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Smart Energy Sharing of Access Points in Wireless Local Area Networks

A thesis submitted in partial fulfilment of the requirements for the award of the degree

Bachelor of Engineering (Computer)

from

University of Wollongong

by

Mark Cai Yee Lee

School of Electrical, Computer and Telecommunications Engineering

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Supervisor: Associate Professor Kwan-Wu Chin

Abstract

The Internet is growing at an unprecedented rate. This growth is shown in the increase in networked devices. However, the growth of the internet increases energy expenditure and directly increases the carbon dioxide emissions due to electricity generation. Renewable energy is used to address these problems. Wireless networks powered using renewable energy is an alternative to accommodate the growth of the Internet with a lesser impact of carbon emissions.

This thesis presents the existing research that aims to optimise Wireless Local Area Network (WLAN) design and to improve efficiency of energy harvesting. The existing research proposes on demand allocation of online access points. This network demand is determined using the number of associated users, network traffic volume and data transmission events. Next, several studies propose planning the network topology with optimisations on maximising network throughput and minimise network cost. In addition, studies show that networks can integrate with the grid to reduce cost of network operations. In this case, excess harvested energy is sold to the grid. The efficiency of energy harvesting can be improved to sustain networks for longer amounts of time. Several works show that this efficiency can be improved by predicting solar irradiance based on previous environment data. This thesis identifies that energy arrival of renewable energy harvesting is random which affects the sustainability and reliability of renewable energy powered wireless networks.

Hence, this thesis proposes a WLAN which consists of access points (APs) powered using renewable energy. These APs each have a renewable energy source and are able to share energy with other APs using the smart grid. This thesis presents the research models which replicate the proposed WLAN. Next, this thesis presents two AP transmission policies an six energy sharing policies which aim to maximise the total number of serviced users in a WLAN.

This thesis also presents a simulator to model the proposed WLAN. This simulator is modular and customisable. The parameters considered for the experiments in this thesis are number of APs, number of users, Lambda for Poisson Point Process, maximum energy storage capacity, solar panel size, maximum users movement distance, geometric series ratio value, load balancing user limit, energy sharing budget,

epsilon for Epsilon Greedy and data frame length for smart energy sharing.

Finally, this thesis presents the relationship between the total number of serviced users and the different parameters of a WLAN. In addition, this thesis also presents how APs can service the most users. This thesis also discusses the performance difference of energy sharing algorithms. The results show that WLANs can service the most users when the number of APs, total number of users, maximum energy storage capacity, Poisson Point Process Lambda and load balancing user limit is high. Moreover, maximum user movement distance do not affect number of serviced users. All energy sharing policies need to be tested and tuned for specific environments to maximise total number of users serviced.

Acknowledgements

I would like to thank my supervisor, Associate Professor Kwan-Wu Chin. I am very grateful for his guidance and supervision. His patience and responsive feedbacks have no doubt improved the quality of my thesis. I am also thankful for him to initiate conversations about everyday life during meetings which helped mitigate some stress from university.

I am grateful for my parents for supporting me both financially and emotionally. Without their continuous support and understanding, I would not be able to be the person that I am today.

Statement of Originality

I, Mark Cai Yee Lee, declare that this thesis, submitted as part of the requirements for the award of Bachelor of Engineering, in the School of Electrical, Computer and Telecommunications Engineering, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications or assessment at any other academic institution.

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Abbreviations and Symbols

N	Number of Access Points
K	Number of Users
M	Number of Serviced Users
L	Grid Size
P_{gen}	Energy Arrival, Watt per cm^2
E_{arrive}	Energy Arrival, Joule
A_{panel}	Solar Panel Size, cm^2
$E_{efficiency}$	Energy Harvesting Efficiency
D_{max}	Maximum User Movement Distance
B_{max}	Maximum Energy Storage Capacity
E_c	Energy Consumption, Joule
E_{cb}	Base Energy Consumption, Joule
E_{cs}	Service Energy Consumption, Joule
P_u	Transmission Power, Watt per second
P_r	Received Power, Watt per second
α	Path loss exponenet
d	Euclidean Distance

List of Changes

Section	Statement of Changes	Page Number
Abstract	Revised abstract to include information from new chapters.	ii
Glossary	Revised to include change in mathematical notations used.	xi
Chapter 3	Removed Simulator, modified System Model and added energy sharing solutions.	12
Chapter 4	Changed to simulation system.	17
Chapter 5	Revised results chapter with new results.	27
Chapter 6	Added conclusion and updated future works.	41

Chapter 1

Introduction

1.1 Motivation

The Internet is expected to continue to grow at an unprecedented rate in the future. According to [1], it is projected that 66% of the global population will have Internet access by 2023 as compared to the 51% in 2018. In addition, the projected data also estimates an increase in networked devices per capita from up to 2.4 devices per capita in 2018 to 3.6 devices per capita by 2023. The report in [1] also indicates that Wi-Fi hotspots will increase from an estimate of 169 million to 628 million by 2023 and as a result increasing the global annual Internet traffic to a total of 4.2 Zettabytes per year by 2022 indicated in [2]. Wireless Local Area Network (WLAN) or Wi-Fi has been driving many digital innovations and is projected to grow in value to $4.9 trillion in 2025 from $3.3 trillion in 2021 [3]. There are several factors driving the growth of value of WLANs discussed in the study by the Wi-Fi Alliance [4]. Most notably, the introduction of Wi-Fi 6, the Coronavirus pandemic and the mass availability of Wi-Fi enabled devices had been driving the growth of Wi-Fi [4]. The demand of data services will increase exponentially.

The rapid growth of the Internet comes at a cost of increased energy expenditure. In 2017, the International Energy Agency reported that data networks alone consumed around 185 Terawatt-hour globally in 2015 [2]. As a comparison to the 51% of the global population having access to the Internet in 2018, an additional 1.4 billion individuals will contribute to the Information and Communication Technology energy consumption by 2023. A study by [5] concluded that Information and Communication Technology and trade globalisation index directly impact CO_2 emissions in ASEAN countries. In addition, Information and Communication Technology was also concluded to improve environment quality in other sectors of the economy. Next, the International Energy Agency reported in 2019 that CO_2 emissions increased 1.7% to 33.1 Gigatonnes CO_2 in which the power sector is responsible for nearly two-thirds of the growth [6]. The projected increase in carbon dioxide (CO_2) emissions shown in [7] is detrimental to the environment [8]. The data reported in

[9] indicates that a total of 222,520,655 MWh of electricity was generated in 2019-20. This produced a total of 158,583,243 tonnes of carbon dioxide equivalents in Australia.

Renewable energy is expected to address the issues described above. It will be an important alternative for powering Internet of Things-enabled devices [10]. The study [11] highlights the opportunity and direct positive impact of switching to renewable energy sources such as solar, wind, hydro and geothermal heat [12]. To date, there are many works that have used a renewable energy source to power network equipment. For example, Google now nearly operates its data centers using renewable energy sources [13]. In addition, Intel developed IoT solutions to improve renewable energy generation and distribution such as the Intel-based Active Grid Management Architecture to improve grid monitoring and performance [14]. Another example is WindFi [15]. This is a low power base station design able to operate entirely on solar and wind power.

1.2 Wireless Local Area Network (WLAN)

A Wireless Local Area Network (WLAN) is defined as a network medium linking multiple devices forming a Local Area Network (LAN) with wireless communication between devices.

IEEE 802.11 is the common standard for WLANs. Fundamentally, IEEE 802.11 is a universal standard that provides guidelines for implementing medium access control (MAC) and physical layer technologies in wireless networking [16, 17]. IEEE 802.11ax or Wi-Fi 6 is the latest standard and will be able to provide higher data rates, perform better under dense wireless environments and higher power efficiency [18]. IEEE 802.11ax will utilise 1024-Quadrature amplitude modulation to provide data rates up to 9.6 Gigabit per second [19]. Next, the IEEE 802.11ax variant introduces the operation of WLANs between 1 GHz and 6 GHz spectrum. In addition, IEEE 802.11ax is backward compatible with previous variants, IEEE 802.11/a/b/g/n/ac [20].

The infrastructure network shown in Fig. 1.1 is a common WLAN architecture. It consists of access points, stations, basic service sets, an extended service set and a common distribution system [16]. Access points are devices which have a direct link to the wired local area network and enable wireless connectivity in the basic service area. Stations are any components equipped with a wireless network interface controller that are able to connect to a wireless network. Infrastructure networks enable the packet transfer between devices in the area of service by utilising the range extension of access points.

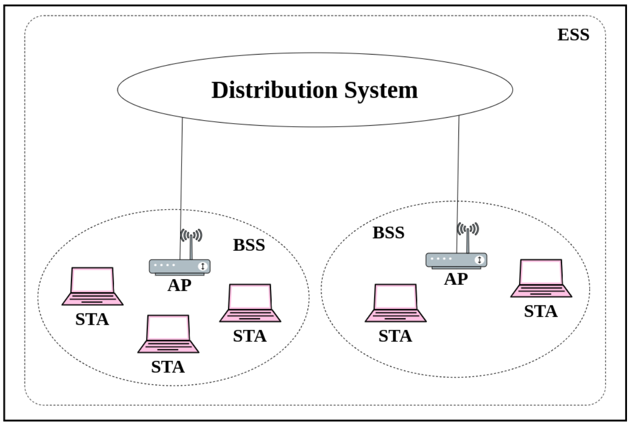

Figure 1.1: Wireless Local Area Network Architecture: Infrastructure Network. Access Point (AP). Basic Service Set (BSS). Extended Service Set (ESS). Station (STA).

1.3 Thesis Aim

The aim of the thesis is to study and develop algorithms to utilise harvested energy efficiently to meet traffic demand of a WLAN. In this case, the thesis will study the existing works on WLANs powered using renewable energy, the factors influencing efficient energy sharing and machine learning algorithms that will enable smart energy sharing between access points.

Given the system powered with renewable energy sources in Fig. 1.2. The access points will have energy sharing capabilities connecting to a smart grid. Moreover, the environment and location of access points will affect the rate of energy harvesting. As the energy level of an access point handling lower traffic load saturates, it should send energy to the smart grid for sharing excess energy with other access points handling more traffic workload. This will enable all access points to handle network traffic efficiently without sacrificing quality of service while operating on renewable energy.

Next, the problem comes with several challenges. First, the timing for energy sharing for access points. The appropriate timing for energy sharing is important as access

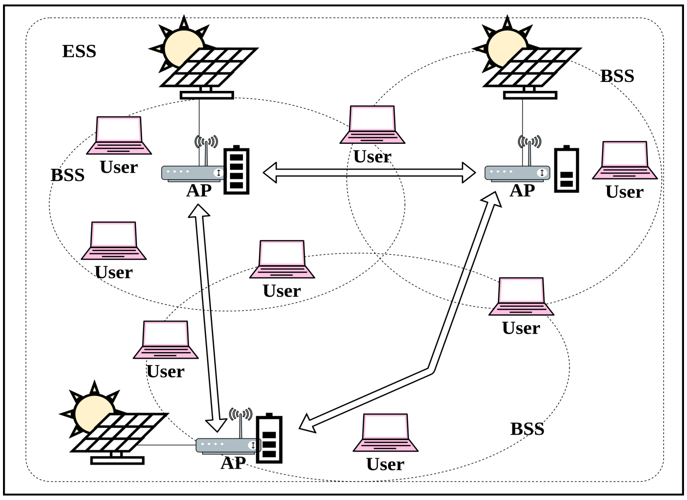

Figure 1.2: Smart Energy Sharing of Access Points in Wireless Local Area Networks

points that have high traffic should not sacrifice its operations for other access points. Secondly, the factors influencing energy sharing. This is essential to ensure energy is shared efficiently. Finally, the amount of energy shared to maintain operations. The access points will need to determine the appropriate amount of energy that can be shared to maintain its operations.

1.3.1 Thesis Structure

The remainder of the thesis is organised with the following structure. Chapter 2 outlines the previous literature on energy efficient WLANs. Chapter 3 presents the research methodology of the thesis. Next, Chapter 4 outlines the details of the Experiment Methodology. Chapter 5 presents and analyses the results. Finally, Chapter 6 presents the conclusion and future works.

Chapter 1 discusses the motivation to improve the energy efficiency of WLANs and the architecture of a WLAN. Chapter 2 presents the current research and implementations that aim to optimise WLAN designs and to improve the efficiency of energy harvesting. Chapter 3 discusses the research methodology, aim, problem and presents several solutions to maximise the energy efficiency of WLANs. Chapter 4 presents the details of the simulator and parameter values used for the experiments. Chapter 5 discusses the results obtained from experiments using the simulator. Chapter 6 presents the conclusion obtained from experimentation and analysis.

Chapter 2

Literature Review

2.1 Optimisation of WLAN Design

Wireless networks powered using renewable energy sources are not as reliable due to the variability in renewable energy harvesting rate [21, 22]. Hence, a WLAN design needs to consider this energy arrival variability and improves the energy efficiency of APs to sustain network demand.

The study in [23] reports the factors that affect power consumption of WLANs. The authors consider the characteristics of WLANs based on the IEEE 802.11g standard which are modulation type, bit rate and size of transmitted messages.

2.1.1 On Demand Resource Allocation

Network resources in WLANs powered using renewable energy sources are the number of powered APs. Several works have reported that network resources can be provided to connected users depending on the network load demand [24–27], data transmission events [28] and optimal AP energy allocation [29].

The study in [24] builds on the research from [25] and shows a resource on demand WLAN design which utilises AP clustering, network demand estimation and blacklisting clients to enforce user association to APs. The authors aim to change the basic design of enterprise WLANs to focus on energy efficiency. To do this, the authors propose Survey, Evaluate, Adapt and Repeat (SEAR), which is a policy-driven Resource on-Demand design for WLANs. SEAR provides options for conservative or aggressive power saving in terms of client connectivity, wireless coverage and bandwidth. Specifically, APs can be grouped into clusters to provide better wireless network coverage using SEAR. SEAR aims to maintain the same coverage and performance of a traditional WLAN.

Next, the study in [28] proposes a Radio-on-Demand WLAN design utilising a low powered wireless receiver to control the wake-up of APs. The authors aim to reduce AP power consumption by waking up the APs only when required. To do this, the authors use the IEEE 802.11 frame length to produce a wake up signal. The wireless receiver attached to the APs are all assigned a wake-up ID. The low powered receiver is always on to listen to the transmission channel. The wake-up signal which represents the assigned wake-up ID is generated by STAs using software. The low powered receiver decodes the signal and switches the designated AP to high powered state when the assigned ID is identified within the received signal.

The researchers in [26] propose MORFEO which is a practical energy saving decision solution utilising energy and network monitoring. The authors classify the operating modes of APs as full power mode, active mode, partial or sector sleep mode and off mode. This represents the transmission power level of the AP. It switches the operation modes of APs by classifying APs based on network performance. The authors aim to reduce the power consumed by wireless access devices during periods of low or no traffic. In a previous study, the authors reported that most of the energy consumed in wireless access devices are not traffic dependent. MORFEO can report instantaneous energy consumption data and network traffic load to the user.

The study in [29] proposes using optimisation to manage a wireless network. It simulates a realistic wireless network which accounts for baseline power consumption, path loss and connection quality. The authors aim to find the optimal network configuration which minimises the total power consumption of the network. The aim is to determine the APs which should be powered on and the additional power spent by an AP for transmission. To do this, the authors propose an optimisation approach based on integer linear programming. The system is modelled to account for varying power consumption due to path loss and required signal strength at the receiver. It also accounts for network capacity constraints which limit the maximum throughput at the APs.

Next, the practicality of network resource scheduling is studied in [27]. The authors study a resource on demand WLAN strategy with demand estimation using associated clients or traffic load. The authors aim to study the practical problems associated with WLANs which scale the capacity of the network depending on connected users. In the study, the authors propose two methods to determine traffic demand for Resource On-Demand strategies. They first consider the number of associated users and the next takes into consideration the traffic load of the APs.

The number of active APs are decided depending on the load of the network. The authors utilise an upper and lower threshold which serves as a buffer to prevent APs turning on or off too quickly.

The study in [24–28] and [27] presents challenges associated with on demand network resource allocation. First, large-scale WLANs are underutilised at most times. Next, dense WLANs have many overlapping APs which provide wireless connectivity to the same area. Second, the APs which do not have users associated can be powered off. Third, clients connected to WLANs which turn on and off APs on demand require a similar throughput, transmission latency, network client capacity and service coverage when compared to always-on WLANs. In addition, resource on demand WLANs need to respond quickly when scaling the number of APs to the required load. Moreover, the network needs to re-evaluate the current network demand to power on or off APs to reduce energy consumption. Next, the WLAN needs to satisfy the capacity demand of the network with the optimal amount of APs. Lastly, clients associated with a powered off AP require to be automatically re-associated by the system.

2.1.2 Network Topology Planning

Several studies optimise the network topology of a WLAN in terms of AP and physical link placement. The aim is to maximise network throughput [30] and minimise cost of network operations [31] by planning the network before practical deployment.

The study in [30] maximises the throughput of a WLAN by employing neighbouring APs to transfer data. This cooperative communication uses relays to increase network throughput. The authors aim to maximise the overall throughput in cooperative communicating WLANs which operate entirely on renewable energy. In this case, the APs are able to transmit signals by cooperating with other wireless nodes to relay the signals within the network. The authors investigate optimal power allocation and AP placement to maximise data throughput. The study considers additive white Gaussian noise in transmission path loss and renewable energy powered APs which do not experience outage.

Next, the study in [31] presents an energy sharing framework for cellular networks which utilise both physical links between BSs and the smart grid for sharing energy. The study minimises the cost of operating the network considering different degrees of knowledge on energy generation information. The authors aim to minimise the energy cost of a cellular network integrated with a combination of physical power lines and the smart grid. To do this, the authors propose an energy management framework which takes into consideration energy storage limitations and real-time energy pricing. The authors also aim to determine the optimal physical links between BSs for energy sharing depending on type of information on rate of energy harvesting. Next, the energy cost is minimised with consideration of the availability of information on rate of energy harvesting. The BSs are optimised with regards to zero knowledge, perfect knowledge and partial knowledge of the information on energy harvesting in future time slots.

The issues associated with WLAN design planning are presented in [30] and [31]. First, the APs which transfer at a high data rate consumes more energy. Next, the energy storage capacity of an AP affects the optimal energy cost of operating a cellular network. Higher energy storage capacity APs are placed in locations which generate the most energy. Lastly, knowledge of future energy generation rate affects the cost of operating the system.

2.1.3 Grid Integration

Studies have shown that some wireless networks cannot be powered solely using renewable energy as it has shown to be unreliable and inconsistent [32]. In addition, networks which occasionally require high uptime and cannot tolerate delay will require a reliable source of energy at times of need. Sourcing energy from the power grid only when needed can reduce cost of network operations.

The study in [32] provides an energy consumption analysis framework by minimising the cost of operation of BSs using conservative convex approximation. The authors aim to determine the distribution of energy a cellular network procures from several energy sources. The energy sources are the smart grid and locally generated renewable energy. To do this, the authors propose an optimisation problem to maximise the profit of operating a cellular network. The authors consider the smart grid energy price variation, the renewable energy generation and the energy storage capacity at the BS. The excess energy generated at the BS is sold to the electrical grid. Next, the authors use conservative convex approximation to prevent non-convex constraints. The methods considered are Chernoff and Chebyshev-based. The authors also investigate the relationship between profit of operating a network and energy consumed of networks with different storage capacity.

The study in [33] optimises the operating duration of a network powered either only with renewable energy or the power grid. The authors present a BS sleep control system. In this case, only the BSs powered using renewable energy are switched to low power mode. The sleeping of BSs are optimised with dynamic programming to ensure it can operate when needed the most. The authors aim to ensure that the BSs do not consume all of the harvested energy at any time if required to operate in the future. To do this, the authors consider a known statistical energy arrival information and a normally distributed traffic load to model the system. The authors also consider that the system will consist of a combination of BSs powered with renewable energy sources and the grid. Next, the authors minimise the energy consumption of the system with a heuristic algorithm to determine the appropriate number of active BSs powered by renewable energy in consideration of the network traffic. The authors address several problems. First, renewable energy powered BSs create coverage holes and data transmission latency when powered off. Next, optimising BSs sleeping times can prolong the availability of a network. Lastly, an optimal number of BSs operating at a time can maximise network availability.

Network reliability affects user satisfaction [34]. The authors relate the reliability of networks as the amount of energy procured from the electrical grid. The study analyses the relationship between dependence of networks on renewable energy as opposed to grid energy and the effect on network user satisfaction. The study considers different resource allocation methods, traffic types and network utilisation. The authors model the user satisfaction using network utilisation. To do this, the authors calculate average network utilisation taking into account the traffic transmission priority. The authors also consider two network schedulers. The first is a Round-Robin scheduler which divides network resources equally. The next is a maximum utility scheduler which allocates network resources depending on user traffic type. The study considers three types of network traffic, hard quality, soft quality and best effort. Hard quality traffic cannot tolerate delay while soft quality traffic can tolerate some delay. Best effort traffic is very tolerant to delay. The authors solve several problems in the study. First, increasing the ratio of grid energy used increases the network utilisation. Next, different traffic types require different priority and transmission delay to increase user satisfaction. Finally, network resource scheduling methods which prioritise maximum network utilisation increases users satisfaction.

2.2 Improvement of Energy Harvesting

Energy harvesting is commonly used to power wireless networks [35]. The rate of energy harvesting is yet to be optimised and is associated with challenges such as initial startup cost, large physical footprint and location dependent harvesting efficiency [21, 22]. Hence, the efficiency of energy harvesting needs to be improved to power wireless networks for longer durations.

2.2.1 Solar Irradiance Prediction

Several works aim to maximise the availability of solar powered BSs by predicting solar irradiance. These works use previously collected data [36] and identify the environment factors that influence solar irradiance [37].

In [36], the authors aim to model the global horizontal irradiance to predict the rate of energy harvesting for small cell BSs. To do this, the authors investigate the available irradiance data to fit a model for future data prediction. The authors consider the monthly averages for the data collected and the parameters affecting the global horizontal irradiance. Next, the study creates models to predict solar irradiance by fitting previously collected data using linear regression and logistic regression. The study also uses k-means clustering to categorise the networks which benefit most from solar energy harvesting.

Next, reference [37] aims to predict the energy arrival with a simplified solar radiation model. The authors also aim to investigate the method to allocate harvested energy efficiently at an energy harvesting base station. To do this, the authors propose a general solar energy model considering cloudless and cloudy days. The models take into consideration solar irradiation, date, time and location to estimate the availability of solar energy. Next, the authors also propose several energy allocation algorithms to maximise the utility time of the BS which only uses solar as the energy source.

The study in [36] and [37] report that reliability of energy harvesting using solar energy is heavily reliant on weather and geographic location. Next, the solar irradiance is affected by air temperature, humidity, wind direction, wind speed, rainfall and pressure. In addition, deployment of solar powered networks requires an accurate model for predicting the energy availability of the system for resource allocation and planning.

2.3 Summary

This chapter presented the potential design improvements for traditional WLANs. There are two main areas of improvement, WLAN design and energy harvesting design. WLANs powered using renewable energy optimise energy efficiency by allocating network resources on demand, network topology planning and grid integration. Next, solar energy harvesting is optimised by predicting the solar irradiance.

These design improvements enable WLANs to be powered partially or entirely using renewable energy harvesting. However, there are limitations to these approaches. First, the rate of energy arrival is random and changes depending on the environment. This randomness in the rate of energy arrival of renewable energy harvesting causes a varying degree of energy stored in APs each powered using a renewable energy source. Next, the network load is not distributed evenly in a WLAN. This results in APs with different energy consumption rates. As a result of varying rate of energy harvesting and network loads, APs are powered off when it is unable to meet energy consumption needs.

To address these limitations, Chapter 3 presents a WLAN which consists of APs powered using renewable energy. These APs can share energy by sending excess energy to other APs within the same system.

Chapter 3

System Model

3.1 System Architecture

The model of the system is shown in Fig. 3.1. It is made up of multiple BSSs which consist of APs and Users. Moreover, each APs have a renewable energy source with random energy arrival. In this case, this system harvests solar energy at the end of every time slot. The APs are connected to the smart grid which allows APs to share energy.

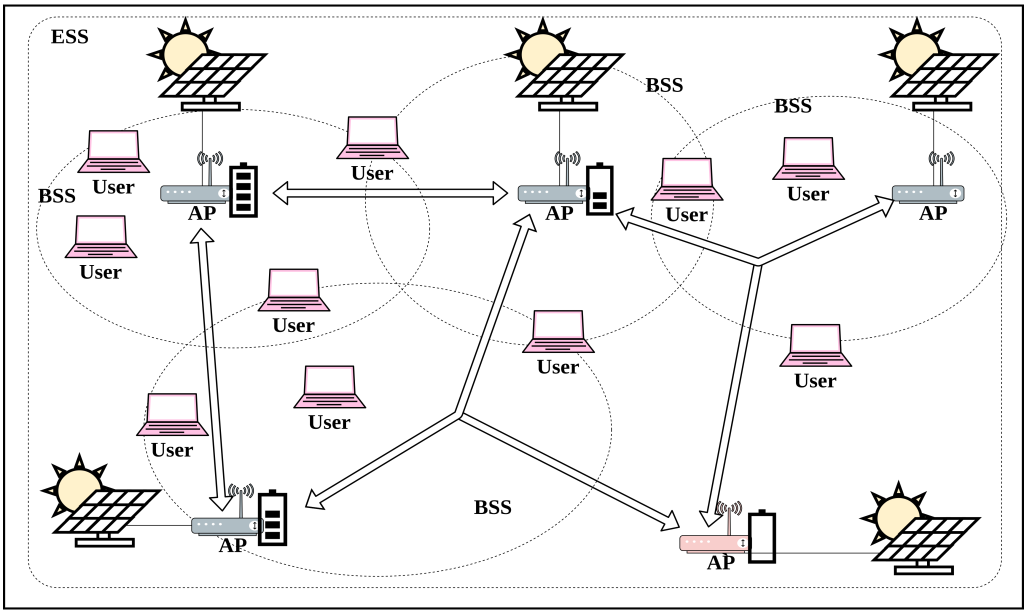

Figure 3.1: System Architecture

Firstly, the time of the system is discrete, where each time slot is five minutes. The APs and Users remain at the same state until the next time slot commences. Moreover, the same time interval is used for AP energy arrival.

Next, the system is modelled on a grid with the size of $L \times L$. This grid is two dimensional and uses Cartesian coordinates which start at $(0, 0)$ at the bottom left corner and end at (L, L) at the top right corner. The grid size L is in the unit of meters.

Third, the system models N number of APs which service users on the generated grid. An AP has a randomly generated coordinate on the grid in the range of

$-L$ to L in the x and y coordinates. These APs can associate with any user on the grid. APs start with a random amount of energy and will continue to harvest energy at random. Energy arrival is also affected by solar panel size, A_{panel}. This energy harvesting is restricted by the total energy storage capacity, B_{max}. APs will consume energy after each time slot. An AP which cannot service the users with the remaining energy will power off. Similarly, the AP which harvests enough energy to remain active will power on at the end of each time slot.

The system models K number of users which are serviced by APs. Users can only be serviced by one AP at a time. Moreover, users have a randomly generated coordinate on the grid in the range of $-L$ to L in the x and y coordinates. Next, users connect to the active AP with the smallest Euclidean distance. APs which are closer but not set in the active state will not be considered by the user. Next, disconnected users will only re-associate with a new AP at the start of the next time slot. Moreover, users move within the predefined grid with a limitation in maximum movement distance, D_{max} at the end of each time slot. Users which attempt to move out of the defined grid will bounce back by moving backwards with the remaining movement steps.

Next, the system uses a discrete Markov chain from [38] to model energy arrival for APs. In this case, state transition probabilities for five minute intervals are considered for this thesis. Each state is a normal distribution with a respective mean and variance. All APs in the system use the same Markov chain. This indicates that all APs will also have the same state as other APs in any given time slot. The energy arrival is picked at random from the normal distribution with the mean and variance associated with their respective states. The value picked from the normal distribution has the unit of W/ cm^2 and denoted by P_{gen}. In addition, energy arrival is also affected by energy harvesting efficiency, $E_{efficiency}$. The solar panel size is denoted by A_{panel}. The energy arrival, E_{arrive} is calculated using Eqn. 3.1.

$$E_{arrive} = P_{gen} \times A_{panel} \times E_{efficiency} \times 60 \times 5 \text{ J} \tag{3.1}$$

Energy consumption of APs is modelled with two components, base energy consumption, E_{cb} and service energy consumption, E_{cs}. The base energy consumption of APs when not servicing any users is 5.3 W/h [23]. The base energy consumption, E_{cb} is calculated using Eqn. 3.2.

$$E_{cb} = \frac{5.3 \times 3600}{60 \times 5} \text{ J} \tag{3.2}$$

Next, the service energy consumption, E_{cs} is determined based on the distance between the user and the AP. Let P_r be the required received power at the client. The channel gain is $\frac{1}{d^\alpha}$ in which d is the Euclidean distance between an AP and a user. The α is the path loss exponent set at 2 for this system. The transmit power from AP to the user is P_u. The transmit power is calculated using Eqn. 3.3. Moreover, the service energy consumption for one user is calculated using Eqn. 3.4. The total number of users serviced by an AP is M. In addition, the total energy consumption of an AP, E_c is obtained using Eqn. 3.5.

$$P_u = P_r \times d^\alpha \text{ W/s} \tag{3.3}$$

$$E_{cs} = P_u \times 60 \times 5 \text{ J} \tag{3.4}$$

$$E_c = E_{cb} + \sum_M E_{cs} \text{ J} \tag{3.5}$$

Finally, the performance of the system is evaluated by using the total number of serviced users after the last time slot is reached. A higher total number of serviced users signify that the system use energy efficiently to service users.

3.2 Aim, Problem and Solution

The thesis aims to optimise the total number of serviced users of WLANs. The thesis considers the problem to determine the best AP parameters, transmission algorithms and energy sharing algorithms which maximises the total number of serviced users.

The thesis presents two transmission policies and six AP energy sharing policies to determine the factors which maximise the total number of serviced users of a WLAN.

3.2.1 Transmission Policies

This thesis compares two transmission policies No Transmission Policy and Cheapest User. These transmission policies affect how APs will prioritise servicing users connected to it.

Firstly, the No Transmission Policy transmission policy services users without bias. Users are serviced on a First In, First Out basis. This transmission policy does not collect any metrics which affect the decision for APs to service a user.

Next, the Cheapest User transmission policy services the users will consume the least energy. This transmission policy assumes that APs have prior knowledge about the distance between AP and users. Cheapest User service all cheapest users until all the energy stored is expended.

3.2.2 Energy Sharing Policies

This thesis presents six AP energy sharing policies which aims to maximise the total number of serviced users in a WLAN. The energy sharing policies AP Energy Efficiency, AP Energy Use, AP Energy Arrival distribute energy using a geometric ratio. The energy sharing policies Epsilon Greedy and UCB1 distribute energy to one target AP for each energy sharing AP at a time.

First, the AP Energy Efficiency policy rewards APs which use the least energy to service the most users. This policy requires APs to collect metrics such as past energy consumption and the total number of serviced users. This policy considers all past values of energy consumption and total number of serviced users to obtain an average efficiency value.

Next, the AP Energy Use policy rewards APs which use the most energy. This policy requires APs to only collect past energy consumption data. Moreover, this policy considers the last 12 energy consumption data to calculate the average total energy consumption.

Third, the AP Energy Arrival policy rewards APs which have the lowest energy arrival. This policy only requires APs to collect past energy arrival data. This policy ranks APs based on the average energy arrival in the last 12 time slots.

Fourth, the Shared Evenly policy distributes energy to all APs evenly. APs using this policy pool energy at the end of every time slot and redistribute this to all APs. This policy disregards energy consumption, energy arrival and serviced users of APs.

Next, the Epsilon Greedy energy sharing policy distributes energy depending on AP decisions. It is a greedy Multi Armed Bandit algorithm. This policy collects past scores based on the resulting action of selecting an AP to share energy. APs decide to explore or share energy to the best performing AP using a binomial distribution given an epsilon value. In this case, APs will choose another AP at random epsilon percent of the time.

Finally, the UCB1 (Upper Confidence Bound) energy sharing policy distributes energy based on AP decisions. It is also a Multi Armed Bandit algorithm. This policy also collects past scores based on the resulting action of APs. This policy constructs a confidence interval for all target APs for each AP. The more a target AP is chosen, the smaller the confidence interval. APs will also pick a target AP depending on the size of confidence interval. This policy will be more likely to pick target APs with high average performance. However, it will periodically pick targets with a large confidence interval. As the confidence interval for all targets decreases, target APs with high average performance will always be chosen.

The next chapter, this thesis presents a simulator and several experiments to find the parameters which maximise the total number of serviced users. This simulator is modular and supports all the energy sharing and transmission algorithms that was presented in this chapter.

Chapter 4

Research Methodology

4.1 Simulation System

The thesis presents a simulator written in Python. A high level program flow is shown below. The source code of the simulator is available on Github [39]. Next, the simulator is modular and can be broken into several components which reside in its own file. The code which handles running experiments is stored in `network_simulator/test`.

```
read_Components_from_binary()

initialise_Environment()

for time in range(0, TIME_MAX):
    for user in user_list:
            user.moveUser()
            user.connectAP()

    for ap in ap_list:
            ap.discharge()
            ap.disconnectUser(usrlist)
            temp_energy = energyArrival(markovStateOutput())
            ap.charge(temp_energy)
```

4.1.1 main.py

This is the python script which starts every experiment for this thesis. There are two variables `gen_vars` and `save` which need to be set. In this case, setting it both to 1 will result in the simulator generating a new simulation environment and saving it into `generated/init_vars.data`. Otherwise, the previously generated data will be read into the simulator.

Generating a new simulation environment will execute `initVariable()`. This function sets the default simulation parameters in the dictionary `init_vars`. In addition, a Markov Model for energy arrival and a descending unit array will be generated by calling `energyArrivalStates()` and `genDescendUnitArray()`. These functions are from a submodule helpers.py. Next, initVariable() generates a list of APs with the AccessPoint class in the size of AP_TOTAL with a random pair of floats as the coordinate and random starting energy. Subsequently, the function generates the locations of users by calling generateUsersPPP() with arguments GRID_SIZE and lambda from the submodule poissonPointProcess.py. The function then generates a list of users with the User class with the previously generated starting coordinates. Experiments will use the variables generated from initVariable(). These experiment calls are organised into modules in network_simulator/test.

4.1.2 testAPnumber.py

This script is an example of a test module which runs the experiments for this thesis. All experiment scripts that are called in main.py have the same format and behave similarly.

When plot_from_saved is set to 1, the simulator will create plots using pre-existing simulation data from a binary file in sim_cache by calling readSimCache() with the appropriate file name. Otherwise, simulations will run for all the axes in _sim_dict_axes and change the parameter of apnum in the range of number_ap for a total of len(total_runs). The data from the simulations is then saved into a dict _output with the key of the respective policy enforced. The simulator will call writeSimCache() from the submodule helpers.py to save the output into a binary file located in sim_cache. Next, the function APNumberCompare() saves the interactive plot into interactive as a html file and displays the plot in the web browser. The figure is returned to main.py for saving.

4.1.3 components.py

This module contains the main components of the simulator which includes the classes AccessPoint, User and Location. In addition, the functions simulator() and initialiseEnv() are also a part of this module.

The AccessPoint Class represents an AP in the simulator. Each AP has an id, location, energy storage, service counter and a list of users. In addition, an AP object contains several data logging variables which records the energy arrival, energy use, serviced users at the end of each time slot. Next, this class has several functions which simulates a real AP that can share energy. This includes `charge()`, `discharge()`, `connectUser()` and `disconnectUser()`. The `charge()` function adds the value of `energy_gen` to the energy storage. Next, the `discharge()` function calls `energyPolicy()` from the submodule `energyDistribution.py`. The energy consumed is deducted from energy storage and the service counter for the AP is incremented. If too much energy is consumed, the AP switches to the off state. The `connectUser()` function appends the id and distance of a user to the list of the AP for use in `discharge()`. The `disconnectUser()` function removes all users that are in the user list and sets the status of users.

The User class represents a user in the simulator. Each user has an id, location and the AP which it is connected to. This class has several functions which are used to simulate a real user. This includes `connectAP()`, `moveUser()` and `removeConnected()`. The `connectAP()` function calculates the distances of the user to active APs by calling `calcAPDistance()` and connects to the AP with the nearest euclidean distance. If `LOAD_BALANCE` is set and the user limit is reached, the user will connect to the next available AP. The `moveUser()` function relocates the user to a new coordinate that was generated in `initiliseEnv()`. The `removeConnected()` function sets the connection status of the user to ensure reconnection is done for every time slot.

The Location class contains the `x` and `y` coordinates of either an AccessPoint or User object.

The `initialiseEnv()` function is called at the start of the simulator to set global variables for parameters of the simulation environment. In addition, this function calls `generateHistory()` from the `multiArmBandit.py` module to create a history dictionary for use in Multi Arm Bandit algorithms. Next, this function calls `genUserMovementLoc` from `helpers.py` to generate predefined lists for user movement during the execution of the simulator. This is pre-generated for speed optimisations. The `initialiseEnv()` function returns the generated history for usage in Multi Arm Bandit algorithms.

The `simulator()` function is the main driver for the simulation. The function calls `initialiseEnv()` to set global environment parameters and runs the simulator to `TIME_MAX + 1`. Events which occur during a time slot of the simulator are as follows. Firstly, users are moved to a new location and attempt to connect to the active AP nearest to it. Next, APs are discharged based on the users connected to it in the previous time slot. Third, all users in each AP are disconnected. Fourth, `energyArrivalOutput()` from the submodule `discreteMarkov.py` is called for each AP to generate an energy arrival. This energy charged into the AP. Next, energy use and energy arrival for this time slot is recorded. If energy sharing is enabled and the energy sharing budget is not zero, the energy allocated for sharing is taken from the APs depending on the percentage of energy sharing. Next, `energyDistributeSel()` from the `energyDistribute.py` module is called with key arguments such as the AP list, energy sharing policy, list of shared energy and the current time. This `energydistributed` variable returned is then used to distribute the appropriate amount of energy to APs depending on the energy sharing policy enforced. The time slot ends and the next time slot continues until `TIME_MAX + 1` is reached. `simulator()` returns the total number of serviced users for all APs.

4.1.4 poissonPointProcess.py

The `poissonPointProcess.py` module generates starting coordinates for users using the function `generateUsersPPP()` and `generateUsers()`.

The function `generateUsersPPP()` models the Poisson Point Process to generate user coordinates. This function requires two arguments, `areasize` and `lambda`. First, the function generates a number using the Poisson Process given `lambda`. Next, the function generates a list of x and y coordinates with the length of the previously generated Poisson number. Finally, the list of x and y coordinates are returned.

The function `generateUsers()` generates user coordinates using the default python libraries. This function returns a list of x and y floating type coordinates given the area size and total number of users.

4.1.5 discreteMarkov.py

`discreteMarkov.py` models a discrete Markov Chain which provides energy arrival for APs in the simulator. This module requires the `pydtmc` python library from [40]. This module consists of two functions, `energyArrivalStates()` and `energyArrivalOutput()`.

First, `energyArrivalStates()` returns a list of energy arrival condition states with the length of `TIMEMAX`. The state transition probabilities are used with the function call `MarkovChain()` from the `pydtmc.py` module. This function calls `walk` which iterates through the Markov Chain and returns the Markov states for energy arrival. This chain is a list with energy arrival conditions. These energy arrival conditions are represented by Poor, Fair, Good and Excellent.

Next, `energyArrivalOutput()` returns the energy value given the energy arrival condition state. This function returns a random value given a normal distribution with the mean and variance of the current energy arrival condition state.

4.1.6 energyPolicy.py

This module returns the amount of energy consumed and the number of serviced users depending on `sel` which selects an AP transmission policy. This module consists of several functions, `noTransmitPolicy()`, `pickCheapTransmitOnce()`, `pickCheapTransmitGreedy()` and `energyPolicy()`. The function `energyPolicy()` calls the respective function which corresponds to the selected transmission policy.

Next, `noTransmitPolicy()` calculates the total energy consumption without enforcing any transmission policy. This function constructs a list of energy consumption values for each user in the AP user list. The sum of possible energy consumption is ensured to not exceed the amount of energy in storage.

`pickCheapTransmitOnce()` calculates the total energy consumption by finding the cheapest user. This function constructs a list of energy consumption values for each user in the AP user list. This function sorts the constructed list and returns the energy consumption.

Finally, `pickCheapTransmitGreedy()` calculates the total energy consumption of the cheapest users in the user list of each AP. This function constructs a list of energy consumption values. The function sorts this list and ensures that the total energy consumption will not exceed the available energy in storage.

4.1.7 energyDistribution.py

This module returns an indexed list of energy shared to target APs which satisfies the respective energy sharing policy. The functions in this module are `efficiencyDistribute()`, `energyUseDistribute()`, `energyArrivalDistribute()`, `evenDistribute()`, `smartDistribute()`, `genEnergyStats()` and `energyDistributeSel()`. The `energyDistributeSel()` function calls `genEnergyStats()` to organise collected data from APs and calls the respective energy sharing policy.

First, `efficiencyDistribute()` rewards the most energy to APs which use energy efficiently. This function constructs a list of efficiency values and sorts the list in descending order. This function then finds the sum of shared energy. Next, this function uses an array generated by a geometric series ratio to allocate energy to APs based on the energy efficiency of APs.

Next, `energyUseDistribute()` rewards the most energy to APs which use the most energy. This function constructs a list of energy usage values and sorts this list in descending order. Moreover, this function finds the sum of all shared energy. `energyUseDistribute()` then allocates energy to AP using an array generated using a geometric series.

Third, `energyArrivalDistribute()` rewards the most energy to APs with the lowest amount of energy arrival. This function performs similar actions as `efficiencyDistribute()` and `energyUseDistribute()`. The same array generated by a geometric series ratio is used to allocate energy.

Fourth, `evenDistribute()` pools all the shared energy and divides the total by the total number of APs. APs will receive an equal amount of energy.

Finally, `smartDistribute()` calls the corresponding Multi Armed Bandit algorithm given `sel`. Next, an array of energy sharing destinations is constructed using `actions` generated from `multiArmBanditSel`. This array has the same format as all energy sharing policy functions in this module.

4.1.8 multiArmBandit.py

This module consists of functions which model Multi Armed Bandit energy sharing algorithms. The functions in this module are `epsilonGreedy()`, `ucb1()`, `updateHistory()`, `generateHistory()` and `multiArmBanditSel()`. The function `multiArmBanditSel()` calls `updateHistory()` to store the increase given the previous action determined by the algorithm. Next, this function calls the corresponding Multi Armed Bandit algorithm given `sel`. This module returns an indexed list of APs and corresponding energy sharing targets.

First, `epsilonGreedy()` models an Epsilon Greedy energy sharing policy. This function generates an action for all APs. This function generates `explore` given `epsilon` from a binomial distribution. If `explore` is set to `1` or there was no previous action, the algorithm will pick a random candidate for energy sharing. If `explore` is `0`, the algorithm will exploit the AP target with the highest mean. Moreover, the algorithm can also decide that APs will not share energy.

Next, `ucb1()` models an Upper Confidence Bound energy sharing policy. This function iterates over all APs to find an energy sharing target with the best UCB mean. The function saves the current target AP into `action["now"]` and increments the AP action counter. APs using this algorithm can decide not to share energy. This function also returns an updated action-score history dictionary.

Third, `generateHistory()` creates an action-score dictionary structure for data logging. This dictionary is used to store action counts, score lists, mean scores and ucb mean scores. This dictionary has several key elements. The key `_history[_apid]["action"]["count"]` stores the count which target APs are selected to share energy. Next, `_history[_apid]["action"]["now"]` stores the current action selected by the algorithm. The key `_history[_apid]["score"]["list"][_targetapid]` stores the score generated by the target AP with `_targetapid` when it is selected for energy sharing. Moreover, `_history[_apid]["score"]["mean"][_targetapid]` stores the corresponding mean of scores. The key `_history[_apid]["score"]["mean-ucb"][_targetapid]` stores the ucb mean. An example of this dictionary is shown below.

```
# This is an example for a system with 3 APs.
# These APs have the id 0, 1 and 2.
history = {
    # This is for AP with the id 0.
    0 : {
        "action" : {
            "count" : {
                0 : 2,
                1 : 10,
                2 : 3,
            },
            "now" : 1
        },
```

```
        "score" : {
            "list"  : {
                0 : [3, 2],
                1 : [10, 10, 10 ,10, 10, 9, 8, 10, 8, 11],
                2 : [5, 6, 2]
            },
            "mean" : {},
            "mean-ucb" : {}
        }
    }
}
```

Finally, `updateHistory()` updates the action-score dictionary created above before calling energy sharing algorithms. This function also trims unused scores to increase simulation speed. First, this function saves the increase in total number of serviced users which corresponds to the result of the action taken by APs. In addition, this function also calculates and stores a new mean for the corresponding action taken. If the UCB1 algorithm is selected, ucb means for each action will be updated.

4.2 Simulation Methodology

The simulation is conducted on a grid of 50m^2 in size. This grid is constructed with Cartesian coordinates with $(0, 0)$ at the origin and $(50, 50)$ at the other edge. The simulation runs with events occurring at 5 minute intervals over a time span of one month. Next, the simulation environment consists of five APs which are placed randomly on the grid. These APs will start with a randomly generated starting amount of energy. This generated value will be in the range of 8000J to 120000J. In addition, each AP will consume a total of 1950J every 5 minutes when active. APs will power off when it does not have energy to sustain 1950J at the end of each timeslot. Moreover, APs generate energy based on the Markov Model from [38] with parameters shown in Table 4.1. The state transition probability is shown in Tab. 4.2. APs service users with energy required to satisfy a required received power of -70 dBm. Next, users are generated and placed on the grid using a Poisson Point Process with the $\lambda = 0.04$ to meet an average of 100 users in a 50m^2 grid. These users will move a randomly generated distance up to a maximum of 5 m at the end of each timeslot. In the simulation, APs will share 20% of stored energy and this will be allocated based on ranking which depends on the energy sharing policy that is enforced.

Sampling Period	5 minutes			
State	**Poor**	**Fair**	**Good**	**Excellent**
Mean	1.75	4.21	7.02	9.38
Variance	0.65	1.04	2.34	0.54
Steady State Probability	0.16	0.36	0.21	0.27

Table 4.1: Mean, Variance and Steady State Probability for Discrete Markov Chain

Sampling Period	5 minutes			
State Transition	**Poor**	**Fair**	**Good**	**Excellent**
Poor	0.979	0.015	0.006	0
Fair	0.005	0.988	0.007	0
Good	0.006	0.009	0.975	0.010
Excellent	0	0	0.008	0.993

Table 4.2: State Transition Probability of Discrete Markov Chain

This thesis investigates parameters which affect efficiency of energy sharing with six energy sharing policies. The policies investigated in this thesis are Epsilon Greedy and Upper Confidence Bound (UCB1).

The experiments investigate the total number of access points, total number of users, energy storage capacity, lambda of Poisson Point Process for user placement, maximum user movement distance, geometric series ratio for energy sharing, load balancing of APs, energy sharing budget, epsilon for Epsilon Greedy Multi Arm Bandit and data frame length for smart energy sharing algorithms. The parameter ranges for simulation are shown in the Tab. 4.3. The simulation is run for a total of 20 times for each step size and averaged to produce the results shown in the next chapter.

Parameter	Range(min, max)	Step Size
Total Number of APs	**(1, 38) Units**	**2**
Total Number of Users	(10, 200) Units	10
Lambda for Poisson Point Process	(0.01, 0.20)	0.05
Energy Storage Capacity	(50000, 600000) Joules	50000
Solar Panel Size	(5, 20) cm^2	1
Maximum User Movement Distance	(1, 15) Meters	1
Geometric Series Ratio	(0.01, 0.99)	0.01
Load Balancing of APs	(10, 150) Units	10
Energy Sharing Budget	(1, 100) %	1
Epsilon for Epsilon Greedy Algorithms	(0.01, 0.5)	0.01
Data frame length for Smart Energy Sharing	(1, 40) time slots	2

Table 4.3: Experiment Parameter Ranges

Chapter 5

Results and Analysis

5.1 Impact of Total Number of APs

This experiment generates a new set of APs for each simulation. The results from this experiment is shown in Fig. 5.1. First, the AP Energy Efficiency policy is able to service the most users when the total number of APs is high. It is able to service 168000 users when the number of APs is 38. This policy is able to achieve the largest rate of increase of 4232 serviced users per added AP. This is because energy distribution using a geometric ratio always provides the highest amount of energy to the AP which is ranked highest in terms of energy efficiency. The larger number of APs results in APs which service less users to act only as an energy generator. Next, the UCB1 and Epsilon Greedy results in 10% and 10.7% lower total number of serviced users on average compared to AP Energy Efficiency as the number of APs increases. These two policies show the highest total number of serviced users when the number of APs is in the range of 2 to 10. This is because UCB1 and Epsilon Greedy ensure a less biased distribution of energy among APs. Third, the AP Energy Use shows 3.6% and 2.8% lower total number of serviced users on average when compared to UCB1 and Epsilon Greedy respectively. This is because APs are limited by energy arrival. Fourth, the AP Energy Arrival policy demonstrates a 20% increase in serviced users per AP as the total number of APs increases above 24 units. This policy has a 13% lower performance on average as compared to AP Energy Use, Epsilon Greedy and UCB1 as total number of APs increases. This is because APs which have low energy arrival does not imply that it will be servicing a large number of users. Most of the energy allocated to these APs are being stored. Finally, the Shared Evenly policy results in a consistent total number of serviced users as the number of APs increases. This policy has the lowest performance as compared to other energy sharing policies. This is because APs require more energy to be active as compared to servicing users. Most energy is being used to keep APs active and only the excess amount of energy is used to service users. In this experiment, the transmission policy did not affect the total number of serviced users as the total number of APs increases.

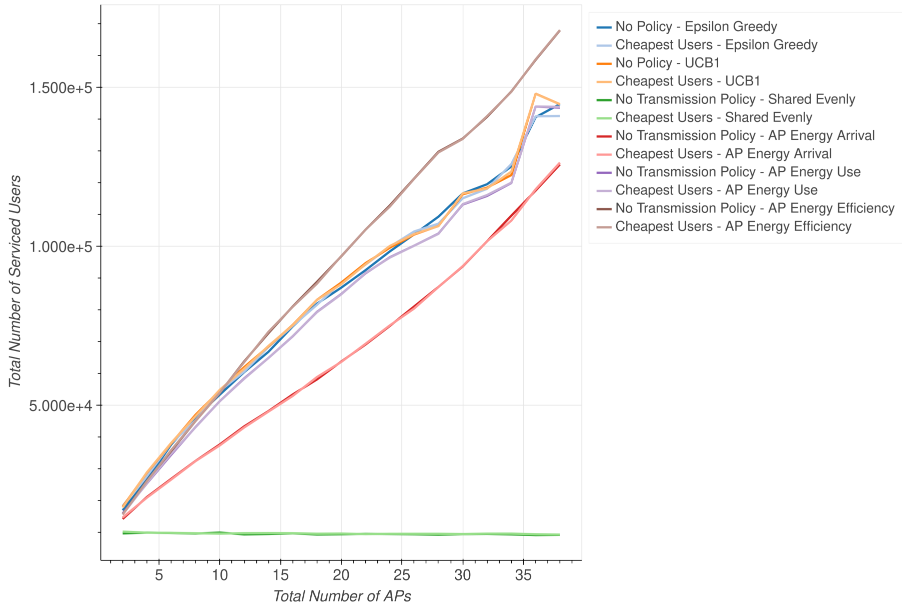

Figure 5.1: Impact of Total Number of APs: Total Number of Serviced Users Increases as Total Number of APs in the Simulation Increases.

5.2 Impact of Total Number of Users

This experiment generates a new set of users for each simulation. In this case, generation of users utilise the random generator of Python. Moreover, this experiment generates new user movement for each simulation. The results for this experiment is shown in Fig. 5.2. First, the UCB1 policy results in the highest total number of serviced users for all values of total number of users. This policy also has the largest gradient of 334 serviced users per user in the simulation. This is because APs in the upper boundary of total number of serviced users are prioritised for energy sharing. In this case, APs which do not service users with a high average are ignored. Next, the Epsilon Greedy policy services 2.4% less users as compared to UCB1 as users in the simulation increases. This is because some energy is wasted when APs experiment with sharing energy to APs at random. Third, the AP Energy Efficiency policy results in 6.2% lower serviced users compared to Epsilon Greedy on average as the number of users in the simulation increases. This is because traditional policies are unable to experiment with sharing energy to alternate target APs. Fourth, the AP Energy use policy shows 2.1% less serviced users when compared to AP Energy Efficiency. This is because APs are limited by energy arrival. APs using AP Energy Use to share energy spend more energy to service a similar amount of users as compared to AP Energy Efficiency. Fifth, the AP Energy arrival policy services 20.7% less users when compared to AP Energy Use. This policy achieves a gradient of 234 serviced users per user in the simulation. This is because APs are limited by energy arrival. In this case, large amounts of energy is being used to ensure APs with low energy arrival can remain active. Finally, the Shared Evenly policy performs 58.2% worse when compared to AP Energy Arrival. This policy results in the least gradient at 98 serviced users per user in the simulation. This is because energy required to power APs is much larger than the energy required to service users. When energy is used to keep all the APs active, little amounts of energy are used to service users. In this experiment, transmission policies do not affect the total number of serviced users.

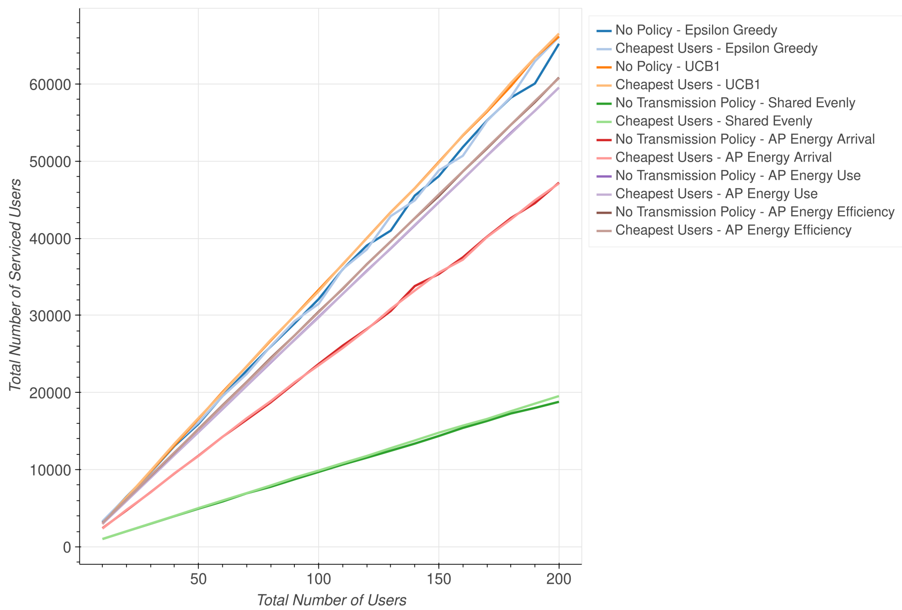

Figure 5.2: Impact of Total Number of Users: Total Number of Serviced Users Increases as Total Number of Users in the Simulation Increases.

5.3 Impact of Energy Storage Capacity

The maximum energy storage capacity influences the amount of energy that can be stored in each AP. The results are shown in Fig. 5.3. First, the UCB1 policy achieves the best performance when the maximum energy storage capacity increases. This policy scales the best with increasing maximum energy storage capacity. This is because UCB1 prioritises energy sharing for APs which service the most users on average. This policy reaches saturation of total serviced users when the maximum energy storage capacity is 350000J. Next, the Epsilon Greedy policy results in 15%

lower total number of serviced users as compared to UCB1 at the point of saturation. This is because this policy is more likely to experiment sharing energy with APs with a low average of total number of serviced users as compared to UCB1. A large amount of energy is wasted to keep poor performing APs active. Third, the AP Energy Use policy achieves the best performance on average when compared to other traditional energy sharing policies. This policy has a better performance when compared to AP Energy Efficiency when the maximum energy storage is greater than 250000J. This is because APs which consume the most energy are limited by energy arrival. When this limitation is overcome, APs can service more users. Next, the AP Energy Efficiency policy reaches saturation of total number of serviced users when the maximum energy storage is greater than 300000J. This policy performs the best when maximum energy storage is very low at 50000J. This is because AP with the best performance on average is prioritised. However, there are APs which do not spend energy efficiently but are responsible for more users. Fifth, the AP Energy Arrival policy performs 20% worse when the total number of serviced users are saturated compared to AP Efficiency. This is because APs which have lower energy arrival do not imply that an increase in energy storage capacity can service more users. Finally, the Shared Evenly policy results in the worst total number of serviced users on average. This policy achieves the maximum total number of serviced users of 98140 when maximum energy storage capacity is 150000J. This is because the increased maximum energy storage capacity is still limited by APs being unable to generate enough energy to power all APs and service users. In this experiment, smart energy sharing policies achieve saturation of the total number of serviced users at a larger maximum energy storage value as compared to traditional policies. This is because traditional policies are unable to adapt to the environment. In addition, traditional energy sharing policies are also limited by the geometric ratio energy distribution method. Transmission policies do not affect the total number of serviced users as maximum energy storage increases for all energy sharing policies except Shared Evenly. Shared Evenly shows a 2% increase in total serviced users when using the Cheapest Users policy. This is because the APs can service more users when sparse energy is used efficiently.

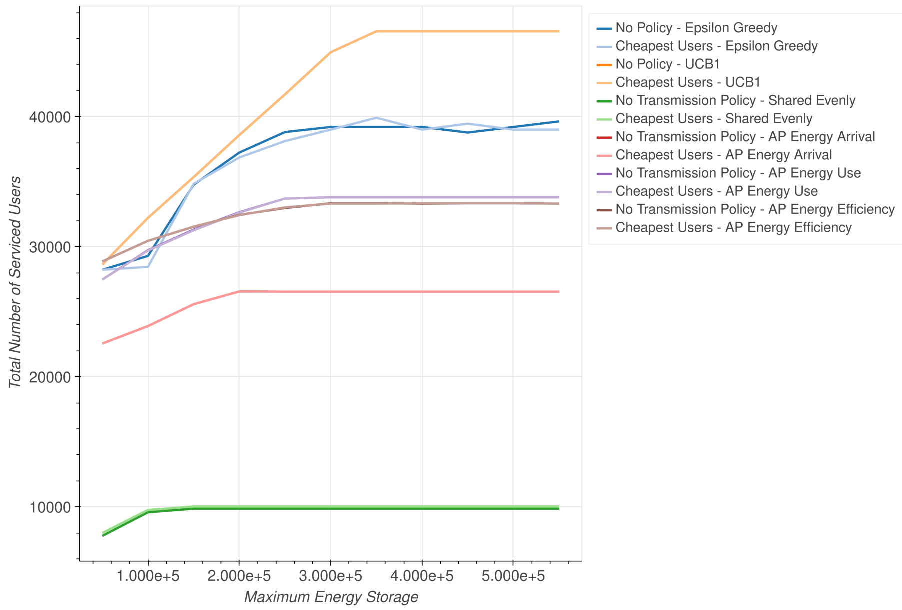

Figure 5.3: Total Number of Serviced Users Increases as Maximum Energy Storage Increases.

5.4 Impact of Poisson Point Process Lambda

The Poisson Point Process Lambda determines the average density of users given an area. The results for this experiment is shown in Fig. 5.4 In this experiment, new users are generated for each simulation. These users have a new set of movement actions. All energy sharing policies show an increase in total number of serviced users as lambda increases. The difference in total number of service users is a result of a random total number of users picked from a Poisson Distribution. On average, all policies perform similarly to previous experiments. The performance difference in this case for all energy sharing policies are consistent.

5.5 Impact of Maximum User Movement Distance

The maximum user movement distance restricts the length of movement step a user can take at the end of each timeslot. The results for this experiment is shown in Fig. 5.5. Maximum user movement distance does not affect the total number of serviced users. All energy sharing policies demonstrate a consistent result with a maximum of ±1.35% difference in total number of serviced users. Firstly, the UCB1 policy has the highest average total number of serviced users. This is because the policy prioritises APs which service a higher number of users on average. Next, the Epsilon Greedy policy performs 1.2% worse compared to UCB1. This is because

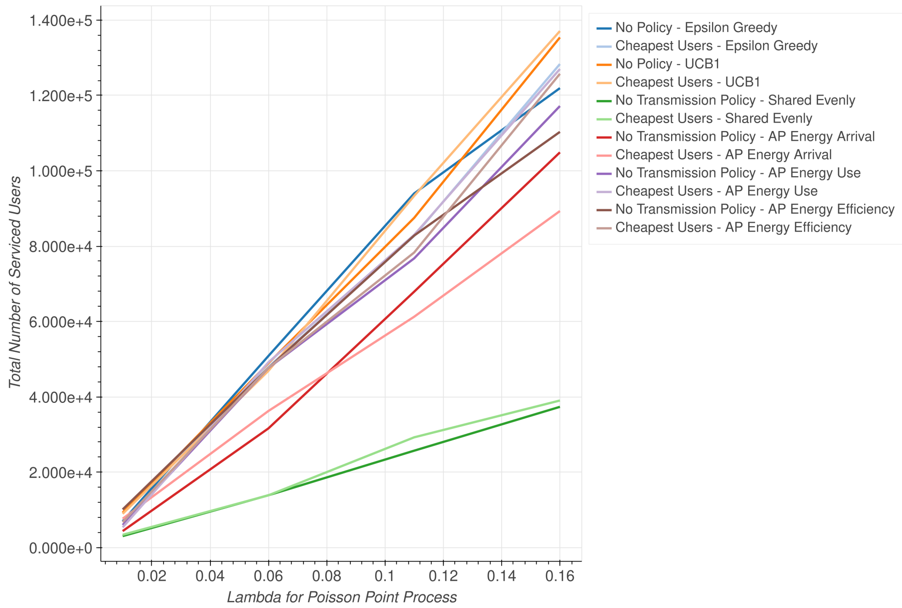

Figure 5.4: Impact of Poisson Point Process Lambda: Total Number of Serviced Users Increases as Poisson Process Lambda Increases.

some energy is being used when testing alternate APs to maximise total number of serviced users. Third, AP Energy Efficiency, AP Energy Use and AP Energy Arrival performs 7%, 8.7% and 26% worse on average compared to Epsilon Greedy. This is because traditional energy sharing policies have fixed parameters and are unable to adapt like smart algorithms. In addition, these traditional policies are limited by energy distribution using geometric ratio. Finally, the Shared Evenly policy has the lowest total number of serviced users. This is because this policy spends a large quantity of energy to ensure APs are active. In this experiment, transmission policy only affects Shared Energy. This is because energy used to power APs is significantly greater than the energy used to service users. As a consequence of spreading energy evenly, APs have little energy to service users. This increases the need for APs to service cheap users to achieve a higher total number of serviced users.

5.6 Impact of Geometric Series Ratio

The geometric series ratio values influence the amount of energy allocated to the APs. The results for this experiment is presented in Fig. 5.6. First, the AP Energy Use policy is able to service the most users when the geometric series ratio is low. It is able to service 32640 users when the geometric series ratio is 0.02. Total number of serviced users for AP Energy Use policy decreases as the geometric ratio value

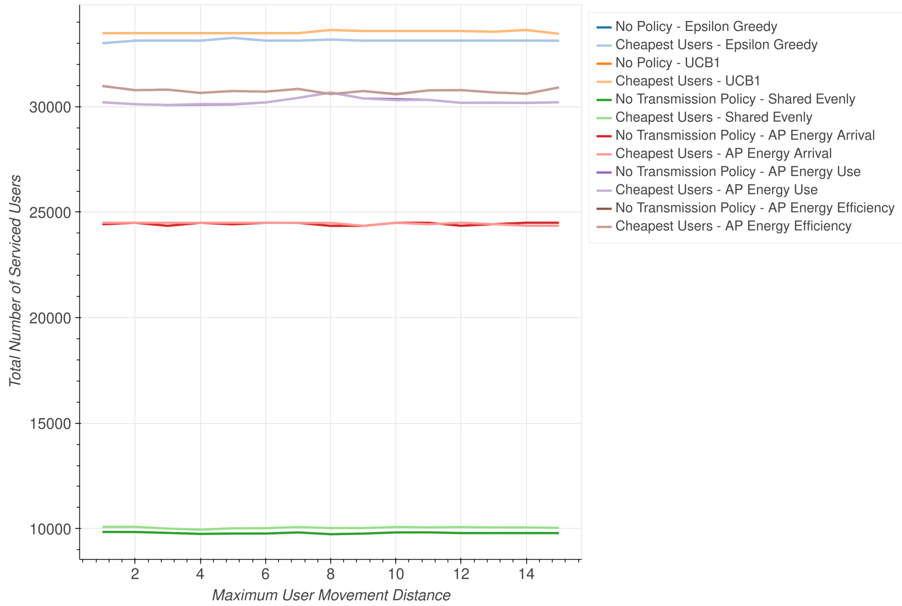

Figure 5.5: Impact of Maximum User Movement Distance

increases. This is because energy is prioritised for the APs which have higher energy consumption rate when the geometric series ratio is small. Next, the AP Energy Efficiency policy results in a consistent range of total number of serviced users. The increase in geometric series ratio only slightly affects the number of serviced users. The geometric series ratio value in the range of 0.01 to 0.72 only resulted in a five percent decrease in total number of serviced users. This is because not only one AP services larger numbers of users in each time slot on average. A geometric series ratio in the range of 0.01 to 0.72 ensures that the higher ranked APs have more energy to service users. Third, the AP Energy Arrival policy services the most users at a geometric ratio value of 0.78. This policy shows the highest serviced users when geometric ratio value is within 0.70 and 0.85. In addition, this policy services 20% and 23% less users on average for all geometric ratio values when compared to AP Energy Use and AP Energy Efficiency respectively. This is because the APs which have the least energy arrival does not imply that an increase in stored energy will increase the number of users it can service. Lastly, the Shared Evenly policy results in the lowest total number of serviced users at 10070. This is because the policy ensures that all APs will have the same amount of energy at the end of each time slot. Transmission policies of APs do not affect the total number of serviced users for different values of geometric ratio value for all energy sharing policies except Shared Evenly. The Shared Evenly policy shows a 1.5% increase in total number of serviced users when transmissions prioritise the cheapest users. This is because the APs require more energy to be active as compared to servicing users. When energy is prioritised to keep APs active, only little amounts of energy is able to be used to service users.

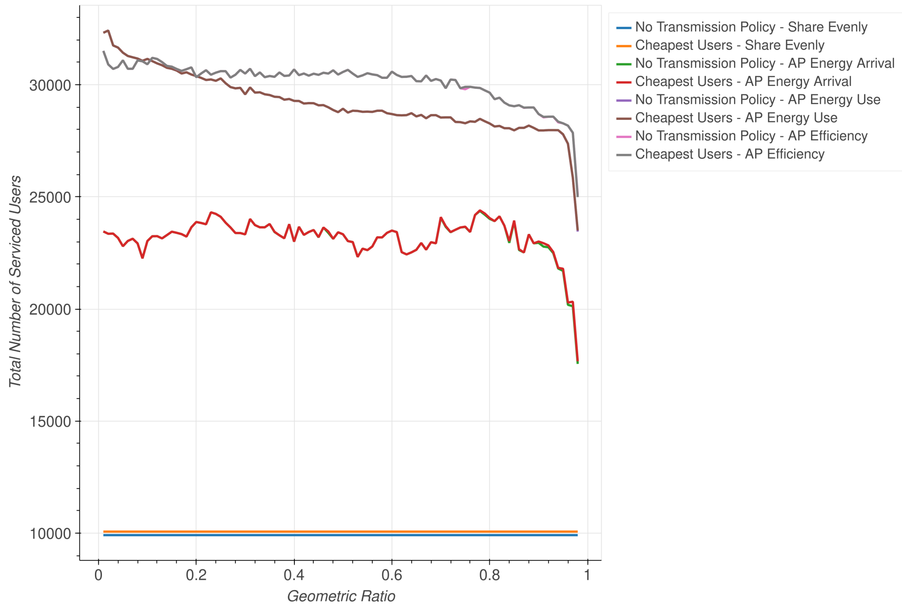

Figure 5.6: Impact of Geometric Series Ratio: Total Number of Serviced Users Decreases at High Geometric Series Ratio Values.

5.7 Impact of Load Balancing of APs

Load balancing limits the number of users each AP can service in any time slot. Users will connect to the next closest Active AP if the user limit of an AP has been reached. In this experiment, all energy policies achieve a saturation of total serviced users when the user limit is 100. This is because the number of APs is low. These energy sharing policies eventually distribute most of the energy to one AP which services all the users. Firstly, the UCB1 policy has the highest gradient at 454 serviced users per user limit increase. This policy has the highest total number of serviced users when the total user limit is 100. Next, the Epsilon Greedy policy results in the best performance on average as user limit increases. This is because Epsilon Greedy has high flexibility. This policy gives all APs an even opportunity to become a target when deciding to explore. This policy performs 1.2% worse compared to UCB1 at user limit saturation. Next, the AP Efficiency policy services less users compared to AP Energy Use when the user limit for load balancing is in the range of 30 to 85. However, AP Efficiency performs better than AP Energy

Use when the user limit is greater than 85. This is because AP Efficiency has APs which service a lot of users. Load balancing prevents AP Efficiency from performing well. However, AP Energy Use is unable to perform well when the user limit is high. This is because energy is being wasted on APs which do not service users efficiently. Next, the AP Energy Arrival policy shows a gradual increase of 200 serviced users per increase in user limit. In this case, APs still have a heavily biased amount of energy allocation. These APs cannot use energy efficiently. Energy is wasted servicing users which are far away from APs. Lastly, the Shared Evenly policy shows a slight increase in total number of serviced users as load balancing user limit increases. This is because APs which are limited by low energy arrival have an even distribution of users. In this experiment, transmission policies do not affect the total number of serviced users for all energy sharing policies except Shared Evenly. These APs using the Cheapest User policy gain 1% total number of serviced users. This is because most energy is being consumed to ensure APs remain active.

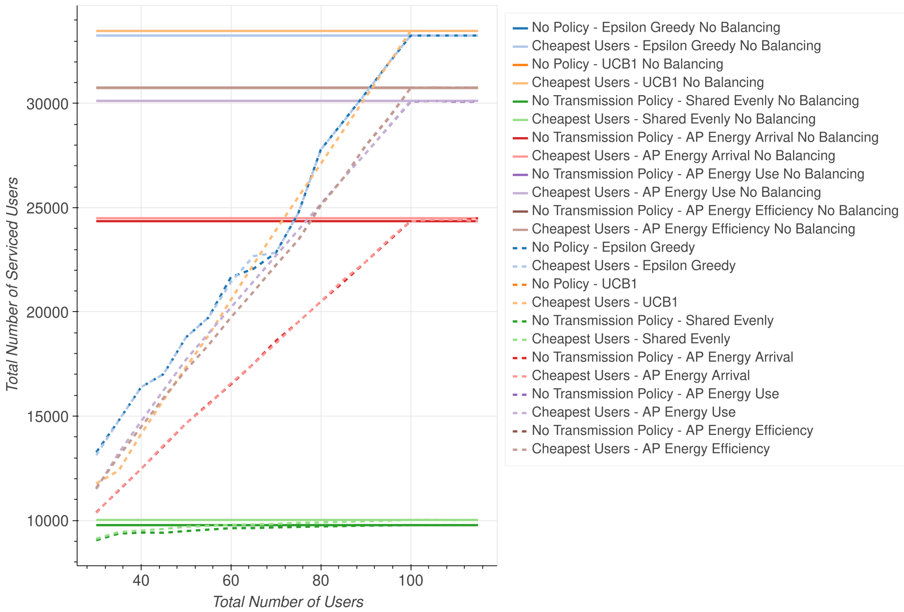

Figure 5.7: Impact of Load Balancing User Limit: Total Number of Serviced Users Saturates for All Policies when User Limit = 100.

5.8 Impact of Energy Sharing Budget

The energy sharing budget influences the percentage of energy APs share at the end of every time slot. The results for this experiment is shown in Fig. 5.8. In this experiment, all policies except AP Energy Arrival and Shared Energy demonstrate an improvement in total number of serviced users when energy sharing is enabled.

Firstly, UCB1 has the highest overall performance compared to all other policies. This policy services the most users when the energy sharing budget is 6%. Next, the Epsilon Greedy policy services 3.3% less users compared to UCB1 as the energy sharing budget increases. This policy demonstrates the highest total number of serviced users when the energy sharing budget is 20%. However, this policy shows the highest fluctuation when the energy sharing budget is in the range of 12% to 50%. This is because Epsilon Greedy will experiment sharing energy to alternate AP targets. Third, the AP Energy Efficiency policy shows services 5.8% less users on average compared to Epsilon Greedy as energy sharing budget increases. The total serviced users gradually decreases as the energy sharing budget increases. This policy shows the best performance when the energy sharing budget is 2%. This is due to energy distribution by geometric ratio. When the energy sharing budget is high, energy is prioritised only at one AP. Not all users are close to this AP which has the highest amount of energy. Next, the AP Energy Use policy results in 5.4% less serviced users on average when compared to AP Energy Efficiency. AP Energy Use demonstrates a sharper decline in total number of serviced users as energy sharing budget increases when compared to AP Energy Efficiency. This is because APs service users with more than the minimum energy required. Energy is shared to an AP which uses the most energy but does not service users efficiently. This policy shows the highest total number of serviced users when the energy sharing budget is 4%. Fifth, the AP Energy Arrival policy results in 16% lower total number of serviced users on average compared to AP Energy Use. This policy shows a consistent performance when the energy sharing budget is in the range of 16% to 74%. This is because APs are limited by energy arrival. Distributing energy to the AP with the least energy arrival results in users being serviced with low efficiency. The total number of serviced users decreases as the energy sharing budget increases above 74%. Finally, the Shared Evenly policy has the highest total number of serviced users when the energy sharing budget is 4%. The performance of this policy gradually decreases as the energy sharing budget increases. This is because sharing little amounts of energy evenly can increase energy storage in APs with lower energy arrival. When energy is distributed evenly, APs can service more users. In this experiment, transmission policy does not affect the total number of serviced users in all policies but Shared Evenly. Shared Evenly can service 1.5% more users on average when picking the cheapest users. This is because APs have limited energy. When most energy is used to keep all APs active, little amounts of energy can be spared to service users.

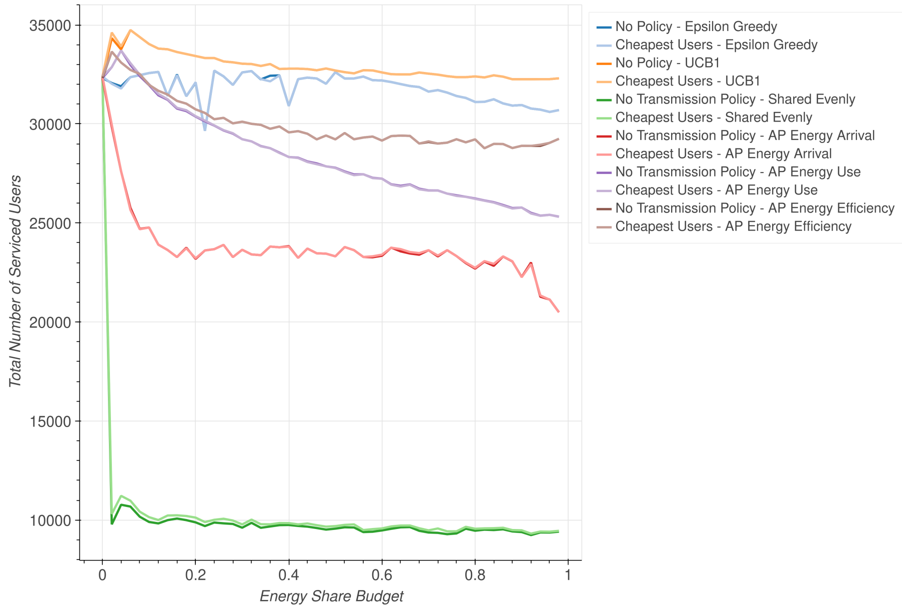

Figure 5.8: Impact of Energy Sharing Budget: UCB1 shows the best overall performance for all energy sharing policies.

5.9 Impact of Solar Panel Size

The solar panel size affects the amount of energy arrival for APs at the end of each time slot. In this experiment, all policies show that increasing solar panel size increases the total number of serviced users. Firstly, the UCB1 policy results in the highest average total number of serviced users as solar panel size increases. This policy shows the best performance for solar panel size in the range of 5 to 14cm^2. Next, the Epsilon Greedy performs 2.3% worse as compared to UCB1 on average as solar panel size increases. This is because the Epsilon Greedy policy experiment sharing energy with other APs at random. Third, the AP Energy Efficiency policy demonstrates the highest gradient of total serviced users per increase in solar panel size. This policy has the highest total number of serviced users when solar panel size is greater than 15cm^2. This is because the energy distribution algorithm for AP Energy Efficiency is very biased towards one AP. UCB1 distributes energy more evenly among the APs in the upper bound. Next, the AP Energy Use policy shows a gradient that is similar to UCB1 and Epsilon Greedy. However, this policy results in a 6.9% and 4.7% lower total number of serviced users on average when compared to UCB1 and Epsilon Greedy respectively. This is because this policy does not service users efficiently. This policy uses more than the minimum required energy to service users. Next the AP Energy Arrival policy results in a 21.2% lower total number of serviced users when compared to AP Energy Use. This policy shows a similar performance in previous experiments. Finally, the Shared Evenly policy shows the lowest total number of serviced users for all solar panel sizes. This policy achieves 61.4% lower total number of serviced users when compared to AP Energy Arrival. This is because a large amount of energy is being used to power APs. In this experiment, transmission policies do not affect the performance for all policies except Shared Evenly. Shared Evenly using Cheapest User achieved a 1.54% increase in total number of serviced users compared to No Transmission Policy.

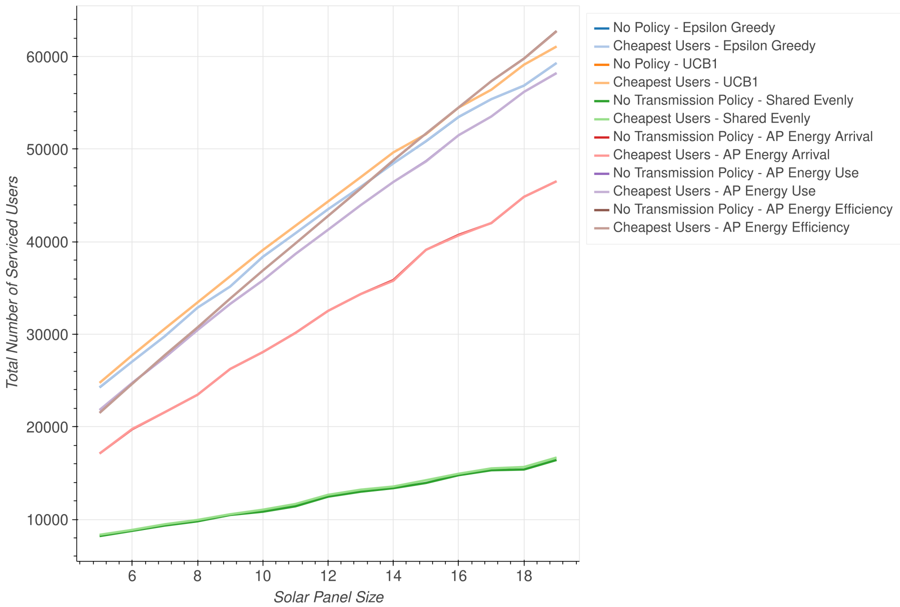

Figure 5.9: Impact of Solar Panel Size: Increasing Solar Panel Size Increases Total Number of Serviced Users.

5.10 Impact of Epsilon for Epsilon Greedy

The epsilon for Epsilon Greedy Multi Armed Bandit algorithms influence the likelihood of APs to switch energy sharing targets to maximise total number of serviced users. This experiment tests the Epsilon Greedy energy sharing policy with several energy sharing budgets. The results for this experiment is presented in Fig. 5.10. In this experiment, all five energy sharing budget percentages achieve the highest total number of serviced users when epsilon is low. This is because a lower epsilon value reduces the probability of APs sharing energy to APs which service less users. First, the Epsilon Greedy policy with 10% energy sharing budget achieves the highest total number of serviced users when epsilon is in the range of 0.01 to 0.34. Next, the policy which shares energy with 1% of energy sharing budget services the most users when the epsilon value is greater than 0.34. This energy sharing budget shows the lowest decrease in total number of serviced users as epsilon increases. This is because the low energy sharing budget reduces the effect of energy sharing on the total number of serviced users. Third, sharing 60% of energy results in the second highest total number of serviced users as epsilon increases from 0.01 to 0.16. This energy sharing budget has the lowest total number of serviced users when epsilon is greater than 0.26. This is because sharing 60% of energy causes energy to be distributed evenly among APs. Epsilon Greedy is unable to use 60% energy sharing budget to find the optimal target when epsilon is greater than 0.26. Next, sharing 90% of energy results in 1.3% higher total number of serviced users on average when compared to a 60% energy sharing budget. This is because a 90% energy sharing budget can distribute energy with bias. More energy can be distributed to specific sets of APs at high epsilon values. Finally, an energy sharing budget of 30% results in the lowest average of total number of serviced users as epsilon increases. This energy budget is also unable to distribute enough energy to APs which service the most users. In this case, energy is distributed almost evenly among all APs.

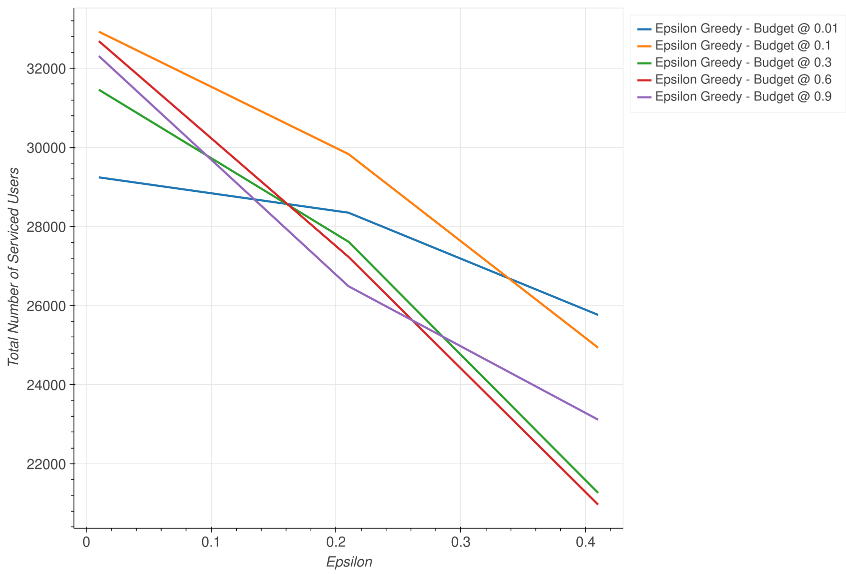

Figure 5.10: Impact of Epsilon for Epsilon Greedy: Total Number of Serviced Users Decreases as Epsilon Value Increases.

5.11 Impact of Data frame Length

The data frame size influences the length of the data frame which smart energy sharing algorithms consider to determine the resulting score from previous time slots. In addition, increasing the length of the data frame can increase processing time for APs. The results for this experiment is shown in Fig. 5.11. In this experiment, increasing the length of the data frame increases the total number of serviced users for both UCB1 and Epsilon Greedy policies. Firstly, UCB1 has the best performance when the data frame length is greater than 6. UCB1 also reaches a saturation of the total number of serviced users at this value. Next, the Epsilon Greedy policy results in the highest total number of serviced users when the data frame length is greater than 32. This data frame length allows Epsilon Greedy to achieve a similar performance to UCB1. The Epsilon Greedy policy shows an inconsistent performance as the data frame length increases. This is because APs will experiment sharing energy with alternate target APs at random. These target APs do not need to satisfy any performance metric unlike UCB1. In this experiment, the transmission policy does not affect the total number of serviced users.

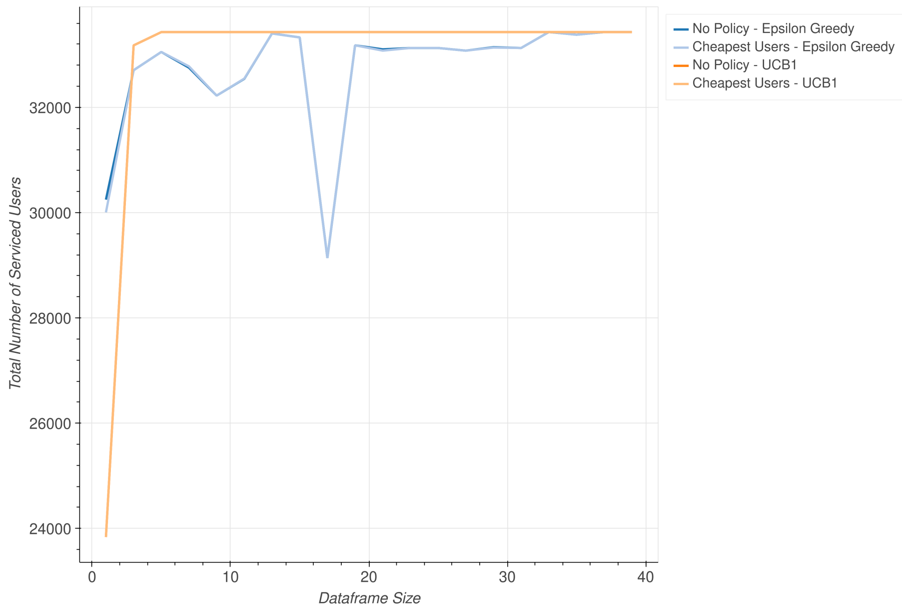

Figure 5.11: Impact of Data frame Length: Total Number of Serviced Users Increases as the Data Frame Length for Smart Energy Sharing Algorithm Increases.

Chapter 6

Conclusion and Future Works

WLANs power using renewable energy are used to reduce network operating costs and overall carbon footprint. However, there are many limitations to powering WLANs using renewable energy harvesting. This is due to the randomness of the energy arrival from renewable energy harvesting. As a result of these limitations, APs are unable to service associated users consistently. In this case, overall uptime and coverage area of WLANs are directly affected by APs switching off due to insufficient energy. Thus, this thesis presents a WLAN which consists of APs that each have a renewable energy source. These APs can share energy by sending energy to other APs. This thesis aims to maximise the total number of serviced users in the WLAN discussed above. Moreover, this thesis presents two AP transmission policies and six energy sharing policies. This thesis also presents a simulator which simulates a WLAN and the policies presented to find the parameters of a WLAN and characteristic of each policy which can maximise total number of serviced users. First, an increase in total number of APs, total number of users, maximum energy storage capacity, Poisson Point Process Lambda, load balancing user limit increases the total number of serviced users for all energy sharing policies. Next, the maximum user movement distance does not affect the total number of serviced users. Third, different transmission policies have little impact on the total number of serviced users. This is only apparent for Shared Evenly. This impact is only obvious when APs have energy that is evenly distributed. The thesis also finds that the energy sharing budget has a significant impact on the total number of serviced users. In this case, smart energy sharing policies UCB1 and Epsilon Greedy service the most users when the energy sharing budget is 6% and 20% respectively. However, there is no definite value for traditional energy sharing policies. This is because traditional energy sharing policies also depend on the energy distribution algorithm. This requires compatibility with the geometric ratio value. The thesis also finds that the base energy consumption for APs are significantly greater than energy used to service users. Next, an increase in data frame length increases the total number of serviced users for smart energy sharing algorithms. The thesis finds that all energy sharing policies require prior tuning before deployment. This is because the performance of each energy sharing policy is dependent on the deployment environment.

The transmission and energy sharing policies presented in this thesis requires APs to constantly log data on other APs. In this case, a future research direction is to design a simplified smart energy sharing WLAN for practical testing. Next, alternate energy distribution algorithms for APs using traditional energy sharing algorithms can also be considered for future works. The thesis can also consider other smart energy sharing algorithms to compare with the solutions presented in this thesis. Moreover, the optimal timing to share energy can also be tested to further improve existing energy sharing algorithms presented in this thesis. This can enable APs to share energy less aggressively. Finally, future works can also consider increasing the scale of the simulation to experiment on the scalability of the energy sharing policies previously discussed in this thesis.

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Appendix A

Project Proposal

University of Wollongong

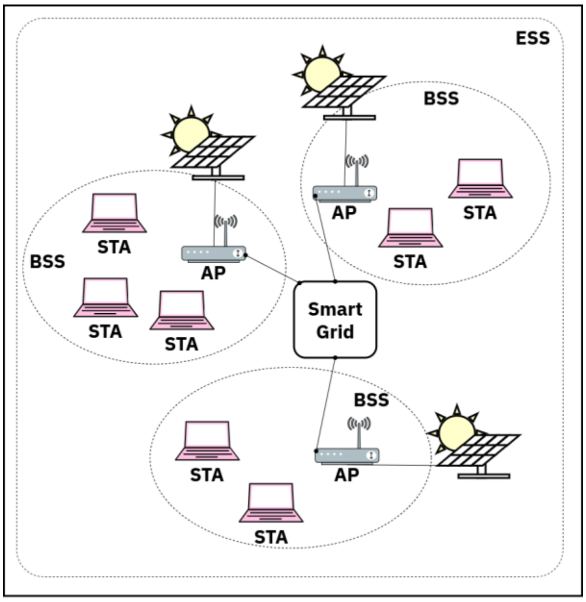
SCHOOL OF ELECTRICAL, COMPUTER AND TELECOMMUNICATIONS ENGINEERING
ECTE457 PROJECT PROPOSAL FORM

1. Candidate Details	
Name: Mark Cai Yee Lee	**Student No: 6143611**
Supervisor: Kwan-Wu Chin	
Title of Project: Smart Energy Sharing of Access Points in Wireless Local Area Networks	
Brief Overview: The Internet is expected to grow rapidly in the future, and this comes at a cost of increased energy expenditure. As energy generation using non-renewable sources is not environmentally friendly, the project utilises solar energy to power the networked components. In this case, the main networked components will be access points. The access points will each have a renewable energy source and able to share energy with each other. Moreover, the extra energy that an access point has will be better utilised to assist the operations of another access point lacking in energy. The main goal of the project is to develop algorithms to share energy between access points efficiently. Additionally, the project will be studying reinforced learning, a machine learning technique at the access points. This will help access points to learn to share energy effectively.	

2. Project Description: (Expand to one page maximum)

The Internet is expected to continue to grow at an unprecedented rate in the future. It is projected that 66% of the global population will have Internet access by 2023 as compared to the 51% in 2018. It is also projected that networked devices will increase from 2.4 devices per capita in 2018 to 3.6 devices per capita by 2023. The global annual Internet traffic had also been projected to increase to total of 4.2 Zettabytes per year by 2022.

In this case, the growth of the Internet comes at a cost of increased energy expenditure. In 2017, the International Energy Agency reported that data networks alone consumed around 185 TWh globally in 2015. Renewable energy can solve the issue stated above. It had been proven that switching to renewable energy will provide a direct positive impact on the environment. Several Multinational Information and Communication Technology companies worldwide had already taken the initiative on moving towards renewable energy sources.



Given the figure above, the project is aimed to determine an efficient method and timing for energy sharing between access points using machine learning. In this case, the access points will be assumed to have a renewable energy source powered with solar energy. Next due to the environment of each access point, each access point will have different rate of energy harvesting. As the energy level of an access point handling low traffic saturates, it will send energy into the smart grid for sharing with other access points handling more traffic workload. This will enable all the access points to operate efficiently without sacrificing quality of service. The project will study and develop algorithms which utilise reinforced learning for energy sharing between access points in wireless local area networks.

There are several questions in which the project will attempt to answer. The timing for energy sharing for access points. The algorithm for machine learning will be studied to ensure that access points understand the appropriate timing for sharing energy. Next, the factors influencing learning of energy sharing. The factors taken into consideration for machine learning will have to be studied to understand the parameters influencing efficient energy sharing. Finally, the amount of energy shared to maintain operations. The access points should know how much energy can be spared to ensure the same operating efficiency all the time.

3. Project Plan: (Two pages maximum)

The project will be organised into three phases, motivation, understanding and implementation.

The motivation phase involves research on real-world data of the problem needs to be addressed. In this case, the importance and growth of wireless local area networks and the Internet will have to be studied. Next, the relation between the growth of the Internet and the effect of it on the environment will have to be realised. In addition, research will have to be done to understand the methods available to combat the problem. Next, the architecture of wireless local area networks will have to be studied. This will help with the implementation and finding the optimisations available to overcome the effect on wireless local area networks and the Internet on the environment.

Next, the understanding phase will look at the previous literature which attempted to implement similar approaches. This phase will be a continuation of the previous motivation phase which looks at a general view of the problem. The understanding phase will be observing and studying the literature which tries to solve the problem. The focus of the literature in the project will be studying renewable energy, energy harvesting, wireless local area networks, machine learning and energy sharing.

Lastly, the implementation phase will attempt to simulate and attempt to solve the problem from the knowledge obtained in the previous two phases. The implementation phase will first simulate the environment where the wireless access points will reside. In addition, several factors will be taken into consideration such as energy harvesting rate, wireless traffic and energy consumption. Next, a machine learning algorithm will be implemented at the access point. This will enable the access point to understand when to share energy. The implementation will first be simulated on software and later brought into hardware if the simulation is successful.

The experimental results will be validated with several different environmental conditions in simulation. In this case, the operations of the access points will have to be optimal in all or most cases. Next, a hardware experiment can be presented to verify the solution is probable in real-life scenarios.

The motivation phase will have to be completed by Week 4 of Autumn 2021. Next, the understanding phase will be complete by Week 8 or Week 9 of Autumn 2021. Finally, the implementation phase will be concluded by Week 11 of Autumn 2021. At the end of ECTE457 session 1, the project will have concluded and achieved a good understanding of the connection between Information and Communication Technology and the environment, the solutions proposed to use renewable energy in wireless local area networks, the machine learning algorithms implemented for energy sharing. The project is also planned to have simulated the scenario and have a hardware implementation ready to be implemented in session 2 of ECTE457.

The risk associated with the project is negligible as most work will be conducted as simulation and further amendments for risk will be investigated in session 2 of ECTE457.

4. Resources Required: (Expand to a half a page maximum)
The project will require MATLAB and python programming language for simulation and machine learning.

5. Literature Planner: (Expand to as required)
Attach as an appendix

6. Mind Map: (single A4 page)
Attach as an appendix

Student Signature ***Declaration by the student: I have understood the feedback provided to me by the supervisor.***		
	Signature	**Date**
Student Name:		

Note: the typical over all page count should not exceed 15 pages

A marked assessment rubric will be appended once completed

Appendix B

Revised Project Proposal

University of Wollongong

SCHOOL OF ELECTRICAL, COMPUTER AND TELECOMMUNICATIONS ENGINEERING

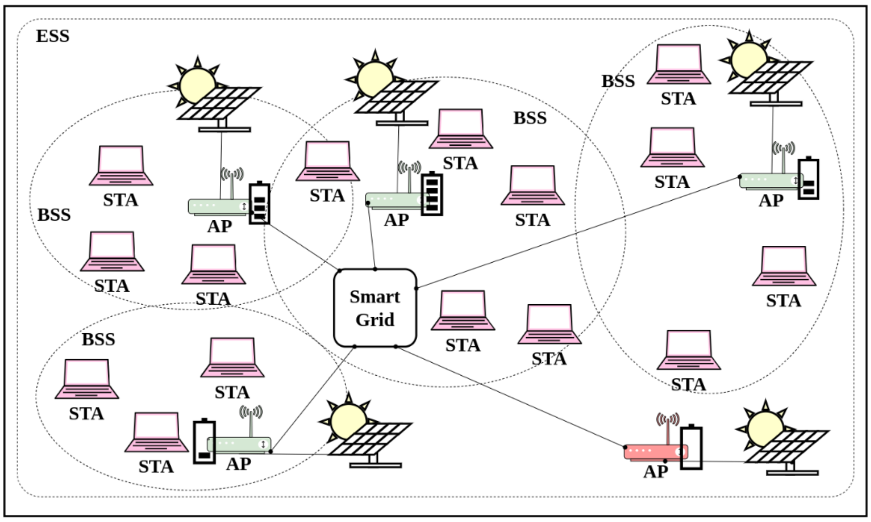
ECTE457 REVISED Project Proposal Form

(maximum 8 pages on completion)

1. Candidate Details	
Name: Mark Cai Yee Lee	**Student No: 6143611**
Supervisor: Kwan-Wu Chin	
Title of Project: Smart Energy Sharing of Access Points in Wireless Local Area Networks	
Brief Overview: The Internet is growing at an unprecedented rate. Wireless networks powered using renewable energy is an alternative to accommodate the growth of the internet with a lesser impact of carbon emissions. The project proposes a Wireless Local Area Network which consists of access points which are powered using solar energy. These access points can share energy with each other. The project consists of a simulator which replicates the behaviour of Smart Energy Sharing WLANs, a study on the factors which influence access points from using energy efficiently and to develop algorithms which improve the operating efficiency of access points which share energy.	

2. Project Description: (One page maximum)

The problem addressed by the project has not changed from session 1. As the Internet grows, the amount of networked devices will grow. This will cause a large increase in energy expenditure which increases pollution. Renewable energy can reduce the impact brought on by the growth of the Internet but the efficiency of networked devices has to improve.



The project proposes a system shown in the figure above. The system consists of access points which service the users closest to it. These access points will have a renewable energy source and energy storage capabilities. In addition, access points are able to share energy with other access points using a smart grid. Access points will also enforce a user servicing policy to ensure that the most users are serviced in the duration of the simulation. The project simulator will have several energy arrival models, user placement models and path loss models for a more realistic simulation.

The project aims to determine the relationship between total number of serviced users and parameters which affect the characteristics of a WLAN. In addition, these parameters will be used to determine the factors which influence efficient use of energy for an access point. Next, energy consumption policies for access points will be investigated to identify the most efficient way for energy sharing enabled access points to service users.

In this session, the simulator will be improved to account for a more realistic energy arrival model, user placement locations and enabling energy sharing of access points. In addition, several policies for energy consumption will be investigated to determine the most efficient method for access points to service the most users.

3. Project Plan: (Two pages maximum)

In the previous session, the project focused on identifying the research which aims to optimise WLANs and improve energy harvesting efficiency. In addition, a basic WLAN simulator was produced and written in Python. This session, the project will focus on identifying the factors which makes access points use energy efficiently. Next, the project will build on the relationship and enable these access points to share energy to service more users. Several algorithms will be developed to find the most efficient way for energy sharing WLANs to operate.

In this session, the project will consist of three phases, investigation, implementation and optimisation.

The investigation phase will identify the determine the relationship between the total number of serviced users and the parameters which affect the characteristics of a WLAN. This phase will focus on studying the parameters of the simulated WLAN environment and to fix the shortcomings of the simulator when encountered. In addition, the simulator will also be improved to take into account a more realistic energy arrival model and user placement model. A base result will be taken in this phase to compare the efficiency of access points after energy sharing has been enabled.

The implementation phase will produce and test several algorithms which affects the operating policy of access points in the simulator. In this phase, these algorithms will be tested to compare with the base results which did not account for energy sharing. Access points will use conservative, greedy and smart policies to operate. This phase will identify the shortcomings of operating algorithms and the most efficient method for energy sharing wireless access points to service users.

The optimisation phase of the project will focus on improving the simulator and discussing the results obtained from the previous phases. The simulator can account for other energy arrival models, user and access point placement models and access point operating models. This will enable more realistic models to be simulated in the future.

The experimented results will be validated with several different environment conditions in simulation. Next, a hardware experiment can be presented to verify the solution is probable in real-life scenarios.

The investigation phase will have to be completed by Week 5 of Spring 2021. Next the implementation phase will be completed by Week 8 or 9 of Spring 2021. The implementation phase will be concluded by Week 11 of Spring 2021. The additional weeks will be allocated for report writing and as a fallback plan should inconveniences occur during the duration of the project. At the end of session 2 of ECTE457, the project will have concluded with achieving a good understanding of how wireless access points can use energy efficiently. A simulator which will be able to model real world environments will be produced and tested with several user servicing policies.

The ongoing COVID-19 pandemic increases some risk associated to the success of the project. However, the project will mostly be conducted as a simulation and is projected to succeed at the end of the session.

4. Adaption of Supervisor and Examiners feedback in the ECTE451 report: (Half a page maximum)
In overall the review comments are positive and the project will be conducted similarly to session 1 with several improvements. First, the abstract will be further condensed to a single paragraph to summarise the work and important details on methodology and findings. Next, the equations used in the project will be numbered and referred in the text. Finally, the findings from the project will be compared to the current research to add value to the outcome of the project.

Student Signature *Declaration by the student: I have understood the feedback provided to me by the supervisor.*		
	Signature	Date
Student Name: Mark Cai Yee Lee		14/08/2021

A marked assessment rubric will be appended once completed