposed problem is evaluated by Lagrange dual decomposition method. Results express that proposed algorithm increases the green energy utilization that leads to decreased grid energy consumption.

[59] considers the co-operative beam-forming with front-haul capacity and stable data queue improvement in EE of multimedia rich H-CRAN. An optimization problem which maximizing the EE of a queue aware H-CRAN system is formulated which is constrained by individual fronthaul capacity and interior interference. The problem is reformulated on the basis of Lyapunov optimization technique. After transformation, this problem is now converted to a co-operative beam forming design algorithm which is constrained by inter-tier interference, instantaneous power and average power. To solve the reformulated problem, generalized weighted minimum mean-square error technique is used. Simulation shows the achievement of trade-off between EE and queuing delay strictly depending on the fronthaul capacity constraint.

In [60], to mitigate the inter-tier interference between RRHs and high power nodes

(HPN) and to improve the system EE, characterization of association of users with RRH or HPN is considered. Soft fractional frequency reuse (S-FFR) is further enhanced to achieve the objective. Based on constraint of association of users and enhanced S-FFR, a non-convex EE maximization problem is formulated for OFDMA based H-CRAN. The non-convex problem is re-formulated to an equivalent convex feasible problem and resource and power allocation expressions are derived in close form by using Lagrange dual decomposition method. EE is improved significantly by using e-SFFR.

[61] studies a joint resource allocation and congestion control optimization to energy efficient trade-off between throughput and delay. A stochastic optimization problem if formulated, which maximizes the average throughput constrained by required EE, power allocation, admission control, resource allocation and user association constraints. Lyapunov optimization technique is used decompose the formulated problem in three sub-problems, which can be solved in each slot in slotted downlink H-CRAN system. Results show that proposed solution stabilizes the queue and optimizes the power consumption of the system.

[62] considers user association, power allocation and admission control to maximize the throughput of the system. The formulated problem is mixed integer non-linear programming problem and is of NP-Hard nature. The NP-Hard problem is simplified using Outer Approximation Approach (OAA) from linear programming. OAA ensures the convergence of the problem in a finite computations. Summarized literature review is given in Table. 2.1.

2.4 Common Objectives Functions and Constraints

After going through the literature review in previous section, some common objective functions and constraint functions in network optimization problems can be extracted.

Few of the common objective functions are listed below:

- User association maximization.
- Throughput maximization.
- Transmit power minimization.

Ref.	Objective	Constraints	Problem Type	Solution Technique	EH	U.A	P.A	A.C	Centralized/ Decentralized
[34]	Multicell Cooperation	Max. Power, Max. Capacity	NP-Hard	Problem decomposition	✓		✓	✓	Decentralized
[35]	Min. transmit power	Max. SNIR, Data reliability	Semidefinite programming	SeDuMi solver by CVX	✓		✓		Decentralized
[36]	Traffic Shaping	Max. Power, Max. Capacity	NP Hard	Optimization	✓		✓		Decentralized
[37]	Min. Grid Energy	QoS constraint, Traffic Delay	Convex problem	IDEA algorithm	✓	✓	✓	✓	Decentralized
[38]	Min. Grid Energy	Energy Causality, Battery Capacity	Convex prob.	Convex optimization	✓	✓	✓		Decentralized
[39]	Min. Grid Energy	Energy Causality, Min Rate	Stochastic problem	Lyapunov optimization theory	✓	✓	✓		Decentralized
[40]	Min. Grid Energy	QoS constraint, Max. Transmit Power	Convex Problem	Lyapunov optimization theory	✓	✓	✓		Decentralized

[41]	Min. Grid Energy	Energy Causality, Min. Throughput	Markov decision process	Standard MDP algorithms	✓	✓	✓		Decentralized
[42]	Min. Grid Energy	Energy Consumption by buyer	Matching theory	Game Theory	✓		✓		Decentralized
[43]	Max. Capacity	Energy Causality, Battery Capacity	Convex and mixed integer	Heuristic	✓		✓		Decentralized
[44]	Max. Capacity	BS resources, Connectivity	NP-Hard	Gradient Decent based algorithm	✓	✓			Decentralized
[45]	Max. Capacity	Max. Transmit Power	Non Convex	Difference -of-convex-function prog.	✓		✓		Decentralized
[46]	Max. Capacity	Min. Throughput	Mixed Integer Non-Linear Programming	Scalarization of multi objective prog.	✓		✓		Decentralized
[47]	Max. EE	Energy Causality, Max. Capacity	Non-Linear Fractional Programming	Lagrangian Duality Method	✓		✓		Decentralized
[48]	Max. EE	Energy Causality, QoS	Non-Convex	Convex Lagrange functions	✓		✓		Decentralized

[49]	Max. EE	Rate Constraint	Non-Convex	2-layer iterative algorithm	✓		✓		Decentralized
[50]	Max. EE	Energy Causality, Min. data rate	Mixed Integer Non-Linear Programming	QPSO	✓	✓	✓		Decentralized
[51]	Max. EE	Energy Causality, Transmit Power	Non-Convex	Difference of convex program	✓	✓	✓		Decentralized
[53]	Max. Throughput	Energy Causality	Non-Convex	Constraints relaxation	✓		✓		Centralized
[54]	Max. User Association	Energy Causality, Stable Data Queue	Stochastic problem	Lyapunov Optimization	✓	✓	✓		Centralized
[55]	Max. Throughput	User Association, QoS, Transmit Power	Dual Optimization Problem	Lagrange dual decomposition		✓	✓		Centralized
[56]	Min. Energy Cost	Energy Causality, user association	Stochastic problem	Multi-time scale Markov decision process	✓	✓	✓		Centralized
[57]	Max. EE	User Association, QoS, Transmit Power	Mixed Integer Non-Linear Programming	Model Based Dynamic Programming Problem		✓	✓		Centralized

[58]	Max. EE	Energy causality, Min. data rate	Mixed Integer Programming	Lagrange dual decomposition	✓	✓	✓		Centralized
[59]	Max. EE	Max. Transmit power, Min. data rate	Non-Linear Programming	Lyapunov optimization technique		✓	✓		Centralized
[60]	Max. EE	QoS Constraints, user association	Mixed Integer Programming	Lagrange dual decomposition		✓	✓		Centralized
[61]	Max. Throughput	QoS constraint, Transmit Power	Stochastic problem	Lyapunov optimization technique		✓	✓		Centralized
[62]	Max. Throughput	QoS constraint, Transmit Power	Mixed Integer Non-Linear Programming	Outer Approximation Algorithm		✓	✓		Centralized
This work	Max. EE	Energy Causality, QoS, Transmit Power	Mixed Integer Non-Linear Programming	MADS	✓	✓	✓	✓	Centralized

Table 2.1: Literature Review: A.D=Admission Control, U.A=User Association, P.A= Power Allocation, EE=Energy Efficiency

- Grid energy minimization.
- Harvested Energy consumption maximization.
- Energy Efficiency maximization.
- Energy cost minimization.

Few of the common constraint functions are explained below:

2.4.1 User Association

User association constraint defines that a single user must be connected to single BS for communication. It is usually a binary constraint having value of $\{0,1\}$.

2.4.2 Maximum transmit power

This constraint makes sure that the transmission power of all connections of the BS must be less than or equal to the total transmit power of the BS. Similarly transmission power of the user must be less than or equal to its total transmit power.

2.4.3 QoS constraint

QoS constraint makes sure that the data rate assigned to the user must be equal to or greater than the minimum threshold defined by the operator. If the channel conditions do not allow to provide the data rate equal to or greater than the threshold than the user will not be allowed to connect to the specific BS.

2.4.4 Energy Causality

This constraint is applied in the problems where the system is solely powered with harvested energy. This constraint makes sure that the amount of energy stored in the battery or incoming harvested energy rate (in case where no battery is attached) must be equal to or greater than the static power consumption plus minimum transmit power required to connect with a user.

Along with above mentioned constraints, battery capacity constraint, data buffer constraint, admission control constraints are also being used in the literature.

It is observed from the literature review that studies focus solely on resource allocation, power allocation, EE optimization and EH integration. The lack of energy efficient joint power and resource allocation in H-CRAN based cellular network that is also aided with harvested energy, is key reason of motivation for the proposed work i.e., to take into account all these metrics to optimize EE of H-CRAN cellular network.

Chapter 3

SYSTEM MODEL AND PROPOSED TECHNIQUE

3.1 System Model

CRAN consist of BBU and several RRHs. BBU is a centralized processing and signalling unit, connected to all RRHs via front haul links. The CRAN in which there is also a MBS is known as H-CRAN. MBS do all the signalling directly to user equipment to improve mobility and is connected to BBU pool via back haul link. Proposed system model considers H-CRAN consisting of only one MBS, which is connected to grid power and *I* number of Green RRHs (GRRHs), which are solely connected to harvested energy (solar, Wind, etc.). Energy harvested in GRRH can be stored in battery connected to them. GRRH can only serve when it has sufficient energy to establish the communication link. Centralized BBU have knowledge of power status of every GRRH connected to it so that it can decide whether to assign resources to them or keep them on sleep until there is enough energy stored in battery. There are *N* number of User Equipment (UEs) which can be connected to either MBS or any of GRRH. UEs with high data rate demand can be served by GRRH and UEs with low data rates are served by MBS. UEs can also be served by GRRH, if MBS has high traffic and resources cannot be allocated to any further UE. Efficient user allocation is done by centralized BBU pool. Proposed system model is shown in Fig. 3.1.

3.1.1 Resource Allocation Model

Proposed model considers downlink, OFDMA based H-CRAN. Let there be one MBS *M* and *i* GRRHs such that $i \in \mathcal{R} = \{1, 2, ..., I\}$. There are *n* number of users where $n \in \mathcal{N} = \{1, 2, ..., N\}$.

Let x_s^n be the binary indicator for user connection mode, i-e, user is either connected with MBS or any GRRH R_i, where $s \in \mathcal{S}$ and $\mathcal{S} = \{M, R_1, R_2, R_3, ..., R_I\}$. This mode selection indicator can be written as: $x_s^n = \{0, 1\} \forall n \in \mathcal{N}, s \in \mathcal{S}$. Let y^n be the

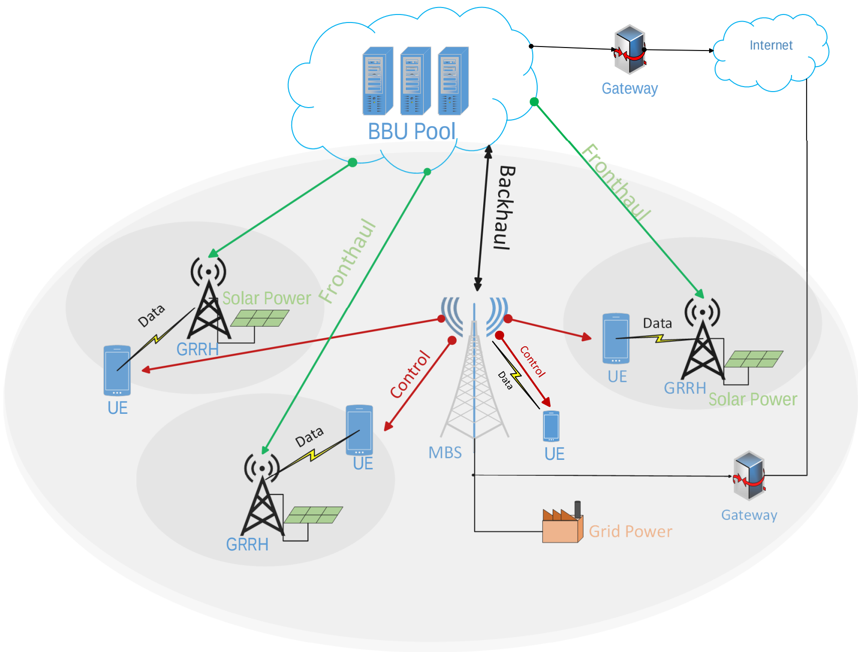

Figure 3.1: System Model - Downlink in H-CRAN with EH powered RRHs and grid energy powered MBS

user selection indicator which decides whether user is admissible to connect with MBS or any GRRH or not, such that, $x_s^n \leq y^n$. Let p_M^n and $p_{R_i}^n$ be the power allocated to user n while connected to MBS or any GRRH R_i respectively. Channel gain of MBS and GRRH is denoted by ϕ_M^n and $\phi_{R_i}^n$ respectively and stated as:

$$\phi_M^n = \phi_M'^n \eth G_o \left(\frac{d_o}{d_M}\right)^\alpha \phi_{R_i}^n = \phi_{R_i}'^n \eth H_o \left(\frac{d_o}{d_{R_i}}\right)^\alpha \tag{3.1}$$

where $\phi_M'^n$ and $\phi_{R_i}'^n$ are Rayleigh random variables for MBS and GRRHs respectively. $\eth$ be the lognormal shadowing. G_o and H_o are the antenna gain for MBS and GRRH respectively. d_o is antenna far field reference distance. d_M and d_{R_i} are the distances of UE n from MBS and GRRH R_i respectively with path loss constant α.

According to proposed resource allocation policy, the total data rate of the system as:

$$\varsigma_{total} = \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} x_s^n c_s^n \tag{3.2}$$

where c_s^n is the data rate of user *n* served by MBS or any of GRRHs and is given by:

$$c_s^n = log_2\left(1 + \frac{p_s^n \phi_s^n}{N_0}\right) \quad \forall n \in \mathcal{N}, s \in \mathcal{S} \tag{3.3}$$

where p_s^n is power received by the UE *n* from MBS or any GRRH R_i. N_0 is the channel noise suffered by the signal.

3.1.2 Energy Model

As mentioned earlier that all GRRHs are solely operated by ambient source of energy which is harvested and stored in a rechargeable battery though EH modules such as wind turbines and solar panels at each GRRH location. Let maximum storage capacity of battery of GRRH R_i is ε_i. Let $E_{R_i}^{avail}$ denotes the available energy at GRRH R_i and e_{R_i} denotes the amount of energy harvested by GRRH R_i in each time slot such that:

$$0 \leq e_{R_i} \leq \gamma_{R_i} \tag{3.4}$$

where γ_{R_i} is the maximum amount of energy that an GRRH R_i can harvest in one time slot. EH model is proposed to be a random process and for any GRRH, $\gamma(t)$ is independent and identically distributed over [0, γ_{max}] at each time slot *t* i.e., $\gamma_{R_i}(t) \leq \gamma_{max}$. It is assumed that proposed system may have no a priori information about $\gamma_{R_i}(t)$ which is practically valid when no statistical data is available for EH process.

According to proposed resource allocation model the total power consumption of MBS and GRRH R_i is given by:

$$P_s = \mu_s^{eff} \sum_{n \in \mathcal{N}} p_s^n \quad \forall s \in \mathcal{S} \tag{3.5}$$

where P_s is further explored as:

$$P_M = \mu_M^{eff} \sum_{n \in \mathcal{N}} p_M^n \tag{3.6}$$

$$P_{R_i} = \mu_R^{eff} \sum_{n \in \mathcal{N}} p_{R_i}^n \quad \forall i \in \mathcal{R} \tag{3.7}$$

where μ_M^{eff} and $\mu_{R_i}^{eff}$ are the drain efficiency of MBS and GRRH R_i respectively. Drain efficiency is the ratio of RF output power to the input direct current power of the amplifier. It is assumed that drain efficiency of all GRRHs are same. Total power consumption of the system will be:

$$p_{total} = \sum_{s\in\mathcal{S}} P_s + P_M^{static} + P_R^{static} \tag{3.8}$$

where P_M^{static} and P_R^{static} are static power consumption of MBS and GRRH respectively.

Now as the total power consumption of GRRHs is known, the energy available at GRRH will be given as:

$$E_{R_i}^{avail} = [e_{R_i} - P_R^{static}, 0]^+ \tag{3.9}$$

where $[x]^+ = max\{x, 0\}$. Equation (3.10) shows that to serve any UE, GRRH R_i should harvest the energy greater than the static power consumption. Successful communication by GRRH is constrained by the available energy in its battery, that is:

$$E_{R_i}^{avail} \geq P_{R_i} \quad \forall i \in \mathcal{R} \tag{3.10}$$

Moreover, as the battery has a finite maximum storage capacity it is possible that energy charging overflows the battery capacity. To limit the charging of battery to the maximum battery capacity, following limitation is considered:

$$E_{R_i}^{avail} + e_{R_i} \leq \varepsilon_{R_i} \tag{3.11}$$

3.2 Problem Formulation

For a given period of time, number of transmitted bits consuming one joule of energy is termed as EE. Hence EE of the system will be the ratio of the total data rate of the system to the the total consumption of power, and is given by:

$$EE = \frac{TotalDataRate}{TotalPower} \tag{3.12}$$

If the total capacity is in *bits/sec* and total power is in *watts* then EE can be measured in *bits/sec/watt* or *bits/joule*. This classic metric of EE does not take into account the spectral efficiency (SE) of the system. System capacity per unit of bandwidth is defined as SE and is measured in *bits/sec/Hz*. Hence the resulting metric *bits/sec/Hz/watt* also take the SE into account. According to proposed system model, EE can be stated as:

$$EE = \frac{\varsigma_{total}}{p_{total}} \tag{3.13}$$

After defining EE, an EE maximization problem is formulated with objective function, $\mathcal{U}$, mathematically stated as:

$$\mathcal{U}_{(x,y,p)} = \frac{\sum_{n \in \mathcal{N}} \sum_{s \in \mathcal{S}} x_s^n c_s^n}{P_M^{static} + P_R^{static} + \sum_{s \in \mathcal{S}} P_s} \tag{3.14}$$

subject to following constraints:

$$\begin{aligned}
C1: &\quad \sum_{s \in \mathcal{S}} x_s^n \leq 1 \qquad \forall n \in \mathcal{N} \\
C2: &\quad c_s^n \geq y_n C_{min}^n \quad \forall n \in \mathcal{N} \\
&\quad where \\
&\quad x_s^n \leq y^n \qquad \forall n \in \mathcal{N}, s \in \mathcal{S} \\
C3: &\quad p_M^n \leq y^n P_M^{max} \qquad \forall n \in \mathcal{N} \\
C4: &\quad p_{R_i}^n \leq y^n P_{R_i}^{max} \qquad \forall n \in \mathcal{N}, i \in \mathcal{R} \\
C5: &\quad \sum_{n \in \mathcal{N}} p_M^n \leq P_M^{max} \\
C6: &\quad \sum_{n \in \mathcal{N}} p_{R_i}^n \leq P_{R_i}^{max} \qquad \forall i \in \mathcal{R} \\
C7: &\quad E_{R_i}^{avail} \geq P_{R_i} + P_R^{static} \qquad \forall i \in \mathcal{R} \\
C8: &\quad E_{R_i}^{avail} + e_{R_i} \leq \varepsilon_{R_i} \qquad \forall i \in \mathcal{R} \\
C9: &\quad x_s^n, y^n \in \{0, 1\} \qquad \forall n \in \mathcal{N}, s \in \mathcal{S}
\end{aligned} \tag{3.15}$$

where C_n^{min} is the minimum data rate that can be allocated to a user by MBS or GRRH. P_M^{max} and $P_{R_i}^{max}$ are the maximum transmit powers of MBS and GRRHs respectively. P_R^{static} and P_M^{static} are the static power consumption of GRRHs and MBS respectively. Static power is used to power up the circuit board, cooling system, front haul and back haul power in GRRH and MBS respectively. Constraint C1 ensures that the user is connected to MBS or any one of the GRRHs at a given time. Constraint C2 is the QoS constraint ensuring the minimum data rate that can be allocated to a user.

Constraints C3 and C4 ensure that if user is not connected to any base stations its power will not be taken into account. Constraints C5 and C6 are maximum power constraint that MBS and GRRHs can transmit to their users respectively. Constraint C7 is the energy causality constraint which ensures that energy stored in the battery should be equal to or greater than the transmit power needed for communication and static power consumption of GRRH. Constraint C8 expresses the battery overflow constraint, i.e., stored energy in the battery cannot exceed the maximum battery capacity. Constraint C9 limits the value of resource allocation indicator to binary values $\{0,1\}$.

3.3 Proposed Technique

For proposed optimization problem, Mesh Adaptive Direct Search (MADS) algorithm [21] is used. This method is an iterative algorithm which performs an adaptive search on the tower of basic meshes on domain space along with the control over resizing and refinement of the mesh. MADS algorithm is composed of a *search* and *poll* method as in each iteration there are two steps called SEARCH step and POLL step. The objective of an iteration in MADS is to find the function minimum among some trial points on a predefined mesh of points with the help of SEARCH and POLL steps. In SEARCH step solutions over the trial points are calculated and compared with current incumbent point. If there is a better solution than the current point is found, then it is updated with new improved solution point as a starting point for next iteration. If SEARCH step fails in finding the improved solution, then the POLL step is invoked which tries to find the solution with its new parameters. If POLL also does not succeed in finding the improved solution, the iteration then be called an *unsuccessful iteration*. The mesh is redefined by reducing its size and hence increasing its resolution, and whole process is repeated. The pseudo code explaining the algorithm is depicted in Fig. 3.2. The four main steps of the algorithm, initialization, SEARCH step, POLL step, parameter update, are explained in detail below:

3.3.1 Initialization

Iteration is initialized given $x_0 \in \Omega$ where Ω is the domain space and x_0 is the initial iteration. Mesh size, poll size and direction set are also defined in this step. Trial

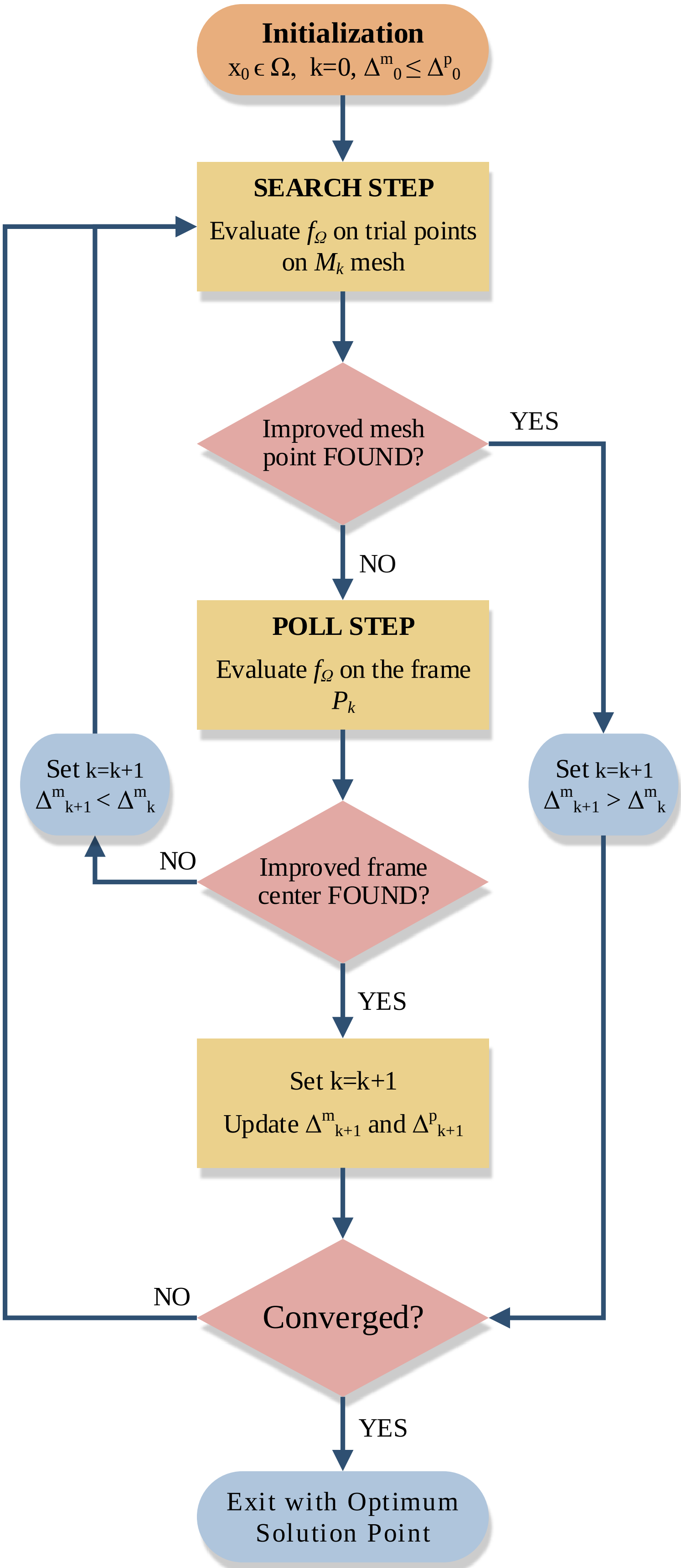

Figure 3.2: Flow chart of Mesh Adaptive Direct Search (MADS) algorithm

points will be the member of current mesh M_k which is constructed with the help of direction set $D \subset \mathbb{R}^n \to \mathbb{R} \cup \{+\infty\}$ having finite number of n_D directions scaled by a *mesh size parameter* $\triangle_k^m \in \mathbb{R}_+$. Mesh is not actually constructed but just overlies the MADS algorithm. Mesh will be defined as in [21]:

$$M_k = \bigcup_{x \in S_k} \{x + \triangle_k^m D_z \; z \in \mathbb{N}^{n_D}\} \tag{3.16}$$

where S_k is set of points where objective function *f* had been evaluated by the start of first iteration.

3.3.2 SEARCH Step

After initialization the SEARCH step tries to trace a function *f* minimum over Ω by assessing f_Ω at some trial points. At each iteration, algorithm generates a finite number of trial points. Among these trial points the infeasible ones are discarded, and the feasible ones are considered. At the feasible trial points, objective function values are compared with the current value $f_\Omega(x_k)$, i.e., the best value of feasible objective function, found so far. Strategy same as Generalized Pattern Search (GPS) algorithm can be used in the SEARCH step to generate the points [21, 63]. When an improved mesh point is found, its up to the user to continue to search further improved solution point or stop the algorithm. In either case the next iteration will be started with new improved incumbent solution point $x_{k+1} \in \Omega$ such that $f_\Omega(x_{k+1}) < f_\Omega(x_k)$ with mesh size parameter $\triangle_{k+1}^m$ equal to or larger than $\triangle_k^m$.

3.3.3 POLL Step

When the SEARCH step is failed to locate an improved mesh point then the POLL step is called before the iteration is terminated. The POLL step explores the space of optimization variable locally near the current incumbent solution x_k. POLL steps involves another parameter called *poll size parameter* $\triangle_k^p \in \mathbb{R}_+$ for iteration *k*. The set of trial points generated by the POLL step is called *frame*. This frame is constructed using current incumbent point x_k as a *frame center* and the new direction set D_k. D_k is constructed with the help of mesh and poll size parameters $\triangle_k^m$ and $\triangle_k^p$ respectively such that D_k is not the subset of *D*. MADS frame defined in [21] is as follow:

$$P_k = \{x_k + \triangle_k^m d : d \in D_k\} \subset M_k \tag{3.17}$$

The way $\triangle_k^m$ is updated should satisfy that $\triangle_k^m \leq \triangle_k^p$ and $\lim_{k \in K} \triangle_k^m = 0$ if and only if $\lim_{k \in K} \triangle_k^p = 0$ for all $k \in K$. If the poll step finds an improved solution then it moves its frame centre x_k to the new improved point x_{k+1} for next iteration $k + 1$. If the POLL step does not succeed in finding the improved mesh point then the frame will be labeled as a *minimal frame* and the frame center x_k is said to be the *minimum frame centre*. This leads to the mesh refinement, i.e., mesh size is reduced to increase the resolution of the mesh for next iteration: $\triangle_{k+1} < \triangle_k$. This whole process is shown in the flow chart given in Fig. 3.2.

3.4 Complexity Analysis of MADS

Unlike traditional optimization techniques which require first or higher derivative information to get to optimal solution, MADS algorithm has capability to solve a nonlinear programming problem without requiring information about the gradient of the objective function. MADS, uses extreme barrier approach with the constraints, by considering the objective function as infinity for infeasible points and treats the problem as unconstrained programming problem [21], hence reducing its computational complexity. Global optimal solution can be obtained Exhaustive Search Algorithm (ESA) but its complexity increases exponentially as the number of users in the network is increased. Let $\mathcal{C}$ denotes the computational complexity of an algorithm and *N* be the number of users than complexity of ESA will be given as:

$$\mathcal{C} = 2^{2N} \tag{3.18}$$

But with MADS, $\epsilon -$ *optimal* solution can be obtained in finite number iterations [66]. MADS converges in finite number of iterations with independence of initial point knowledge and the gradient of the objective function. Complexity of MADS is given by:

$$\mathcal{C} = \frac{N^2}{\vartheta} \tag{3.19}$$

where ϑ is the error tolerance of $\epsilon - optimal$ solution from the global optimal solution. Similarly, complexity of OAA is given by:

$$\mathcal{C} = \frac{N^2\omega}{\vartheta} \tag{3.20}$$

where ω denotes the number of constraints [62]. Complexity of OAA is number of constraints times higher than the complexity of MADS. Computational complexity trend of ESA, MADS and OAA are presented in Fig. 3.3.

3.4.1 Convergence Analysis of MADS

In [21], complete proof regarding convergence of the MADS is presented. The algorithm converges to point $\hat{x}$ globally, where it satisfies all the local optimalityl conditions. Convergence of MADS does not depend on the starting point x_0 but depends totally on local properties of the objective and constraint functions. It is assumed in the algorithm that at least one starting point in *X* is given, which may or may not lye in feasible domain space Ω, and all the iterations are from a compact set. If there is no information available about the objective function *f* then $\hat{x}$ can be considered as limit for local optimizer for the infinitely fine meshes. The resulting solution is called the zeroth order result. If at $\hat{x}$, hyper tangent cone of domain space is non-empty and *f* is Lipschitz near $\hat{x}$, then at $\hat{x}$ the Clarkes generalized directional derivatives of *f* [64] in all of the directions in the Clarke tangent cone are non-negative. The authors in [65], extend the convergence analysis of MADS algorithm to second order stationary points.

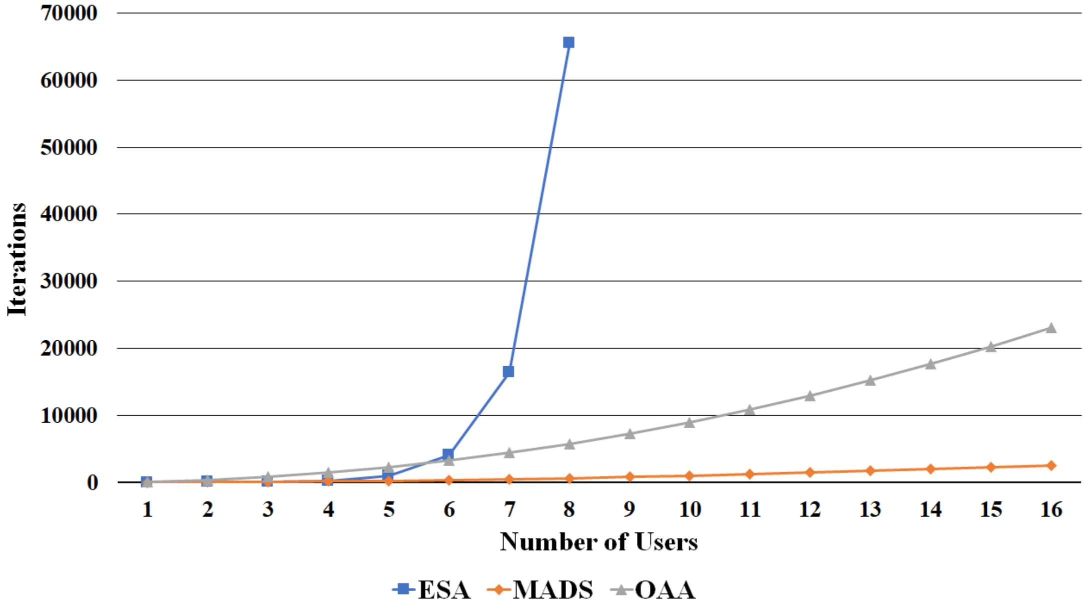

Figure 3.3: Computational complexity of ESA, MADS and OAA vs number of users

Chapter 4

RESULT AND ANALYSIS

4.1 Simulations, Result and Analysis

Experimental results for this work is obtained with a simulation setup to optimize equation (3.15) which is a fractional programming problem to evaluate the EE of the system. Results include efficient power allocation and user association to attain maximum throughput. The effect on grid energy is also highlighted. To solve the problem open source nonlinear mixed integer optimization using Mesh Adaptive Direct Search (NOMAD) [67] solver is used.

4.1.1 Simulation Setup

Parameters used for the simulation system are given in table 4.1. For all the simulation radius of macro cell is set to 1000 m and for each GRRH radius is set to 200 m. Maximum transmit power for macro cell P_M^{max}, and each GRRH R_i,$P_{R_i}^{max}$ is set to 24 W and 12 W respectively. Minimum data rate threshold for any user is set to 100 kbps. Reference distance as per antenna far field d_0 is set to 10 m and *d* is always greater than d_0. Path loss exponent α is set to 2 and zero mean Gaussian variable for shadowing ð is set to 10 dB. Circuit power for macro BS is set to 10 W and for each GRRH is set to 0.3 W. EH rate for any GRRH range from 0 W to 15 W per unit time. Maximum battery capacity ε_i attached to GRRH is 5 kWh. Users are supposed to be uniformly distributed in the network.

4.1.2 Results and Discussion

Optimization of the network EE is achieved using MADS algorithm. In Fig. 4.1, EE is plotted against the number of users. The general trend of this relation is that EE of the system increases when number of users is increased. It is observed that using MADS we achieve the same trend i-e., EE increases as number of users is increased. It becomes constant when maximum system capacity limit reached. System will not

Table 4.1: System Parameters

Parameter	***Value***
P_M^{max},	24 W
$P_{R_i}^{max}$	12 W
d_o	10 m
Macro BS cell radius	1000 m
GRRH cell radius	200 m
Min. data rate requirment	100 kbps
ε_i	5 kWh
ei	0-15 W
P_M^{static}	10 W
P_R^{static}	0.3 W
G_0	50
ð	10 dB
Min, Users	2
Max Users	16

admit the users to keep the QoS constraint ensured.

Fig. 4.2 shows the plot of user associated to each BS when the number of users increased. User association is maximized formulated problem. System tend to admit maximum number of users while keeping the quality constraint in consideration. It is observed that almost all users have been admitted up to sixteen users. Moreover it is also observed that more number of users are connected to GRRH as compared to macro BS hence increasing the utilization of green energy. This minimizes the grid energy cost effectively.

Fig. 4.3 shows the total system throughput vs number of users. Plot depicts that as the number of users increased system throughput also increases. if the number of users are further increased, data rate will stay constant to maximum system capacity limit. System throughput also depends on the channel state between the BS and the user. Proposed formulation keep the minimum rate constraint in to account so that QoS is kept ensured.

Fig. 4.4 shows the utilization of grid energy when EH is integrated with the system. In the plot bars show 100% utilization of grid energy when EH is not integrated. When

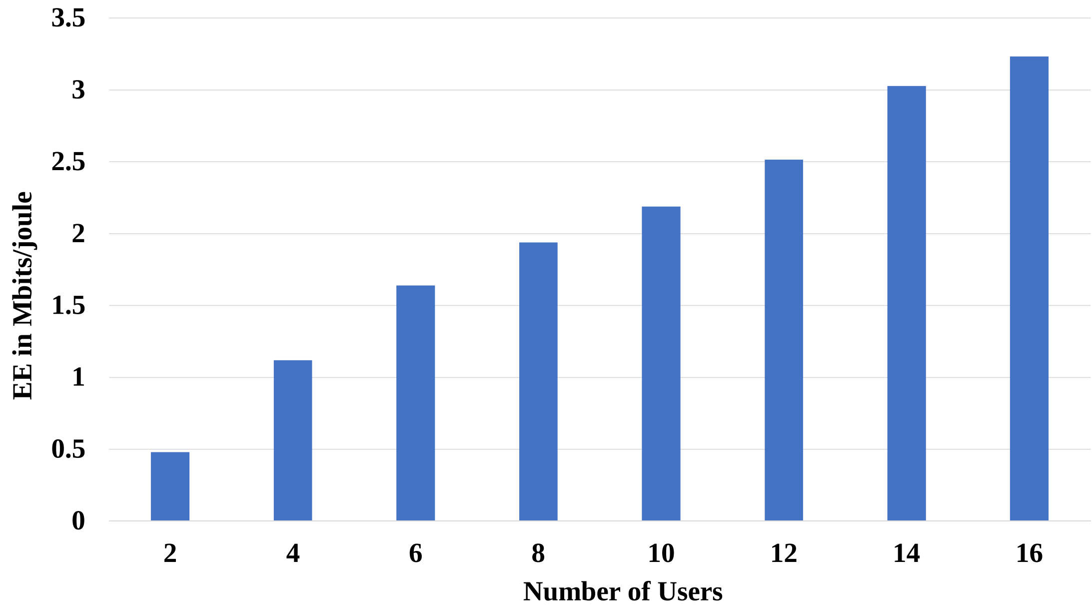

Figure 4.1: Energy Efficiency of System as Mbits/Joule for different number of users

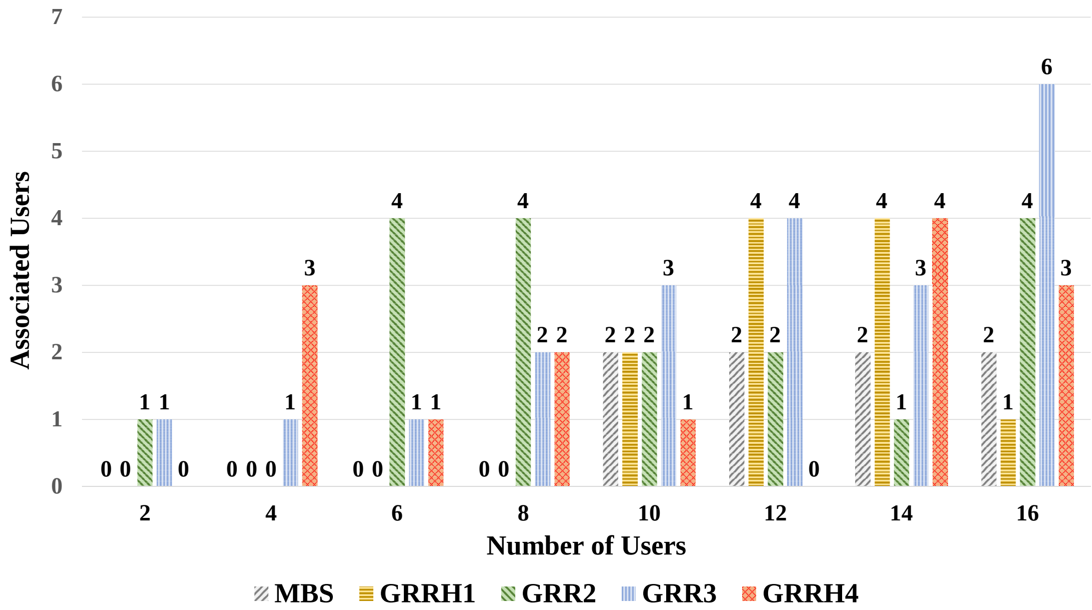

Figure 4.2: User Association with MBS or any GRRH vs different number of users

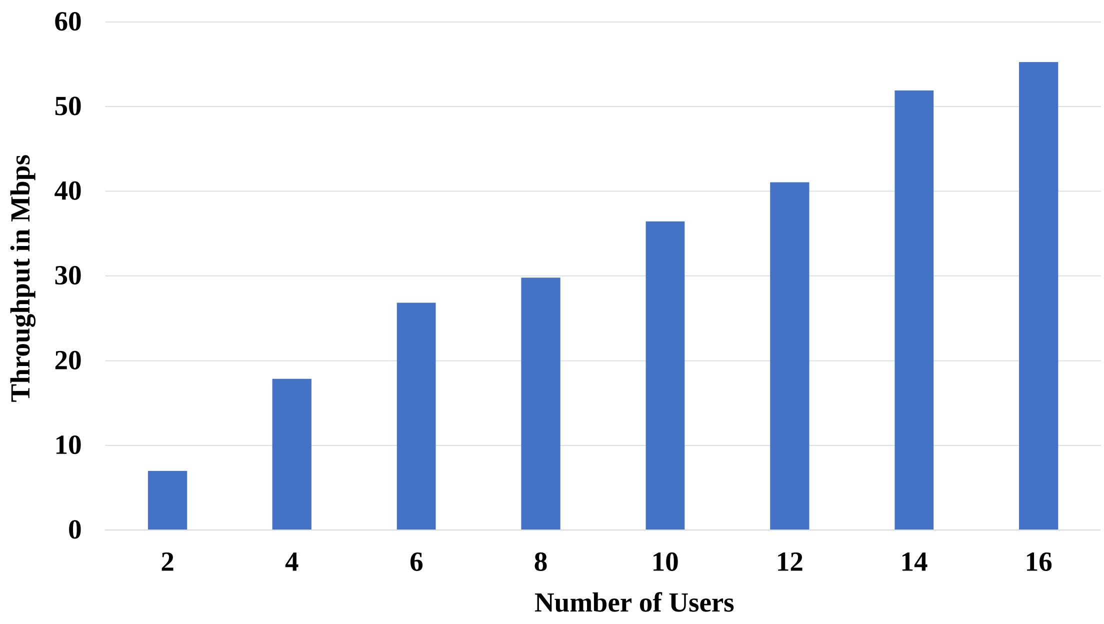

Figure 4.3: Total system throughput vs different number of users

EH is integrated, only circuit and transmission power of MBS is taken into account. Grid energy minimization is obvious as all the RRHs are off the grid. But it is also observed that due to efficient resource allocation, most of the users are connected to GRRHs hence maximizing utilization of green energy. It is observed that grid power utilization is cut to approximately half due to efficient user association with EH aided GRRHs.

Fig. 4.5 shows the EE of the system with different QoS requirements. Graph shows that as the data rate requirement gets high, EE decreases. This is due to the reason that system rejects the users when they don't meet the QoS requirements. As the QoS threshold gets high system tend to allocate more power to the users and controlling the admission.

Energy efficiencies calculated by MADS and OAA are compared in Fig. 4.6 It is observed that EE values in OAA are slightly higher than MADS. As discussed in previous chapter, OAA is more complex than MADS so if the complexity graph of MADS and OAA in Fig. 3.3 is considered, complexity comparison shows that with much less complexity of MADS algorithm, approximately same EE values can be attained. This slight trade off in EE values is acceptable.

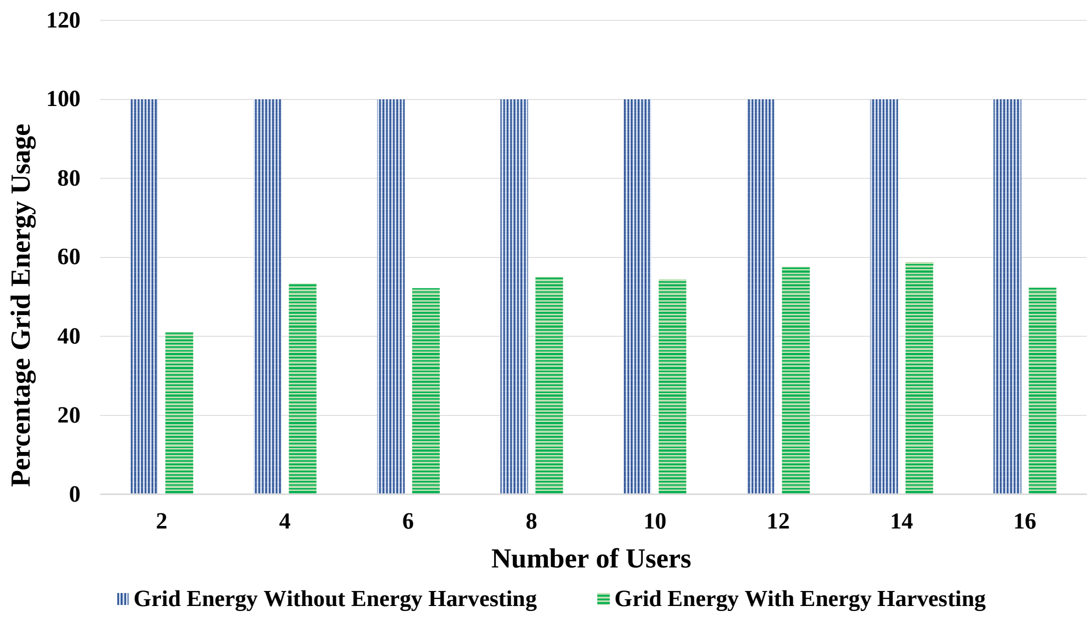

Figure 4.4: Percentage usage of grid energy with and without EH

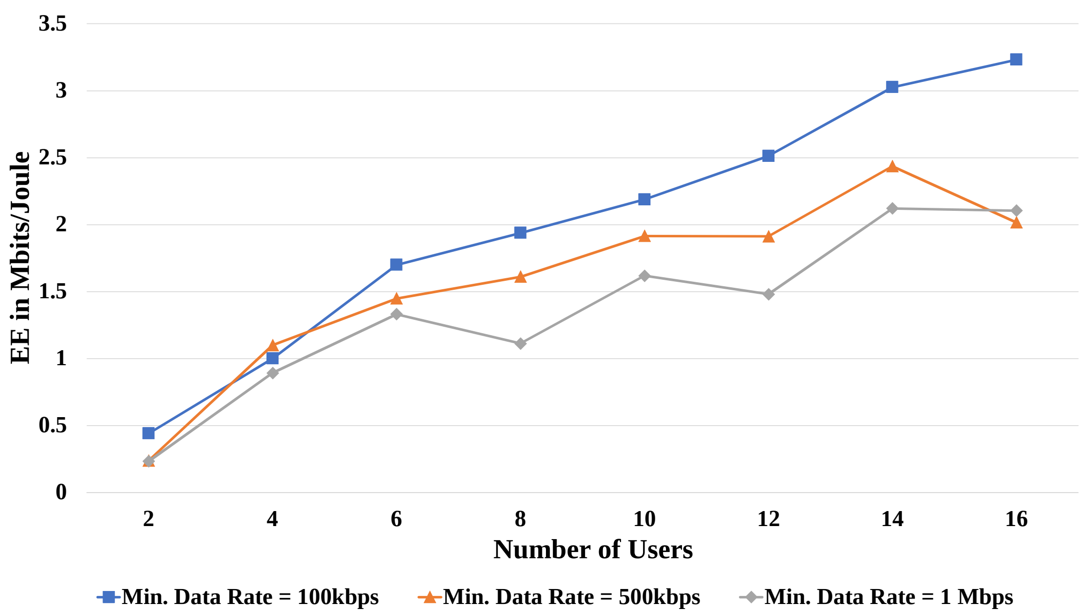

Figure 4.5: Energy Efficiency w.r.t minimum data rate requirment for each user, i.e., 100 kbps, 500 kbps and 1 Mbps.

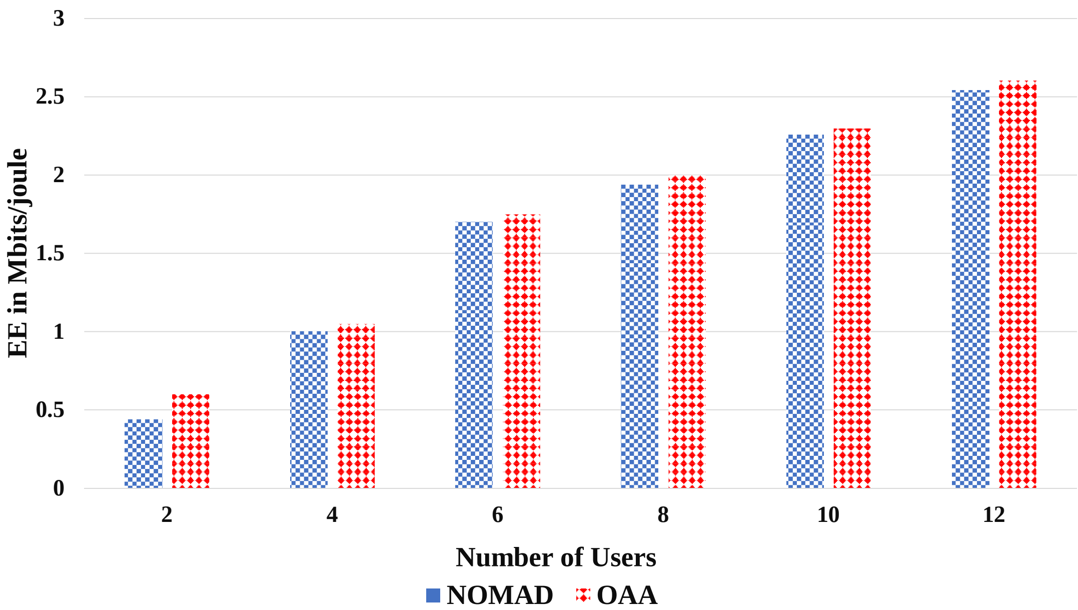

Figure 4.6: Energy efficiency - MADS versus OAA alogrithm

Chapter 5

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

In the very dense 5G H-CRAN architecture, an extra ordinary burden is put on grid energy. In this thesis, EH is integrated in the system to reduce the grid energy consumption. An optimization problem is evaluated which considers, user association, power allocation and EH constraints to maximize the system EE in bits/sec/Hz/watt for downlink in H-CRAN that is comprised of one macro base station connected to grid energy and several green RRHs (GRRHs) empowered solely with harvested energy. An EE optimization problem in HCRAN is formulated as fractional mixed integer nonlinear programming problem and is solved using MADS algorithm. Proposed algorithm is also less complex and yields $\epsilon-optimal$ solution in finite and fewer iterations than outer approximation algorithm and exhaustive search algorithm. Different metrics of the system and effects of EH on grid energy and power allocation to the users are observed. Results show that EE is improved as the number of users is increased for proposed algorithm. Moreover, users are associated, in majority, to energy harvested GRRHs hence decreasing the load on grid energy which in turn enables green communication. Results show that the consumption of grid energy is approximately reduced to half, as much of communication is done by GRRHs.

5.2 Future Works

Future direction for this work can be in different aspects of the nature of the system model. User equipment may also be equipped with EH modules which can harvest energy from RF waves. Simultaneous wireless information and power transfer may also be integrated. The heterogeneous nature of the H-CRAN also allows us to incorporate device to device (D2D) communication, which will result in more data off-loading from the network and increase the capacity of the system several times. Due to large number of RRHs and more efficient RRH management algorithms and interference management algorithms can be studied.

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