

Impact of Incentive Pricing on Users' Migration in the Next-Generation Mobile Network



Prepared by:

Omolemo Kegakilwe

Prepared for:

Dr O.E. Falowo

Dept. of Electrical and Electronics Engineering
University of Cape Town

Submitted to the Department of Electrical Engineering at the University of Cape Town in partial fulfilment of the academic requirements for a Bachelor of Science degree in Electrical And Computer Engineering

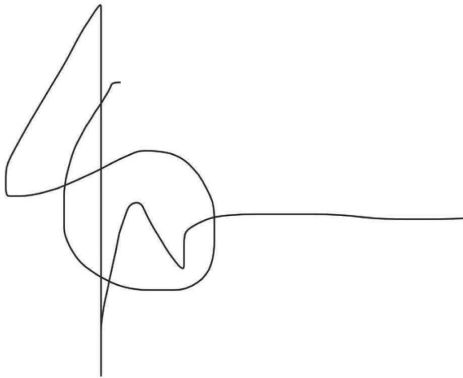
October 30, 2023

Keywords: Incentive Pricing, Multi-Attribute Utility Theory, Utility-Difference Threshold, User Migration Acceleration, HWNs, Resource Utilisation, Call Dropping Probability, Call Blocking Probability

Declaration

word count: 16920

1. I know that plagiarism is wrong. Plagiarism is to use another's work and pretend that it is one's own.
2. I have used the IEEE convention for citation and referencing. Each contribution to, and quotation in, this report from the work(s) of other people has been attributed, and has been cited and referenced.
3. This report is my own work.
4. I have not allowed, and will not allow, anyone to copy my work with the intention of passing it off as their own work or part thereof.

A handwritten signature in black ink, consisting of a large, stylized 'S' or 'L' shape with a horizontal line extending to the right.

October 30, 2023

Name Surname

Date

Acknowledgements

Great discoveries and improvements invariably involve the cooperation of many minds.

— *Alexander Graham Bell*

I am immensely grateful to everyone who has contributed to the successful completion of this thesis. Even though the work is my own, I am certain I would not have gotten this far if it was not for the assistance of the many individuals I met along the way that have aided my journey in their respective capacities. This work represents the culmination of months of research, and I owe my deepest appreciation to the following individuals and institutions:

I express my heartfelt gratitude to my Supervisor Dr O. Falowo, for their invaluable guidance, continuous support, and encouragement throughout this journey. Their expertise, patience, and dedication were instrumental in shaping the direction of this research and helping me overcome challenges along the way. I thank him for imparting his knowledge and inspiring my intellectual growth. His lectures and discussions have been instrumental in broadening my understanding of the subject. I would like to acknowledge the support and resources provided by the University of Cape Town and the IEEE. Their facilities, libraries, and research infrastructure played a crucial role in the completion of this thesis.

I am grateful to ISFAP for providing financial support for my undergraduate career. Their funding has enabled me to get through my studies without having to worry about external factors related to funds. Their overall support eased my mind as they are very understanding and put very little pressure on me.

I am thankful to my friends for standing by my side, cheering me on, and offering words of motivation during moments of doubt. Their camaraderie made the journey more enjoyable and reminded me of the importance of work-life balance.

Last but certainly not least, I would like to thank my mother. Her continued support in all that I do is what encourages me to keep on keeping on. To my family, who have always been my pillar of strength and support, I am deeply grateful. Their unwavering belief in my abilities and constant encouragement has been the driving force behind my academic pursuits.

If there are other individuals, organizations, or institutions that have contributed in any way to the completion of this thesis, though not mentioned explicitly, I am grateful for their support.

In conclusion, I am indebted to everyone who has played a part in this academic endeavour. The completion of this thesis would not have been possible without your unwavering support, guidance, and encouragement. Thank you for being an integral part of this journey.

Abstract

Incentive pricing is a technique commonly used to encourage consumers to behave in a particular way that may be beneficial to the parties inciting this behaviour. In the context of telecommunications, network providers may want to encourage users to adopt the newer generations of mobile cellular networks to achieve improved QoS provisioning and resource utilisation.

This project aims to review incentive pricing schemes and their potential for accelerating the adoption of newer generations of cellular networks within heterogeneous wireless networks. This research underscores the critical need to comprehend how incentive pricing schemes can influence user choices considering the lag in adoption in Africa compared to the rest of the world. An incentive pricing model is then proposed which involves multi-attribute utility theory and utility-difference threshold concepts in accordance with the literature for modelling the migration of users. Its effectiveness on users' migration is then evaluated and its implementation will be analysed in terms of the impact it has on QoS Provisioning and resource utilisation in HWNs.

The results found that higher incentives have a greater potential for eliciting the migration of users in scenarios where the threshold for migration. However, instances where users may not be as sensitive to incentives resulted in little to no migration. Furthermore, the migration of users to newer generations as a result of incentive pricing is shown to have a positive impact on the network, with an improvement in call-blocking probability, call-dropping probability and resource utilisation.

Terms of Reference

Student proposed?	Y/N N If Y, student name
ID:	OF-08
SUPERVISOR:	Olabisi Falowo
TITLE:	Impact of Incentive Pricing on Users' Migration in the Next Generation Mobile Network
DESCRIPTION:	Incentive pricing can be used for accelerating users' adoption of the next-generation mobile network, and thereby enhance radio resource utilization and QoS provisioning in heterogeneous wireless networks. Existing works in the literature have used incentive pricing for traffic offloading and peak-time traffic reduction in heterogeneous wireless networks. The objective of this project is to develop a model for investigating how incentive pricing can be used to accelerate the adoption of the newest RAT in a heterogeneous wireless network.
DELIVERABLES:	A review of incentive pricing schemes, a model for investigating the impact of incentive pricing on users' migration, simulation results, and report.
SKILLS/REQUIREMENTS:	MATLAB or any other programming language, EEE4121F.
GA1: Problem solving: Identify, formulate, analyse and solve complex engineering problems creatively and innovatively	The student is expected to develop and implement a scheme for investigating the impact of incentive pricing on users' migration in heterogeneous wireless networks.
GA 4**: Investigations, experiments and analysis: Demonstrate competence to design and conduct investigations and experiments.	The student is expected to investigate the impact of incentive pricing on users' migration in heterogeneous wireless networks.
EXTRA INFORMATION:	For a student interested in pursuing a master's degree, the project can be expanded to an MSc dissertation.
BROAD Research Area:	Wireless Networks
Project suitable for ME/ ECE/EE/All?	EE/ECE students who have taken EEE4121F course.

Contents

List of Figures	1
1 Introduction	2
1.1 Background	2
1.2 Objectives	2
1.2.1 Problems to be investigated	3
1.2.2 Purpose of the Study	3
1.3 Scope & Limitations	4
1.4 Report Outline	5
2 Literature Review	7
2.1 Overview of next-generation mobile network (5G)	7
2.1.1 Progression of Mobile Networks	7
2.1.2 5G Use Cases	8
2.1.3 5G Frequency Bands	9
2.2 Migration to 5G	10
2.2.1 Deployment of Cells	10
2.2.2 5G challenges	11
2.2.3 User Adoption	12
2.3 Heterogeneous Wireless Networks	16
2.3.1 RAT Characteristics	16
2.3.2 Effect of users migration on QoS and overall resource utilisation	17
2.4 Consumer Profiles	17
2.4.1 Diversity of consumers	17
2.4.2 Digital Lifestyle Measures	19
2.5 User Satisfaction Modelling	19
2.5.1 Customer Experience Metrics	19
2.5.2 Utility Functions	19
2.5.3 Machine Learning and Predictive Models	21
2.6 Incentive Pricing Schemes	21
2.6.1 Evolutionary Game Theory: Replicator Dynamics	21
2.6.2 Evolutionary Game Theory: Stackelberg Game	22
2.6.3 Win-Coupon Approach	24
2.6.4 Price-Incentive Resource Auction Mechanism (PIRA)	25
2.7 Closing Remarks	26
3 Proposed Solution	28

3.1	Multi-Attribute Utility Theory	28
3.1.1	Defining alternatives and value-relevant attributes	28
3.1.2	Evaluating each alternative separately on each attribute	29
3.1.3	Assigning relative weights to the attributes	32
3.1.4	Total Utility of a network for a user	32
3.2	Migration Threshold	33
3.3	Incentive Model	33
3.3.1	Determining User Incentive Coupon	34
3.3.2	Maximum incentive imposed by Network Provider	35
4	System Model	36
4.1	Heterogeneous Wireless Network	36
4.1.1	RAT Parameters	36
4.2	Markov Model	37
4.2.1	Admissible States	38
4.2.2	Probability of being in Admissible State s	38
4.2.3	Probability of being in Admissible State s	40
4.3	Network Performance Evaluation	40
4.3.1	Average Resource Utilisation	40
4.3.2	Call blocking Probability	41
4.3.3	Call Dropping Probability	41
5	Results	43
5.1	Evaluated User Utilities	44
5.2	Migration of Users & and Network Performance	44
6	Discussions	54
6.1	Analysis of Evaluated User Utilities	54
6.2	Migration of Users	54
6.2.1	Effects of Varying Maximum Incentive	54
6.2.2	Effects of Varying Migration Thresholds	55
6.3	Effects on Network Performance	55
6.3.1	QoS in the Network	55
6.3.2	Resource Utilisation in the Network	55
6.4	Real-World Implications	55
7	Conclusions	57
8	Recommendations	59
	Bibliography	61
A	Fuzzy Inference System: Cost	65
B	Code: MAUT Function	67

C Code: Incentive Model	69
D Code: Simulation	70
E Code: MarkovModel	74
F Code: Network Performance	76
G Ethics: Research Proposal	78
H Ethics: Ethics Clearance	79

List of Figures

1.1	Global Projections of 5G Adoption	4
2.1	Evolution of Mobile Networks.[1]	8
2.2	Options for deployment of 5G architecture[2]	11
2.3	Total Mobile Subscriptions in African Countries with 5G.[3]	13
2.4	National Mobile Subscriptions in South Africa[4]	14
2.5	Urban population NetworkCoverage in South Africa[4]	14
2.6	Rural population Network Coverage in South Africa[4]	15
4.1	Visual Diagram of Heterogeneous Wireless Network	36
5.1	Box Plot of Users' Utilities	44
5.2	Mobile Cellular Subscriptions in HWN	45
5.3	Network Subscriptions and Performance with maximum incentive of 0.0	46
5.4	Mobile Cellular Subscriptions in HWN	47
5.5	Network Subscriptions and Performance with maximum incentive of 0.05	48
5.6	Mobile Cellular Subscriptions in HWN	49
5.7	Network Subscriptions and Performance with maximum incentive of 0.15	50
5.8	Mobile Cellular Subscriptions in HWN	51
5.9	Network Subscriptions and Performance with maximum incentive of 0.25	52
A.1	Fuzzy Inference System Plot	66

Chapter 1

Introduction

1.1 Background

In recent years, the world has witnessed the emergence of the fourth industrial revolution characterized by the fusion of digital, physical and biological innovations. In the context of telecommunications, it has led to the rapid deployment of 5G networks, and IoT connectivity revolutionising how people and machines communicate and interact. At the heart of this transformative era lies internet connectivity, serving as the foundational element from which all innovations and advancements emerge. We have seen the demand for mobile data services increase attributed to the increased use of mobile devices, multimedia applications and the increasing need for ubiquitous internet connectivity. As a result, ISPs in the telecommunications industry are working towards rapidly deploying next-generation mobile networks with the higher data rates, lower latency and improved QoS. However, the successful adoption of these mobile networks is mainly dependent on the migration of users from legacy RATs to newer ones such as 5G.

To accelerate users' adoption of the latest RAT and improve radio resource utilization and QoS provisioning in heterogeneous wireless networks, research is needed to explore the use of incentive pricing strategies. Incentive pricing has been used in various applications to entice consumers to behave in a certain way which may be advantageous to the party incentivising them. In the context of users' migration in next generation mobile networks, incentive pricing can be used to motivate users to switch to newer networks by offering them attractive pricing plans or rewards giving them better value for money or QoS. This approach has already shown promise in incentivizing traffic offloading and managing peak-time traffic in heterogeneous wireless networks.

1.2 Objectives

The objective of this project is to develop a model for investigating how incentive pricing can effectively accelerate the adoption of the newest RAT in a heterogeneous wireless network. By understanding the impact of incentive pricing on users' migration, the research seeks to devise an effective incentive framework that encourage a smoother transition to the next-generation mobile network. The incentive model is then to be implemented with further investigations on the impact of the incentive pricing model on users' migration in heterogeneous wireless networks (HWNs) and the effects this may have on them.

1.2.1 Problems to be investigated

The main questions to be investigated in this study are as follows:

1. How can incentive pricing schemes be designed to encourage users to migrate from legacy RATs to the latest generation mobile network?
2. What is the impact of incentive pricing on users' migration behaviour in a heterogeneous wireless network?
3. How does the adoption of incentive pricing impact radio resource utilization and QoS provisioning in the network?

A summary of the Objectives is seen in table 1.1 below.

Table 1.1: Objectives and Deliverables

<ol style="list-style-type: none"> a. An understanding of next-generation mobile networks. b. A review of incentive pricing schemes. c. A model for investigating the impact of incentive pricing on users' migration. d. Simulation results of the model. e. Project Report

1.2.2 Purpose of the Study

The investigation of incentive pricing's impact on users' migration is significant as efficient incentive pricing strategies can facilitate the successful adoption of next-generation networks, leading to enhanced user experience, improved network efficiency, and increased revenue for service providers due to improved resource utilisation. As network providers are deploying next-generation mobile networks for greater coverage, in order to lower costs and increase revenue through economies of scale, the adoption of these newer RATs is imperative.

In Sub-Saharan Africa, there is a comparatively greater reliance on older generations of mobile cellular networks with users in these regions still very reliant on 2G and 3G and the projected adoption of 5G lower compared to the Global North as can be seen in figure 1.1 below.

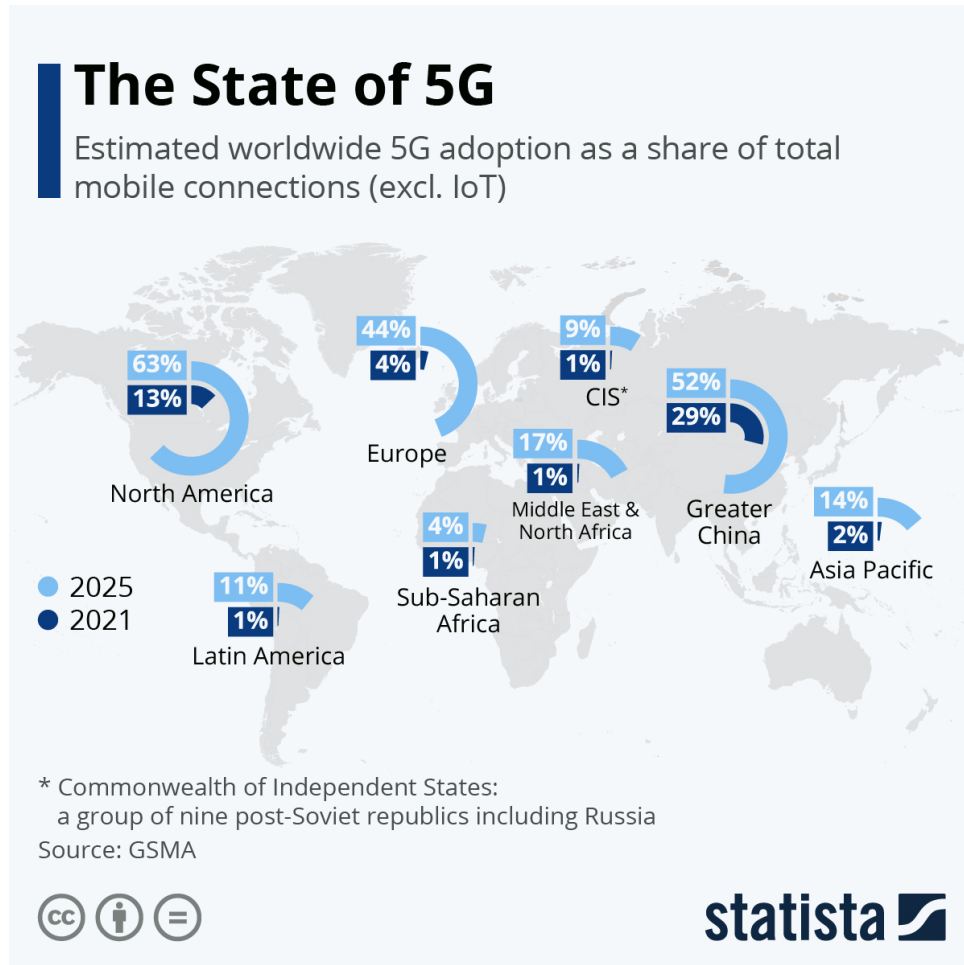


Figure 1.1: Global Projections of 5G Adoption

Incentive pricing can therefore be used to accelerate the adoption of the 5G RAT in these regions, reducing the digital divide between Africa and the rest of the world.. This improved access to internet connectivity can alleviate the information gap between Africans and the rest of the world, fostering an environment conducive to learning and innovation by implication.

Finally, understanding how users respond to different pricing schemes can provide valuable insights into consumer behaviour in the context of mobile network adoption. By optimizing the migration process, we can address potential challenges associated with the coexistence of multiple RATs in a heterogeneous wireless environment.

1.3 Scope & Limitations

The scope of this study encompasses the development and implementation of an incentive pricing model to be analyzed on its impact on users' migration in heterogeneous wireless networks, with a focus on the adoption of the 5G network in South Africa. The investigation will involve an investigation on the effectiveness incentive pricing has on users' migration, and the effects this migration may have on QoS and resource utilization within a modelled heterogeneous wireless networks.

However, there are certain limitations to be considered. The accuracy of the model depends on the

availability of accurate and up-to-date data for modelling user behaviour, network conditions, and pricing strategies. As a result, some assumptions based on logical reasoning are to be done in cases where data may be unavailable. Aspects of the system model which fall outside of the scope are to be simplified within reason such that the results can provide us meaningful information as it relates to the research question. Due to there be no existing works within literature of incentive pricing to get consumers to migrate newer generations of mobile networks, there isn't a comparative scheme that can be used to measure the effectiveness of the proposed model against.

The Radio Access Technologies (RATs) being considered are limited to cellular mobile technologies such as 3G, 4G and 5G as other mobile such as Wi-Fi technologies are easily accessible and don't require a subscription. This is also applicable to fibre to the home (FTTH) as it is accessible as a Wireless Local Area Network (WLAN).

The time available to complete the project is an additional constraint. With a total of 12 weeks, the project needs to be completed under considerable time constraints as it will be done simultaneously with other third-term courses.

Nonetheless, this study strives to provide valuable insights that can inform the design of effective incentive pricing strategies in the context of heterogeneous wireless networks.

1.4 Report Outline

The report starts with an introduction to the topic and objectives, followed by a comprehensive literature review. The proposed solution and system model are then detailed before presenting the research results. The discussion section analyzes the results, and the report concludes with recommendations for further action in this area of study.

Chapter 2: Literature Review

- Overview of Next-Generation Mobile Network (5G): Explores the progression of mobile networks, 5G use cases, and frequency bands.
- Migration to 5G: Discusses the deployment of cells, challenges in 5G, and user adoption.
- Heterogeneous Wireless Networks: Examines RAT characteristics and the effect of user migration on QoS and resource utilization.
- Consumer Profiles: Looks at the diversity of consumers and digital lifestyle measures.
- User Satisfaction Modelling: Covers customer experience metrics, utility functions, and predictive models.
- Incentive Pricing Schemes: Dives into different incentive pricing approaches, including evolutionary game theory and coupon-based schemes.
- Closing Remarks: Summarizes the key points from the literature review.

Chapter 3: Proposed Solution

- Multi-Attribute Utility Theory: Introduces the concept of utility theory and its components.
- Migration Threshold: Discusses the threshold for user migration.
- Incentive Model: Describes the model for determining user incentives and maximum incentives imposed by network providers.

Chapter 4: System Model

- Heterogeneous Wireless Network: Explains the network structure, including RAT parameters.
- Markov Model: Details the Markov model used for analysis, including admissible states and probabilities.
- Network Performance Evaluation: Covers metrics like resource utilization, call blocking probability, and call dropping probability.

Chapter 5: Results

- Evaluated User Utilities: Presents the results of user utility evaluations.
- Migration of Users & Network Performance: Analyzes the migration of users and its impact on network performance.

Chapter 6: Discussions

- Analysis of Evaluated User Utilities: Discusses the findings related to user utility.
- Migration of Users: Explores the effects of varying maximum incentives and migration thresholds.
- Effects on Network Performance: Analyzes the impact on QoS and resource utilization in the network.
- Real-World Implications: Discusses the practical implications of the research.

Chapter 7: Conclusions Summarizes the key findings and conclusions drawn from the study.

Chapter 8: Recommendations Provides recommendations based on the research findings.

Chapter 2

Literature Review

2.1 Overview of next-generation mobile network (5G)

The fifth-generation mobile Network, 5G, is the newest generation of cellular networks, designed within the framework of the 3rd Generation Partnership Project (3GPP), and is aimed at complementing and ultimately replacing the existing fourth-generation (4G) networks. It serves as a catalyst for driving innovation, providing a platform for industries, service providers, communities, and individuals to propel their digital goals, leading to economic expansion, the generation of employment opportunities, and socio-economic progress [5]. This section will give an overview of the 5G mobile network technology to establish what enables its capacity to drive innovation.

2.1.1 Progression of Mobile Networks

Mobile network generations have evolved over time as more advanced technologies become available. This evolution is particularly driven by the increased demand for improved connectivity which enables the various use cases that society has needed to advance. A pattern can be observed in this progression as every decade has given rise to a newer improved mobile network generation [6].

- The 1980s were characterised by the first mobile network generation, 1G, geared at mobile analogue voice communication. 1G leveraged technologies such as AMPS-developed by Bell Labs, NMT-jointly built by Nordic countries and TACS- a derivative of AMPS.
- The 1990s were characterised by the second mobile network generation, 2G, adapted for efficient digital voice communication to reach billions. Significant technologies used include D-AMPS, GSM and CDMA.
- The 2000s was the beginning of the transition from circuit-switched networks to packet-switched networks, characterised by 3G. The focus shifted to mobile data and wireless internet with technologies such as CDMA2000, UMTS and HSPA+ being used.
- The 2010s gave rise to mobile broadband and the emerging expansion of internet connectivity through 4G with technologies such as LTE and LTE-Advanced.
- Currently, the 2020s, are characterised by 5G, aimed at a unified future-proof platform enabling a range of use cases.

Legacy mobile technologies (1G, 2G, and 3G) mainly focus on voice communication through circuit-switched networks. The arrival of 4G brought about a significant change by introducing fully packet-

2.1. Overview of next-generation mobile network (5G)

switched networks, forming the basis of all IP-data services. 5G, being an evolutionary step, not only encompasses all the capabilities of 4G but also has the potential for much more, operating on a much larger scale. As seen in figure 2.1 sourced from ITU [1], 5G offers ultra-fast download speeds, exceptional reliability, and remarkably low latency in comparison to legacy networks.

	1G	2G	3G	4G	5G
Approximate deployment date	1980s	1990s	2000s	2010s	2020s
Theoretical download speed	2kbit/s	384kbit/s	56Mbit/s	1Gbit/s	10Gbit/s
Latency	N/A	629 ms	212 ms	60-98 ms	< 1 ms

Figure 2.1: Evolution of Mobile Networks.[1]

These enhancements in 5G are made possible by its advanced core network technology, coupled with the utilization of more efficient radio technologies, wider spectrum bandwidth, and the deployment of denser networks.

2.1.2 5G Use Cases

The emergence of 5G technology heralds a new era of connectivity, introducing a range of revolutionary applications such as mMTC, URLLC, and eMBB. These applications are poised to facilitate rapid and seamless connections between individuals and devices, ushering in the era of the Internet of Things (IoT), which responds adeptly to the increasing demand for high-speed mobile broadband in our progressively digital societies [1].

Enhanced Mobile Broadband (eMBB)

Within the realm of eMBB, the capabilities of 5G networks truly shine. These networks offer an elevated broadband experience, boasting mind-boggling speeds of up to 1 Gbps and impressively low latency, clocking in at less than 4 milliseconds. Furthermore, they lay the groundwork for the seamless integration of cloud-based services and those driven by artificial intelligence. The potential applications of eMBB are vast, encompassing not only enhanced indoor and outdoor broadband but also fostering the evolution of enterprise collaboration. Augmented and virtual reality experiences are set to be transformed, offering immersive environments that were once thought to be beyond reach.

Massive Machine-Type Communications (mMTC)

At the core of 5G's capabilities lies mMTC, a paradigm that facilitates the widespread proliferation of intelligent Internet of Things (IoT) connections across a diverse array of scenarios. This functionality presents an elevated platform, poised to facilitate the broad adoption of critical communication services. The implications of mMTC extend far and wide, ranging from practical applications like asset tracking and smart agriculture to grander visions of smart cities and comprehensive energy monitoring. It even extends to the conveniences of the smart home and remote monitoring, presenting a new dimension of interconnectedness.

Ultra-Reliable and Low-Latency Communications (URLLC)

URLLC form the foundation upon which an array of transformative innovations will be built. This facet of 5G connectivity opens the doors for groundbreaking applications that demand unparalleled reliability and minimal latency. Autonomous vehicles stand to thrive within the URLLC framework, revolutionizing transportation systems as we know them. Smart grids will gain the ability to seamlessly manage energy distribution, while remote patient monitoring and telehealth services will experience a revolutionizing enhancement. Even the realms of industrial automation are set to undergo a seismic shift, driven by the unparalleled reliability and responsiveness that URLLC facilitates.

The advent of 5G technology ushers in a realm of unprecedented possibilities, as it introduces mMTC, URLLC, and eMBB applications. These applications together redefine the way we connect, communicate, and innovate, steering our digital landscape towards remarkable territories.

2.1.3 5G Frequency Bands

5G technology operates across a range of frequency bands, categorized as low, mid, and high bands. These bands are essential for different aspects of 5G deployment and performance[5].

Low Frequency Bands

Low-frequency bands include spectrum below 1 GHz, like 600 MHz, 700 MHz, and 800 MHz. These frequencies are pivotal as they empower the mobile industry to extend its reach into rural areas, bringing widespread home broadband services to the masses. When combined with the mid and high bands, low-frequency bands ensure comprehensive network coverage.

Mid Frequency Bands

Mid-frequency bands span from 1 GHz to approximately 6 GHz. These bands possess a balanced attribute, striking a crucial harmony between coverage and capacity. They provide a sweet spot in terms of both reach and data-carrying capabilities, making them a crucial component in the 5G spectrum portfolio.

High Frequency Bands

High-frequency bands consist of spectrum above 6 GHz, such as 26 GHz, 28 GHz, and 40 GHz. The availability of these high bands varies based on regional allocations. High-frequency bands play a critical role in delivering immense data capacity in densely populated urban areas, such as city centres and busy urban hubs. Additionally, these bands prove valuable for enhancing in-building connectivity, ensuring strong 5G signals within structures like office buildings, malls, and stadiums.

The combination of low, mid, and high-frequency bands in the 5G spectrum roadmap ensures a holistic approach to meet diverse connectivity needs, catering to both rural and urban areas while accommodating high-capacity demands in various scenarios

2.2 Migration to 5G

As the demand for faster and more reliable communication increases, the successful implementation and adoption of 5G requires an understanding of the infrastructure and its deployment.

2.2.1 Deployment of Cells

The deployment of 5G networks involves a crucial decision between two distinct architectural approaches of architecture that can be deployed by network providers, viz. Non-Standalone(NSA) and Standalone(SA). These choices hold significant implications for the network's performance, capabilities, and overall user experience [7].

Non-Standalone Deployment

The Non-Standalone approach represents an evolutionary step towards 5G, as it builds upon the existing 4G LTE infrastructure. In this deployment, 5G radio access is introduced alongside the existing 4G core network. This integration allows for faster 5G data transmission rates while still leveraging the core network functions of the previous generation.

One of the key advantages of the NSA deployment is its relatively rapid roll-out capability. By reusing the 4G core network, network providers can upgrade their existing infrastructure without a complete overhaul. This approach enables quicker 5G coverage expansion, making it an attractive option for areas with high user demand but limited time for extensive network upgrades.

However, it's essential to note that the NSA approach may not unlock the full potential of 5G. While it provides faster data speeds and lower latency compared to 4G, it may not fully harness the innovative features and use cases that a standalone 5G network can offer.

Standalone Deployment

In this architecture, both the radio access network and the core network are upgraded to 5G technology. This approach enables the network to capitalize on the unique capabilities of 5G fully. Although more complex and time-consuming to implement, the SA deployment lays the foundation for future 5G advancements. It ensures a more robust and flexible network infrastructure, capable of supporting a wide range of emerging technologies and applications. This approach is especially important in scenarios where 5G is expected to revolutionize industries, such as autonomous vehicles, industrial automation, and augmented reality.

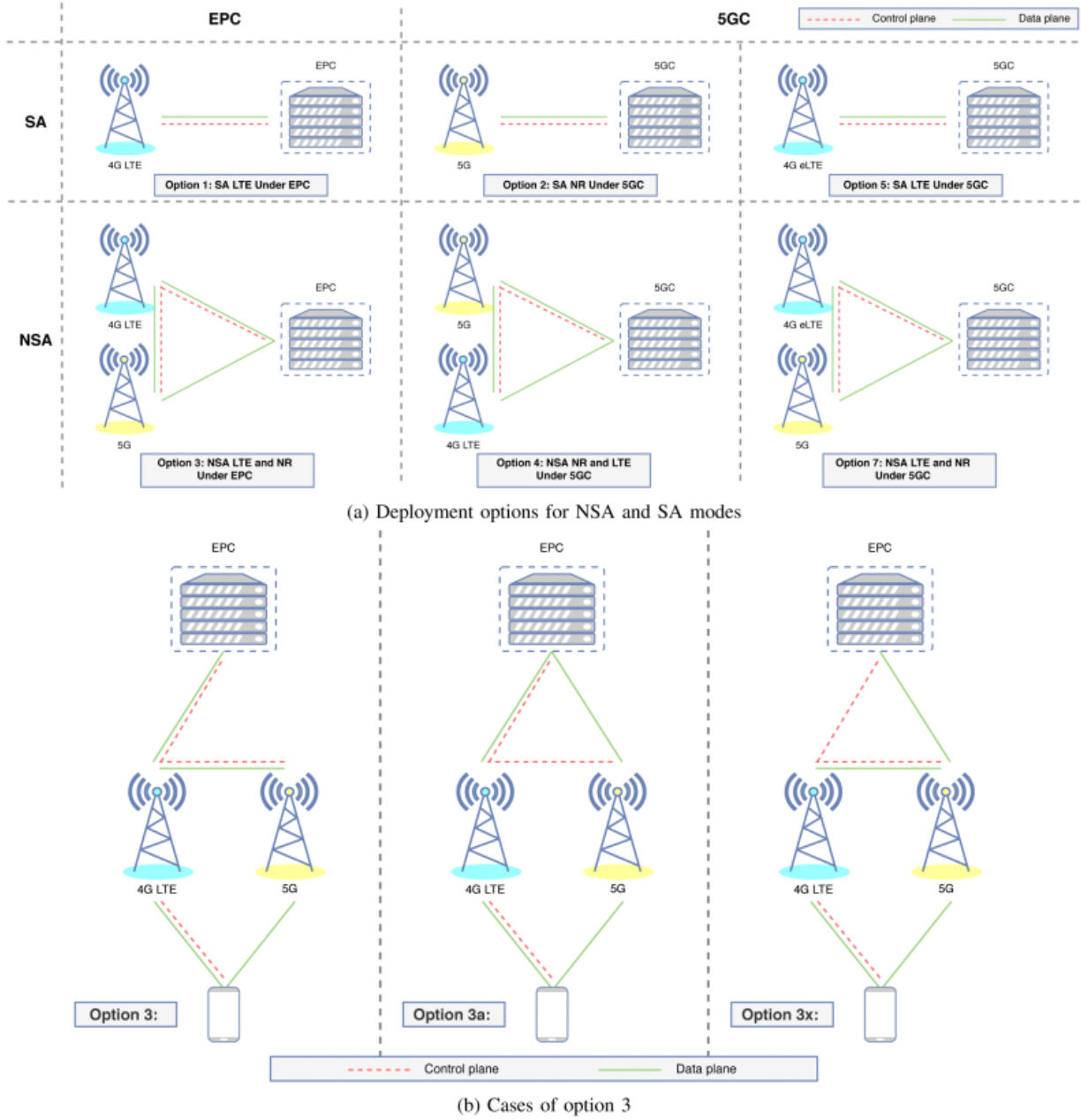


Figure 2.2: Options for deployment of 5G architecture[2]

2.2.2 5G challenges

While 5G technology offers several notable advantages in terms of data transmission speed and capacity, it also comes with certain trade-offs that should need consideration[8]. One of the key benefits of 5G is its utilization of higher frequencies, enabling it to transmit substantial volumes of data at faster rates. However, this advantage is not without its disadvantages.

Firstly, there is a trade-off between the use of higher frequencies and the challenges posed when signals are transmitted. These higher frequencies, while efficient at data transmission, struggle over shorter distances due to increased signal absorption. To achieve comprehensive 5G coverage, network carriers must deploy a more extensive network of antennas compared to previous generations. This expanded antenna infrastructure necessitates a greater density of antennas, which must be positioned closer to

end-user devices. This not only entails increased infrastructure costs but also logistical challenges in terms of installation and maintenance.

Additionally, 5G frequencies at the higher end of the spectrum are more susceptible to environmental factors such as rain, wind, and physical obstructions like buildings, trees, and mountains. These factors can obstruct the line of sight between the antenna and the device, causing signal degradation. Unlike 4G, which operates at lower frequencies, 5G signals have reduced penetration capabilities and are more prone to signal loss in scenarios involving these obstructions.

However, it's important to note that despite these challenges, 5G offers substantial benefits. The faster data transmission speeds and increased capacity empower a wide range of applications, including seamless streaming, real-time communication, and the support of Internet of Things (IoT) devices. Moreover, 5G technology can significantly reduce latency, making it essential for applications such as autonomous vehicles and remote surgery. Therefore, while there are trade-offs and challenges associated with 5G, its advantages in terms of data throughput and low latency make it a critical enabler of the next generation of digital services and innovations.

2.2.3 User Adoption

The adoption of 5G's impact in South Africa is intricately linked to various factors, such as the existing level of industrialization, the influence of politics and stakeholder organizations, state-level relationships, multilateral agreements, and other relevant aspects [5].

Adoption Statistics

As revealed by a recent report published by TeleGeography [3], mobile subscription penetration is higher in South Africa compared to other African countries. The report, named the GlobalComms Database Service, monitored the progression of 5G deployments in the Middle East and Africa (MEA) region. As of March 2023, the findings indicated that a total of 18 countries within this region have embraced operational 5G services, ten of them being in Africa. The mobile subscription penetration in each of these countries is shown in 2.3.

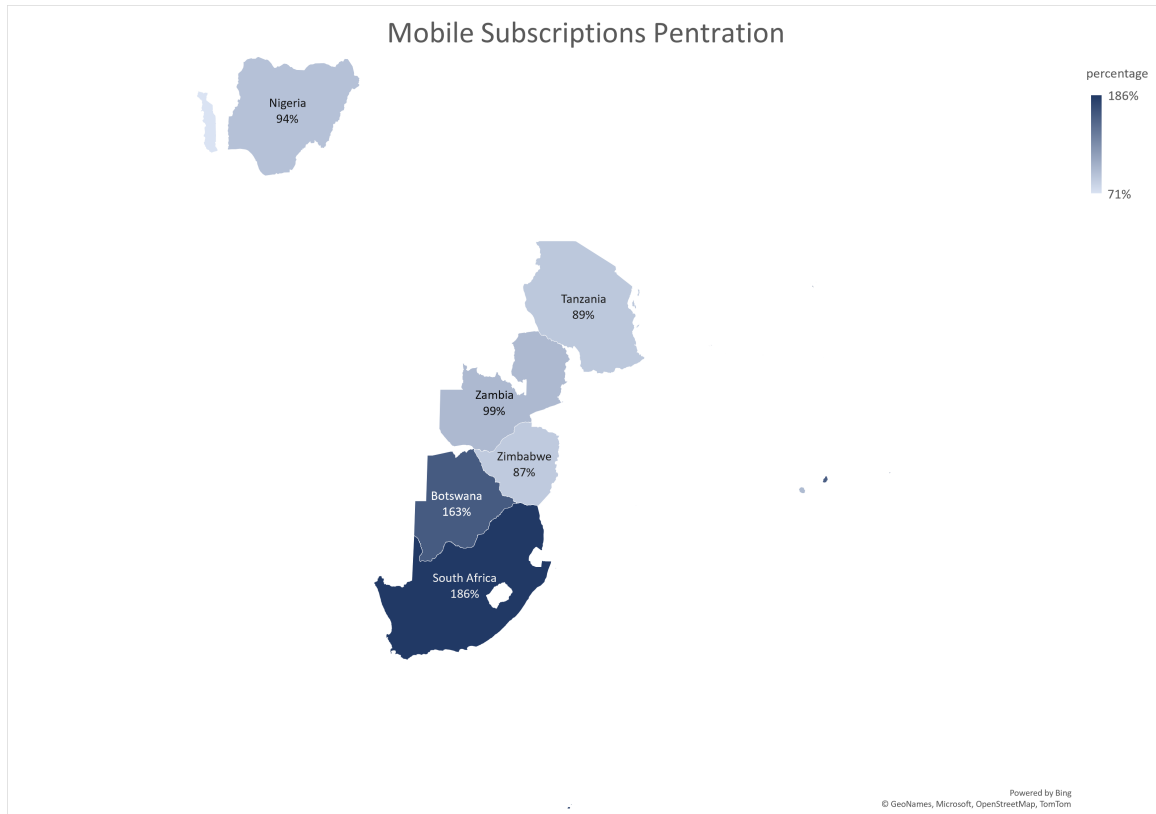


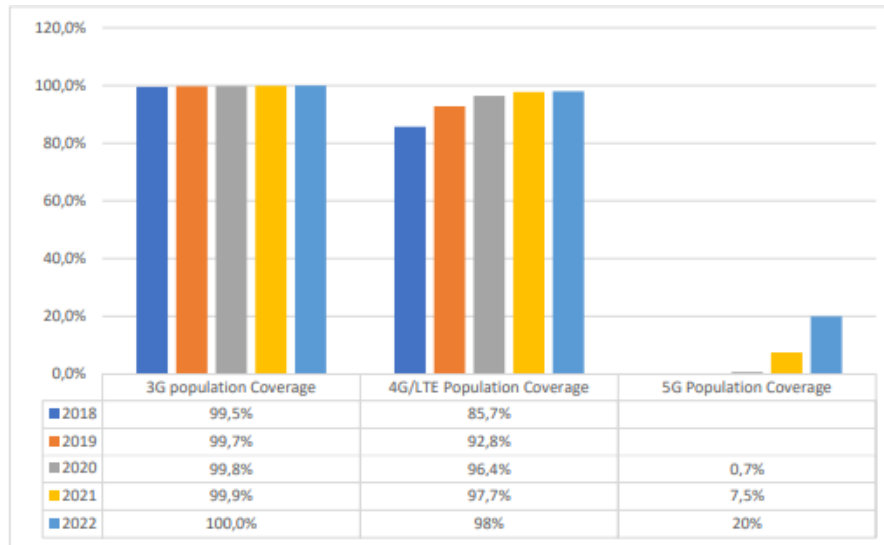
Figure 2.3: Total Mobile Subscriptions in African Countries with 5G.[3]

The adoption of the highly-discussed 5G network is evidently gaining momentum across Africa, with South Africa taking the lead in this advancement. As seen in table 2.1, of the total mobile subscription, South Africa leads in terms of 5G mobile subscriptions among the mentioned countries. However, its 5G adoption, while present, constitutes 4.4% of the overall mobile market. This suggests a potential for further growth in 5G adoption in South Africa. Interestingly, Seychelles and Mauritius stand out as having relatively higher percentages of 5G adoption compared to their total mobile subscriptions.

Table 2.1: 5G share of mobile subscriptions in Africa [3]

Country	Total mobile subs	5G subs	5G share of subs
South Africa	112,397,558	5,000,000	4.4%
Mauritius	2,095,499	80,000	3.8%
Nigeria	209,450,208	50,000	0.0%
Togo	6,402,786	33,000	0.5%
Seychelles	200,750	16,410	8.2%
Réunion	961,000	13,000	1.4%
Zimbabwe	14,570,000	6,000	0.0%
Botswana	4,363,006	5,000	0.1%
Zambia	20,370,000	5,000	0.0%
Tanzania	60,192,331	600	0.0%

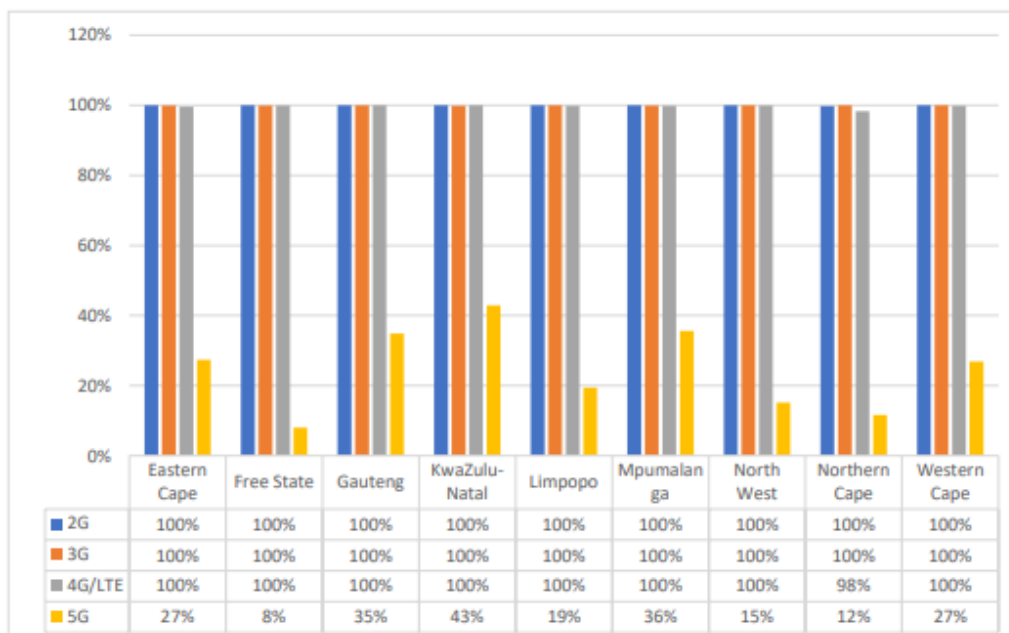
According to a report by ICASA on the state of the ICT sector in South Africa [4], the coverage of the mobile generations in South Africa as of September 2022 is shown in 2.4.



Source: ICASA Electronic Communications Questionnaire 2018 - 2022

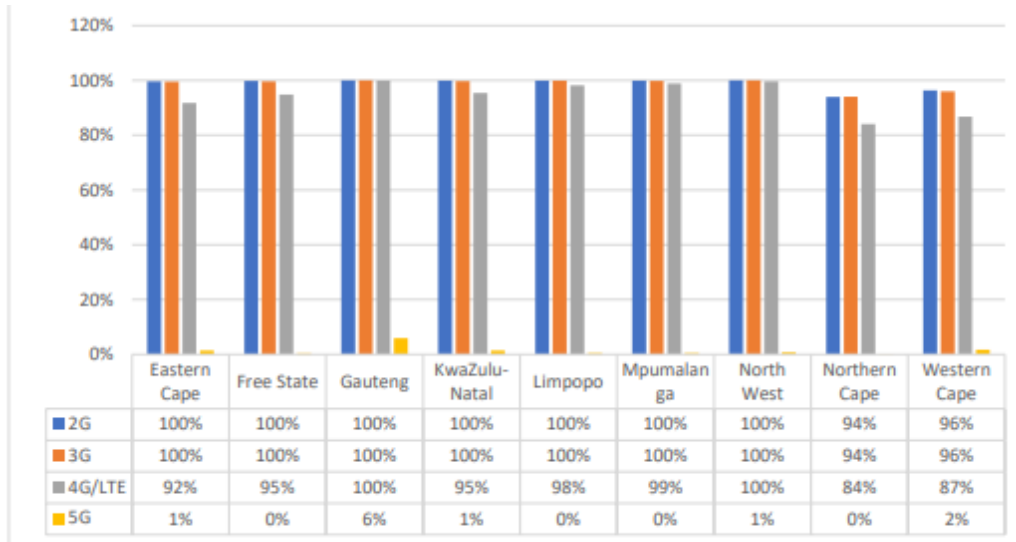
Figure 2.4: National Mobile Subscriptions in South Africa[4]

There are however disparities in the coverage between urban and rural areas with newer generations of cellular networks. There is greater population coverage for 4G and 5G in urban areas compared to rural areas, as seen in figures 2.5 and 2.6.



Source: ICASA Electronic Communications Questionnaire 2022

Figure 2.5: Urban population Network Coverage in South Africa[4]



Source: ICASA Electronic Communications Questionnaire 2022

Figure 2.6: Rural population Network Coverage in South Africa[4]

Barriers to consumer adoption

According to a survey conducted by GSMA [6] in Africa, barriers impeding the adoption of new technologies among consumers include the financial aspects linked to device costs and tariffs, the extent of 5G network coverage, the identification of practical use cases and applications, as well as the level of consumer contentment with previous generations of mobile networks. Among these challenges, the most prominent concern highlighted by 37% of surveyed consumers is the financial factor, particularly the expenses associated with devices and service plans.

In South Africa, the affordability of 5G devices holds significant sway over consumer decisions, given that many 5G upgrades often come with minimal to no additional costs. The initial rollout of 5G devices predominantly targeted the high-end market segment. However, the evolution of more economical chipset designs has led to a noteworthy reduction in the average retail price of 5G smartphones.

While the advent of 5G technology promises improved consumer experiences, certain consumers might opt to stick with older network generations. This could arise from a range of factors including a lack of awareness regarding the advantages of 5G, the financial feasibility of acquiring 5G devices and services, and the absence of innovative use cases that mandate the capabilities of 5G technology. In light of the plausibility of this scenario, network operators should contemplate enhancing their consumer outreach strategies to stimulate demand prior to launching their services. This effort involves addressing controversies related to 5G [9] and fostering awareness about the extensive array of benefits offered by 5G such as faster speeds, minimized latency, increased capacity, and enhanced resilience. Additionally, operators should present tangible examples of fresh use cases that resonate with consumers, underscoring the practical advantages of 5G technology.

2.3 Heterogeneous Wireless Networks

Today's mobile network landscape consists of various RATs which coexist to form a heterogeneous wireless network. The available RATs in such a network include terrestrial access networks such as 2G, 3G, 4G and 5G digital cellular technologies mentioned in 2.1.1 and Wi-Fi, as well as non-terrestrial access networks such as satellite connectivity. Each of these RATs has its own unique characteristics and capabilities [10]. HWNs are becoming more widespread due to their capacity to accept the variety of currently existing network infrastructures that enable connectivity. Various RATs operate in the same region and can thus service various mobile customers.

2.3.1 RAT Characteristics

This project is particularly focused on mobile cellular network technologies, and as such, it is necessary to understand the characteristics of these technologies. Other RATs such as non-terrestrial access networks and WiFi fall outside of the scope of this project.

There is a large range of characteristics which contribute to users' satisfaction with their mobile network. These characteristics include but are not limited to:

Cost
 Delay
 Jitter
 Dropping Probability
 Network Utilisation
 Total bandwidth
 Data Rates
 Security
 Packet loss rate
 Reliability

In relation to the adoption of a mobile network generation, characteristics related to the QoS experienced by a user, its accessibility and the cost of the user equipment are the most relevant. Table 2.2 compares these characteristics in finer detail.

Table 2.2: Mobile Cellular Network Generation Characteristics

Attributes	Mobile Cellular Network Generation			
	2G	3G	4G	5G
Cost: User Equipment ¹	low	moderate	moderate	high
Data Rate (typical data speed) [8]	200kbps	3Mbps	30Mbps	100Mbps
minimum latency [11]	600ms	40ms	5ms	1ms
Availability(In South Africa) [12]	99%	98%	97%	6%

¹Cost is typically a market-driven and commercially sensitive aspect of the telecommunications industry, as such these values were determined by comparing the prices of mobile devices on [13]

2.3.2 Effect of users migration on QoS and overall resource utilisation

Because of the increased capabilities of 5G technology, the migration of users from earlier networks to 5G technology has gained interest. According to GSMA [6], the number of 5G subscribers is projected to increase substantially in the future years. It is thus important to understand how user migration impacts QoS and resource utilisation in HWNs.

5G is envisioned as a platform that will accommodate a wide spectrum of user and societal requirements, The 5G Infrastructure Public Private Partnership (5G-PPP) has established key performance indicators for 5G networks [14]. These indicators encompass significantly higher data volume, device connectivity, data rates, lower energy consumption, and lower packet delay (latency) compared to previous network generations. These requirements are set to meet the growing demands of users and their evolving usage patterns. As a result, users can expect improved QoS on 5G due to its superior performance.

Newer 5G phones and subscriptions are designed to be backwards compatible and operate on older networks like 4G, 3G, and 2G. However, a 4G or older phone or subscription, will not be compatible with 5G technology[15]. As a result, from a network provider perspective, with more users subscribed to the 5G network, this backward compatibility provides greater flexibility in how resources can be allocated, as users aren't limited to using individual RATs. This, in turn, can improve resource utilization across the RATs, making the network more efficient.

This improvement in resource utilisation was corroborated by Falowo in investigating the effect of users' equipment capability on utilization of Heterogeneous Wireless Networks [16] where it was found that resource utilisation in HWNs is improved with more users upgrading their User Equipments (UEs) to newer generations of cellular networks.

2.4 Consumer Profiles

Heterogeneous wireless Networks consist of diverse users who may respond differently to incentives. It is thus important to understand factors such as age, income, the digital divide and the urban/rural divide on how users can be categorised such that their behaviours can be more accurately modelled.

2.4.1 Diversity of consumers

Wealth

In South Africa, wealth distribution is heavily impacted by age, reflecting the country's historical and socioeconomic characteristics[17]. There is a significant wealth disparity across age groups. Older generations, especially those that benefitted from apartheid-era economic benefits, are likely to have amassed greater money and assets over time. They frequently possess property and have access to pension money and investments, which contributes to their greater economic position. Younger generations, particularly those born after the end of apartheid, confront more financial hardships. Their capacity to acquire wealth has been hindered by high unemployment rates, restricted access to good education, and barriers to economic possibilities. Many young South Africans are burdened by debt, restricted access to housing, and insufficient savings, exacerbating the wealth gap between generations.

The age of South African customers is important in defining their spending habits and consumption

patterns. Younger customers are more likely to spend a large part of their money on technology-related items and services such as smartphones, internet subscriptions, and streaming platforms. They are also more likely to use digital payment methods and purchase online. In contrast, older customers, particularly those nearing retirement, emphasize necessities such as healthcare, housing, and living expenditures.

Because South Africa's multi-generational customer base has various requirements and preferences, disparities in spending priorities and consumption preferences between age groups have repercussions for businesses and marketers.

Digital Divide

The phrase 'digital divide' refers to a societal split caused by disparities in access to and competency with technology [18]. This worldwide issue is particularly severe in African countries. The COVID-19 epidemic highlighted South Africa's glaring digital inequities, as remote learning and remote employment became crucial. Digital means were used to convey both critical health information and disinformation, demanding internet literacy in order to distinguish reliable sources. Those who were unsure how to navigate the internet world fell victim to misconceptions. With more employment and educational programs digitizing, equal access to digital skills is increasingly required for meaningful participation in an emerging economy.

The South African digital divide stems from historical apartheid policies which limited access to education and higher-skilled jobs, now necessitating basic computer skills for income. Poor internet access, high data costs, and weak infrastructure hinder progress in disadvantaged areas while poverty restricts device ownership for remote work and learning. Inadequate digital guidance impacts students' academic and career prospects with high-fee schools offering advanced computer courses, increasing inequality.

Urban/Rural Divide

According to World Bank statistics from September 2023, South Africa's urban population accounted for 68.33% of the total population in 2022[19]. This figure demonstrates the country's huge difference in access to digital services between urban and rural areas.

Urban areas typically have a higher percentage of the population with access to digital services compared to rural regions. Access to digital services encompasses a wide range of essential modern amenities, including but not limited to the internet, mobile communication, and online platforms. In urban settings, the infrastructure for these services is generally more developed, making them more accessible to a larger portion of the population.

In contrast, rural areas often face challenges in providing adequate access to digital services. Factors such as limited infrastructure, geographical remoteness, and lower population density can hinder the spread of digital connectivity in these regions. This digital divide can have significant implications for various aspects of life, including education, healthcare, economic opportunities, and social inclusion.

2.4.2 Digital Lifestyle Measures

In 2008, BMIT introduced the DLM segmentation model with the purpose of categorizing consumers based on their digital behaviors. This segmentation method assesses individuals by having them respond to a series of questions regarding their personal digital engagement and the technological assets present in their households. Subsequently, each respondent is assigned a DLM score, which, in turn, determines their placement within one of five distinct DLM segments[20].

- **DLM 1:** These consumers are characterized as ‘low-tech.’ They have minimal engagement with digital technologies. These individuals may have limited access to digital devices and may use them infrequently for basic tasks such as phone calls or simple web browsing.
- **DLM2:** These consumers represent a moderate level of digital engagement. They incorporate digital technologies into their lives but are not on the cutting edge. These individuals may use smartphones and social media regularly, but their interaction with more advanced tech like smart home devices or wearable technology might be sporadic or limited.
- **DLM3:** These individuals exhibit a cautious approach to digital technology. They might have some exposure to digital tools, such as using email for communication or basic internet browsing. However, they tend to be reserved about adopting the latest gadgets and online services, preferring a more traditional approach to many aspects of life.
- **DLM4:** DLM4 represents consumers who are reasonably tech-savvy and open to digital innovations. They comfortably use a variety of digital devices and platforms, often integrating them into their daily routines. These consumers may embrace online shopping, streaming services, and social media, but they are not yet fully immersed in the most cutting-edge technologies.
- **DLM5:** DLM 5 consumers are considered ‘high-tech.’ They are at the forefront of digital adoption and enthusiastically embrace advanced digital technologies. These individuals tend to be early adopters of the latest gadgets, actively engage with various online services and are often the first to explore and adopt emerging tech trends.

2.5 User Satisfaction Modelling

As this research focuses on the impact of users’ migration on overall resource utilisation and QoS provisioning depending on their satisfaction, understanding user satisfaction is essential for incentivising the adoption of newer-generation mobile networks.

2.5.1 Customer Experience Metrics

2.5.2 Utility Functions

Utility functions are important mathematical tools for expressing consumer preferences and satisfaction. They are important in the fields of economics and decision theory, and they have also been used in customer satisfaction studies. Utility functions assign numerical values to distinct alternatives to indicate how much happiness or preference a user obtains from each option.

Utility functions are important in economics and decision theory because they describe the decisions people make when confronted with a variety of options. These functions allow economists and decision-makers to measure the subjective well-being or contentment that people connect with various outcomes or items. Utility functions simplify the comparison of multiple possibilities by giving numerical values to preferences, assisting in logical decision-making.

Many economists hold a consensus that humans, as a fundamental aspect of their nature, are driven by the pursuit of utility maximization [21]. In other words, when faced with choices, individuals tend to select one action over another by considering the anticipated utility associated with each option.

Multi-Attribute Utility Theory

An expansion of the standard utility theory is the multi-attribute utility theory (MAUT). It is particularly useful in making choices among alternative options when faced with multiple criteria or attributes to consider [22]. In MAUT, decisions involve selecting one option from a set of alternatives, each characterized by its performance across several attributes or criteria. These attributes can represent various factors such as cost and quality.

The process of using multi-attribute utility methods typically involves several key steps, as outlined below:

1. **Defining alternatives and attributes:** Listing the different options available to consumers and the relevant attributes for evaluating them
2. **Evaluating alternatives on each attribute:** This step involves assessing each alternative separately for each attribute. Numerical scores based on reliable data are assigned to each alternative as a measure of performance on each of the attributes.
3. **Assigning attribute weights:** As attributes are not of equal importance, it may be necessary to assign weights to attributes that reflect the significance of the attributes in the utility calculations.
4. **Aggregating attribute weights and evaluations:** Once the different weights for each attribute have been assigned, they are combined to produce the total utility for each of the alternatives, indicating its overall desirability. The method for this aggregation varies depending on the specific approach used, such as weighted sum models, weighted product models, or utility function models.
5. **Performing sensitivity analyses:** Sensitivity analyses can then be used to test how changes in attribute values, attribute weights or alternative evaluations affect the final rankings or recommendations. This helps in assessing the impact of uncertainty or changing preferences.

This method has been employed in the selection of appropriate access networks for connected vehicle applications, where the selection took into account multiple decision factors. In this effort, which focuses on vehicle-to-infrastructure networking, Jiang et al. [23] created utility functions that incorporate factors such as energy efficiency, signal intensity, network cost, latency, and bandwidth to thoroughly evaluate user preferences and network performance. They then used multi-criteria utility theory to develop an energy-efficient network selection technique. Their method included developing a combined multi-criteria utility function for network selection and modelling network selection in connected

car applications as a multi-constraint optimization problem. To address this issue, they offered a multi-criteria access selection method, proving the success of their suggested access network selection technique through simulation results.

2.5.3 Machine Learning and Predictive Models

Machine learning and prediction models may be useful in predicting user satisfaction. Researchers have used a variety of machine-learning algorithms to anticipate and comprehend customer pleasure based on a variety of input variables[24]. Predictive modelling approaches such as regression analysis, decision trees, and neural networks have been used to estimate user satisfaction levels with the use of a mix of criteria such as product features, price, consumer demographics, and historical data.

Social media is a common platform for sharing opinions and feedback about services, particularly communication services. The study by Alshamari [25] focused on assessing user satisfaction and employed deep learning techniques on a dataset. The long short-term memory (LSTM) model yielded the highest accuracy, addressing the challenge of how telecom services impact customer decisions.

In the realm of software, user satisfaction is essential for the quality and success of projects, yet predicting it remains intricate. Radliński [24] defined user satisfaction using eight criteria and created predicted models using twelve machine-learning techniques. A random forest model with data imputation performed well on average, with a low mean absolute error.

However, it's important to note that while some models performed well, there was variability in their performance. Hence, careful model selection is crucial for practical implementation.

2.6 Incentive Pricing Schemes

Various research papers have investigated incentive pricing models and their practical implementation across diverse use cases. These studies contribute to the understanding of how incentive pricing mechanisms can shape behaviour, optimize resource allocation, and enhance decision-making in various contexts. By examining the methodologies, findings, and implications presented in these papers, this review aims to provide a comprehensive overview of the current state of research in incentive pricing and how it could be applied to model the impact of incentive pricing on users' migration to next-generation mobile networks.

2.6.1 Evolutionary Game Theory: Replicator Dynamics

Game theory, which has historically found its application predominantly in economic contexts, has been initially used in the domain of telecommunications through an exploration of pricing dynamics. Scholars have leveraged game theory as a tool to propose novel strategies for pricing Internet services. Simultaneously, within the same decade, the scope of game theory extended its reach beyond economic scenarios to include various non-economic implementations within network structures. This expansion encompassed intricate subjects like flow management, admission control, and congestion mitigation [26].

Game Theory

Game Theory serves as a framework that offers tools for comprehending strategic behaviour and rational choices within competitive environments. It enables analysts to investigate the complexities of interactions between intelligent entities, contributing to enhanced decision-making across a spectrum of fields. Game Theory remains a versatile and valuable resource for navigating the complexities of modern-day decision science [27].

Replicator Dynamics

The application of the replicator dynamics framework rooted in evolutionary game theory provides a way for examining the repercussions of employing incentive pricing strategies on the transition of users towards the succeeding generation of mobile networks. By constructing a comprehensive model of the game of technology adoption involving diverse strategies and populations, the replicator dynamics method can be used to determine the trajectory of user migration and the impact of incentive pricing on their decision-making processes. A modified model can take into account the costs and benefits associated with various pricing schemas, as well as the perceived advantages linked with shifting to the forthcoming generation network.

Within this framework, a systematic exploration of the impact of varying levels of incentives, including reduced pricing or supplementary features, becomes possible. This analysis sheds light on how these incentives distinctly influence both the pace and the extent of adoption. Moreover, the replicator dynamics framework encompasses the existence of a technology adoption dilemma, wherein users decide on conflicting payoffs stemming from the choice between embracing the new network or persisting with the existing one. Through an in-depth examination of equilibria and phase portraits within the model, we can glean valuable insights into the circumstances that foster effective utilization of incentive pricing in propelling users toward embracing the upcoming generation of mobile networks[26]. In essence, the replicator dynamics framework holds the potential to investigate the interplay between incentive structures and user behaviour in the context of evolving technological landscapes.

Replicator dynamics are a concept used in various papers to model different aspects of next-generation mobile networks. Loumiotis et al. proposed using evolutionary game theory to model the decision-making process of mobile operators (MOs) migrating to 4G networks [28]. This paper demonstrates the application of replicator dynamics in modelling user migration, decision-making, and network performance in next-generation mobile networks.

2.6.2 Evolutionary Game Theory: Stackelberg Game

As mentioned in 2.6.1, Game Theory has wide uses and implementations. A theory which has been largely explored in incentive pricing mechanisms is the Stackelberg Game. Stackelberg games are better suited for modelling non-symmetric game models where the players aren't privy to the same information or not equal in size.

Structure

The concept of the Stackelberg game involves a scenario where one participant assumes the role of a leader, while the remaining participants act as followers under the leader's influence. Within this framework, the leader maintains a fixed strategy, and the followers respond independently based on the leader's strategy. This strategic interaction can be formally characterized as a two-level game model, with players engaging in sequential actions:

- Initially, the leader, functioning as the sole active player, selects their optimal response strategy;
- Subsequently, at the second level, followers react rationally to the leader's action by attempting to minimize their individual game cost functions in consideration of the leader's decision

Eventually, the leader adjusts their strategy iteratively to minimize the overall cost incurred in the game [27].

The solution to the Stackelberg game is termed the 'Stackelberg equilibrium.' In this equilibrium, each follower observes the leader's chosen strategy and subsequently responds with a strategy that maximizes their expected payoff while adhering to their optimal decision. There are two distinct types of Stackelberg equilibrium points [27]:

- The Strong Stackelberg Equilibrium (SSE). The SSE scenario assumes that followers prioritize the defender's advantage in case of ties, implying that they select their best strategy that aligns not only with their perspective but also optimally from the leader's viewpoint.
- The Weak Stackelberg Equilibrium (WSE). The WSE scenario assumes that followers intentionally opt for the worst strategy according to the leader's perspective.

A particularly interesting implementation of the Stackelberg Game relative to this research project is the proposal of an incentive pricing mechanism where Wireless Service Providers(WSP) offer benefits to femtocell owners (FO) to motivate the adoption of hybrid access in femtocells formulated as a two-stage Stackelberg game by Qi et al. [29].

To determine the pricing policy the WSPs assume the role of the leader and the FOs respond as the followers. The distribution of shared resources, essential for the functioning of each FO, and the pricing factor assigned by WSP are two distinct decisions made independently.

Their implementation involved the maximisation of the utility of WSPs and FOs. The primary objective of FOs is to optimize their individual utilities. The utility function is split into two main components. The initial segment pertains to the earnings generated from the data transmission of femto users, while the subsequent part involves the reimbursements received from the WSPs for the incorporation of hybrid femtocell resources.

The utility function attributed to the WSP is similarly constructed from two distinct constituents. The first is the earnings arising from the data throughput of macro users, and the second component involves the reimbursements provided to FOs in exchange for the implementation of hybrid access mechanisms.

As a result of an effective incentive strategy, their work demonstrated an improvement in the utilities

of both the WSPs and FOs observed through the results of their numerical analysis.

2.6.3 Win-Coupon Approach

Win-Coupon is a novel approach in cellular network management that revolves around a reverse auction-based framework. Within this model, the cellular network operator takes on the role of a buyer, while the users of the network become the sellers. The users leverage a resource of theirs in exchange for coupons from network operators. In the context of this research project, the users would receive coupons that they can use to get charged less, increasing their utility should they subscribe to a network provider's 5G network.

Implementation

The implementation of the Win-Coupon approach by Zhou et al. [30] aimed to efficiently offload cellular traffic by striking a balance between user satisfaction and network efficiency. In their implementation, the network operator obtains bids from users in order to assess their willingness to accept delays and to predict the degree of their potential for offloading. Based on this evaluation, a reverse auction is undertaken, which includes two principal phases, viz. allocation and pricing. Within this process, the network operator issues coupons to users as compensation for tolerating longer delays. This serves as an incentive for them to shift their cellular traffic onto alternate paths.

The compensation that the network operator disburses to users is determined by their bids and their indicated capacity to withstand delays. Users who exhibit greater tolerance for delays and a greater potential for traffic offloading are given preference and consequently receive more substantial coupon payments.

The key concepts of their implementation which may be significant in this research project are listed below:

reserve price: Their implementation made use of a 'reserve price', which pertains to the maximum cost of incentive that the operator of the network is prepared to allocate for the offloading of a singular unit of traffic. In instances where the requested coupon value by bidders goes beyond this reserve price, the network operator will opt not to engage in transactions with them.

Through the establishment of a reserve price, the network operator achieves two key objectives. Firstly, it ensures a profit that is non-negative in nature. Secondly, it has the ability to regulate the outlay incurred in motivating users to carry out the offloading of their traffic.

The reserve price emerges as a critical parameter, enabling the network operator the means to effectively navigate the trade-off between the need to offload traffic and the costs involved. This parameter empowers the network operator to strike a balance between the augmentation of offloaded traffic and the financial implications incurred.

VCG-style pricing: A strategy commonly applied in forward auctions where a single seller interacts with multiple buyers. In these auctions, winning bidders are charged not just their bid amounts, but also an 'opportunity cost' linked to their impact on other bidders. This approach involves distributing

coupons to bidders, with each coupon's value representing the opportunity cost caused by the bidder's participation.

The key principle of VCG-style pricing revolves around the notion of opportunity cost. This refers to the cost incurred by a bidder's involvement, affecting the behaviour of other participants. Instead of solely charging winning bidders their bids, they are charged an amount equivalent to the opportunity cost they impose on others. The network operator issues compensation to bidders in the form of coupons. These coupons offset the bidder's impact on others, ensuring fairness in pricing.

The ultimate transaction price for each winning bidder is determined through a complex calculation considering the combined value of coupons requested by all bidders and a predefined benchmark called the 'offloading target.' VCG-style pricing functions as an advanced approach to achieving balance in auctions, especially in scenarios with one seller and multiple buyers. By accounting for the effects of bidders on each other and appropriately compensating, this pricing strategy ensures fairness and provides bidders with the incentive to bid truthfully.

2.6.4 Price-Incentive Resource Auction Mechanism (PIRA)

This approach involves the understanding of market-related pricing and exploiting unused or idle resources to be auctioned off at a lower price. As opposed to charging static prices, secondary users can be charged less for making use of these idle/unused resources. The lower prices incentivise users to make use of resources they otherwise would not have used as well as increase revenue for resource providers as there are more consumers using their services albeit at a lower price. The provisioning of idle/unused resources compensates for the lower cost being charged to consumers as the cost of operating the idle resources was being accrued to the resource provider and not the consumer. In the context of this research project, since 5G consists of various slices performing different services [31], consumers could be incentivised to use other services at a lower cost, resulting in these 5G slices resources not being wasted due to a lack of demand.

This incentive pricing mechanism is popular with cloud providers. For instance, The Amazon EC2 operator employs a price modulation strategy for these idle resources termed 'Spot Instances', adjusting prices based on long-term trends in supply and demand for Spot Instance capacity [32]. These Spot Instances typically have lower prices compared to on-demand instances. In order to maximize the utilization of idle EC2 instances, Yang et al. [33] introduced a novel approach involving a reserved-instance reselling algorithm for cloud users. This algorithm identifies reserved instances that are likely to remain unused in the future and repurposes them as Spot Instances. This innovative approach effectively reduces the wastage of unused reservations.

Another noteworthy contribution in this domain comes from Khodak et al [34], who leveraged the cost-saving potential of Spot Instances. By predicting the demand of both Spot and on-demand instances, users are enabled to purchase resources in a manner that ensures applications run within acceptable QoS parameters. This approach optimizes resource allocation and minimizes economic costs for cloud users.

Building upon the principles underlying Amazon EC2 Spot Instances, Kamiyama [35] devised an inventive strategy for Virtual Machine (VM) trading across multiple cloud providers. This approach

facilitates the transfer of idle VM instances between different providers, ensuring their productive utilization and contributing to enhanced resource efficiency.

In summary, recent research related to Amazon EC2 Spot Instances primarily centres around two main themes: the resale of idle resources and the exploitation of the cost advantages associated with Spot Instances to drive down operational expenses for cloud users. These studies collectively highlight the dynamic nature of cloud resource management and the ongoing pursuit of innovative strategies to enhance efficiency and cost-effectiveness.

Huang et al. [36] proposed a resource auction system within the cloud environment, where users consider the price of cloud resources, their budget, and quality of service requirements to strategically purchase resources based on their needs. This approach enables the cloud provider to balance user resource demands using a market-based pricing strategy that prevents excessively low prices from affecting operational costs or very high prices causing user attrition.

The proposed mechanism aims to encourage a large number of users to use cloud resources while ensuring the cloud provider maintains a minimal profit rate. It also guarantees budget balance, truthfulness, and fairness among users through the use of a single-price auction as opposed to the VCG auction strategy discussed in 2.6.3 as it is more widely accepted in its fairness ie. the same item cannot be priced differently [36]. Their PIRA mechanism develops a user utility function to reflect complex user interests with the aim of maximising their utility.

2.7 Closing Remarks

In conclusion, the literature review has provided a comprehensive understanding of the current next-generation mobile network 5G, use cases, frequency bands, migration strategies, cellular mobile network evolution and incentive pricing models. The evolution of mobile networks from 1G to 5G has been driven by the increasing demand for improved connectivity and diverse use cases. 5G represents a significant leap forward, offering ultra-fast download speeds, low latency, and the potential to enable revolutionary applications in eMBB, mMTC and URLLC.

The spectrum allocation for 5G is divided into low, mid, and high-frequency bands, each serving specific deployment and coverage purposes. The migration to 5G involves deploying cells through two primary approaches: NSA and Standalone SA, each with its own advantages and implications. User adoption of 5G technology is influenced by various factors, including industrialization levels, affordability of devices, network coverage, and perceived benefits.

The exploration of the mobile network landscape has revealed the intricacies of Radio Access Technologies (RATs) that form a heterogeneous wireless network. Our specific focus on mobile cellular network technologies has illuminated the critical factors of Quality of Service (QoS) and network cost, especially relevant in the context of mobile network generation adoption.

Within a South African context, issues like the digital divide and the urban/rural gap further complicate the mobile network landscape, highlighting the need for tailored strategies to cater to the varied needs and preferences of consumers. The implementation of incentive pricing models, such as the replicator dynamics approach from evolutionary game theory, Stackelberg games, the Win-Coupon approach,

and the PIRA mechanism, may have the potential to impact user migration to 5G. Although there are no current models that have been developed to accelerate users' migration to the 5G network, these models can be modified and used to explore different strategies to motivate users to adopt 5G networks, ranging from compensation for network delays to market-based pricing mechanisms that exploit idle resources and offload cellular traffic efficiently.

Furthermore, utility functions and multi-attribute utility theory (MAUT) have been identified in this chapter, along with machine learning and predictive models, as adequate tools for assessing and understanding user preferences and user satisfaction. These methodologies have the potential to unlock insights into user behaviours and preferences, which are crucial for encouraging the adoption of newer-generation mobile networks.

In the broader context, these incentive pricing models can contribute to the network operator's ability to manage user migration, optimize resource allocation, and enhance decision-making processes. As 5G adoption continues to grow, understanding these models becomes crucial for both providers and users to ensure efficient and effective utilization of the technology.

Chapter 3

Proposed Solution

The proposed solution involves a computational model based on a multi-attribute utility theory that is mathematically sound for modelling the migration of users from their current network to higher networks. To ensure the model is capable of addressing the research question effectively, it is made up of smaller components which would integrate with each other to identify the threshold for when a user would migrate and which network they would migrate to in response to the introduction of incentives. This information is then used to determine the distribution of users in a HWN in response to different incentives. The last part was evaluating the effects this would have on the QoS and resource utilisation.

3.1 Multi-Attribute Utility Theory

3.1.1 Defining alternatives and value-relevant attributes

Alternatives to be evaluated in the MAUT

In selecting the alternatives to be evaluated for users' migration within the HWN, only cellular mobile networks are to be considered, particularly packet-switched mobile cellular networks which focus on the transmission of mobile data. These alternatives are:

- 3G
- 4G
- 5G

This selection of cellular enhances the flexibility of users and ensures that the proposed solution is attuned to their diverse connectivity needs and is realistic.

Value-Relevant Attributes

To effectively assess these alternatives, we focus on the following value-relevant attributes:

- Cost
- Available Data Rates
- Delay
- Network Coverage

These attributes play a crucial role in evaluating the performance and suitability of each alternative, helping us make informed decisions within the Multi-Attribute Utility Theory framework.

3.1.2 Evaluating each alternative separately on each attribute

Having stated the alternatives and determined the salient attributes, each alternative is evaluated on each of the attributes. The values of the attributes for the cellular networks are all evaluated to range from 0 to 1. This uniformity is a requirement for aggregating all the values to calculate the overall utility of a cellular network to a user.

Cost value attribute

The cost of cellular network subscriptions to consumers is two-fold, the cost of the user equipment and the cost of utilising the network services with the cost of the user equipment being the greater barrier to adoption. The salient factors that are considered in determining the overall cost of a cellular network are the cost of the user equipment required, the available data speeds at a price, and the data allowance - the maximum amount of data usage (uploads and downloads) that can be used in a billing month under a plan without incurring excess charges. Due to these factors being qualitative, a fuzzy inference system was used to obtain a fuzzy logic value that can be used in the analysis.

The method used for determining the defuzzified value for the cost attribute involves the use of a Matlab tool called Fuzzy Logic Designer [37] popularly used in estimation and prediction techniques within different fields of study. The fuzzy inference system was designed to have three input values (data allowance, cost, and data speed) and determines the fuzzy cost value as a measure of value for money. The fuzzy inference system essentially aggregates the salient factors which are relevant to the cost perceived by consumers for the various networks such that they are comparable. This approach can be seen in the work done by Soetanto [38] for determining the selling price of goods and is similar to the method used by Ravneet Preet Singh Bedi et al. [39] in determining the estimated cost of developing software. The membership functions, rules and inference system plot for the fuzzy inference system used for the project can be found in Appendix A.

The fuzzy logic values obtained for each of the cellular networks from the fuzzy inference system are shown in table 3.1 below.

Table 3.1: Cellular Network Cost Fuzzy Value

Mobile Cellular Network	fuzzy cost
3G	0.3843
4G	0.5816
5G	0.7522

To determine the cellular network cost attribute value, denoted by $v_{cost}(x_i)$ in equation 3.1 below is used, where x_i is the cellular network and c the fuzzy logic cost value of the network.

$$v_{cost}(c) = \begin{cases} 0 & \text{if } c \leq 0 \\ 1 - c & \text{if } 0 < c < 1 \\ 1 & \text{if } c \geq 1 \end{cases} \quad (3.1)$$

Formula 3.1 above results in a higher cellular network cost attribute value for lower-costing cellular networks and a lower cellular network cost attribute for higher-costing cellular networks. It also restricts the attribute value to be between 0 and 1.

Data Rate value attribute

The mobile data rate available to a user is dependent on the cellular network they are subscribed to. The data rate for a user is randomly determined as a value between the maximum and minimum data rates achievable by the cellular network being evaluated shown in table 3.2. The data rate is randomly chosen because the actual performance of each network is subject to variations determined by the service provider, network configuration, the number of active users within a particular cell, the radio conditions at a specific location, the services being utilized, and various other factors that impact wireless performance.

Table 3.2: Cellular Network Typical Data Rates Ranges

Mobile Cellular Network	minimum data rate(typical)	maximum data rate(typical)
3G	500 Kbps	5 Mbps
4G	1 Mbps	50 Mbps
5G	25 Mbps	450 Mbps

Shown in equation 3.2 below, the selection of the data rate, r , is performed by selecting a random value from a normal distribution of the network data rates, with the mean being the midpoint of the minimum, r_{min} , and maximum, r_{max} , data rates of the network and the standard deviation being one-fourth of the network range width.

$$r \sim \mathcal{N}\left(\frac{r_{max} + r_{min}}{2}, \left(\frac{r_{max} - r_{min}}{4}\right)^2\right) \quad (3.2)$$

To determine the cellular network data rate attribute value, the randomly generated network rate, r , in 3.2 is transformed into an attribute value using equation 3.3 below.

$$v_{rate}(r) = \max\left(0, \min\left(1, \frac{\log(r)}{\log(450)}\right)\right) \quad (3.3)$$

Equation 3.3 above scales the network rate to a value between 0 and 1, with 0 representing low data rates and 1 representing the highest data rates. The logarithmic transformation is used to map the wide range of network rates to a normalized attribute value range.

Delay value attribute

The delay experienced by a user on a cellular network is another crucial attribute that can vary based on network conditions and various factors. Similar to the data rate, the delay for each cellular network type has a range of possible values. These ranges are typical values and may vary in practice based on network-specific conditions. The values to be used in the simulations are shown in table 3.3 below.

Table 3.3: Cellular Network Typical Delay Ranges

Mobile Cellular Network	Minimum Delay (typical)	Maximum Delay (typical)
3G	100 ms	500 ms
4G	5 ms	100 ms
5G	0.5 ms	5 ms

The delay experienced by a user can vary due to factors such as network congestion, signal strength, packet routing, and other network conditions. Therefore, the delay is considered a random variable. To determine the delay attribute value, a random delay value (d) is selected from a normal distribution of the network delays. This is similar to the approach used for data rate. The mean of the distribution is set to the midpoint of the minimum (d_{min}) and maximum (d_{max}) delay values for the network, and the standard deviation is one-fourth of the range width. This is expressed as follows:

$$d \sim \mathcal{N}\left(\frac{d_{max} + d_{min}}{2}, \left(\frac{d_{max} - d_{min}}{4}\right)^2\right) \quad (3.4)$$

To map the sampled delay (d) to an attribute value, the equation 3.5 below is used:

$$v_{delay}(d) = \max\left(0, \min\left(1, 1 - \frac{\log(d)}{\log(1000)}\right)\right) \quad (3.5)$$

Equation 3.5 scales the delay value to a range between 0 and 1, where 0 represents minimal delay, and 1 represents the maximum delay. A logarithmic transformation is used to normalize the wide range of delay values across different networks. The scaled value is subtracted from one such that low delays result in higher attribute values for the delay of cellular networks. Networks with higher delays would result in lower values for the delay attribute value.

Coverage value attribute

Population coverage of a cellular network represents the percentage of the population within a geographic area that can access and use a specific cellular network. is a significant attribute that influences user experience and accessibility. It is an essential metric for assessing the network's reach and availability. Each cellular network type is modelled as having differing population coverage values for urban and rural areas, determined by adding the weighted population coverage of the nine South African provinces in rural and urban areas presented in 2.2.3. For illustration, consider the following table 3.4 below:

Table 3.4: Cellular Network Population Coverages

Mobile Cellular Network	Rural Population Coverage	Urban Population Coverage
3G	99.3%	100%
4G	95.6%	99.9%
5G	2.8%	30%

The simulations are to be conducted for both urban and rural areas to see the effects in both scenarios. As these percentages are already in the range of 0 to 1, the population coverage attribute value of a network is simply equal to its population coverage(p), seen below in equation 3.6.

$$v_{coverage}(p) = p \quad (3.6)$$

3.1.3 Assigning relative weights to the attributes

To model users' preferences, users are categorized into one of five categories. Each category represents a class of users with different preferences. The categories are formed on the basis of the classification of users done by the BMIT [20]. The user weights, which rate the importance of an attribute to them, for users in each category for the different attributes can be seen in table 3.5 below:

Table 3.5: User Attribute Weights

User Category	Cost Weight	Data Rates Weight	Delay Weight	Coverage Weight
DLM1	$w_{cost} \in [0.7, 1.0]$	$w_{rate} \in [0.0, 0.4]$	$w_{delay} \in [0.0, 0.4]$	$w_{coverage} \in [0.4, 0.6]$
DLM2	$w_{cost} \in [0.5, 0.8]$	$w_{rate} \in [0.2, 0.5]$	$w_{delay} \in [0.3, 0.7]$	$w_{coverage} \in [0.4, 0.6]$
DLM3	$w_{cost} \in [0.3, 0.6]$	$w_{rate} \in [0.3, 0.7]$	$w_{delay} \in [0.0, 0.3]$	$w_{coverage} \in [0.4, 0.6]$
DLM4	$w_{cost} \in [0.1, 0.4]$	$w_{rate} \in [0.5, 0.8]$	$w_{delay} \in [0.5, 0.8]$	$w_{coverage} \in [0.4, 0.6]$
DLM5	$w_{cost} \in [0.0, 0.2]$	$w_{rate} \in [0.7, 1.0]$	$w_{delay} \in [0.7, 1.0]$	$w_{coverage} \in [0.4, 0.6]$

These weights in table 3.5 are chosen such that users with greater network needs have higher weights for QoS Attributes and reduced cost preference and users with lower network needs have lower weights for QoS Attributes and increased cost preference.

With the weights for each attribute having been assigned, they are normalised according to equation 3.7 below, where w_i is the normalised value for the attribute (i) and n is the total number of attributes.

$$w_i = \frac{w_i}{\sum_{i=1}^n w_i} \quad (3.7)$$

3.1.4 Total Utility of a network for a user

The final step of the MAUT involves aggregating the weights of attributes and the single-attribute evaluations of alternatives to obtain an overall evaluation of alternatives. Equation 3.8 below shows

how the utility of a cellular network subscription (x), denoted as $u(x)$, for a user with normalised preferences (w_i) for attribute values (v_i) is determined.

$$u(x) = \sum_n^{i=1} w_i v_i(x) \quad (3.8)$$

The code for the complete MAUT calculations can be found in Appendix B.

3.2 Migration Threshold

A utility-difference threshold [40], shown in equation 3.9 below, is used to determine whether or not a user will migrate. As the scope of the experiment is focused on the incentivisation of users to migrate to 5G, the incentive pricing model is only applied to the 5G network. As a result, only the utility difference before and after applying the incentive to 5G is considered.

$$u_I(5G) - u_c(5G) > T \quad (3.9)$$

The utility for a user if they were to be on the 5G network with no incentives, denoted as $u_c(5G)$, and the estimated utility for a user if they were to be on the 5G network with the incentive pricing model employed, denoted as $u_I(5G)$, are both determined using the MAUT in 3.1. For a user to migrate to 5G, the difference between $u_I(5G)$ and $u_c(5G)$ has to be greater than the threshold value, denoted as T . The value of T would represent the sensitivity of users to incentive pricing. The value is arbitrarily chosen but is varied to see how user sensitivity would impact the migration results. A lower value of T would represent high sensitivity while higher values would represent low sensitivity.

In addition to the utility difference threshold being met, the following condition needs to be true for a user to migrate:

$$u_I(5G) > u_b(\text{currentsubscription}) \quad (3.10)$$

The solution also assumes a one-way migration, ie. users can only migrate to newer-generation network subscriptions and can't migrate backwards should there be an older-generation network that offers them greater utility.

3.3 Incentive Model

The proposed incentive model follows a similar approach done by Zhuo et al. [30] where users are given personalised incentives, in the form of a one-time coupon, based on their preferences. The incentive framework involves users leveraging the sum of the individual utilities for each of the network attributes, listed in 3.1, on their current network subscription which are greater than what their utility would be for the corresponding attribute utilities on the unincentivised 5G network.

Due to device and tariff costs having been identified as the main barriers to 5G adoption [6], the incentive model aims to reduce the cost of users acquiring UE needed for the 5G network through a

coupon. The value of the coupon is to be interpreted relative to the cost attribute values determined for the different cellular network technologies in 3.1.

3.3.1 Determining User Incentive Coupon

The coupon received by a user for migrating to the target network, in this case, 5G, is based on the benefit a user forfeits from their current network subscription by migrating to 5G. This benefit is the difference between the user's utility on their current network(x) and their utility on the 5G network. Both utilities are determined using the MAUT presented in 3.1.

Thus, given the utility of the user on their current subscription(x), denoted with subscript b :

$$\begin{aligned}
 U_b(x) &= \sum_n^{i=1} w_i v_i(x) \\
 &= v_1(x)w_1 + v_2(x)w_2 + v_3(x)w_3 + v_4(x)w_4 \\
 &= u_{b1}(x) + u_{b2}(x) + u_{b3}(x) + u_{b4}(x)
 \end{aligned} \tag{3.11}$$

And the utility of the user on the unincentivised 5G network, denoted with subscript c :

$$\begin{aligned}
 U_c(5G) &= \sum_n^{i=1} w_i v_i(5G) \\
 &= v_1(5G)w_1 + v_2(5G)w_2 + v_3(5G)w_3 + v_4(5G)w_4 \\
 &= u_{c1}(5G) + u_{c2}(5G) + u_{c3}(5G) + u_{c4}(5G)
 \end{aligned} \tag{3.12}$$

with i representing attributes:

- $i = 1$: Network UE Cost attribute
- $i = 2$: Network Data rate attribute
- $i = 3$: Network Delay attribute
- $i = 4$: Network coverage attribute

The incentive coupon, α , given to a user is determined as follows.

$$\alpha = \max(0, u_{b1}(x) - u_{c1}(5G)) + \max(0, u_{b2}(x) - u_{c2}(5G)) + \max(0, u_{b3}(x) - u_{c3}(5G)) + \max(0, u_{b4}(x) - u_{c4}(5G)) \tag{3.13}$$

The maximum of 0 and the difference between the individual attribute utilities for the user on their current subscription and on the unincentivised 5G is taken such that only the benefit of their current subscription is leveraged for the incentive. This also ensures that incentive is always a positive value and the model won't discourage users from migrating in instances where the single attribute utility

for users on the unincentivised 5G network is greater than that of the utility of the corresponding attribute on their current network subscription.

3.3.2 Maximum incentive imposed by Network Provider

The incentive would of course be at the expense of the network provider. A maximum incentive value is thus introduced, which represents the maximum coupon value which can be given to users, to limit the costs incurred by the network provider for incentivising users. This is similar to the reserve price used in the Win-Coupon incentive framework by Zhou et al. [30] mentioned in 2.6.3.

The cost attribute value is thus adjusted as follows:

$$v_{cost_with_incentive}(c) = \begin{cases} 0 & \text{if } c \leq 0 \\ \max(1 - (c - m), 1 - (c - \alpha)) & \text{if } 0 < c < 1 \\ 1 & \text{if } c \geq 1 \end{cases} \quad (3.14)$$

To obtain the utility for a user on the incentivised 5G network, equation 3.14 is used to evaluate the utility as opposed to equation 3.1 used in the unincentivised 5G network. The codes for this incentive model can be found in Appendix C.

Chapter 4

System Model

4.1 Heterogeneous Wireless Network

A heterogeneous wireless network, shown in figure 4.1, consisting of three RATs- namely 3G UMTS, 4G LTE and 5G Standalone NR- is considered for investigating the impact of the incentive model proposed in 3 on users' migration and the effect this would have on the network.

The HWN supports users with 3G, 4G and 5G subscriptions. It is assumed users have the necessary UE required for their network subscription. Users with 5G subscriptions can access any of the RATs, 4G subscriptions can only access the 3G and 4G networks, and 3G subscriptions can only access the 3G network.

4.1.1 RAT Parameters

The RAT parameters were determined using similar logic to that done by Falowo in [16]. With 3G using Broadband internet service, 4G using Ultra-Broadband internet service and 5G using Wireless World Wide Web internet service, there are differences in the bandwidth requirements for each RAT [41]. The physical meaning of a unit of radio resources is determined by the radio interface's unique technological implementation. Regardless of the multiple access technique employed, system capacity can be expressed in terms of effective bandwidth [42]. The bandwidth required for a call is denoted by b_{bu} in this system model.

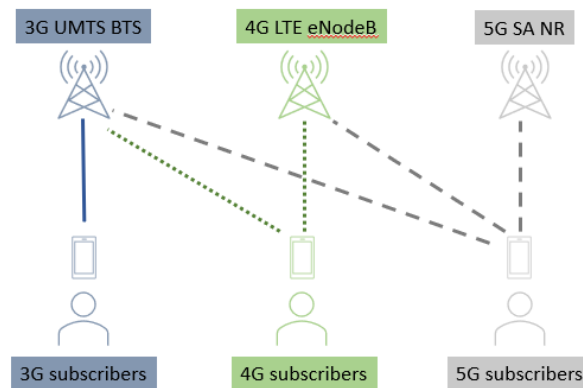


Figure 4.1: Visual Diagram of Heterogeneous Wireless Network

RAT Capacities

With the bandwidth for 5G being 100MHz divided into 180KHz sub-channels spanning over 12 contiguous sub-carriers [16], the approximate number of channels available for the service calls being considered is 555. This is scaled by a scaling factor:

$$scalingfactor = 0.09 \quad (4.1)$$

and rounded up such that the capacity of the 5G network in the system model is 50bbu. The scaling factor is introduced to reduce the computational load required to investigate the performance of the HWN as a result of the proposed solution.

With the 3G RAT having a required bandwidth of 25MHz [41] with 5MHz for each sub-carrier and a spreading factor of 32, the available number of channels in the 3G RAT is 160. This translates to a capacity of 15bbu when multiplying with the scaling factor of 0.09 and rounding up for the 3G RAT in the system model.

With the 4G RAT having a total bandwidth of 60MHz and 180KHz for each sub-carrier, the available number of channels in the 4G RAT is 333. This translates to a capacity of 30bbu when multiplying with the scaling factor of 0.09 and rounding up for the 4G RAT in the system model.

New service Call Threshold

The thresholds for new service calls in the HWN for each of the RATs are taken as a proportion, 65%, of the capacity of the respective RAT rounded up.

The capacity and threshold for the different RATs are therefore:

- 3G: C1=15bbu ; T1=10bbu
- 4G: C2=30bbu ; T2=20bbu
- 5G: C3=50bbu ; T3=33bbu

4.2 Markov Model

The RAT selected by a user performing a service call request can be modelled as a multi-dimensional Markov chain (Code found in Appendix E). The HWN network comprises $J = 3$ number of RATs, RAT1 being the 3G network, RAT2 being the 4G network and RAT3 being the 4G network.

$$H = \{RAT1, RAT2, RAT3\} \quad (4.2)$$

One class of service calls is to be considered, the transfer of typical data traffic (eg. large document file transfer).

$$\therefore C = \{class1\} \quad (4.3)$$

It assumed that the spectrum efficiency of the 5G network is two times that of 4G and the spectrum efficiency of 4G is two times that of 3G. Thus, for QoS provisioning purposes, the following policies are placed in the network to ensure that the service calls in 4.3 are serviced with a sufficient level of quality such that the service calls are serviced for a shorter duration with the older generations, reducing the need for retransmission should the connection be interrupted due to dynamic factors such as the mobility of users within the HWN.

- 4bbus are needed for servicing the class of service call in 4.3 by RAT1.
- 2bbus are needed for servicing the class of service call in 4.3 by RAT2.
- 1bbu is needed for servicing the class of service call in 4.3 by RAT1.

4.2.1 Admissible States

The HWN being considered as the system model is a 6-dimensional Markov chain and can be written as:

$$\Omega = (n_{11}, h_{11}, n_{12}, h_{12}, n_{13}, h_{13}) \quad (4.4)$$

where:

- n_{11} is the number of new service calls of type 1 accepted into RAT1 (3G).
- h_{11} is the number of handoff service calls of type 1 accepted into RAT1 (3G).
- n_{12} is the number of new service calls of type 1 accepted into RAT2 (4G).
- h_{12} is the number of handoff service calls of type 1 accepted into RAT2 (4G).
- n_{13} is the number of new service calls of type 1 accepted into RAT3 (5G).
- h_{13} is the number of handoff service calls of type 1 accepted into RAT3 (5G).

An admissible state, denoted by s , is a combination of the numbers of new and handoff service calls of type 1 that can be simultaneously supported in the network by all the RATs while maintaining QoS requirements with the constraints in capacity. The state, S , of all admissible states in the network is:

$$\begin{aligned} S \in \Omega : & (n_{11} + h_{11})b1 \leq C1 \wedge n_{11}b1 \leq T1 \wedge \\ & (n_{12} + h_{12})b2 \leq C2 \wedge n_{12}b2 \leq T2 \wedge \\ & (n_{13} + h_{13})b3 \leq C3 \wedge n_{13}b3 \leq T3 \end{aligned} \quad (4.5)$$

4.2.2 Probability of being in Admissible State s

Arrival Rates

The selection of which network is chosen for a user making a service request happens when the request is made. A simple JCAC algorithm to determine if a user is admitted into the network, and into which

RAT, is used where the network is selected based on the network subscription the users have. It is assumed that service requests arrive according to Poisson processes [16] with:

- $\lambda_{n_{11}}$ describing new class 1call arrival rate into RAT1,
- $\lambda_{h_{11}}$ describing handoff class 1call arrival rate into RAT1,
- $\lambda_{n_{12}}$ describing new class 1call arrival rate into RAT2,
- $\lambda_{h_{12}}$ describing handoff class 1call arrival rate into RAT2,
- $\lambda_{n_{13}}$ describing new class 1 call arrival rate into RAT3,
- and $\lambda_{h_{13}}$ describing handoff call of class 1 arrival rate into RAT3.

Given the total service calls made into the network x_m and assuming are uniformly distributed according to their network subscription, the new call arrival rates are determined as follows:

$$\lambda_{n_{11}} = (Q_{3G} + \frac{1}{2}Q_{4G} + \frac{1}{3}Q_{5G}) \quad (4.6)$$

$$\lambda_{n_{12}} = x_m(\frac{1}{2}Q_{4G} + \frac{1}{3}Q_{5G}) \quad (4.7)$$

$$\lambda_{n_{13}} = x_m\frac{1}{3}Q_{5G} \quad (4.8)$$

where Q_x is the proportion of users in the HWN with network subscription y. The arrival rates for the different RATs will thus vary depending on the number of subscriptions for each RAT with the sum of the arrival rates for each RAT equal to the total arrival rate x_m for the HWN. This simplification of uniformly distributing the users with different subscriptions to be admitted across the RATs they can access is used as the implementation of a sophisticated JCAC algorithm is not the focus of this project. Determining the arrival rates in this manner is sufficient for giving us an indication of how the HWN performs with varying proportions of network subscriptions.

The handoff class 1 call arrival rates $\lambda_{h_{11}}$, $\lambda_{h_{12}}$ and $\lambda_{h_{13}}$ are a fraction, 0.2, of the new call arrival rates $\lambda_{n_{11}}$, $\lambda_{n_{12}}$, and $\lambda_{n_{13}}$, respectively.

The simulations for the system model will be run for different values of the total arrival rate, x_m , in the network to investigate the effect this has on the network performance.

Departure Rates

The channel holding time for class-i calls can be expressed as an exponential distribution with a mean of $1/\mu_i$ [42].

The channel holding time, $1/\mu_i$, for class of call i for new calls and handoff calls, are expressed with a superscript m and n, respectively, and as such, the channel holding time is expressed with $1/\mu_i^m$ and $1/\mu_i^n$ for new and handoff calls, respectively. It is assumed that channel holding time for new

and handoff in the network are equal for the same service call. $1/\mu_i$ will be used hereafter to denote channel holding times for both new and handoff

The value to be used for the channel holding time in simulating the system model for class of call 1 is:

$$1/\mu_1 = 2 \quad (4.9)$$

4.2.3 Probability of being in Admissible State s

The steady-state probability that the system is in state s ($s \in S$) can be found as a result of the Markovian property of the model. With the traffic intensity of new calls of class i in RAT j denoted as $\rho_{n_{i,j}}$, it can be determined using the arrival rate of new calls of type i in RAT j , $\lambda_{n_{i,j}}$, and the channel holding time for call of class i , μ_i , as shown in equation 4.10 below.

$$\rho_{n_{i,j}} = \frac{\lambda_{n_{i,j}}}{\mu_i} \quad (4.10)$$

The same method is followed for determining the traffic intensity of handoff calls of class i in RAT j denoted as $\rho_{h_{i,j}}$ as seen in 4.11 below.

$$\rho_{h_{i,j}} = \frac{\lambda_{h_{i,j}}}{\mu_i} \quad (4.11)$$

The steady-state probability P_s that the system is in state s ($s \in S$) can then be found, given by equation 4.12:

$$P_s = \frac{1}{G} \prod_{i=1}^I \prod_{j=1}^J \frac{(\rho_{n_{i,j}})^{n_{ij}} (\rho_{h_{i,j}})^{h_{ij}}}{n_{ij}! h_{ij}!} \quad (4.12)$$

where G is the normalisation constant given by equation 4.13:

$$G = \sum_{s \in S} \prod_{i=1}^I \prod_{j=1}^J \frac{(\rho_{n_{i,j}})^{n_{ij}} (\rho_{h_{i,j}})^{h_{ij}}}{n_{ij}! h_{ij}!} \quad (4.13)$$

4.3 Network Performance Evaluation

To evaluate the performance of the HWN, three metrics are used, namely the call blocking probability, call dropping Probability and the average network utilization.

4.3.1 Average Resource Utilisation

The average resource utilisation, U in the network can be calculated by summing up the product of the probability (P_s) of the network being in state s and the resource utilisation (U_s) in state s off all the admissible states ($s \in S$). This is shown in equation 4.14 below.

$$U = \sum_{s \in S} U_s P_s \quad (4.14)$$

P_s is obtained from equation 4.12 and U_s is described as the total amount of bbu resources being used by all the service calls in the HWN for admissible state s . It is determined as follows:

$$U_s = (n_{11} + h_{11})b1 + (n_{12} + h_{12})b2 + (n_{13}, h_{13})b3 \quad (4.15)$$

Having found the average resource utilisation U , the normalised utilisation can be found by dividing it by the total resource available in the HWN. This is shown in equation 4.16 below.

$$U_{normalised} = \frac{U}{C1 + C2 + C3} \quad (4.16)$$

4.3.2 Call blocking Probability

A new call is blocked if it being admitted into a RAT would result in the capacity of the RAT being exceeded. This means that there are not enough bbu resources to accommodate the new call in the network. The call blocking probability P_b can be found by summing the probability of all the blocking states S_b where the blocking states are a subset of all admissible states in the network. The blocking states are determined as follows:

$$\begin{aligned} S_b \subset S : & b1(n_{11} + h_{11}) + b1 > C1) \vee (b1(n_{11}) + b1) > T1) \vee \\ & (b2(n_{12} + h_{12})) + b2 > C2) \vee (b2(n_{12}) + b2) > T2) \vee \\ & (b3(n_{13} + h_{13})) + b3 > C3) \vee (b3(n_{13}) + b3) > T3) \end{aligned} \quad (4.17)$$

The call blocking probability P_b can thus be expressed as:

$$P_b = \sum_{s \in S_b} P_s \quad (4.18)$$

4.3.3 Call Dropping Probability

A handoff call is dropped if it being admitted into a RAT would result in the capacity of the RAT being exceeded. This means that there are not enough bbu resources to accommodate the handoff call in the network. The handoff call dropping probability P_d can be found by summing the probability of all the dropping states S_d where the dropping states are a subset of all admissible states in the network. The dropping states are determined as follows:

$$\begin{aligned}
S_d \subset S : & b1(n_{11} + h_{11}) + b1 > C1) \vee \\
& (b2(n_{12} + h_{12})) + b2 > C2) \vee \\
& (b3(n_{13} + h_{13})) + b3 > C3)
\end{aligned} \tag{4.19}$$

The call-dropping probability P_b can thus be expressed as:

$$P_d = \sum_{s \in S_d} P_s \tag{4.20}$$

The code for evaluating the Network Performance can be found in Appendix F.

Chapter 5

Results

The simulation (code found in Appendix D) was run for 10,000 users with already existing cellular network subscriptions, defined as their baseline subscriptions. The baseline subscriptions were determined based on the reported number of subscriptions for the different cellular networks by ICASA as of their latest 2022 data [4]. The baseline subscriptions are assumed to reflect the maximum number of users who have migrated to 5G without the presence of the proposed incentive framework described 3. The baseline subscriptions are as follows:

3G subscriptions= total number of users in the network x 59%
4G subscriptions= total number of users in the network x 40.7%
5G subscriptions= total number of users in the network x 0.3%

These users are split up into the categories and weights described in 3.5, with the weights for a user in a category having randomly assigned weights within the ranges of possible weights in that category. The distribution of users across the categories is as follows:

DLM1 users= total number of users in network x 0.1
DLM2 users= total number of users in network x 0.2
DLM3 users= total number of users in network x 0.3
DLM4 users= total number of users in network x 0.2
DLM5 users= total number of users in network x 0.1

These weights are kept constant for the entirety of the simulation, the same user weight being used to determine the baseline utilities for the users on their current network, utilities for the users on the unincentivised 5G network and utilities for the users on the incentivised 5G network.

5.1 Evaluated User Utilities

The baseline utilities for users as well as their expected utility on the unincentivised and incentivised 5G network, with varying levels of maximum incentives by network providers, were calculated and the results are shown with box-plots in figure 5.1 below.

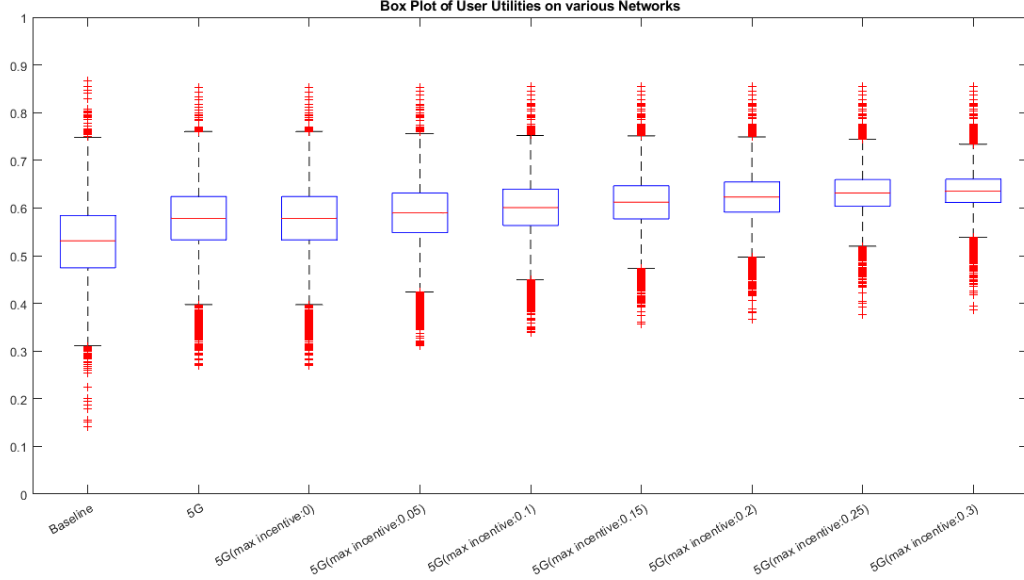


Figure 5.1: Box Plot of Users' Utilities

The mean value of the users' baseline network utility was determined to be 0.5283 with a standard deviation(σ) 0.0777 compared to an expected mean value of 0.5726 ($\sigma = 0.0711$) on the unincentivised 5G network. The expected mean value for the users' utility on the incentivised 5G is greater than the users' utility on the unincentivised 5G network and increases proportionally with an increase in the maximum incentive offered by network providers.

As stipulated in the migration threshold section 3.2, the baseline utilities and expected utilities on the unincentivised 5G network are then used to determine if the user would migrate to the 5G network.

5.2 Migration of Users & and Network Performance

This section reports on the resulting proportion of subscriptions of each RAT in the HWN in response to the incentive model being introduced into the HWN. To investigate the effect of applying the coupon incentive model proposed in chapter 3 on the migration of users in the network, the values for the maximum incentive offered by network providers and the levels of migration thresholds(ie. the incentive sensitivity) were varied from 0.0 to 0.25 and 0.0 to 0.30, respectively.

The network performance metrics- resource utilisation, call blocking probability and call dropping probability- are then calculated in accordance with the methodology described in the Network Performance Evaluation section in the System Model Chapter 4.3.

Results for maximum incentive=0:

Figure 5.2 shows the number of subscriptions for the various RATs in the HWN when there is no incentive introduced into the network at varying levels of threshold for migration.

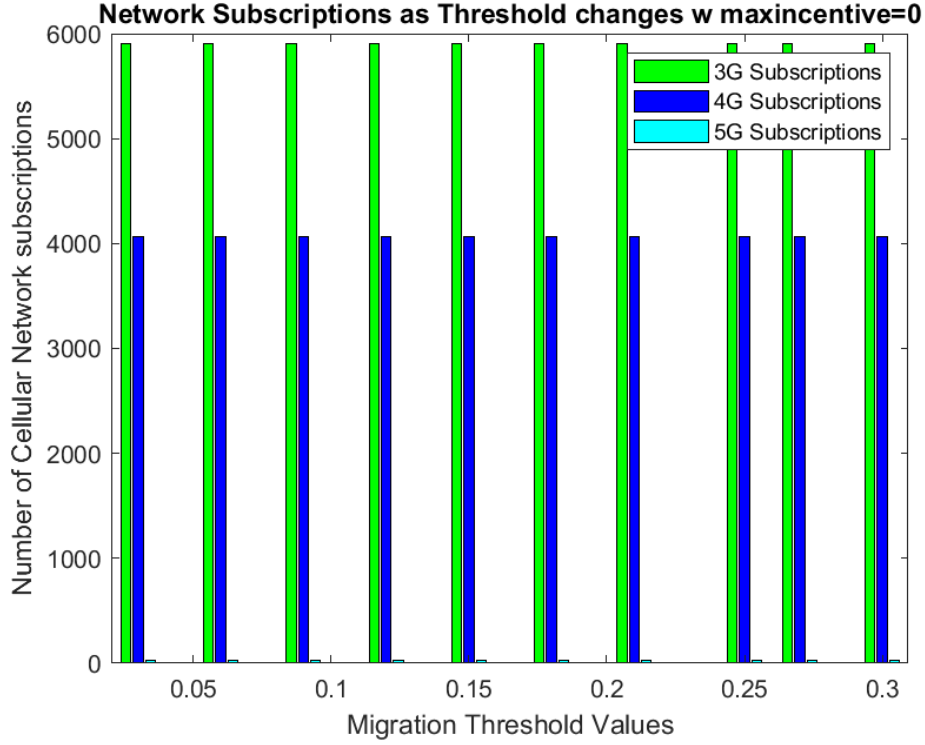


Figure 5.2: Mobile Cellular Subscriptions in HWN

As seen in figure (5.2), there's no change in the number of RAT subscriptions for the different levels of migration thresholds for a maximum incentive of 0.0 being introduced into the HWN. Figure 5.3 below shows the resource utilisation (5.3.c), call blocking probability (5.3.a) and call dropping probability (5.3.b) for network subscriptions (5.2) when there is no incentive introduced into the HWN.

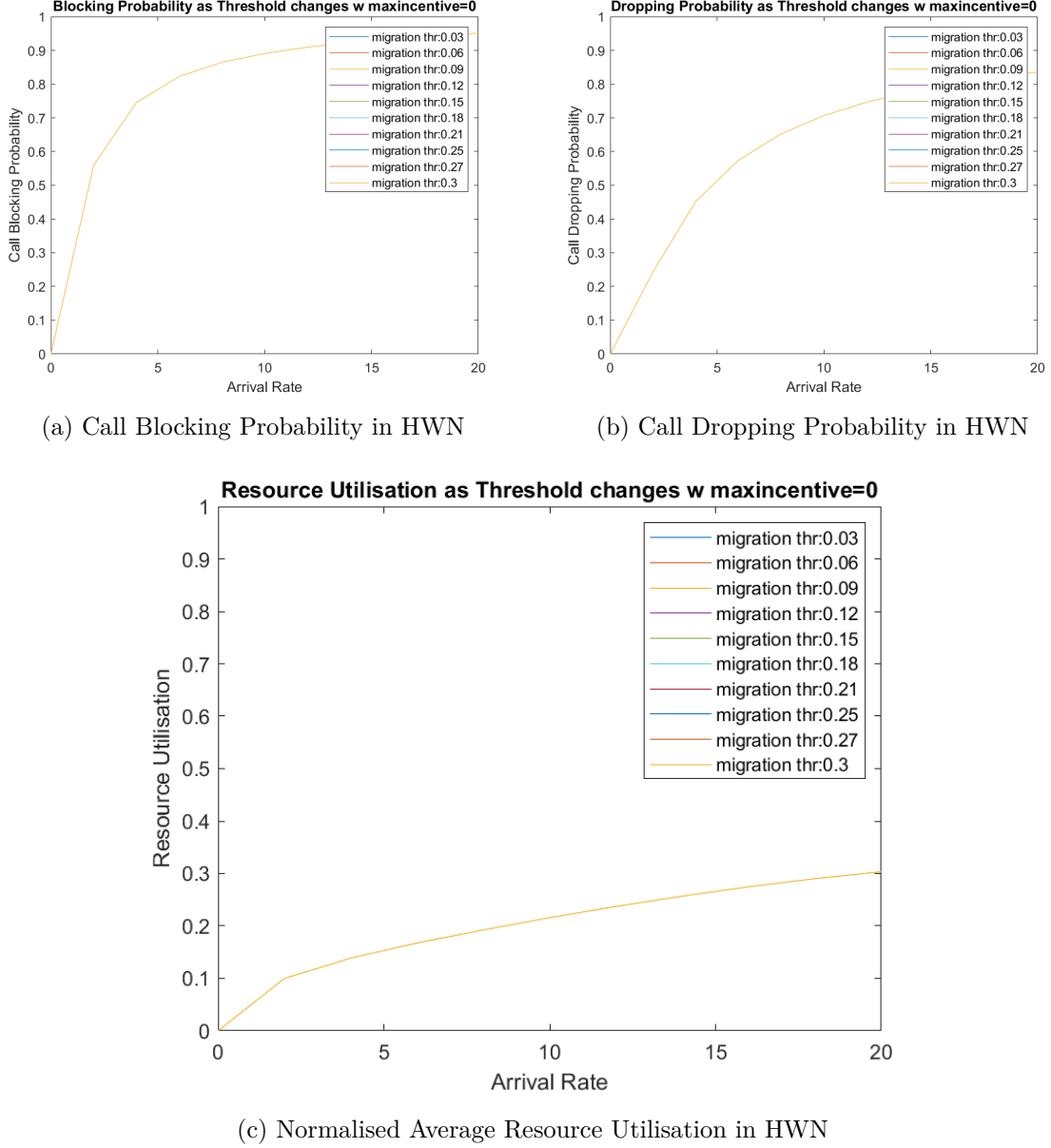


Figure 5.3: Network Subscriptions and Performance with maximum incentive of 0.0

The resource utilisation, call dropping probability and call blocking probability remain unchanged as the migration threshold varies. As seen in figure 5.3.c, the normalised resource utilisation increases concave-down from 0 to approximately 0.3 as the total service arrival rate of calls in the HWN increases from 0 to 20. This is the case at all levels of migration thresholds. The call-blocking (fig. 5.3.a) and call dropping (fig. 5.3.b) both increase concave-down from 0% to approximately 95% and 84%, respectively for all the levels of migration threshold. The call-blocking probability is greater than the call-dropping probability irrespective of the arrival rate.

Results for maximum incentive=0.05:

Figure 5.4 shows the number of subscriptions for the various RATs in the HWN when there is a maximum incentive of 0.05 introduced into the network at varying levels of threshold for migration.

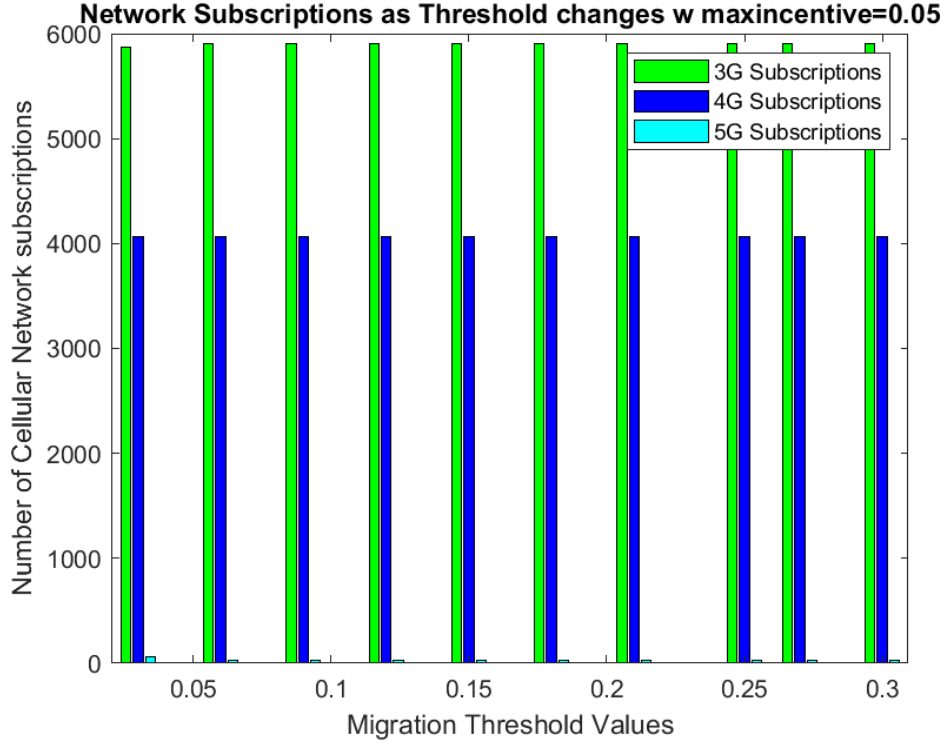


Figure 5.4: Mobile Cellular Subscriptions in HWN

As seen in figure 5.4, approximately 5% of 3G users migrate to the 5G network when the threshold level is 0.03. There's no change in the number of RAT subscriptions for the other levels of migration thresholds when a maximum incentive of 0.05 is introduced into the HWN. Figure 5.5 below shows the resource utilisation (5.5.c), call blocking probability (5.5.a) and call dropping probability (5.5.b) for network subscriptions (5.4) when the incentive introduced is capped at maximum value of 0.05.

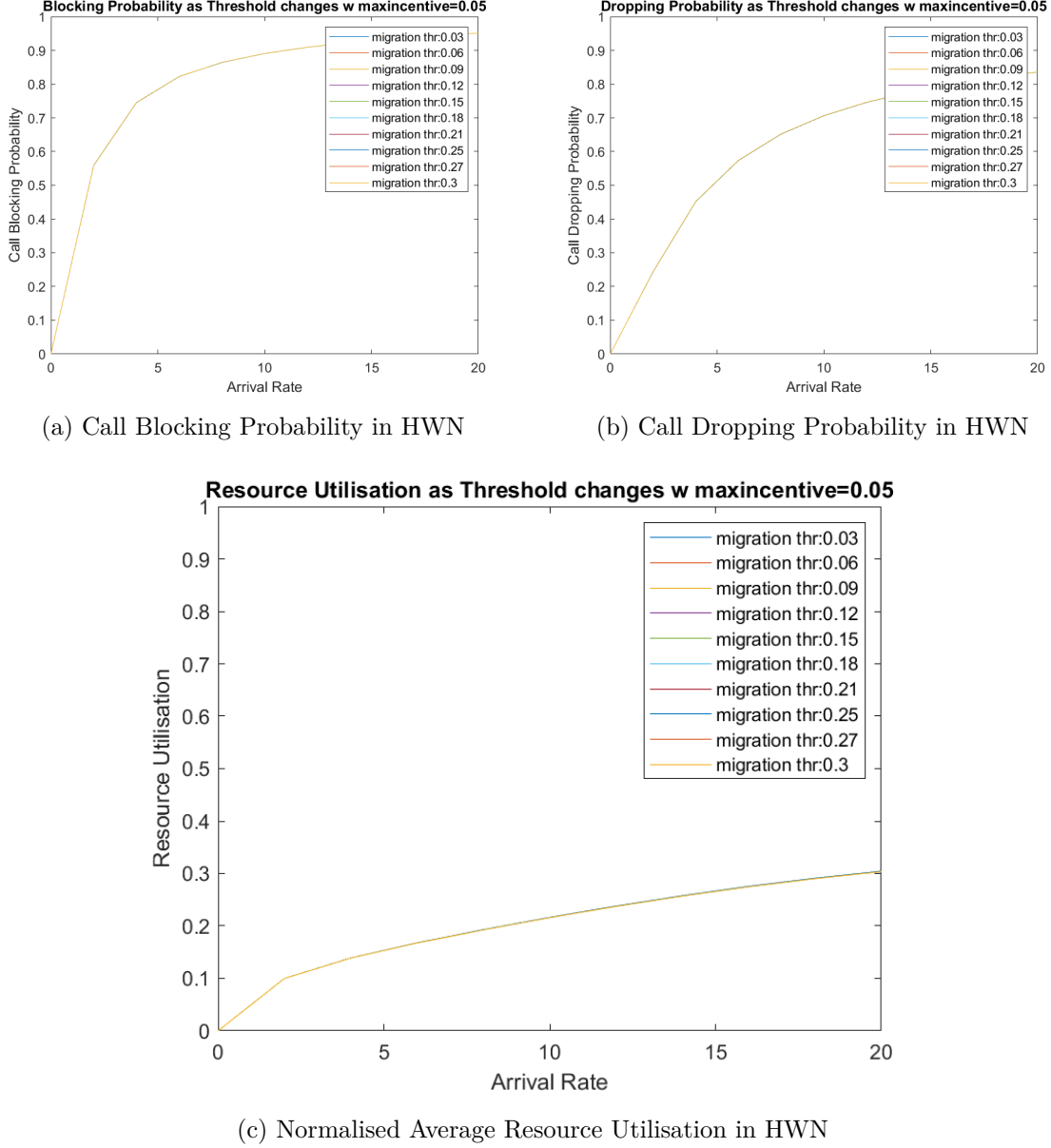


Figure 5.5: Network Subscriptions and Performance with maximum incentive of 0.05

There is no significant change in the resource utilisation, call dropping probability and call blocking probability at a migration threshold of 0.03 as all three metrics change by no more than 1% and they remain unchanged as the migration threshold increases beyond 0.03. As seen in figure 5.5.b, the normalised resource utilisation increases concave-down from 0 to approximately 0.3 as the total service arrival rate of calls in the HWN increases from 0 to 20. This is the case at all levels of migration thresholds. The call-blocking (fig: 5.5.a) and call-dropping (fig: 5.5.b) both increase concave-down from 0% to approximately 95% and 84%, respectively for all the levels of migration threshold. The call-blocking probability is greater than the call-dropping probability irrespective of the arrival rate.

Results for maximum incentive=0.15:

Figure 5.6 shows the number of subscriptions for the various RATs in the HWN when there is a maximum incentive of 0.15 introduced into the network at varying levels of threshold for migration.

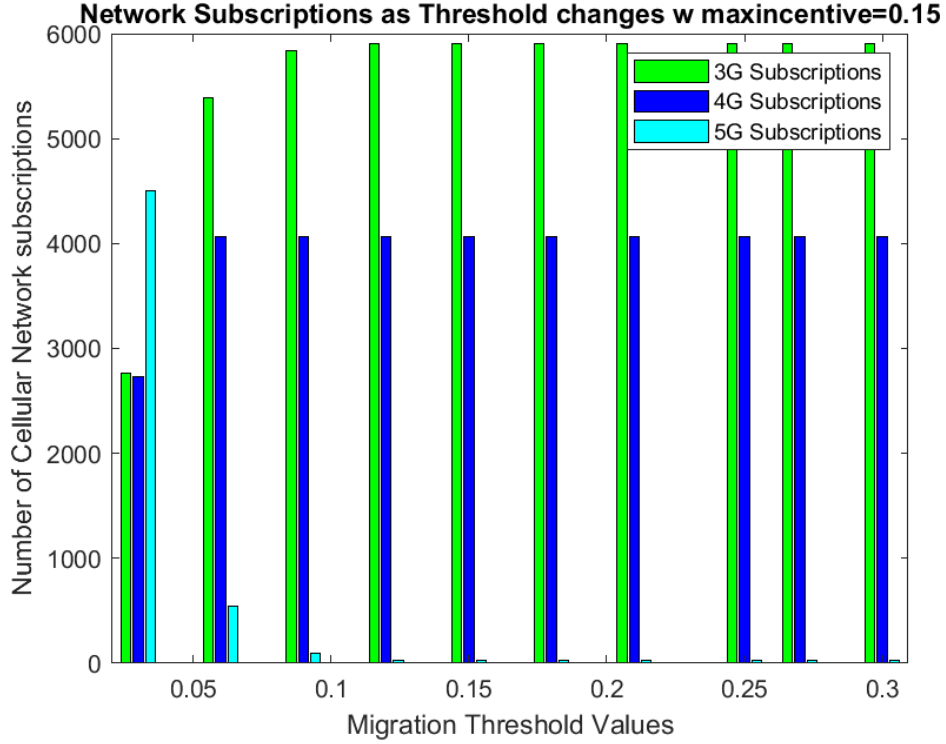


Figure 5.6: Mobile Cellular Subscriptions in HWN

As seen in figure 5.6, approximately 53%, 9% and 1% of 3G users migrate to the 5G subscription when the threshold level is 0.03, 0.06 and 0.09, respectively. 33% and less than 1% of 4G users migrate to the 5G subscription for migration threshold levels of 0.03 and 0.06. There's no change in the number of RAT subscriptions for the other levels of migration thresholds when a maximum incentive of 0.15 is introduced into the HWN. Figure 5.7 below shows the resource utilisation (5.7.c), call blocking probability (5.7.a) and call dropping probability (5.7.b) for network subscriptions (5.6) when the incentive introduced is capped at maximum value of 0.15.

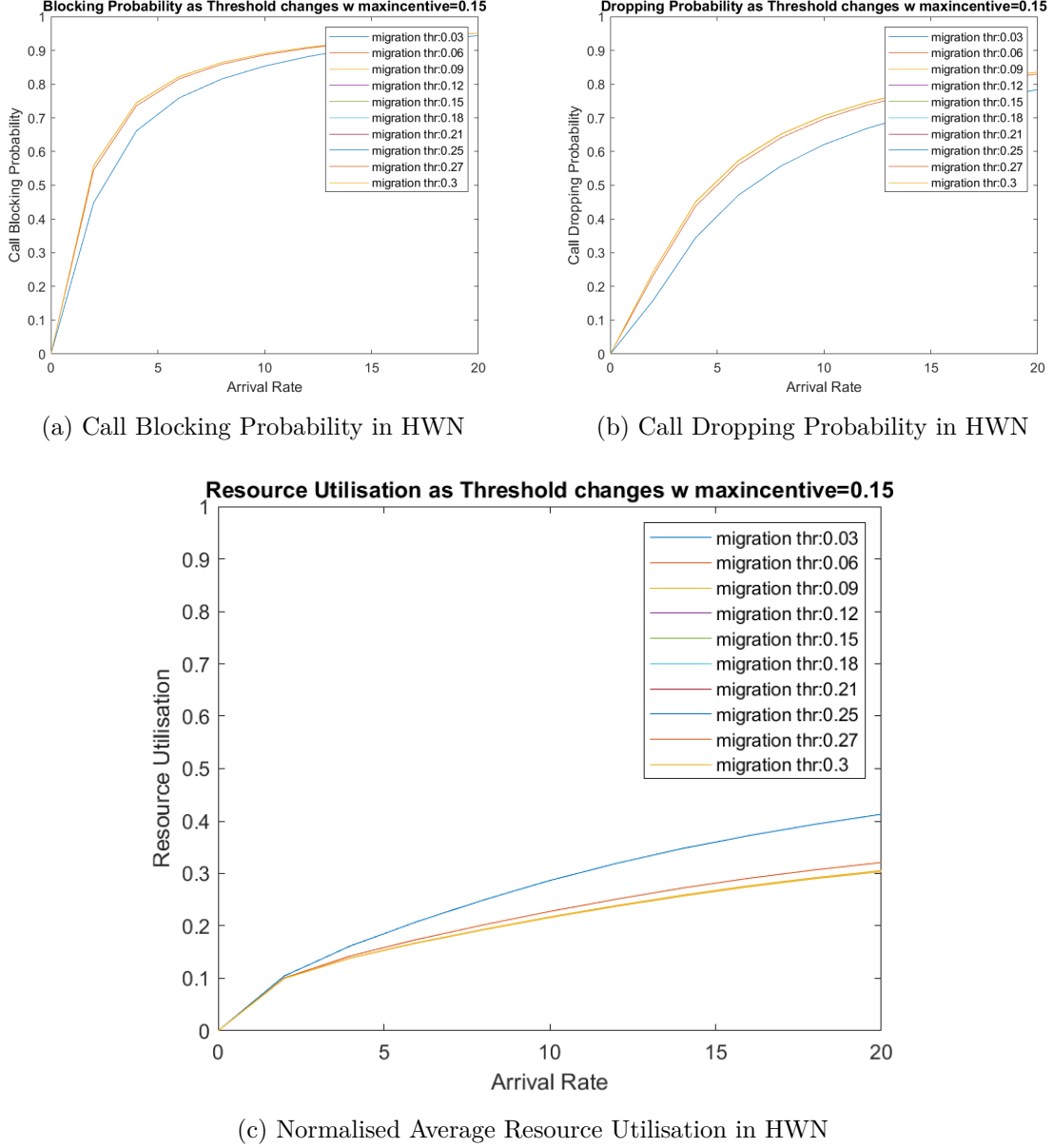


Figure 5.7: Network Subscriptions and Performance with maximum incentive of 0.15

The resource utilisation (seen in figure 5.7.c) increases concave-down from 0 to 0.41 and 0.32 at migration thresholds 0.03 and 0.06, respectively, as the total arrival rate of calls in the network increases to 20. There is no significant change ($< 1\%$) in the resource utilization when the migration threshold is 0.09. For all other migration threshold levels the resource utilisation increases from 0 to approximately 0.3.

The Call blocking probability (seen in figure 5.7.a) increases concave-down from 0% to approximately 95% for all levels of the migration threshold as the total arrival rate of calls in the network increases to 20. A slight difference is seen in the slopes between migration thresholds greater than 0.03, with the blocking probability at the migration threshold of 0.03 being less than at the other migration thresholds.

As the total arrival rate into the HWN is increased from 0 to 20, the call dropping probability (seen in figure 5.7.c) increases concave-down from 0% to approximately 78% at a migration threshold level of 0.03 with all the other call dropping probabilities for migration thresholds greater than 0.03 rising, within 1% of each other, to 83%. The call-blocking probability is greater than the call-dropping probability irrespective of the arrival rate.

Results for maximum incentive=0.25:

Figure 5.8 shows the number of subscriptions for the various RATs in the HWN when there is a maximum incentive of 0.25 introduced into the network at varying levels of threshold for migration.

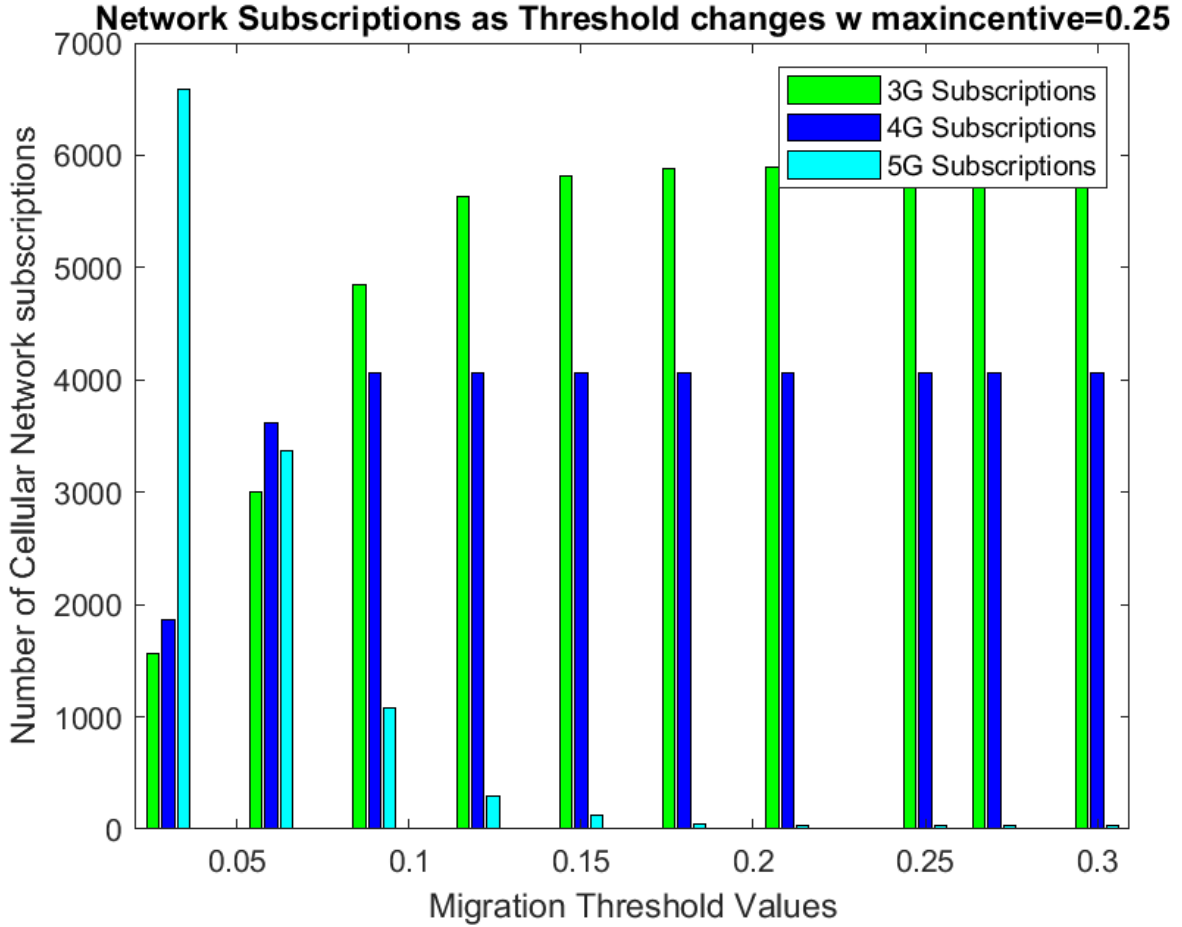
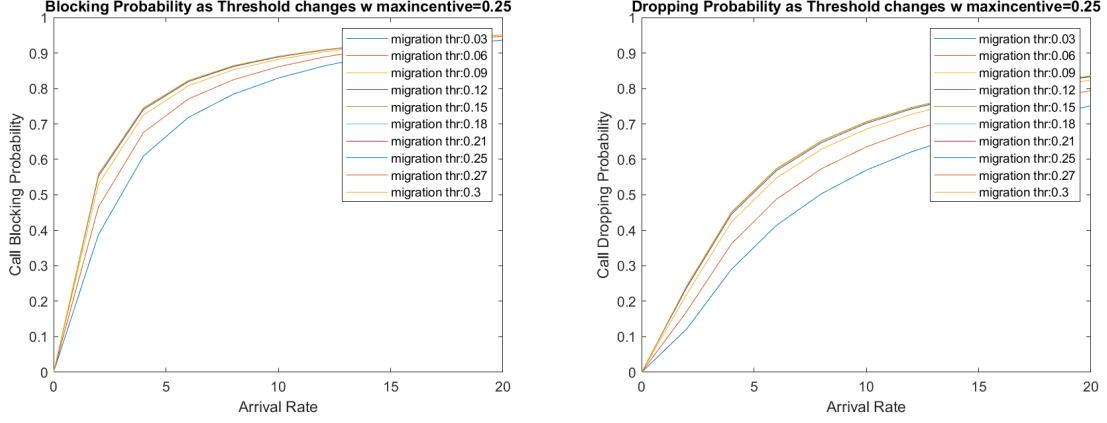


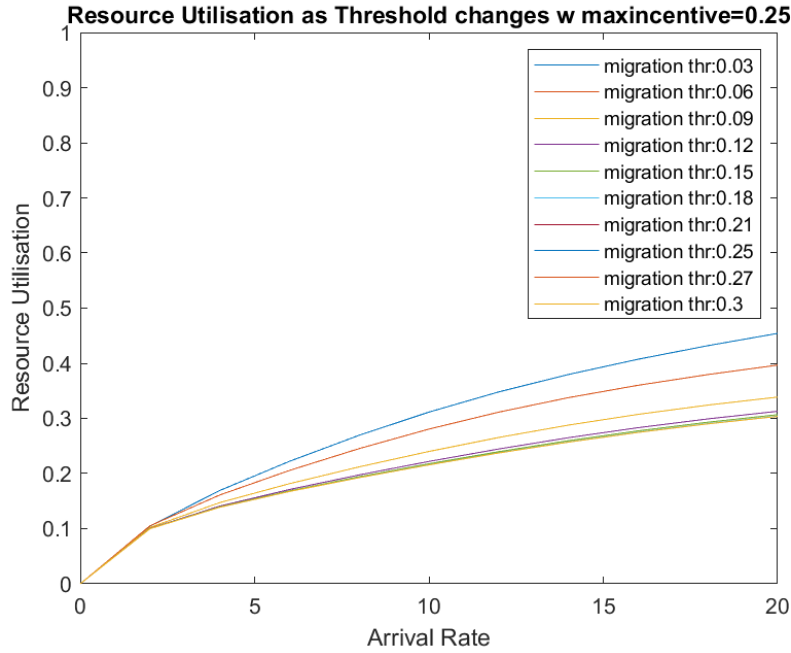
Figure 5.8: Mobile Cellular Subscriptions in HWN

As seen in figure 5.8, approximately 73%, 49%, 18%, 4.5%, 1.5% and less than 1% of 3G users migrate to the 5G subscription when the migration threshold level is 0.03, 0.06, 0.09, 0.12, 0.15 and 0.18, respectively. 54%, 11% and less than 1% of 4G users migrate to the 5G subscription for migration threshold levels of 0.03, 0.06 and 0.09, respectively. There's no change in the number of RAT subscriptions for the other levels of migration thresholds when a maximum incentive of 0.25 is introduced into the HWN. Figure 5.9 below shows the resource utilisation (5.9.c), call blocking probability (5.9.a) and call dropping probability (5.9.b) for network subscriptions (5.8) when there is a maximum incentive of 0.25 introduced into the HWN.



(a) Call Blocking Probability in HWN

(b) Call Dropping Probability in HWN



(c) Normalised Average Resource Utilisation in HWN

Figure 5.9: Network Subscriptions and Performance with maximum incentive of 0.25

As the total arrival rate of calls in the network increases from 0 to 20, the resource utilisation (seen in figure 5.9.c) increases concave-down from 0 to 0.45, 0.39, 0.34 and 0.31 at migration thresholds 0.03, 0.06, 0.09 and 0.12, respectively. There is no significant change ($< 1\%$) in the resource utilization when the migration threshold is greater than 0.15, with the resource utilisation increasing from 0 to an approximate value 0.30.

As the total arrival rate of calls in the network increases to 20, the call blocking probability (seen in figure 5.9.a) increases concave-down from 0% to within a 2% range of 94% for all levels of the migration threshold, with a threshold of 0.03 resulting in the lowest blocking probability, 93.5%. A slight difference is seen in the slopes at lower arrival rates between migration thresholds greater than 0.09, with the blocking probability at the migration threshold of 0.03 and 0.06 being less than at the other migration thresholds. The slope of the blocking probability at a threshold of 0.03 is the lowest at

all the arrival rates.

As the total arrival rate into the HWN is increased from 0 to 20, the call dropping probability (seen in figure 5.9.b) increases concave-down from 0% to approximately 75% and 79% at migration threshold levels of 0.03 and 0.06, respectively, with all the other call dropping probabilities for migration thresholds greater than 0.06 rising, within 1% of each other, to 83%. Smaller dropping probabilities are seen at lower migration thresholds for lower arrival rates. The call-blocking probability is greater than the call-dropping probability irrespective of the arrival rate.

Chapter 6

Discussions

6.1 Analysis of Evaluated User Utilities

This section analyses the results of the Evaluated User Utilities section 5.1 where user utilities were illustrated through a box plot of user utilities, which are calculated for three different scenarios: baseline network utilities, expected utilities on the unincentivized 5G network, and expected utilities on the incentivized 5G network with varying levels of maximum incentives offered by network providers.

The baseline utilities represent the user experience on their current networks. The relatively stable baseline utilities indicate that users are content with their existing network subscriptions. However, it's worth noting that the baseline utilities can vary among different user categories, and some users may have a stronger or weaker incentive to migrate due to better or reduced potential utility on 5G.

The most notable finding is that the mean utility on the incentivized 5G network is greater than that on the unincentivized 5G network. The increase in mean utility with higher incentive levels suggests that users are responsive to incentives, with an increasing potential for their migration decisions to be influenced by the coupon value. Higher incentives are more likely to motivate users to switch from their existing networks to 5G.

6.2 Migration of Users

6.2.1 Effects of Varying Maximum Incentive

The simulation results presented in the Migration & Network Performance section of Chapter 5:Results indicate that the maximum incentive level has a substantial impact on user migration. As the maximum incentive level increases from 0 to 0.25, more users migrate to the 5G network. The results show that a substantial number of 3G users tend to migrate when higher incentives are offered. This migration is most prominent when both the maximum incentive level and migration threshold are high. In the case of 4G users, their migration is less pronounced compared to 3G users, but it still occurs when the incentives are enticing enough.

The results strongly suggest that incentives play a significant role in encouraging users to migrate to 5G networks. Higher incentives lead to a greater mean utility on 5G, indicating a stronger willingness to migrate. However, the model is more attuned to incentivising users who have higher utilities on their current subscription. This implies that users who are on 4G are less likely to migrate to 5G in response to the incentive.

6.2.2 Effects of Varying Migration Thresholds

Migration thresholds, representing the users' sensitivity to incentives, also play a crucial role. When the migration threshold is low (e.g., 0.03), a significant proportion of users migrate, especially when the maximum incentive is substantial. As the migration threshold increases, meaning users require a larger utility gain to switch to 5G, the percentage of users migrating to 5G decreases. This is an expected outcome, as users are less likely to switch if the threshold for migration is set high.

This suggests that the sensitivity of users to incentives is a crucial factor in determining the success of network migration strategies. In scenarios where users are not as price-sensitive, demonstrated with a high threshold for migration, they may not react to the incentive being introduced whereas in instances where consumers are sensitive to the price (lower threshold for migration), they may react positively to the incentive being introduced.

This observation indicates that migration is less likely to occur when consumers are indifferent to the cost of acquiring 5G subscriptions. Other means of incentivising these consumers without reducing the cost may be more effective.

6.3 Effects on Network Performance

6.3.1 QoS in the Network

The research shows that both call blocking and call dropping probabilities increase as the migration threshold decreases. This is because a lower migration threshold means more users migrate to 5G, which consequently decreases the probability of call blocking and dropping as users can be serviced by more than one cellular network when making a service request and the data traffic in older generations is reduced. This can be attributed to the decreased congestion in older generations of cellular networks when users migrate to newer generations. As newer generations are faster in servicing calls, the overall congestion in the network is effectively reduced as the load in newer generations is less than in older generations if the arrival rate into the RATs were equivalent.

6.3.2 Resource Utilisation in the Network

The findings suggest that introducing incentives for users to migrate to 5G networks can lead to improved resource utilization in a wireless network. This improvement is more prominent when high incentives are offered, as a higher number of users migrate to 5G. Improved resource utilization could mean fewer dropped calls, reduced call blocking, and overall better network performance.

These results are consistent with the section in the reviewed literature (chapter 2) on the Effects of users' migration on QoS and overall resource utilisation as an improvement in QoS provisioning and resource utilisation can be noted.

6.4 Real-World Implications

In a real-world scenario, this indicates that network operators can strategically use incentives to steer users towards 5G adoption. Network operators should carefully design incentive structures to attract

users while managing the costs associated with the incentives. The optimal balance between attracting users and maintaining profitability is crucial.

The results of the incentive model performing differently with varying thresholds for migrations suggest that network operators should understand their user base and tailor incentives accordingly. Different user categories may have varying sensitivity to incentives, and a one-size-fits-all approach may not be as effective. Because 4G users are more likely to migrate to 5G than 3G users, the incentive scheme can be optimised to be less preferential towards 3G users and ultimately incentivise 4G users to shift to 5G.

Regulatory bodies should consider the role of incentives in promoting network technology transitions. Encouraging operators to offer compelling incentives may help expedite the adoption of advanced networks, benefiting consumers and the overall industry.

Chapter 7

Conclusions

Incentive pricing models can contribute to the network operator's ability to accelerate user migration and optimize resource allocation. The purpose of this project was to investigate the impact of incentive pricing on users' migration in the next generation mobile networks. It sought out to propose an incentive pricing model and evaluate its effectiveness in the impact it may have on the QoS and resource utilisation performance in a heterogeneous wireless network.

This report began with a general introduction to the problem statement in Chapter 1, highlighting the significance of incentive pricing strategies in accelerating user migration to next-generation mobile networks, with an emphasis on 5G adoption in South Africa.

The literature review followed in Chapter 2, which provided an overview of the progression of mobile networks, 5G use cases and it explored the deployment and migration to 5G, addressing the challenges in 5G implementation, and user adoption. This established an understanding of the network landscape in Southern African review and set the context for the investigations to follow. A thorough review was then conducted on existing incentive pricing schemes, which revealed that little to no emphasis has been placed on the implementation of incentive pricing to motivate users to migrate to newer generation mobile networks.

The bulk of the design work for this project followed next, in Chapter 3, where the solution of an incentive model was proposed. The method for using the multi-attribute utility theory and utility-difference threshold for determining the contentment users had with their current network subscriptions and if they would migrate was also introduced in this chapter.

Chapter 4 detailed the system model upon which the incentive scheme proposed in chapter 3 would be evaluated. The heterogeneous wireless network, its related parameters and Markovian properties, which would enable the analysis of its performance, were defined. The process of determining resource utilisation and call blocking and dropping probability, as they relate to the QoS in the network, was detailed.

Chapter 5, presents the outcomes of a simulation involving 10,000 users with existing cellular network subscriptions, evaluating user utilities on baseline, unincentivized, and incentivized 5G networks with varying maximum incentives and thresholds for migration. Elaborate discussions on these results were presented in Chapter 6 which established that as the maximum incentive offered by network providers increases with smaller thresholds for migration, the expected mean utility on the incentivized 5G network rises proportionally, influencing user migration behaviour and network performance. Higher values for migration thresholds resulted in little to no migration happening, which indicates that the

model may not be as effective in scenarios where users may not be easily persuaded by incentives (eg. rural areas). With the cost and availability of the 5G network being its main disadvantages, network providers may need to consider ways to increase availability through faster deployment or reduce the influence this may have on consumers' decision not to migrate to 5G.

In summary, the project achieved the goals that were set out, by designing and demonstrating an incentive pricing model to accelerate user migration to next-generation mobile networks, particularly 5G in South Africa. The model, based on multi-attribute utility theory and utility-difference threshold, highlights the significance of incentive schemes in improving network performance by influencing user migration behaviour. Future work can build upon this research to optimize incentive pricing models for mobile network operators in the context of heterogeneous wireless networks.

Chapter 8

Recommendations

The simulation model may not account for all the nuances of a real-world cellular network. It might not capture the full complexity of user behavior, network infrastructure, and external factors that can influence migration patterns. Future research should focus on developing more realistic models for user behavior. This may include considering a broader range of factors that influence user decisions to migrate to 5G, such as pricing, coverage, device compatibility, and user experiences.

While randomly assigning user weights can provide a controlled setting for the simulation as was done in this project, in the real world, user preferences and decisions to switch networks are influenced by a wide range of factors, including pricing, coverage, quality of service, device compatibility, and personal preferences. These factors are not fully captured in the simulation so the introduction of dynamic user weight assignments to capture the evolving nature of user preferences over time should be considered for future work. User weights could change based on user experiences, network quality, and evolving market conditions.

Real cellular networks are dynamic, with cellular network providers in competition with each other. There are continuous with continuous changes in user demand, network capacity, and technological advancements. The simulations do not account for these dynamic elements as well as incentive programs which can vary widely, with their effectiveness depending on multiple factors, including the perceived value of the incentives by users. The exploration of the effectiveness of different incentive programs should be considered, particularly how different types of incentives such as price discounts, free devices and bundled services impact user migration and network performance and how feasible their implementation is.

External factors such as regulatory policies, economic conditions, and global events can also significantly impact user migration and network performance. These factors are not considered in the simulation and could be for future works.

While the simulation assesses network performance metrics, it may not fully capture the intricacies of real-world network management, including load balancing, network optimization, and the deployment of additional infrastructure to accommodate increased demand. It also does not consider incentive schemes which have a direct effect on resource management. Future work could include the simulations which account for incentive pricing schemes which have an effect on resource management in HWNs.

The simulation uses a utility model to predict user behavior, which is a simplification of the complex decision-making processes of real users. The utility model used is static by design and may impractical for modelling dynamic factors which may occur in the network. Further research may be required to

establish which method is best for measuring satisfaction.

Bibliography

- [1] I. T. U. (ITU), “5G Technology: A Comprehensive Overview,” ITU, Tech. Rep., 2018. [Online]. Available: https://www.itu.int/en/ITU-D/Documents/ITU_5G_REPORT-2018.pdf
- [2] A. Khakimov, D. Poluektov, E. Mokrov, Y. Koucheryavy, and K. Samouylov, “Prototyping 5g network in laboratory testbed with virtual deployment environment,” in *2020 International Scientific and Technical Conference Modern Computer Network Technologies (MoNeTeC)*, 2020, pp. 1–7.
- [3] G. Oloruntade. (2023) With 5 million subscriptions, south africa leads the 5g race in africa. [Online]. Available: <https://technext24.com/2023/04/05/south-africa-leads-5g-in-africa/>
- [4] ICASA, “The State of the ICT Sector Report in South Africa (updated version),” 2023.
- [5] ICASA, “5g annual report,” ICASA, Tech. Rep., 2021. [Online]. Available: <https://www.icasa.org.za/uploads/files/ICASA-2021-5G-Annual-Report.pdf>
- [6] E. K. K. Okeleke, J. Joiner, “5g in africa: realising the potential,” GSMA, Tech. Rep., 2022. [Online]. Available: <https://www.gsma.com/subsaharanafrica/wp-content/uploads/2022/10/5G-IN-AFRICA-REPORT.pdf>
- [7] A. Khakimov, D. Poluektov, E. Mokrov, Y. Koucheryavy, and K. Samouylov, “Prototyping 5g network in laboratory testbed with virtual deployment environment,” in *2020 International Scientific and Technical Conference Modern Computer Network Technologies (MoNeTeC)*, 2020, pp. 1–7.
- [8] B. P. Center. Cellular data and the digital divide. <https://bipartisanpolicy.org/blog/cellular-data-and-digital-divide/>.
- [9] F. Fransman, “Opinion | the 5g effect and covid conspiracies: Why these notions must be dispelled,” *News24*, 2021. [Online]. Available: <https://www.news24.com/news24/opinions/columnists/guestcolumn/opinion-the-5g-effect-and-covid-conspiracies-why-these-notions-must-be-dispelled-20210408>
- [10] E. Obayiuwana and O. Falowo, “Network selection in heterogeneous wireless networks using multi-criteria decision-making algorithms: a review,” *Wireless Networks*, vol. 23, pp. 2617–2649, 2017. [Online]. Available: <https://doi.org/10.1007/s11276-016-1301-4>
- [11] “On the ultra-reliable and low-latency communications for tactile internet in 5g era,” [Accessed 21 Sep, 2023]. [Online]. Available: https://www.researchgate.net/figure/Throughput-and-latency-in-1G-to-5G_tbl1_346066286

- [12] R. Wyrzykowski, “South Africa Mobile Network Experience Report,” Opensignal, Tech. Rep., March 2023.
- [13] GSM Arena. Accessed: 15/09/2023. [Online]. Available: <https://www.gsmarena.com/>
- [14] 5G PPP. (Year or n.d.) The 5g infrastructure public private partnership (5g ppp). Accessed: Date. [Online]. Available: <https://5g-ppp.eu/kpis/>
- [15] J. Mortensen. (2023) Are 5g phones backwards compatible? <https://techevaluate.com/are-5g-phones-backwards-compatible/>. Last Updated April 29, 2023.
- [16] O. Falowo, “Effect of users’ equipment capability on utilization of heterogeneous wireless networks,” in *2022 IEEE Wireless and Mobile Computing, Networking and Communications (WiMob) Short Papers, Posters and Demos Track*. University of Cape Town, Department of Electrical Engineering: IEEE, 2022.
- [17] A. Chatterjee, L. Czajka, and A. Gethin. (2020, April) Estimating the distribution of household wealth in south africa. [Online]. Available: <chrome-extension://efaidnbmnnnibpcajpcgclefindmkaj/https://wid.world/document/estimating-the-distribution-of-household-wealth-in-south-africa-wid-world-working-paper-2020-06/>
- [18] I. Edge. (2022, Nov) The digital divide in south africa. Blog. [Online]. Available: <https://innovationedge.org.za/the-digital-divide-in-south-africa/>
- [19] T. Economics. (2023) South africa urban population percent of total. Accessed: 20/09/2023. [Online]. Available: <https://tradingeconomics.com/south-africa/urban-population-percent-of-total-wb-data.html>
- [20] BMIT Africa. (2023) Digital lifestyle measure. <https://www.bmit.africa/digital-lifestyle-measure/>. [Online; accessed September 20, 2023].
- [21] S. Ross. (2023) Utility in microeconomics: Origins, types, and uses. <https://www.investopedia.com/ask/answers/032615/what-concept-utility-microeconomics.asp>. Investopedia. Updated September 16, 2023. Reviewed by Somer Anderson. [Online]. Available: <https://www.investopedia.com/ask/answers/032615/what-concept-utility-microeconomics.asp>
- [22] S. Jansen, “The multi-attribute utility method,” pp. 101–125, 05 2011.
- [23] D. Jiang, L. Huo, Z. Lv, H. Song, and W. Qin, “A joint multi-criteria utility-based network selection approach for vehicle-to-infrastructure networking,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 10, p. 3305, October 2018.
- [24] Łukasz Radliński, “Predicting user satisfaction in software projects using machine learning techniques,” *Faculty of Computer Science and Information Technology, West Pomeranian University of Technology in Szczecin*, 2020.
- [25] M. A. Alshamari, “Evaluating user satisfaction using deep-learning-based sentiment analysis for social media data in saudi arabia’s telecommunication sector,” *Computers*, vol. 12, no. 9, p. 170,

2023, received: 26 June 2023 / Revised: 15 August 2023 / Accepted: 23 August 2023 / Published: 26 August 2023. [Online]. Available: <https://doi.org/10.3390/computers12090170>

- [26] L. A. Dasilva, H. Bogucka, and A. B. Mackenzie, “Game theory in wireless networks,” *IEEE Communications Magazine*, vol. 49, 2011.
- [27] A. Wilczyński, A. Jakóbik, and J. Kołodziej, “Stackelberg security games: Models, applications, and computational aspects,” *AGH University of Science and Technology, Cracow, Poland*, 2016.
- [28] I. Loumiotis, E. Adamopoulou, K. Demestichas *et al.*, “Road to next generation mobile networks: An evolutionary dynamics approach,” *Mobile Networks and Applications*, vol. 21, no. 2, pp. 237–246, April 2016.
- [29] Y. Qi and H. Wang, “Incentive pricing mechanism for hybrid access in femtocell networks,” *IEEE Communications Letters*, vol. 21, no. 5, 2017.
- [30] X. Zhuo, W. Gao, G. Cao, and S. Hua, “Win-coupon: An incentive framework for 3g cellular traffic offloading,” *IEEE Transactions on Mobile Computing*, vol. 13, no. 3, pp. 535–548, March 2014.
- [31] R. V. J. Dayot and I.-H. Ra, “Slice admission and deployment strategies in resource-constrained 5g network slices using an actor-critic approach,” in *2022 Joint 12th International Conference on Soft Computing and Intelligent Systems and 23rd International Symposium on Advanced Intelligent Systems (SCIS&ISIS)*, 2022, pp. 1–4.
- [32] Amazon Web Services. (2023) Amazon EC2 - Elastic Compute Cloud. [Online; accessed 21/08/2023]. [Online]. Available: <https://aws.amazon.com/ec2/>
- [33] S. Yang, L. Pan, and S. Liu, “An online algorithm for selling your reserved IaaS instances in Amazon EC2 marketplace,” in *Proc. IEEE Int. Conf. Web Services (ICWS)*, 2019, pp. 296–303.
- [34] M. Khodak, L. Zheng, A. S. Lan, C. Joe-Wong, and M. Chiang, “Learning cloud dynamics to optimize spot instance bidding strategies,” in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, 2018, pp. 2762–2770.
- [35] N. Kamiyama, “Virtual machine trading in public clouds,” *IEEE Transactions on Network and Service Management*, vol. 17, no. 1, pp. 403–415, Mar. 2020.
- [36] S. Li, J. Huang, and B. Cheng, “A price-incentive resource auction mechanism balancing the interests between users and cloud service provider,” *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 2030–2045, 2021.
- [37] MathWorks. Fuzzy logic designer. <https://www.mathworks.com/help/fuzzy/fuzzylogicdesigner-app.html>. Accessed: 25/08/2023.
- [38] D. P. Soetanto, “Implementing fuzzy logic in determining selling price,” *Universitas Kristen Petra Industrial Journal*, vol. 43, 2000. [Online]. Available: <http://puslit.petra.ac.id/journals/industrial>
- [39] R. P. S. Bedi and A. Singh, “Software cost estimation using fuzzy logic technique,” *Indian Journal of Science and Technology*, vol. 10, no. 3, January 2017.

- [40] X. Pan and Z. Zuo, “Exploring the role of utility difference threshold in choice behavior: An empirical case study of bus service choice,” *International Journal of Transportation Science and Technology*, vol. 9, no. 2, pp. 128–136, June 2020.
- [41] RantCell. What are the differences between 2g, 3g, 4g lte, and 5g networks? Accessed: 10/10/2023. [Online]. Available: <https://rantcell.com/comparison-of-2g-3g-4g-5g.html>
- [42] O. E. Falowo, “Joint call admission control algorithm for reducing call blocking/dropping probability in heterogeneous wireless networks supporting multihoming,” in *2010 IEEE Globecom Workshops*, 2010, pp. 611–615.

Appendix A

Fuzzy Inference System: Cost

[System] Name='fuzzycost' Type='mamdani' Version=2.0 NumInputs=3 NumOutputs=1 NumRules=27
AndMethod='min' OrMethod='max' ImpMethod='min' AggMethod='max' DefuzzMethod='centroid'

[Input1] Name='data_speed' Range=[0 1] NumMFs=3 MF1='3g': 'gaussmf',[0.1769 -1.388e-17]
MF2='4g': 'gaussmf',[0.1769 0.5] MF3='5g': 'gaussmf',[0.1769 1]

[Input2] Name='data_allowance' Range=[0 1] NumMFs=3 MF1='low': 'trimf',[-0.3532 0 0.3532]
MF2='moderate': 'trimf',[0.1468 0.5 0.8532] MF3='high': 'trimf',[0.6468 1 1.353]

[Input3] Name='device cost' Range=[0 1] NumMFs=3 MF1='low': 'trapmf',[-0.45 -0.05 0.05 0.45]
MF2='moderate': 'trapmf',[0.05006 0.45 0.55 0.9499] MF3='high': 'trapmf',[0.5501 0.95 1.05 1.45]

[Output1] Name='cost' Range=[0 1] NumMFs=3 MF1='low': 'trimf',[-0.3532 0 0.3532]
MF2='moderate': 'trimf',[0.1468 0.5 0.8532] MF3='high': 'trimf',[0.6468 1 1.353]

[Rules] 1 1 1, 1 (1) : 1 2 1 1, 2 (1) : 1 3 1 1, 2 (1) : 1 1 2 1, 1 (1) : 1 2 2 1, 1 (1) : 1 3 2 1, 3 (1) : 1 1 3
1, 1 (1) : 1 2 3 1, 1 (1) : 1 3 3 1, 2 (1) : 1 1 1 2, 1 (1) : 1 2 1 2, 2 (1) : 1 3 1 2, 3 (1) : 1 1 2 2, 1 (1) : 1
2 2 2, 2 (1) : 1 3 2 2, 3 (1) : 1 1 3 2, 1 (1) : 1 2 3 2, 2 (1) : 1 3 3 2, 3 (1) : 1 1 1 3, 1 (1) : 1 2 1 3, 3 (1)
: 1 3 1 3, 3 (1) : 1 1 2 3, 2 (1) : 1 2 2 3, 3 (1) : 1 3 2 3, 3 (1) : 1 1 3 3, 2 (1) : 1 2 3 3, 3 (1) : 1 3 3 3, 3
(1) : 1

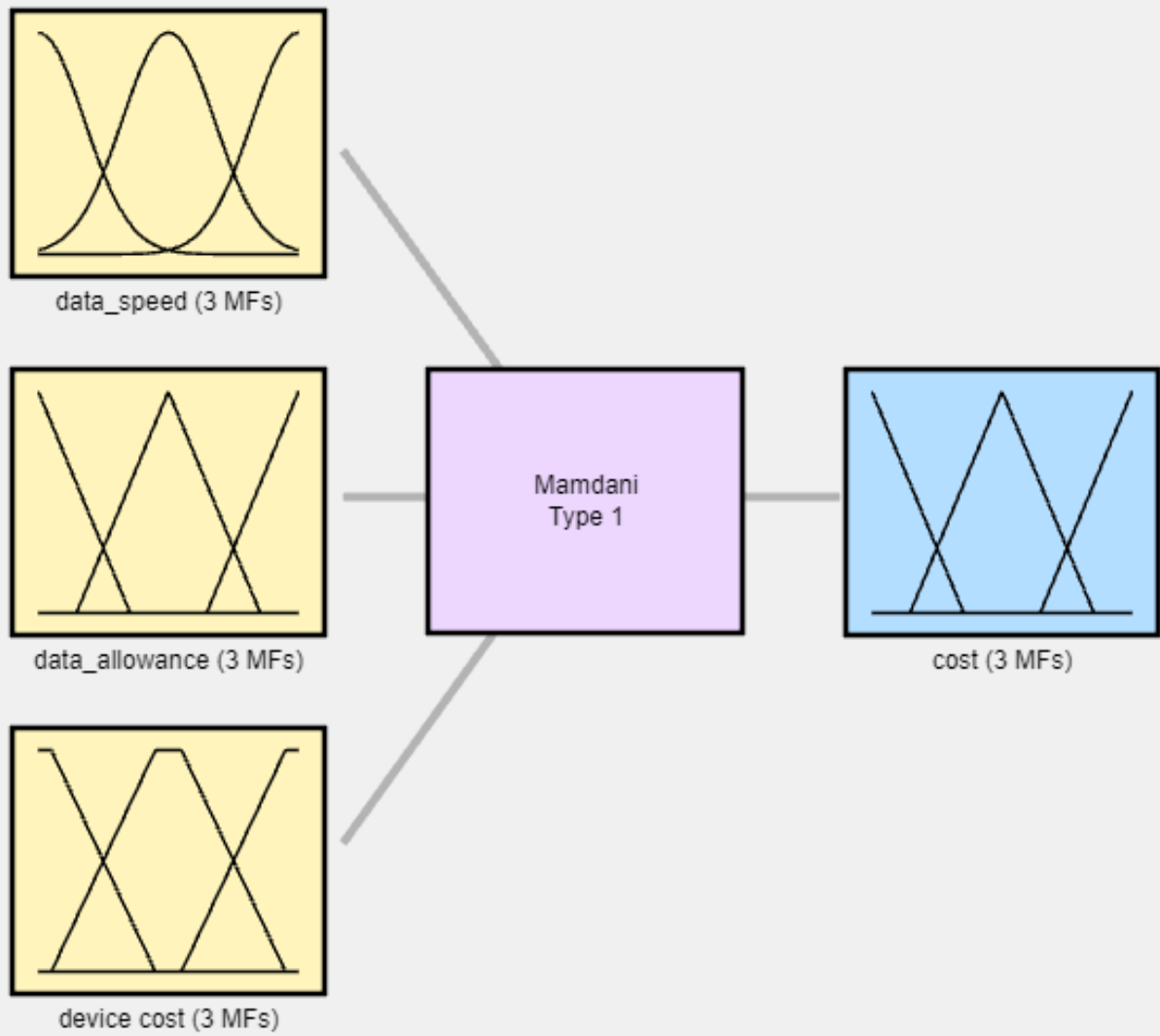


Figure A.1: Fuzzy Inference System Plot

Appendix B

Code: MAUT Function

```
%Omoemo Kegakilwe KGKOM0001 EEE4022S Project Model
%computing utilities for users

classdef attr_val
    methods(Static)

        % Cost Attribute Value
        function cost_vals = cost(nwType)
            nwCostValues = struct( 'G3', 0.3843, 'G4', 0.5816, 'G5', (0.7522));

            % Initialize an array to store cost values
            cost_vals = zeros(length(nwType),1);

            % Iterate through network types and calculate cost for each
            for i = 1:numel(nwType)
                % Get the cost value for the specified network type
                networkCost = nwCostValues.(nwType{i});

                cost_vals(i) = 1-networkCost;
                cost_vals(i) = max(0, min(1, cost_vals(i)));
            end
        end

        % Data Rate Attribute Value
        function rate_vals = datarate(nwType)
            nwRateRanges = struct('G3', [0.5 5], 'G4', [1 50], 'G5', [50 450]);
            rate_vals = zeros(length(nwType),1);

            for i = 1:numel(nwType)
                nwRange = nwRateRanges.(nwType{i});
                nwRate = normrnd((nwRange(1) + nwRange(2)) / 2, (nwRange(2) - nwRange(1)) / 4);
                rate_vals(i) = max(0,min(1,real(log(nwRate)/log(450))));
            end
        end
    end
end
```

```

function covrge_vals = coverage(nwType)
    nwcoverageValues = struct('G3', 1.00, 'G4', 0.99, 'G5', 0.30);
    covrge_vals = zeros(length(nwType),1);

    for i = 1:numel(nwType)
        nwcovrge= nwcoverageValues.(nwType{i});
        covrge_vals(i) = max(0,min(1,nwcovrge));
    end
end

function attr_vals= all(nwType)
    attr_vals= [attr_val.cost(nwType), attr_val.datarate(nwType),...
        attr_val.delay(nwType), attr_val.coverage(nwType)];
end

function [weighted_attr_vals,user_u]=utility(weights, attr_vals)
    user_u = zeros(length(attr_vals),1);
    weighted_attr_vals= zeros(length(attr_vals),4);

    % Calculate the utility for each row
    for i = 1:length(weights)
        weighted_attr_vals(i,:)=weights(i, :) .* attr_vals(i, :);

        user_u(i) = sum(weighted_attr_vals(i,:));
    end
end

```

Appendix C

Code: Incentive Model

```
function [weighted_incentive_attr_vals,incentive_utilites] = incentive_utility(weights, x_attr_vals,...  
    g_attr_vals,max_incentive)  
  
    incentive_attr_vals=g_attr_vals;  
    incentive_utilites=zeros(length(weights),1);  
    weighted_incentive_attr_vals=zeros(length(weights),4);  
  
    % Define the maximum incentive (m) and the weights for the attributes  
    m = max_incentive;  
  
    for i = 1:length(weights)  
        u_weights=weights(i,:);  
        u_x_attr_vals=x_attr_vals(i,:);  
        u_g_attr_vals=g_attr_vals(i,:);  
  
        c=(1-u_g_attr_vals(1));  
  
        alpha=max(0,(u_weights(1)*u_x_attr_vals(1))-(u_weights(1)*u_g_attr_vals(1))+...  
            max(0,(u_weights(2)*u_x_attr_vals(2))-(u_weights(2)*u_g_attr_vals(2)))+...  
            max(0,(u_weights(3)*u_x_attr_vals(3))-(u_weights(3)*u_g_attr_vals(3)))+...  
            max(0,(u_weights(4)*u_x_attr_vals(4))-(u_weights(4)*u_g_attr_vals(4))));  
  
        incentive_attr_vals(i,1)=1-max(c-alpha,c-m);  
  
        weighted_incentive_attr_vals(i,:)=u_weights.* incentive_attr_vals(i, :);  
  
        incentive_utilites(i) = sum(weighted_incentive_attr_vals(i,:));  
    end  
end
```

Appendix D

Code: Simulation

```
%Omoemo Kegakilwe KGKOM0001 EEE4022S Project Model
%Find different HWN distributions

filepath="figures/results/";
if ~isfolder(filepath)
    mkdir(filepath);
end

numUsers = 10000;

% Defining User Weights/preferences
prob_DLM1 = 0.1;
prob_DLM2 = 0.2;
prob_DLM3 = 0.3;
prob_DLM4 = 0.2;
prob_DLM5 = 0.1;

categoryLabels = discretize(rand(1, numUsers), [0, prob_DLM1, prob_DLM1 + ...
    prob_DLM2, prob_DLM1 + prob_DLM2 + prob_DLM3, prob_DLM1 + prob_DLM2 + ...
    prob_DLM3 + prob_DLM4, 1], {'DLM1', 'DLM2', 'DLM3', 'DLM4', 'DLM5'});
categoryLabels = sort(categoryLabels);

weightsMatrix = zeros(numUsers, 4);

for i = 1:numUsers
    switch categoryLabels{i}
        case 'DLM1'
            weightsMatrix(i, :) = [1 * rand(), 0.0 + 0.4 * rand(),...
                0.0 + 0.4 * rand(), 0.0 + 0.4 * rand()];
        case 'DLM2'
            weightsMatrix(i, :) = [rand(), 0.2 + 0.3 * rand(),...
                0.3 + 0.4 * rand(), 0.3 + 0.4 * rand()];
        case 'DLM3'
            weightsMatrix(i, :) = [rand(), 0.3 + 0.4 * rand(),...
                0.4 + 0.4 * rand(), 0.4 + 0.4 * rand()];
        case 'DLM4'
            weightsMatrix(i, :) = [rand(), 0.5 + 0.3 * rand(),...
                0.5 + 0.3 * rand(), 0.5 + 0.3 * rand()];
        case 'DLM5'
            weightsMatrix(i, :) = [rand(), 0.7 + 0.3 * rand(),...
                0.7 + 0.3 * rand(), 0.7 + 0.3 * rand()];
    end
end
normalizedWeights = weightsMatrix ./ sum(weightsMatrix, 2);
```

```

% determine baseline values (control measurement)
scale_users=numUsers/(numUsers-numUsers*0.017);
num3G = round((0.58 * numUsers)*scale_users);
num4G = round((0.4 * numUsers)*scale_users);
num5G = round((0.003 * numUsers)*scale_users);

nw_users = [num3G, num4G, num5G];
baseline = [repmat("G3", round(num3G), 1);
            repmat("G4", num4G, 1);
            repmat("G5", num5G, 1)];

% calculate and plot baseline total user utility
% Determine attribute values
cost_vals= attr_val.cost(baseline);
rate_vals= attr_val.datarate(baseline);
delay_vals= attr_val.delay(baseline);
covrge_vals=attr_val.coverage(baseline);

baseline_attr_vals = [cost_vals, delay_vals, rate_vals, covrge_vals];
[weighted_baseline_attr_vals,baseline_utilities]=...
    attr_val.utility(normalizedWeights,baseline_attr_vals);
baseline_utilities_stats=attr_val.stats(baseline_utilities);
average_utility = cellfun(@mean, mat2cell(baseline_utilities, nw_users, 1));
counts_baseline = countcats(categorical(baseline, ["G3", "G4", "G5"]));

% user utility on 5G current sub
nw_sub=repmat("G5", numUsers, 1);
attr_vals_5G= attr_val.all(nw_sub);
[weighted_5G_attr_vals,utilities_on_5G]=...
    attr_val.utility(normalizedWeights,attr_vals_5G);
utilities_on_5G_stats=attr_val.stats(baseline_utilities);

utilities={baseline_utilities,utilities_on_5G};
utilities_labels = {'Baseline', '5G'};

% Define an array of reserve prices
max_incentives = [0,0.05,0.1, 0.15, 0.2, 0.25,0.30];

% HWN user distribution with differing threshold values
threshold_levels = [0.03, 0.06, 0.09, 0.12, 0.15, 0.18, 0.21, 0.25,0.27,0.30];

% Create a cell array to store results for each reserve price
results = cell(length(max_incentives), 1);

```

```

% user utility on 5G current sub
nw_sub= repmat("G5", numUsers, 1);
attr_vals_5G= attr_val.all(nw_sub);
[weighted_5G_attr_vals,utilities_on_5G]=...
    attr_val.utility(normalizedWeights,attr_vals_5G);
utilities_on_5G_stats=attr_val.stats(baseline_utilities);

utilities={baseline_utilities,utilities_on_5G};
utilities_labels = {'Baseline', '5G'};

% Define an array of reserve prices
max_incentives = [0,0.05,0.1, 0.15, 0.2, 0.25,0.30];

% HWN user distribution with differing threshold values
threshold_levels = [0.03, 0.06, 0.09, 0.12, 0.15, 0.18, 0.21, 0.25,0.27,0.30];

% Create a cell array to store results for each reserve price
results = cell(length(max_incentives), 1);

% Iterate through reserve prices
for m_incentive_index = 1:length(max_incentives)
    max_incentive = max_incentives(m_incentive_index);

    % Evaluate utilities with incentive
    [weighted_incentive_attr_vals, utilities_w_5G_incentive] = ...
        attr_val.incentive_utility(normalizedWeights, baseline_attr_vals,...
            attr_vals_5G, max_incentive);
    utilities{end+1}=utilities_w_5G_incentive;
    utilities_labels{end+1}= strcat('5G(max incentive: ',num2str(max_incentive),')');

    % Initialize cell array for this reserve price
    HWN_distributions = cell(size(threshold_levels));

    % Iterate through threshold levels
    for t_level = 1:length(threshold_levels)
        t = threshold_levels(t_level);
        HWN_distribution = baseline;

        % Iterate through each user
        for userIndex = 1:numUsers
            subscription = char(baseline(userIndex));
            migration_nw = str2double(subscription(2));

            if (migration_nw < 5)
                u_i = utilities_w_5G_incentive(userIndex);
                u_b = baseline_utilities(userIndex);
                u_c = utilities_on_5G(userIndex);

                % Check if migration to 5G is justified
                if (u_i > u_b) && (u_i > (t + u_c))
                    migration_nw = 5;
                end
            end

            HWN_distribution(userIndex) = strcat("G", num2str(migration_nw));
        end

        HWN_distributions{t_level} = HWN_distribution;
    end

    % Store the results for this reserve price
    results{m_incentive_index} = HWN_distributions;
end

```



```

allRATcounts=[];
% %distributions for each threshold, reserve price combination
for max_incentiveIdx=1:length(max_incentives)
    HWN_distributions=results{max_incentiveIdx};
    filepath='figures/results/HWNdistributions/';

    if ~isfolder(filepath)
        mkdir(filepath);
    end

    RATcounts=[];
    for HWNIIdx=1:length(threshold_levels)
        HWN_distribution=HWN_distributions{HWNIIdx};
        RATcounts=[RATcounts;(countcats(categorical(HWN_distribution,...
            ["G3", "G4", "G5"])))')];
        allRATcounts=[allRATcounts;RATcounts];
    end

end

```

Appendix E

Code: MarkovModel

```
%Admissible States
%determine baseline values(control measurement)
num4G = round((0.4 * numUsers)*scale_users);
num5G = round((0.003 * numUsers)*scale_users);
num3G = round((0.58 * numUsers)*scale_users);

baseline = [repmat("G3", num3G, 1);repmat("G4", num4G, 1);repmat("G5", num5G, 1)];
% Network Performance Analysis
arrival_rates = [0,2,4,6,8,10,12,14,16,18,20];

%Capacity, Threshold parameters
nw_param_scale=2;
C1=30/nw_param_scale;    C2=60/nw_param_scale;    C3=100/nw_param_scale;
T1=ceil(C1*0.65);        T2=ceil(C2*0.65);        T3=ceil(C3*0.65);

%Basic bandwidth units
b1=4;        b2=2;        b3=1;

max_m = [ceil(T1/b1),ceil(C1/b1),...
         ceil(T2/b2),ceil(C2/b2),...
         ceil(T3/b3),ceil(C3/b3)];
% Initialize a variable to store the admissible states

adms_states1=[];
adms_states2=[];
adms_states3=[];

for m11 = 0:max_m(1)
    for m21 = 0:max_m(2)
        if ((m11+m21)*b1 <= C1) && (m11*b1<=T1)
            adms_states1=[adms_states1;m11,m21];
        end
    end
end
for m12 = 0:max_m(3)
    for m22 = 0:max_m(4)
        if ((m12+m22)*b2 <= C2) && (m12*b2<=T2)
            adms_states2=[adms_states2;m12,m22];
        end
    end
end

% Get the sizes of the input matrices
size1 = size(adms_states1, 1);
size2 = size(adms_states2, 1);

% Create a matrix with the appropriate dimensions
adms_states12 = zeros(size1 * size2, 4);
```

```

% Populate the columns of admss_states12
for i = 1:size1
    admss_states12((i - 1) * size2 + 1 : i * size2, 1) = admss_states1(i, 1);
    admss_states12((i - 1) * size2 + 1 : i * size2, 2) = admss_states1(i, 2);
end

for j = 1:size2
    admss_states12(j:size2:end, 3) = admss_states2(j, 1);
    admss_states12(j:size2:end, 4) = admss_states2(j, 2);
end

clear admss_states1 admss_states2

for m13 = 0:max_m(5)
    for m23 = 0:max_m(6)
        if ((m13+m23)*b3 <= C3) && (m13*b3<=T3)
            admss_states3=[admss_states3;m13,m23];
        end
    end
end

% Get the sizes of the input matrices
size12 = size(admss_states12, 1);
size3 = size(admss_states3, 1);

% Create a matrix with the appropriate dimensions
admss_states = zeros(size12 * size3, 6);

% Populate the columns of admss_states123
for i = 1:size12
    admss_states((i - 1) * size3 + 1 : i * size3,1) = admss_states12(i, 1);
    admss_states((i - 1) * size3 + 1 : i * size3,2) = admss_states12(i, 2);
    admss_states((i - 1) * size3 + 1 : i * size3,3) = admss_states12(i, 3);
    admss_states((i - 1) * size3 + 1 : i * size3,4) = admss_states12(i, 4);
end

for j = 1:size3
    admss_states(j:size3:end, 5) = admss_states3(j, 1);
    admss_states(j:size3:end, 6) = admss_states3(j, 2);
end

% Clear admss_states12 from memory
clear admss_states12 admss_states3

```

Appendix F

Code: Network Performance

```
for max_incentiveIdx=1:length(max_incentives)
    HWN_distributions=results{max_incentiveIdx};
    filepath='figures/results/NetworkPerformance/';

    utilization_values={};
    labels={};

    call_dropping={};
    call_blocking={};

    if ~isfolder(filepath)
        mkdir(filepath);
    end

    for HWNIIdx=1:length(threshold_levels)
        HWN_distribution=HWN_distributions{HWNIIdx};
        RATcount=countcats(categorical(HWN_distribution, ["G3", "G4", "G5"]));

        HWN_utilization_values = zeros(length(arrival_rates),1);
        HWN_call_blocking = zeros(length(arrival_rates),1);
        HWN_call_dropping = zeros(length(arrival_rates),1);

        for arrIdx = 1:length(arrival_rates)

            total_xm = arrival_rates(arrIdx); % Set the current total arrival rate

            % Calculate the arrival rate for each RAT based on proportions
            lambda_arr = zeros(length(RATcount),1);

            lambda_arr(1)=total_xm*((RATcount(1)/numUsers)+...
                ((RATcount(2)/numUsers)*(1/2))+...
                ((RATcount(3)/numUsers)*(1/3)));

            lambda_arr(2)=total_xm*(((RATcount(2)/numUsers)*(1/2))+...
                ((RATcount(3)/numUsers)*(1/3)));

            lambda_arr(3)=total_xm*((RATcount(3)/numUsers)*(1/3));

            %service rates
            mu_dep = zeros(length(RATcount),1);

            mu_dep(1)=0.5;
            mu_dep(2)=0.5;
            mu_dep(3)=0.5;

        end
    end
end
```

```

rat_params = [
struct('xm', lambda_arr(1), 'xn', lambda_arr(1)/5, 'um', mu_dep(1), 'un', mu_dep(1));
struct('xm', lambda_arr(2), 'xn', lambda_arr(2)/5, 'um', mu_dep(2), 'un', mu_dep(2));
struct('xm', lambda_arr(3), 'xn', lambda_arr(3)/5, 'um', mu_dep(3), 'un', mu_dep(3));
];

%poission processes for determining arrival rates
rho11=rat_params(1).xm/rat_params(1).um;
rho21=rat_params(1).xn/rat_params(1).un;
rho12=rat_params(2).xm/rat_params(2).um;
rho22=rat_params(2).xn/rat_params(2).un;
rho13=rat_params(3).xm/rat_params(3).um;
rho23=rat_params(3).xn/rat_params(3).un;

rho=[rho11,rho21,rho12,rho22,rho13,rho23];

% Calculate the normalization constant G and utilisation in Admissable States
G = 0;SB=0;SD=0;cntD=0;cntB=0;
U_s=zeros(length(adms_states),1);
P_s = zeros(length(adms_states),1);
for i = 1:size(adms_states, 1)
    m = adms_states(i, :);
    product = (((rho(1)^m(1))*(rho(2)^m(2)))/(factorial(m(1))*factorial(m(2))))*...

        (((rho(3)^m(3))*(rho(4)^m(4)))/(factorial(m(3))*factorial(m(4))))*...
        (((rho(5)^m(5))*(rho(6)^m(6)))/(factorial(m(5))*factorial(m(6))));

    G = G + product;
    P_s(i) = product;
    U_s(i)=(m(1)+m(2))*b1+(m(3)+m(4))*b2+(m(5)+m(6))*b3;

    %blocking probability
    if ((b1+(b1*(m(1)+m(2))))>C1) || (b1+(b1*m(1))>T1) ||...
        (b2+(b2*(m(3)+m(4))))>C2) || (b2+(b2*m(3))>T2) ||...
        (b3+(b3*(m(5)+m(6))))>C3) || (b3+(b3*m(5))>T3)

        SB=SB+product;
        cntB=cntB+1;
    end

    %Dropping Probability
    if (b1+(b1*(m(1)+m(2))))>C1) ||...
        (b2+(b2*(m(3)+m(4))))>C2) ||...
        (b3+(b3*(m(5)+m(6))))>C3)
        SD=SD+product;
    end
end

HWN_call_blocking(arrIdx)=SB/G;
HWN_call_dropping(arrIdx)=SD/G;

P_s=P_s/G;
U=sum(P_s.*U_s);
HWN_utilization_values(arrIdx) =U/(C1+C2+C3);
end

utilization_values{end+1}=HWN_utilization_values;
labels{end+1}=strcat('migration thr:',num2str(threshold_levels(HWNIdx)));
call_blocking{end+1}=HWN_call_blocking;
call_dropping{end+1}=HWN_call_dropping;

end

```

Appendix G

Ethics: Research Proposal

		Yes	No
Q1	Does this project involve data collection		x
Q2	Does this project involve utilizing a third-party data set		x
Q3	Does this project utilize machine learning (ML) or artificial intelligence (AI)? (optional)		x
Q4	Does it exceed the minimum risk defined here: Link		x
Q5	Does this project involve external parties, funders, etc		x

Appendix H

Ethics: Ethics Clearance



UNIVERSITY OF CAPE TOWN
IYUNIVESITHI YASEKAPA - UNIVERSITEIT VAN KAAPSTAD

PRE-SCREENING QUESTIONNAIRE OUTCOME LETTER

STU-EBE-2023-PSQ000559

2023/08/05

Dear Omolemo Kegakilwe,

Your Ethics pre-screening questionnaire (PSQ) has been evaluated by your departmental ethics representative. Based on the information supplied in your PSQ, it has been determined that you do not need to make a full ethics application for the research project in question.

You may proceed with your research project titled:

Impact of Incentive Pricing on Users' Migration in the Next Generation Mobile Network

Please note that should aspect(s) of your current project change, you should submit a new PSQ in order to determine whether the changed aspects increase the ethical risks of your project. It may be the case that project changes could require a full ethics application and review process.

Regards,

Faculty Research Ethics Committee