



T.C.

ALTINBAS UNIVERSITY

Institute of Graduate Studies

Electrical and Computer Engineering

**MANAGING 5G LTE ADVANCED NETWORKS  
THROUGH MACHINE LEARNING  
INTELLIGENCE BASED SYSTEM**

Ghassan Hamada Ali ALSHMEEL

Master of Science

Supervisor

Asst. Prof. Dr. Abdullahi Abdu IBRAHIM

Istanbul, 2020

**MANAGING 5G LTE ADVANCED NETWORKS THROUGH MACHINE  
LEARNING INTELLIGENCE BASED SYSTEM**

by

**Ghassan Hamada Ali ALSHMEEL**

Electrical and Computer Engineering

Submitted to the Institute of Graduate Studies

in partial fulfillment of the requirements for the degree of

Master of Science

ALTINBAŞ UNIVERSITY

2020

The thesis titled “**MANAGING 5G LTE ADVANCED NETWORKS THROUGH MACHINE LEARNING INTELLIGENCE BASED SYSTEM**” prepared and presented by **Ghassan Hamada Ali ALSHMEEL** was accepted as a Master of Science Thesis in Information Technologies.

---

Asst. Prof. Dr. Abdullahi Abdu IBRAHIM

Supervisor

Thesis Defense Jury Members:

Asst. Prof. Dr. Abdullahi Abdu IBRAHIM	School of Engineering and Natural Sciences, Altinbas University	_____
Asst. Prof. Dr. Muhammad ILYAS	School of Engineering and Natural Sciences, Altinbas University	_____
Asst. Prof. Dr. A.Mohammed ABUBAKAR	Faculty of Business , Antalya Bilim University	_____

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

Approval Date of Institute of Graduate Studies:  
\_\_\_\_/\_\_\_\_/\_\_\_\_

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Ghassan Hamada Ali ALSHMEEL

## **DEDICATION**

I devote and pledge this research work to my supervisor who is salient for guiding me through whole research work as well as my family for always assisting me in my hard time.



## **ACKNOWLEDGEMENTS**

First and foremost, I would like to thank my supervisor Asst. Prof. Dr. Abdullahi Abdu IBRAHIM for guiding and helping me along the way in writing this dissertation. Discussing my progress, problems, and ideas with my supervisor Asst. Prof. Dr. Abdullahi Abdu IBRAHIM a couple of times every week helped me tremendously in understanding the logic behind the research. It made me better realize the technical need for this research work. He helped me by looking outside of all the machine learning and network-based information, and considering the cryptocurrency-based knowledge from a more holistic perspective than just from the productivity point of view. He patiently explained to me a great number of technical details with regards to block-chain and cryptocurrency, for example how to deal with solving problems and to provide insight into the reliability of those results. Without his time and help none of this research would have been possible, and I'm grateful to him for giving me the opportunity to work on this interesting subject. I am also very thankful to my parents as well as my friends who always supported me through whole of this journey.

## ABSTRACT

### MANAGING 5G LTE ADVANCED NETWORKS THROUGH MACHINE LEARNING INTELLIGENCE BASED SYSTEM

ALSHMEEL, Ghassan Hamada Ali,

M.Sc., Electrical and Computer Engineering, Altınbaş University,

Supervisor: Asst. Prof. Dr. Abdullahi Abdu IBRAHIM

Date: Aug/2020

Pages: 54

The development of 5G mobile communication systems is aiming at meeting the boosting needs of mobile Internet traffic in the next 10 years. Some key technologies have been put forward in the next generation mobile communication technology (5G) such as millimeter waves and Small Cell to meet the requirements. The development of small cell networks offers higher chances in increasing capacity while reducing power consumption, since the small cells are effective supplements to macro cells with less power consumption in each single small cell. The problem is that deploying dense small cells may not actually save the total power of the system. To solve this problem, the small cells could be switched off during the time when traffic load is not that high, and switched on when large number of users appear in the hot spot area. However, switching off the small cells may lead to lower chance of offloading and harm the throughput. The performances of the algorithm are also evaluated by building a simplified LTE model with one macro cell and several small cells in MATLAB. Besides, the main traffic data of the network comes from the simulation in MATLAB which is considered as more realistic. To show the details of power consumption changing, we take the simulation time as a whole day (24 hours) while achieving and accuracy of 97.82%. By using the K-Means clustering machine learning based algorithm, the system power consumption can be largely reduced during peak hours and the decrement of

throughput is within an acceptable range with management. The deployment of around 110 small cells in a macro cell shows the best performance.

**Keywords:** Small Cell; K-Means; Power-Consumption; Management; Base-Station; 5G; Machine Learning.



# TABLE OF CONTENTS

	<u>Pages</u>
<b>ABSTRACT</b> .....	<b>vii</b>
<b>LIST OF TABLES</b> .....	<b>xi</b>
<b>LIST OF FIGURES</b> .....	<b>xii</b>
<b>LIST OF ABBREVIATIONS</b> .....	<b>xiv</b>
<b>1. INTRODUCTION</b> .....	<b>1</b>
1.1 PROBLEM STATEMENT .....	2
1.2 OVERVIEW .....	3
1.3 CONTRIBUTION .....	5
1.4 STRUCTURE OF THESIS .....	6
<b>2. RELATED WORK</b> .....	<b>8</b>
2.1 KEY TECHNOLOGIES .....	9
2.1.1 Millimeter Wave.....	9
2.1.2 Small Cell .....	9
2.1.3 Massive MIMO.....	9
2.2 CHALLENGES OF 5 <sup>TH</sup> GENERATION TECHNOLOGY .....	10
2.3 CAPACITY AND COMPLEXITY.....	11
2.4 NETWORK TRAFFIC PROFILE CONFIGURATIONS .....	13
2.5 MANAGING 5G FREQUENCY BAND SPECTRUM.....	15
<b>3. METHODOLOGY</b> .....	<b>18</b>
3.1 ENERGY MANAGEMENT IN 5 <sup>TH</sup> GENERATION NETWORK .....	19
3.1.1 Managing LTE Frequency Bands.....	20
3.1.2 Managing mm-wave Spectrum.....	20
3.1.3 Managing Pathloss.....	21
3.2 SYSTEM MODELING STRATEGY .....	22
3.3 K-MEAN ALGORITHM .....	24

3.3.1	Data Augmentation.....	25
3.3.2	Managing Base Station in Cell Radius .....	26
<b>4.</b>	<b>RESULTS.....</b>	<b>28</b>
<b>5.</b>	<b>DISCUSSION.....</b>	<b>36</b>
5.1	DISCUSSION.....	36
<b>6.</b>	<b>CONCLUSION.....</b>	<b>39</b>
6.1	CONCLUSION .....	39
6.2	FUTURE RECOMMENDATION .....	39
	<b>REFERENCES.....</b>	<b>41</b>

## LIST OF TABLES

	<b><u>Pages</u></b>
Table 3.1: Comparison of Main Types of Base Stations. ....	19
Table 3.2: Parameters of Base Station. ....	20
Table 3.3: Parameters of managing 5 <sup>th</sup> Generation Base Station. ....	23
Table 3.4: Augmentation for Data .....	26
Table 3.5: Capacity and coverage metrics for network and UE perspective. ....	27
Table 4.1: Simulation Parameters .....	30
Table 5.1: The comparison of different techniques with proposed technique. ....	36

# LIST OF FIGURES

	<u>Pages</u>
Figure 1.1: Proposed use-case scenarios for 5G [10]. .....	4
Figure 2.1: The key characteristics of 5 <sup>th</sup> generation cellular network [11]. .....	8
Figure 2.2: The key technologies of 5 <sup>th</sup> generation network with central massive MIMO for management [16]. .....	10
Figure 2.3: The capacity to complexity issues with the number of users is reduced through cell radius reduction of 5G network [27]. .....	12
Figure 2.4: The slicing of 5 <sup>th</sup> generation network for the purpose of management and orchestration [31]. .....	13
Figure 2.5: The traffic flow in 5G cellular network with respect to access, transport and core networks [35]. .....	14
Figure 2.6: The chart represents the frequency band spectrum for each of the cellular network technology [42]. .....	16
Figure 2.7: Overview of frequency band spectrum with traditional spectrum [47]. .....	17
Figure 3.1: Flowchart of approach being followed. ....	18
Figure 3.2: Distributions of UEs at 7:00 a.m. and 7:01 a.m. ....	23
Figure 3.3: Initialization of the Cell at 1:40 a.m. ....	25
Figure 4.1: Traffic Load Result (packet/sec). ....	29

Figure 4.2: Power Consumption and Management with Algorithm vs. without Algorithm. .... 32

Figure 4.3: Average Throughput in Macro Cell with Algorithm vs. without Algorithm (1 Day).33

Figure 4.4: Classification and pose estimation results of Multiple Cars Scene dataset..... 34



## LIST OF ABBREVIATIONS

5G	: 5 <sup>th</sup> Generation of Mobile Communication
BS	: Base Station
DL	: Downlink
E2E	: End to End
ICT	: Information and Communication Technology
IoT	: Internet of Things
LTE	: Long Term Evolution
MAPL	: Maximum Allowed Pathloss
MIMO	: Multiple-Input-Multiple-Output
ROM	: Residential, Office, Mix Scenario
UL	: Uplink

# 1. INTRODUCTION

The broader goal of this thesis is to investigate how managing 5G LTE advanced networks through machine learning intelligence based system. With the traffic requirements boosting, architectures of previous mobile systems cannot sustain the load anymore. The evolution to 5G mobile communication technology seems to be necessary. According to [1], the major requirements of 5G technology are large mobile data capacity and low power consumption. Various technologies have emerged to meet these requirements from different perspectives. Small Cell is one of the technologies that has been put forward.

Power consumptions are related to many factors. Among them, base station is the most power-intensive element [2]. Even with low level of capacity and coverage, the base station power consumption cannot be ignored. The development of small cell network would efficiently lower the power consumption. Nonetheless, in ultra-dense cellular networks, the density of small cells has a threshold. “When the density is beyond that threshold, the backhaul network capacity will reduce.” [3] In this case, the tradeoff need to be balanced to achieve as low power consumption as possible without sacrifice the network capacity. According to the work in [4], basic types of base stations were modeled and they analyzed the issue from the perspective of energy aware components in the base station. Their work offers a reference of modeling base stations. While the work in [5] viewed the problem from another side. They optimized the network deployment strategies by adjusting the size of small cells dynamically. Both of their works are inspiring and it may be possible to combine their ideas together to reach a better result. Due to the dynamic feature of the network, it is costly for manpower to achieve that kind of adjustment. So intelligent algorithm need to be introduced into the dynamic controlling process. Machine learning is the common used one. In the research [6], they introduced a new initialization method into the algorithm. But the research concentrates more on interference management than reducing energy consumption. Paper [7] developed cooperative to improve traditional algorithm by sharing local knowledge with other cells periodically. But the algorithm’s performance is largely dependent on the environmental and operational parameters.

In a nutshell, some work has been done these years to achieve higher capacity and lower energy consumption of the network as much as possible as proposed in [8]. The goal of this research work focuses on the energy saving method in the real environment scenario where the traffic load is large and can be different on weekday and weekend. MATLAB Modeler has been used to get more realistic traffic data in the real environment scenario. MATLAB has been used in modeling work and evaluate the performance of the algorithm in the real environment scenario. A comparison between the algorithms, on-policy machine learning Algorithm and off-policy K-Means Clustering Algorithm, has been made to illustrate why Machine Learning is used more commonly. Further development on parameters of the Machine Learning algorithm has been done to make the algorithm to meet the capacity requirements and show better performance in saving power. More specific details of the algorithm have been tested to evaluate the algorithm from various aspects.

## 1.1 PROBLEM STATEMENT

In real case, the mobile communication network architecture is very complex, but the modeling work doesn't need all components and features in the network. Some of them can be simplified to make the evaluation of the algorithm easier. To enable the network model to evaluate the algorithm easily while still under a relatively realistic scenario, several assumptions are made.

- The modeling work only considers the radio access 5th generation network.
- It is assumed that the users have the same kinds of applications at time  $t$ . Thus, the network traffic load is simplified to the number of users in the network.
- It is assumed that micro base station has 3 levels of transmission power to represent three potential states (switching on/off/ high load).
- The number of users at time  $t$  is assumed as a Poisson Distribution with a  $\lambda$  equals to the value of the number of users defined in the MATLAB results at time  $t$ .
- Not all users move at the next time slot. The number of moved UEs is subject to Poisson Distribution with  $\lambda$  equals to half of the total number of users in the cell at time  $t$ .

- It is assumed that switching on a small cell will take 30 seconds, so the simulation is run with 1 minute for each time slot to take the switching delay into consideration.

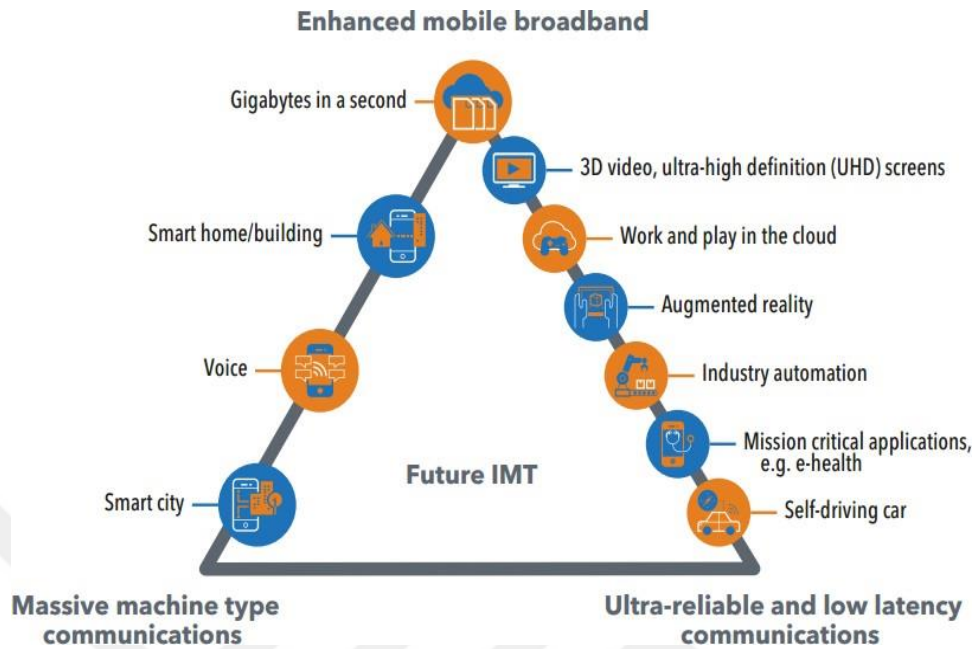
With the above assumptions, the network model can be simplified while still remained some features in the real case. Based on this model, the algorithm put forward to save energy can be simulated and its performance is evaluated both on power consumption and throughput since the power saving function can influence the network throughput.

## **1.2 OVERVIEW**

According to [9], advances in wireless networks are driving commerce as well as enhancing society in new, unexpected and fortuitous ways. A key driving gear for the wireless of the future will be the widespread deployment of 5G wireless networks. Radio access in 5G will be built from existing wireless Radio Access Technologies (RAT) e.g., LTE and Wi-Fi, combined with entirely new ones.

Future wireless systems are expected to use more bandwidth more efficiently by exploiting spatial diversity techniques with massive MIMO and beamforming. Higher user throughput will be achieved mainly through carrier aggregation and the use of new frequency bands. The overall cell density is therefore projected to increase, while more devices with lower transmission power, transmission or reception gains are expected to be supported by 5G networks.

Therefore, the concept of linking more and more devices to the Internet is a strong door opener for more efficient and economical industry frameworks, due to the development of new use-cases, such as machine communication systems in 5G, Smart Cities, Virtual Reality or Augmented Reality. This, together with the increasing number of mobile devices and growing data rates demands from customers, e.g., enhanced mobile broadband, has driven the need for the development of a new mobile communications network, the 5<sup>th</sup> Generation. The key advantage points are better or more efficient techniques to provide better network capacity, latency, mobility and transmission speeds.



**Figure 1.1:** Proposed use-case scenarios for 5G [10].

Although the 5<sup>th</sup> Generation is still currently in late development stages (2018-2020), some operators and mobile phones manufacturers have already started proposing network deployments in 2019. At the present moment the first outline prospects of what the 5G network architecture will consist of have already been established, with the comprehensive release version by 5G to come still in 2018 as mentioned in [10]. Consequently, many operators, chip and phone manufacturers are starting to be in the possession of enough material to conduct substantial studies and testing on 5G technologies. We exhibits the 5G study target roadmap established by Next Generation Mobile Networks. However, works related to a comprehensive simulator approaching the coverage and capacity elements of 5G network have not still been widely studied or widely published. Therefore, the novelty this thesis brings is the study of coverage and capacity characteristics for initial 5G deployments in three propagation environments, urban, suburban and rural, for a much higher diversity of spectrum options compared to LTE, with more bandwidth values and the inclusion of numerology configurations, from 1 to 100 GHz bands. Therefore, the ultimate goal of the simulator is to compute the number of cells from three key elements, the model reference parameters (link budget, propagation models, capacity requirements), the reference traffic profile (service priority, mix share, throughput requirement) and the 5G management regions/district database within the

geographical target deployment area (location area, propagation environment, user density). Since the model should withstand any modification in the input parameters, it should also be time accessible to test the impact of different configurations of input parameters on the number of cells.

In terms of coverage, the model should be focused on the new frequency bands expected to be deployed in early 5G implementations. While the 1 GHz is lower than the LTE's 0.5 GHz, which could provide better coverage to network users, the main goal frequency-wise is to analyse the impact on the higher 100 GHz band of 5G compared to LTE's 50 GHz, in terms of higher propagation losses both indoors and outdoors. In terms of capacity, the model should be able to support every valid spectrum configuration defined by 5G. This includes new bandwidth configurations as well as the numerologies in use for these frequency bands. The ultimate goal is to determine the maximum number of users in the cell and in the network for a reference traffic profile, which measures the performance for a variety of services demanded by users.

### **1.3 CONTRIBUTION**

The goal is to develop a system that manage the power consumption of using the machine learning method that can be implemented at 5th generation network. Therefore, the K-Means Clustering Algorithm should be adaptable to the specific situation of a management and power consumption through the base station of 5th generation network. With this, we might make a serious impact by preventing significant management issues at a wide range of network. Since there exists an inherent uncertainty for the demand of new technology, the K-Mean algorithm should determine prediction intervals for the management and power consumption in 5G advance networks. These intervals quantify the uncertainty for the demand of a management through machine learning based intelligent system. Management and power consumption intervals provide meaningful information for planners and managers to support decision-making. Additionally, the K-Means should also be validated sufficiently, to prove that it can improve the current processes within several 5G networks. It should be able to provide robust management of energy and also lead to improvements within 5G network management with clustering of networks for better accuracy. We want to explore the available data of the 5G network with patterns and relations that might be useful for managing the network.

- Are there certain patterns and relations within the 5G advance network for management of power consumption?
- Which machine learning based technique is more appropriate for the stability and management of advance 5G network?
- Are there patterns in the demand during the clustering of 5G LTE advance networks?
- Are there certain relations between the power consumption and energy management in 5G advanced LTE networks?
- How should the performance of this K-Means algorithm be evaluated?

#### **1.4 STRUCTURE OF THESIS**

In Chapter 1, the fundamental characteristics of the key elements of 5G networks management are presented. It provides a characterization of the network architecture, the radio interface where the novelty aspects concerning 5G are highlighted and some aspects regarding coverage and capacity dimensioning. It also presents a description of the main use cases in terms of services and applications expected to be supported in 5G deployments through performance metrics, such as throughput or latency requirements.

In Chapter 2, a comprehensive view on the literature and background studies with overview state of the art is presented on topics that relate to the work developed in the thesis from academic thesis, industry reports and official telecommunications standards.

In Chapter 3, the most important and relevant models applied in the simulator are described. It consists of models and assumptions taken for simulator elements, such as coverage, capacity and throughput calculations, as well as the inclusion of numerology configurations. The simulator implementation is also explained in this chapter through means of routine inputs and outputs, as well as through means of workflows. In the end, an assessment on key simulator elements is performed in order to guarantee that results are valid and correct for further study.

In Chapter 4, the scenarios to be considered in the simulator are described, as well as the model reference parameters in terms of link budget, propagation models' configurations and capacity related metrics, such as the throughput at cell edge, which numerologies are active, among others, and the reference traffic profile. From these reference parameters a number of analysis are performed from diverse results in order to study the impact of different input parameters mainly on the cell radii, number of active users and number of cells. The traffic profile is modified to study the impact on different service mix share configurations, as well as the impact on changing the average throughput per service.

At last, in Chapter 5 the discussion and main conclusions from the simulation results are taken in comparison with other previously performed studies, presenting the most relevant and important results and a brief analysis on them. Besides, some recommendations for future work are presented, based on 5G standards still to be released and on some key assumptions taken for the model development.

## 2. RELATED WORK

Every new generation of mobile communication network delivers faster speed and more functionalities to the users. The 1st generation technology gives users the very first cell phones. The 2<sup>nd</sup> generation technology (e.g. Global System for Mobile Communication) allows the users to send SMS (Short Message Service). The 3<sup>rd</sup> generation technology (e.g. Wideband Code Division Multiple Access) enables the users to connect to the network and realizes the roaming around the world. The 4<sup>th</sup> generation (e.g. Long Term Evolution) offers much higher bit rates and supports various information transmission like voice, video and image, etc. However, as more kinds of applications come online (e.g. Internet of Things), 4G technology has almost reached its limit in capacity. Under this circumstance, the 5th generation technology is developed to meet these boosting requirements in large amount of data traffic. The main targets for 5G technology is to make the mobile communication network with larger coverage, higher capacity in hotspot areas, shorter delay, higher reliability and lower power consumption.



**Figure 2.1:** The key characteristics of 5<sup>th</sup> generation cellular network [11].

## **2.1 KEY TECHNOLOGIES**

To meet the targets, three technologies have been discussed as key technologies for 5G:

### **2.1.1 Millimeter Wave**

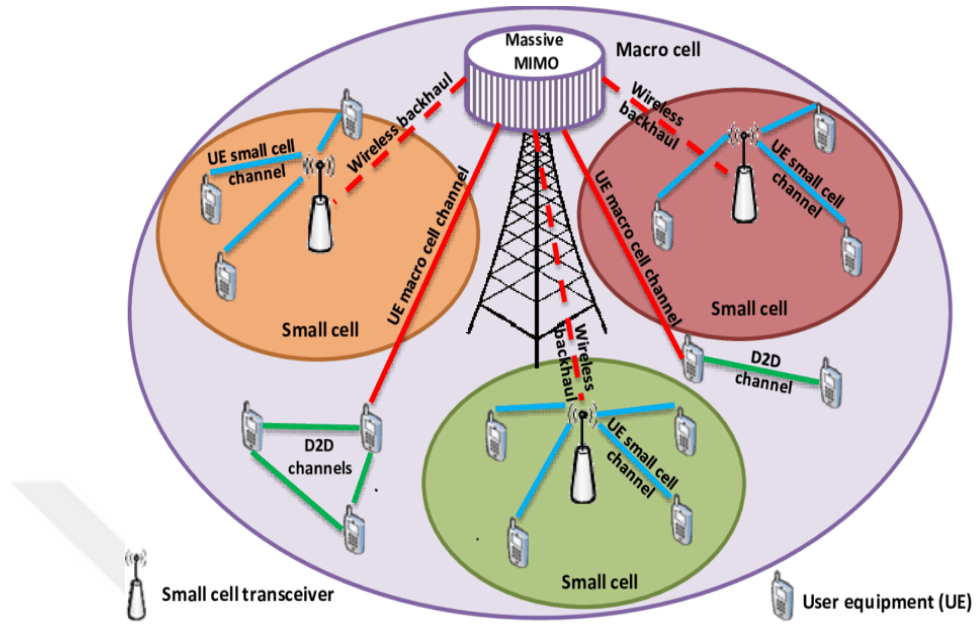
The common devices occupy the radio frequencies spectrum from 3kHz to 6GHz. However, as more applications come out, these frequencies start to get more crowded, which will cause lower bit rates and higher drop rates. The solution is to develop more spectrum resources. The spectrum from 6GHz to 300GHz has been considered to be available for mobile devices as mentioned in [12]. The challenges of this solution are that the millimeter waves will have power loss when they travel through buildings or other obstacles. They also stand a chance to be absorbed by plants and rain.

### **2.1.2 Small Cell**

Nowadays, the most common technology is to transmit signals through a long distance from macro base stations. However, as millimeter waves cannot travel well through the obstacles, those mobile devices far away from the base station cannot connect to the network as mentioned in [13]. To solve this problem, Small Cell technology can ensure better service quality to mobile device by building thousands of low-power micro base stations. An example of this kind of small cell equipment as mentioned in [14]. The deployment of small cells will be helpful especially in the city areas where the traffic demands are large.

### **2.1.3 Massive MIMO**

The base stations now commonly have about dozens of ports for antennas and they are responsible for all cellular traffic. The development of massive MIMO (Multiple-Input Multiple-Output) base stations will improve that and support around a hundred ports. This would raise the capacity of the network by a factor around twenty as mentioned in [15]. The challenge of this technology is that antennas broadcast signals in every direction at once, which can cause large interference between each other.



**Figure 2.2:** The key technologies of 5<sup>th</sup> generation network with central massive MIMO for management [16].

## 2.2 CHALLENGES OF 5<sup>TH</sup> GENERATION TECHNOLOGY

Regarding the benefits, there are still some challenges to realize them and achieve perfect performance of Small Cell in the 5<sup>th</sup> generation network.

**1. Mobility Management:** Since the deployment of 5<sup>th</sup> generation networks are pretty flexible, unreasonable configuration of neighboring cells could lead to complex network, which would be detrimental to network planning and mobility management as mentioned in [17]. Too many neighboring cells may result in excessive handovers, affecting the user experience, severely consuming the energy of the UEs, and consuming network resources. The number of neighboring cells and the handover parameters need to be properly configured for different scenarios to reduce unnecessary measurement of neighboring cells and avoid unnecessary switching between macro cell and small cell.

**2. Backhaul Network:** The backhaul of 5<sup>th</sup> generation networks usually rely on the public network, such as DSL (Digital Subscriber Loop) as given in [18]. But since the public network would have the load of fixed broadband users at the same time, its bandwidth is usually difficult

to guarantee, which could lead to congestion. However, services like OAM (Operation Administration and Management) have high requirements in packet loss and latency and QoS (Quality of Service) of different services must be guaranteed at the transmission level as discussed in [19]. In this way, the backhaul network should also be taken into consideration during the deployment of 5th generation network.

**3. Load Balance:** UEs will choose their Serving based on RSRP (Reference Signal Received Power) to get large SINR (Signal to Interference plus Noise Ratio). Since the macro cells' transmission power and coverage area are both larger than 5th generation network', less UEs will choose small cell as Serving as provided in [20]. Under such case of uneven service distribution, it is difficult to avoid that some 5<sup>th</sup> generation network are congested while the other 5th generation network are idle. How to effectively use Small Cell resources and efficiently divert network traffic would be the focus of the research.

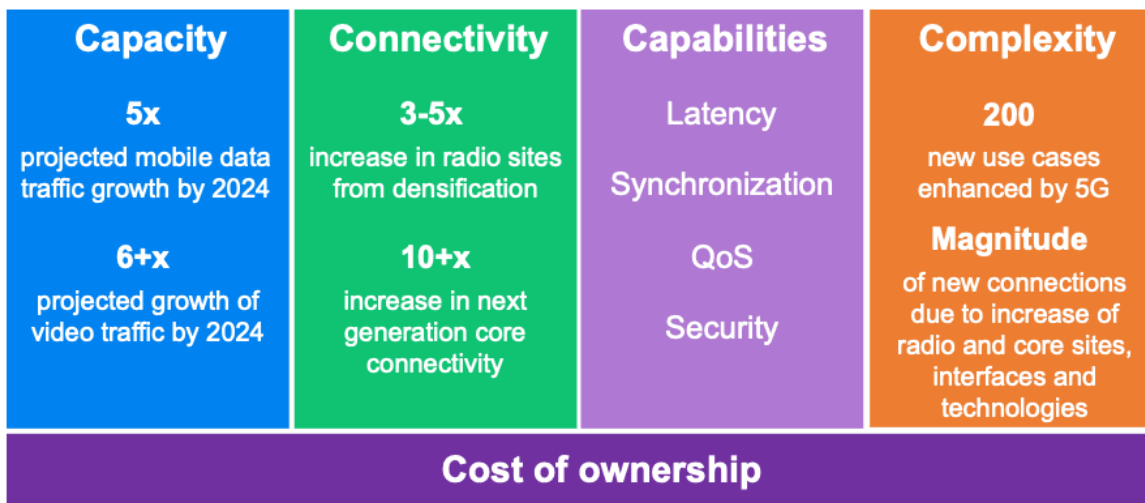
**4. Operation and Management:** The introduction of the 5<sup>th</sup> generation network into the LTE network poses great challenges in terms of operation, management, and optimization, which require highly in network intelligence and simplification. The introduction of technologies like SON (Self-Organized Network) could help minimize the human power in network operation and management as mentioned in [21].

**5. Interference:** In a dense heterogeneous network, a macro base station may bring a certain degree of interference (cross-layer interference) to small cell users due to its high transmission power. Although the transmitting power of small cell is relatively low, 5<sup>th</sup> generation networks are close to each other and mutual interference exists (interference on the same layer) as provided in [22]. The more intensive the deployment is, the more serious the interference will be. Eventually, the overall performance of such a heterogeneous network will become less effective.

## 2.3 CAPACITY AND COMPLEXITY

The main objective of coverage estimation is the computation of the site cell radius and consequently the number of cells. Therefore, the key element here are coverage distances, which are computed from the appropriate propagation models and the maximum path loss (MAPL) given

by the radio link budget formulation as mentioned in [23]. According to [24], the frequency spectrum under consideration for 5G networks spans from the 0 to 100 GHz frequency bands, with expected different deployment dates. This wide spectrum range has to do with different entities being interested in a wide range of devices to be served by 5G. However, in this thesis, one considers the initial spectrum bands that are considered for the first 5G field deployments, the cm-spectrum, specifically the 1 and 100 GHz frequency bands. Therefore, this thesis is focused on the propagation and coverage effects related to these frequency bands. The main objective of capacity estimation is to compute the number of required resources as mentioned in [25], defined in 5G as resource blocks, which support the traffic profile in consideration within a certain quality of service (QoS), such as, for example, defining the maximum acceptable service throughput reduction of 10% in the case of capacity overload in the cell. The initial, and maximum, number of users is given by the coverage estimation, from which the capacity estimation indicates if such users can be served with the required traffic profile as mentioned in [26]. If there is cell capacity overload, the number of users is reduced through cell radius reduction, until or if there is possibility of the cell withstanding the required number of networks. After this estimation, the final number of users in the cell and in the network can be computed.



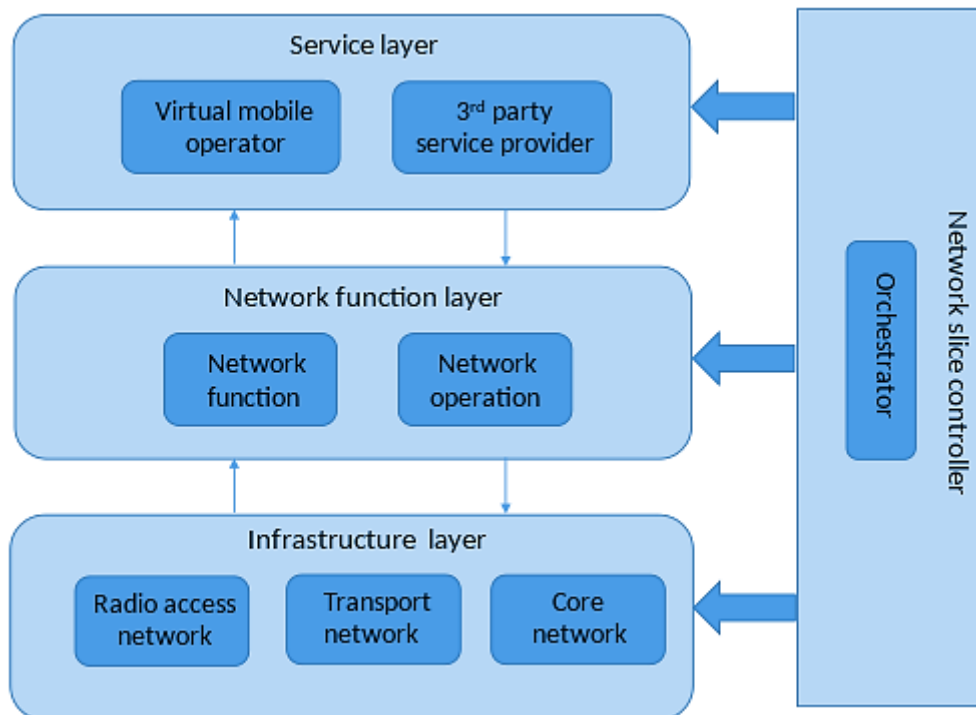
**Figure 2.3:** The capacity to complexity issues with the number of users is reduced through cell radius reduction of 5G network [27].

The number of cells is computed for every 5G management regions and every environment, with the analysis being complemented with data such as the propagation environment share per 5G

management regions. The comparison of the number of cells between both frequency bands is done, using the same bandwidth value of 20 MHz, with different environment types and device densities and compared with the number of cells obtained in the simulator developed by [28]. The main conclusion one can take is that no solid conclusion can be made by only considering the number of cells per 5G management regions in both frequency bands. Hence, one should take other factors into consideration, such as the environment composition per 5G management regions, the average number of devices per user or the set of mean and standard deviation values for the cell radius for all 5G regions for management as mentioned in [30].

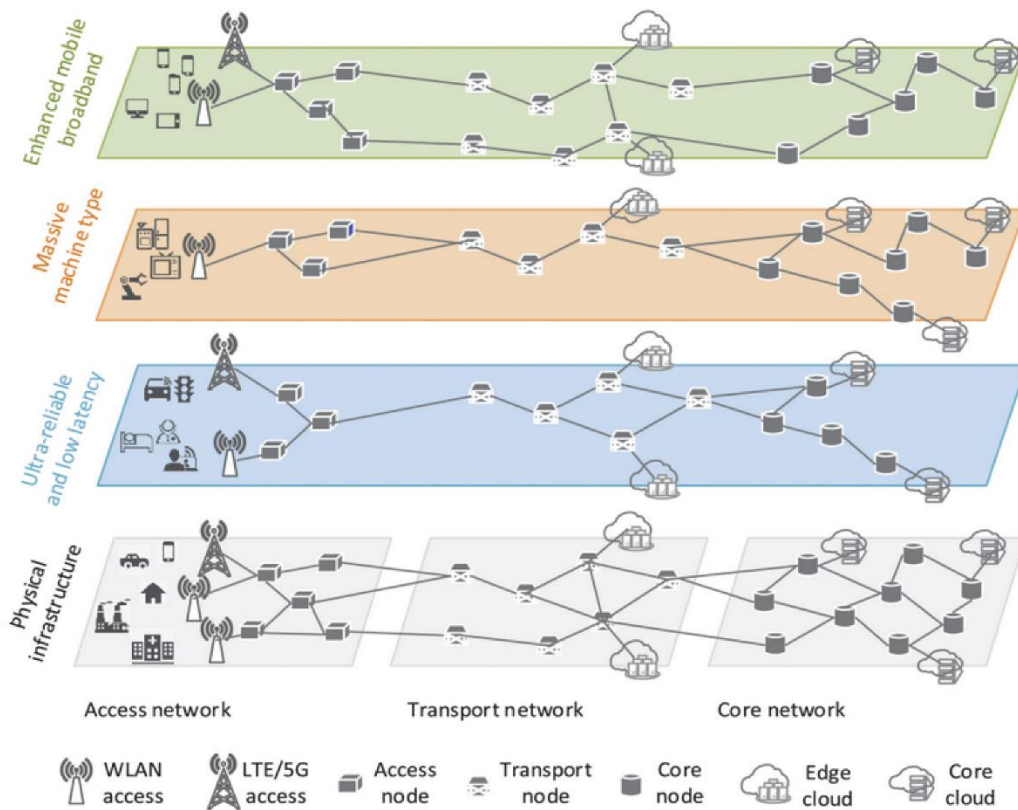
## 2.4 NETWORK TRAFFIC PROFILE CONFIGURATIONS

Studies the impact on some changes on the traffic profile configurations in world. The change in the service mix share yields different traffic profiles (reference, video-centric, voice-centric) and the change in the throughput (minimum, reference, maximum) produce an estimation on the required cell density for each traffic profile configuration.



**Figure 2.4:** The slicing of 5<sup>th</sup> generation network for the purpose of management and orchestration [31].

The simulations provided the absolute number of cells to be lowest for the voice-centric scenario, with 579 cells, the reference with 598 and the video-centric with 681 cells with ROM as mentioned in [32]. The higher mix share of the low-throughput voice-service leads to a lower capacity demand, which translates into fewer required cells, while a high throughput service leads to a significant increase in the number of cells (Management-centric). The traffic profile in this section is similar to the one from [33], but some of the throughput values were increased to match the literature overview on higher throughput demands for some of the services. The impact of this increase can be seen on the number of cells per 10 km<sup>2</sup> in the reference, video and voice-centric scenarios in this thesis, {62, 70, 60} and in [34] with {34, 44, 30}. In both results the density is higher for the video-centric, and for the varying throughput scenario, the same number of cells per 10 km<sup>2</sup> is outputted for the lowest, reference and highest throughput cases with {55, 66, 78} in this thesis and {20, 33, 62} in [34], which shows a similar increase when the throughput increases.



**Figure 2.5:** The traffic flow in 5G cellular network with respect to access, transport and core networks [35].

As a matter of future work, some recommendations that can be applied to this work are an algorithm that could pick the most efficient spectrum configuration for the characteristics for some specific sets of municipalities, since the available bandwidth each operator has may not be the same throughout the whole country, as well as the inclusion of other services or classes of services, such as, e.g., vehicular, which would require specific propagation models such as the vehicular, or latency critical applications which would require an extra model layer, which would deal with the number of cells, distances and propagation times, which is somewhat similar to the works of [36].

Additionally, some topics have been simplified in this thesis, such as the throughput and SNR relationship and the assumption that every numerology is available for capacity regardless of their maximum coverage distance from their different power sensitivity and other topics as mentioned in [37], which have not been covered at all, such as the issue of interference, carrier aggregation that could provide interesting results with the higher bandwidths available for the 100 GHz band, or the exclusion of some of the services expected to be included in future deployments but which are not yet confirmed to be released and commercially available in first 5G network deployments as mentioned in [38].

## **2.5 MANAGING 5G FREQUENCY BAND SPECTRUM**

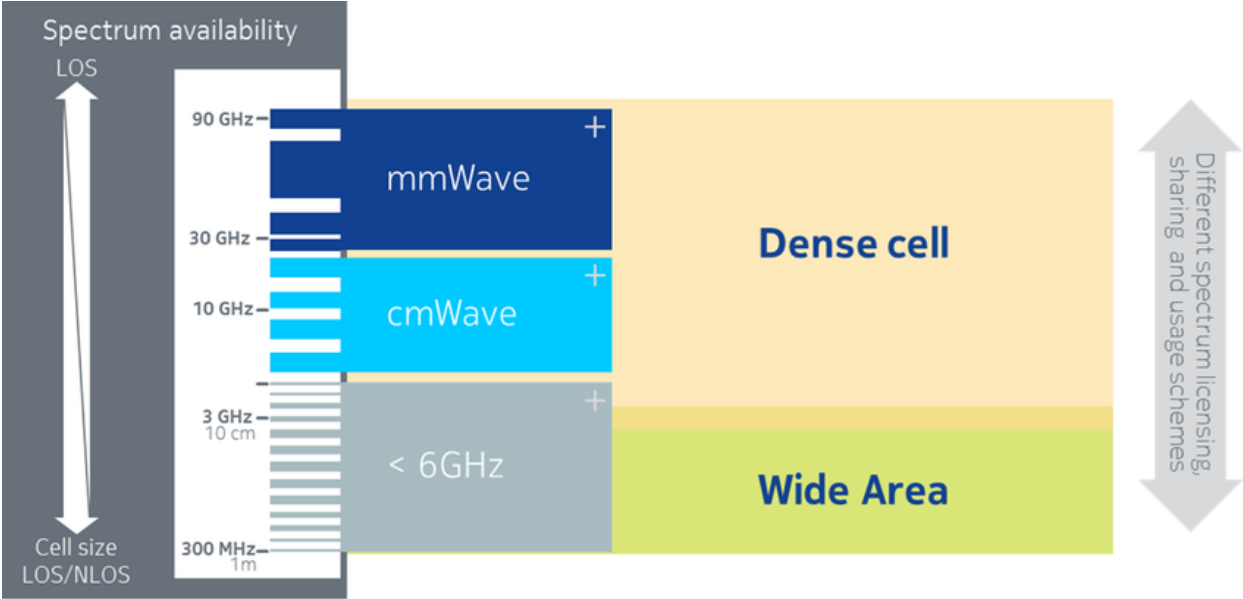
The analysis on the throughput at the cell edge is done for both frequency bands for all valid spectrum configurations defined by 5G network, for both channels (DL/UL), defining the minimum possible cell radius as 100 m as mentioned in [39]. Furthermore, the impact of different imposed maximum cell load ratios in the global cell capacity, measured in Mbit/s, is studied for the minimum, average and maximum spectrum configurations, i.e., lowest frequency band with the lowest bandwidth, the lowest and highest frequency bands with the same bandwidth, and the highest frequency band with the highest bandwidth, for both channels as mentioned in [40]. The impact of bandwidth in the achievable throughput is measured, where for instance, to achieve a throughput at cell edge of 20 Mbit/s one would need a bandwidth of at least 40 MHz at either frequency band as mentioned in [41].

3GPP Release Toolbox Element	LTE: Rel-8, 9	LTE-Advanced: Rel-10, 11, 12	LTE-Advanced Pro: Rel-13,14	5G Phase I: Rel-15 5G Phase II: Rel-16
<b>Frequency bands [GHz]</b>	0.7, 0.8, 1.8, 2.1, 2.3-2.4, 2.5-2.6GHz	0.45 (Brazil), Digital Dividend, 1.5, 3.4-3.8GHz	5GHz ISM; WRC-15 bands	New bands below 6GHz for 5G RAT; mmW: 6-100GHz; WRC-15/19 bands
<b>Spectrum aggregation</b>	Single Carrier (1.4-20MHz), symmetric DL/UL	Dual Connectivity, CA variants: -up to 5CC, FDD and/or TDD -intra-/ inter-band, (non)-continuous, -Co-located, RRH -asymmetric DL/UL	Massive CA (32CC), LAA (5GHz), LWA, eLWA, SDL for CA: 2.3-2.4GHz	Multi-Connectivity with asymmetric DL/UL, SDL for CA: 700MHz, 2.5-2.6GHz, Lean carrier
<b>Spectrum licensing schemes</b>	Licensed spectrum only	Licensed, Carrier Wi-Fi	Licensed, Unlicensed, DL LAA, LWA, LSA, eLWA	Co-existence of: exclusive licensed, shared license-exempt spectrum, enhanced LAA (DL+UL)
<b>Duplexing schemes</b>	Separate FDD, TDD	FDD and TDD (CA-based), eIMTA	FDD Flexible Duplex	Full Duplex, New DL-only TDD configurations
<b>Sharing schemes (network, spectrum)</b>	Static schemes (MOCN, MORAN)	Static schemes (MOCN, MORAN)	RSE, LSA	LSA (new bands), SC sharing, SCaaS, spectrum trading, Cognitive Radio (CR)
<b>Spectrum refarming</b>	Static	Static	Dynamic, DSA, MRAT Joint Coordination	Fully dynamic, opportunistic, CR

**Figure 2.6:** The chart represents the frequency band spectrum for each of the cellular network technology [42].

The analysis is centered on the impact of different frequency bands, bandwidth and numerology configurations on the maximum cell radii distances by assuming a fixed bandwidth of 20 MHz for a certain user density as mentioned in [43]. As it would be expected, the distance values at 1 GHz are much higher than the ones at 100 GHz mainly due to higher losses at the latter, and also the increase of numerology configuration, and thus in the 5G network, leads to a requirement for higher sensitivity power (every doubling of 5G corresponds to more 3 dB) which reduces the overall cell radius, e.g., the decrease from 0.53 to 0.37 km in the suburban environment scenario at 100 GHz as mentioned in [44]. Furthermore, assuming the model reference parameters and the reference traffic profile, the site density is computed for every valid 5G spectrum configuration. The number of cells at 1 GHz is much lower than 100 GHz for the same bandwidth values, which is essentially explained by the higher losses at the latter as mentioned in [45]. For the remaining values, the cell density keeps decreasing until the bandwidth of 100 MHz, but at a much slower pace than from 5 to 40 MHz This can be an indicator on the maximum required bandwidth to fulfil not only the current model reference parameters but also the reference traffic profile, e.g., if many more services are added or the average throughput increases considerably and the maximum

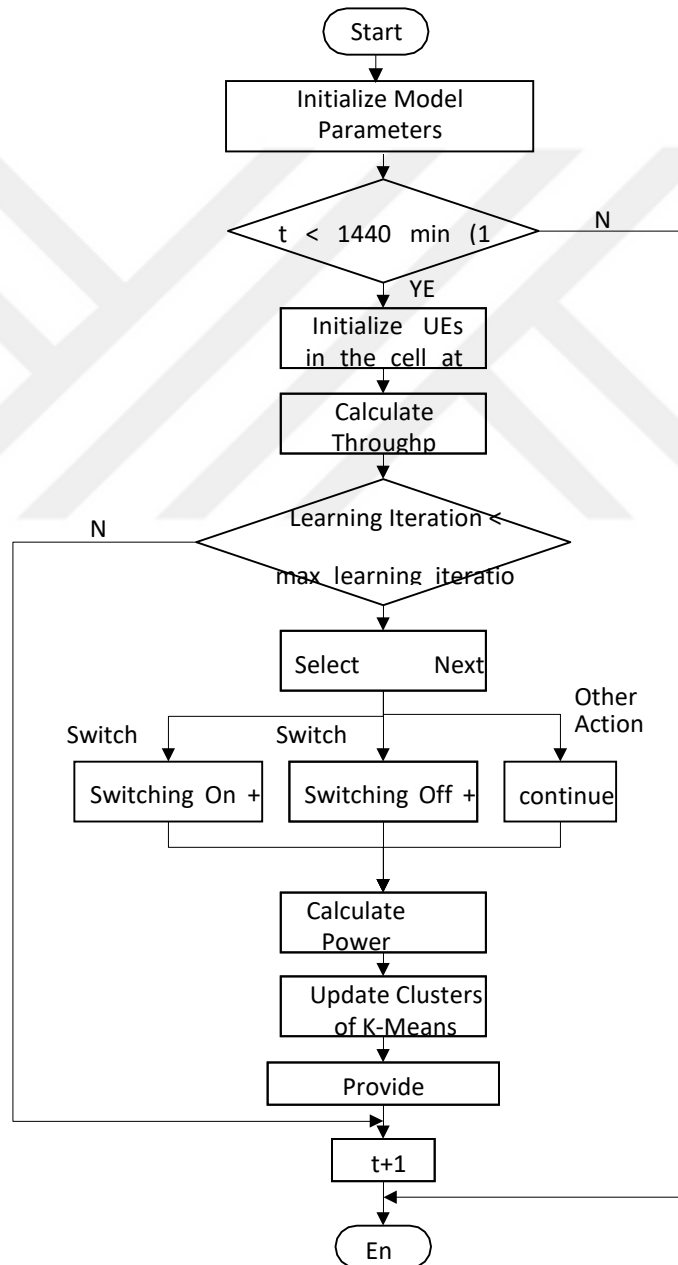
deployment site density, for reasons of cost, is 9 cells per 10 km<sup>2</sup>, in order to achieve this with the increase on the traffic load the required bandwidth could increase from 40 to 80 or 100 MHz as mentioned in [46]. The focus is on the analysis on the impact of some coverage probabilities, 85, 90 and 95%.



**Figure 2.7:** Overview of frequency band spectrum with traditional spectrum [47].

### 3. METHODOLOGY

In the real case, the 5G network structure is very complex and the transmission of information can get various parts of the communication network structure involved in. However, in this research work, controlling the cells to switch on/off won't involve in all the parts like the backhaul network or the physical layer structure.



**Figure 3.1:** Flowchart of approach being followed.

### 3.1 ENERGY MANAGEMENT IN 5<sup>TH</sup> GENERATION NETWORK

Network with the deployment of different types of base stations is defined as 5<sup>th</sup> generation Network. The 5<sup>th</sup> generation network can support large traffic flow for more kinds of applications. In addition to the consideration from the capacity and coverage sides, deploying small cells in the network also potentially consumes less power as mentioned in [15]. Table 3.1 shows the comparison among the 4 main types of base stations deployed in a 5<sup>th</sup> generation network. It is not hard to find that micro cells consume less power in transmission than the macro cells. Correspondingly, the cell radius is smaller. Among them, Femtocell is the kind of small cell base station that technically could be deployed by the users. Other kinds of base stations can only be deployed by the operators as mentioned in [16]. In this research work, Femto base station is studied since it can be installed by users and are commonly deployed in indoor scenarios like home or real environment.

**Table 3.1:** Comparison of Main Types of Base Stations.

Base Station	Power (dBm)	Cell Radius (m)
Macro	43 - 52	> 1000
Micro	33 - 43	250 - 1000
Pico	24 - 33	100 - 300
Femto	< 23	< 50

Although the transmission power of base stations is smaller, the challenge is how to balance the tradeoff between the network capacity and the total power consumption. If the number of SC base stations is large in network, the total power consumption could be larger than only relying on the macro base station. Commonly, a cell is modeled as hexagon-shaped, but the modeling work is based on MATLAB programming, so the macro cell is simplified as a 3000\*3000 meters square. The macro base station has a fixed location and is defined located at the edge of the cell with the coordinate (0,0). The parameters of the base station are initialized as listed in table 3.2.

**Table 3.2:** Parameters of Base Station.

<b>Parameter</b>	<b>Value</b>
Power (dBm)	52
Bandwidth (MHz)	20
Location (m)	(0,0)

### **3.1.1 Managing LTE Frequency Bands**

The main works of research and investigation of LTE frequency bands regarding subjects related to coverage and capacity in 5G networks are provided in this section. Research is considered mainly from three sources, academic works, IEEE based literature and institutional research from entities such as cellular 5G networks. In terms of frequency band studies for cellular network design, literature research has been noted to consist essentially of three elements, the first on previous cellular network design studies for LTE networks from the 0.8 to the 2.6 GHz bands, the second on proposals for developing networks based on the mm-wave spectrum band (28 GHz) where additional propagation effects may provide usefulness when analyzing the impact of 5G's 100 GHz band, and the third on early proposals for dealing with frequency band elements in 5G-NR such as numerology and propagation effects.

Starting with the works based on the first element, provides a comprehensive work on cellular network design for three LTE frequency bands (0.8, 1.8 and 2.6 GHz) in different propagation scenarios, with different traffic load profiles and service profile/share profiles, as well as having some elements that are transversal to early versions of 5G LTE deployment, such as the number of sub-carriers per network. It is based on a number of works from other authors and serves as a key element in this thesis for the lower frequency band study of 700 MHz

### **3.1.2 Managing mm-wave Spectrum**

Regarding works based not only but mostly on the mm-wave spectrum, as we focused on coverage, capacity for management in 5G LTE and protocol design layers for mm-waves, basing the studies on features such as data-rate, latency, energy and cost requirements, as well the implications in terms of propagation characteristics, channel modelling, link outage scenarios and deployment

configurations and scenarios. We have investigated characteristics of indoor coverage at high frequency ranges, but also focused on outdoor to indoor coverage modelling by adapting already existing models into a single one. We have established methods for computing capacity and coverage solutions for mobile broadband in rural and remote areas at the mm-wave spectrum. We have presented the case for propagation mechanisms at mm-waves and characterization of wireless channels in site-specific and stochastic channel approaches, both for narrow and wideband configurations, proposing a method to estimate capacity provisioning.

We have researched cell capacity implications in the context of mm-wave cellular networks, proposing a method based on a set of use cases' requirements and based on cell and device centric architectures, taking noise and interference conditions, cell association schemes, spectral efficiency and carrier aggregation into account. Still on capacity, developed works for 5G cellular systems by proposing a methodology based on application workload requirements, such as outage probability and throughput, to create a network system model. Since massive MIMO will be, along with mm-waves, the main facilitator for much higher capacity in 5G, it has been found to provide a comprehensive study on massive MIMO and mm-wave coverage and capacity implications in the context of 5G cellular networks.

### **3.1.3 Managing Pathloss**

The methodology is based on aspects such as characterization of scenarios, antenna modelling, different types of pathloss for management of 5G LTE, fast fading and other additional modelling components, and the main works on channel models are described:

- We have proposed 5G requirements in terms of frequency range, bandwidth, massive MIMO and polarization modelling, and performed channel measurements at various bands between 1 and 100 GHz with different channel model methodologies, map, stochastic and hybrid models, covering a wide variety of scenarios.
- We have performed studies in propagation and atmospheric loss on mm-waves, focusing on dense urban environment, proposing characterization in the context of blockage modelling, wideband power delay profiles and physics-based path loss model.

- mm-wave has undertaken channel measurements in the 1 to 100 GHz range, while IMT-2020 is doing similar work based on China in comparison with our proposed research.

In broader terms, regarding general 5G network schemes, management is focused on the study of mm-waves in the access radio, front haul and backhaul contexts, in a variety of scenarios. The group has performed analysis on the use of mm-waves in micro-cells for dense radio-access areas in indoors and outdoors, to infer the technical feasibility of network increase capacity. The Fantastic 5G project has researched the primary key indicators needed to be achieved to improve capacity, coverage, reliability and latency for networks operating below 1 GHz, based on LTE model simulations. We developed a model that manages capacity and coverage for mill metric waves in the 5G LTE, in an urban scenario. We have presented a research on the implementation of mm-waves for future 5G networks, having as underlying modelling interface an open source software MATLAB, capable of simulating 5G-network parameters with a 1 GHz bandwidth.

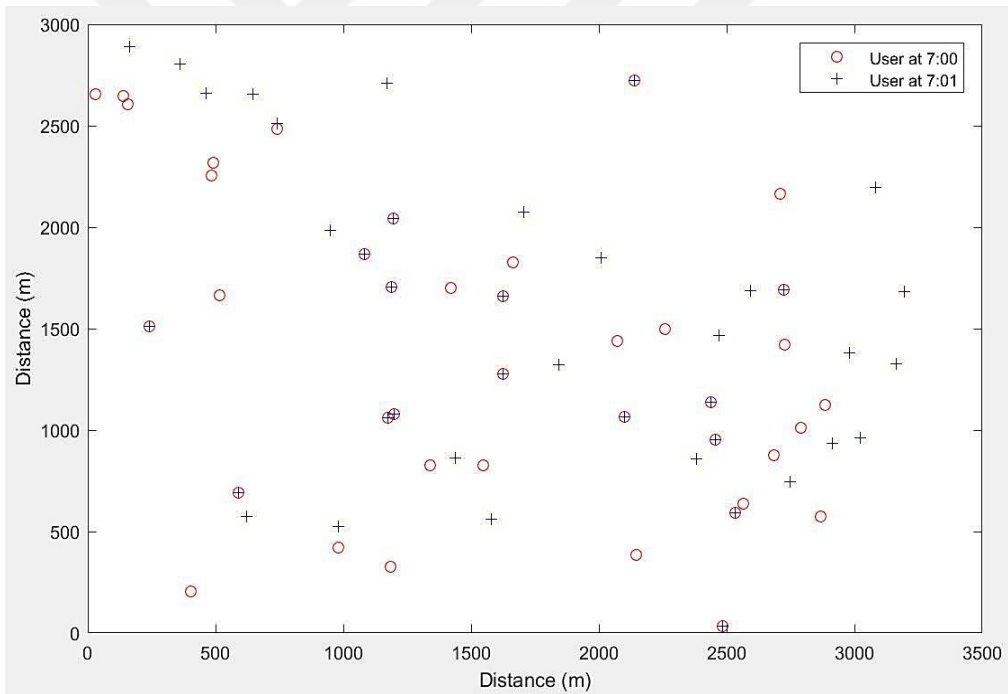
### **3.2 SYSTEM MODELING STRATEGY**

In the 5<sup>th</sup> generation network, several users need to be modeled. Since the research work focuses on the management scenario, the number of UEs (User Equipment) should vary during the day. For example, at midnight, the number of users will be small since people go back home and won't need the data service in the area. While during the working hour (from 8 a.m. to 5 p.m.), the data traffic could be large and varies along with the time. The locations of the UEs are randomly scattered. To make the simulation close to the real case, some of the UEs move to another place within the range of 500 meters at the next time slot while others stay where they are. The number of moved UEs is subject to Poisson Distribution with  $\lambda$  equals to half of the total number of users in the cell at time  $t$ . The distributions of UEs at time 7:00 a.m. and 7:01 a.m. are shown in figure.

At last, the works that relate more to the frequency spectrum in the scope of this thesis and network characteristics, such as numerology or MIMO, presents a simplified but comprehensive overview on 5G deployment considerations, from use-cases to frequency bands' implementation roadway, as well as interoperability architectures with LTE core network. We proceed to study the requirements for new channel models, from frequency bands, bandwidth, types of antenna arrays, mobility and handover issues, as well as presenting an experimentation and validation method for

typical outdoors propagation scenarios in micro and macro-cells and outdoor-to-indoor penetration loss. For this method, it considers elements such as signal blockage, path loss models and shadow fading.

This agglomerate study on different perspectives regarding the multi- numerology schemes in 5G, based on a number of technical configurations such as the power difference for edge users of different numerologies, being an early technique in the numerology- management context, through the use of allocation fairness. Similar work on the numerology field is presented by this research. Concerning experimentation on the 100 GHz band propagation effects and MIMO antennas, there have been field trials by this research, the last one proposes an antenna configuration allowing for MIMO configuration in small devices for 100 GHz



**Figure 3.2:** Distributions of UEs at 7:00 a.m. and 7:01 a.m.

**Table 3.3:** Parameters of managing 5<sup>th</sup> Generation Base Station.

Parameter	Value
Type	Femtocell base station
Number	10

Parameter	Value
Power (dBm)	-20, 10, 20
Bandwidth (MHz)	20
Location (m)	Randomly scattered in the macro cell
Awaken Power (w)	15
Start-up power (w)	30
Time duration to switch on a small cell (sec)	30

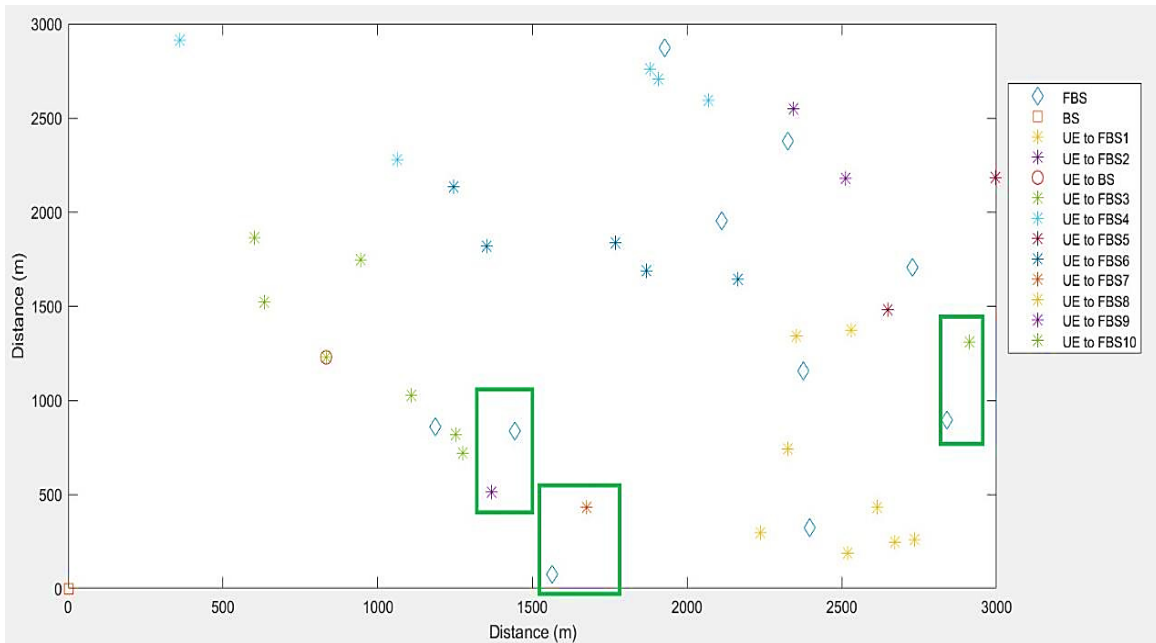
### 3.3 K-MEAN ALGORITHM

In the model simulation, k-means clustering algorithm is used for each UE to decide which base station it connects to. The input of this algorithm is a cluster number  $k$  and  $n$  data objects. In the modeling process, by using the k-means algorithm, UEs are divided based on their distances to the small cell base station. The number of clusters  $k$  equals to the number of small cell base stations in the network. By running the loop until the convergence, all UEs will be clustered to each small cell base stations based on their distance to each small cell base station.

#### Algorithm 1 Pseudo code of k-means Clustering

- 1: **Input** the number and location of both UEs and small cell base stations
- 2: **Initialize** the central points of all base stations
- 3: **For each UE**
- 4: Calculate the distances to all base stations.
- 5: Find the minimum value and record the index of the base station
- 6: **For each index**
- 7: Count the number of UEs that has that index
- 8: Calculate the location of new center point
- 9: Record the number of UEs in a vector as well as all the corresponding location
- 10: **Output** the vector and the locations

This algorithm is used to simulate the connections of each UE in the network. In the real case, the connection transfers between the UE and base station is done by hard handover. To simplify the model, handover process is simplified by clustering the UEs to decide their serving base station. Since a Femtocell base station can only support 4-6 users, after k-means clustering, those excess users have to be connected to the base station.



**Figure 3.3:** Initialization of the Cell at 1:40 a.m.

### 3.3.1 Data Augmentation

The model dimensioning should be as objective and detailed as possible, while also permitting changes in input parameters for different network deployment configurations. This process can be seen as a high-level approach to network dimensioning, where by the use of propagation models and specific algorithms it is possible to produce an output solution with an acceptable degree of accuracy.

The input and output parameters are generically described in the next section, as well as the propagation models used for coverage planning. The most relevant models for coverage and capacity are defined in the next section. Besides these essential elements for cellular network planning there is the traffic density/volume and share/mix profile throughout a typical load day.

From the input parameters the first step is to compute the maximum cell distance through link budget and propagation models, given the reference throughput, then to define the maximum network load, from the traffic profile, which produces an estimation cell radius for the different propagation scenarios from which the cell density configurations are retrieved.

**Table 3.4:** Augmentation for Data

<b>Augmentation type</b>	<b>Parameter</b>	<b>Chance</b>
Horizontal scale	0.5 ~ 1.0	50%
Vertical scale	0.5 ~ 1.0	50%
Shear angle	-90 ° ~ +90 °	50%
Rotation angle	-25°~+25°	50%
Perspective transform	Standard deviation: 0.05 ~ 0.1	50%
Flip	Only horizontal flip	50%
Hue and Saturation	-50 ~ +50 (in scale of 255)	100%
Overall scale	0.2 ~ 1.0	100%

### 3.3.2 Managing Base Station in Cell Radius

The main output will be the number of base stations in the target area, given by the cell radius computed at the level of coverage and/or capacity evaluation. The former has predominance in terms of network planning over the latter, except for when network capacity is exceeded – then the predominant value is the capacity computed cell radius. Nevertheless, it is from capacity evaluation that the metrics of throughput and maximum number of users are determined. The fundamental aspects on the propagation model characteristics is presented Table 3.3. The goal is to, essentially, have an outdoors propagation model for both frequency bands (100 GHz frequency band) and an indoors model that accepts both frequency bands. The outdoors models are valid for the three propagation scenarios (urban, suburban, rural) while the indoors one is an empirical and site-generic model, meaning it is an abstraction based only on the fact if the main wall to be crossed represents a high or low-loss material. The cell structure is assumed to be hexagonal following the concept of tri-vectorization in BSs in use in real-life network cell configuration. This is the optimal geometrical shape, since it minimizes any overlap or gap given, and on top of this assumption a

generic value for handover ratio is defined for any cell size, which finds its limitations if the cell size is too large and thus an approach for absolute handover distance could be considered in a future implementation. The hexagonal cell area can then be computed.

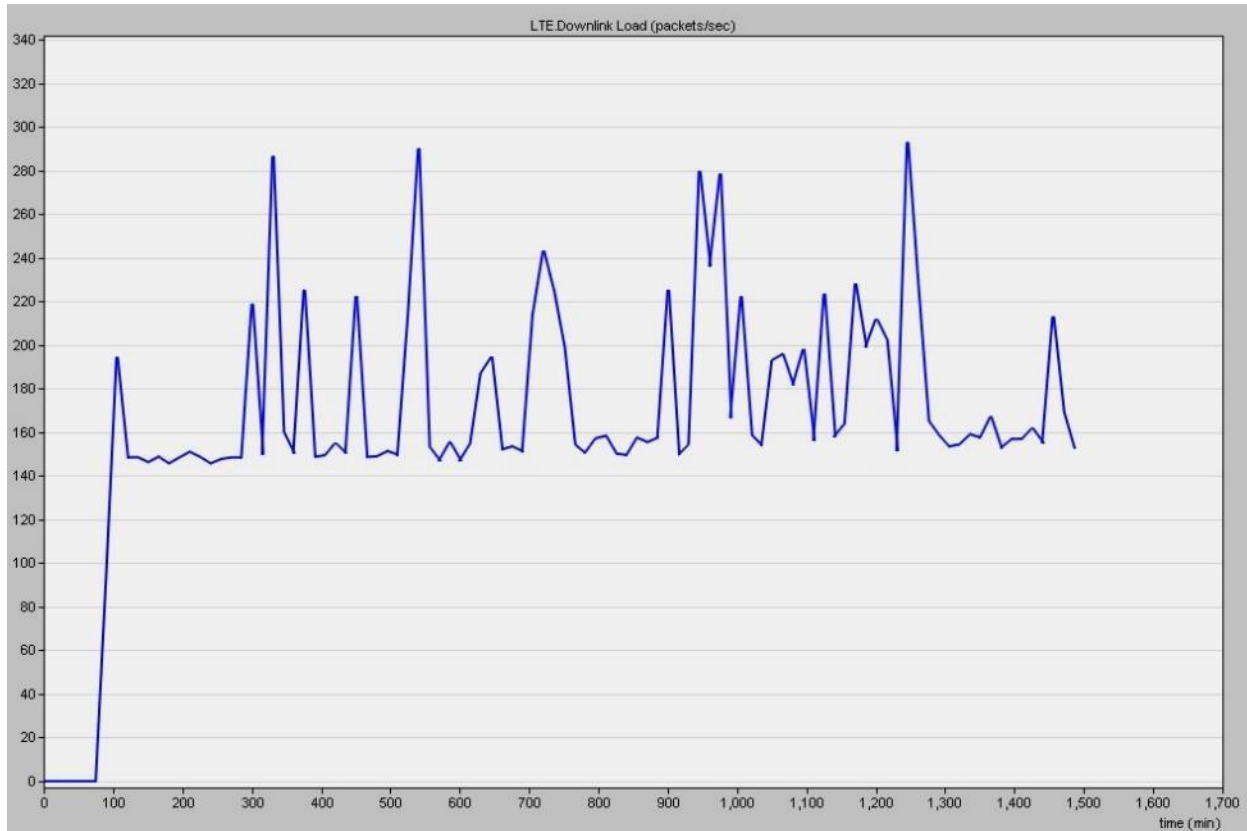
**Table 3.5:** Capacity and coverage metrics for network and UE perspective.

METRICS	PARAMETERS	
	NETWORK	BASE STATION
<b>CAPACITY</b>	Device/connection density, throughput, cell size, latency	Throughput, latency, traffic volume profile
<b>COVERAGE</b>	Propagation scenario, penetration losses, cell size, obstructions	Signal strength, mobility

While there may exist the same parameter in the capacity and coverage field, its meaning is not necessarily the same. For example, a macro-cell could be a suitable solution for coverage purpose while femto-cells could be the most adequate solution to support or increase network capacity in the same coverage area. On the other hand, it is the received power at the base stations that will define their access to the network, but it is through network capacity that base stations can achieve certain parameters.

## 4. RESULTS

Since MATLAB is a software that can simulate the communication network, an LTE network is deployed in this software to get a reference about the simulation results of the traffic load in the macro cell. The LTE network is initialized by using the function “Deploy Wireless Network” in the software. Having the initial network been set, the applications and profile files need to be set then. Since this research work consider the real environment scenario, applications relevant to real environment working are considered. Two rows are set in the profiles, one is staff and the other is user. They are set in this way because customers or other users will step into this real environment area and use the network. User will not be able to get access to some of the applications in the real environment area, so the application settings in these two profiles are different. After the settings, simulation is run with the parameter setting as 1-day duration and 128 seeds. The result of the traffic load of the cell is shown in figure. We first describe the data we collected for training and then describe the data served as a benchmark to evaluate our model and compare it with other existing models. The training and testing process were on operating system Ubuntu 16.04 LTS with CPU Intel i7-6500 3.20GHz, GPU GeForce GTX1080, DRAM 16GB. We built the system with MATLAB.



**Figure 4.1:** Traffic Load Result (packet/sec).

To validate the model built in previous section, MATLAB simulation has been made. The components in the network include Femtocell base stations (FBS) and macro base station (BS).

The standard value considered for throughput evaluation is with the numerology of 15 kHz. There are relevant aspects concerning band guards on higher orders of numerology in 5G which can change the multiplying throughput factor from the 15 kHz throughput curve, but for simplicity purposes one assumes a multiplying factor of 2 every time the 5G bandwidth doubles. It should be noted that this approximation may not be suitable for use with much higher orders of numerology (e.g., bandwidth of 120 or 240 kHz), however since those are not within the scope of this thesis due to it being defined for mm-waves (100 GHz), the factor of 2 is considered in the 15, 30 and 60 kHz throughput curves.

**Table 4.1:** Simulation Parameters

<b>PARAMETER</b>	<b>VALUE</b>
Number of FBS	10
Distance of Area	3 km × 3 km
Baseline Power of BS (w)	750
Transmission Power of BS (w)	600
Antenna Gain of BS (dBi)	0
Cable Loss of BS (dBi)	0
Noise Figure of BS (dB)	6
Baseline Power of FBS (w)	105.6
Transmission Power of FBS (w)	39
Antenna Gain of FBS (dBi)	0
Cable Loss of FBS (dBi)	0
Noise Figure of FBS (dB)	4
Transmission Power of FBS per UE (w)	0.5
Antenna Gain of FBS (dBi)	0
Cable Loss of FBS (dBi)	0
Noise Figure of FBS (dB)	8

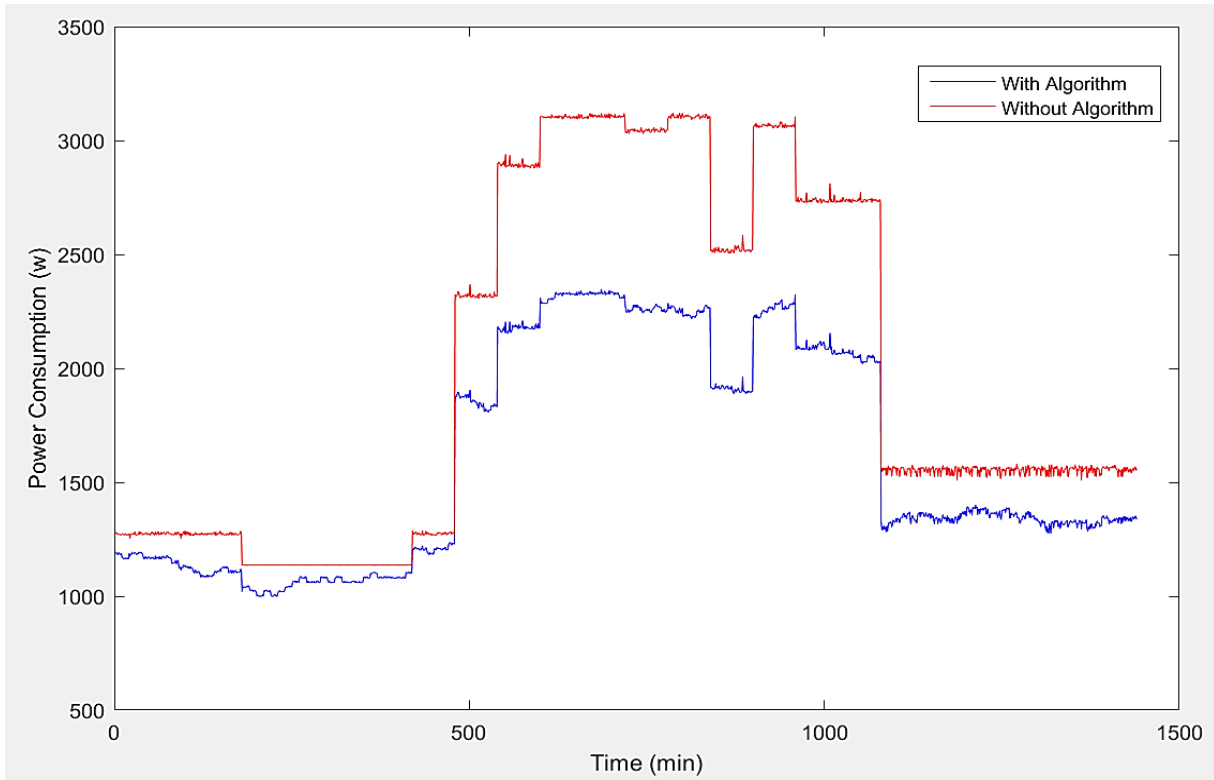
As previously discussed, the model can take any numerology configuration although only the one with highest distance is considered for coverage distance purpose. That is to say, if numerologies 0, 1 and 2 are selected, coverage estimation will always be based on numerology 0 (15 kHz) and consequently the same applies for computing the maximum achievable throughput at the cell edge. Although there is a liberty to pick any numerology configuration, there are certain restrictions imposed by 5G network management. Essentially there are numerologies that are not supported by some pairs of frequency/bandwidth.

The process is then done for every user in the cell and continues until the network exceeds either the number of BS, which in 5G has a maximum value of 100 GHz, either the total bandwidth for a given pre- defined cell load ratio, which is composed of the bandwidth allocated at the cell edge and the useful bandwidth allocated to the cell population. If the process comprises all users and it does not exceed the conditions mentioned above, the cellular design is complete at the specific cellular level, otherwise a re-dimensioning process must take place. The proposed re-dimensioning

techniques are essentially in the sense of reducing some parameter of set of parameters that can suffer adjustments, such as reducing the list of services to the ones with highest priority level or reducing the cell size:

- Reducing list of services: there are a couple of services that can never be excluded, so this technique works only until a certain point. The idea is to remove one service at a time from the lowest priority and evaluate if the cell avoids capacity overload. The degradation of throughput value is considered for non-essential services such as video-streaming.
- Reducing cell radius: this reduction is essentially linked to having less users to be served in the cell and therefore being able to support them with the available cell capacity. This reduction only applies to the cell edge; the remaining BS region boundaries remain unchanged. It can happen that the cell edge is in a closer BS region, e.g., different BS regions, but the remaining BS curves are still available.

To determine k-means algorithm performing better in the controlling process, comparison of the performance in energy saving efficiency and management has been made. The k-means algorithm have the clustering function, but its methods to update the cluster value are different. The power consumption is plotted with the duration of 24 hours. Each time slot is a minute. The curve is compared with the one that without switching algorithm and have all the small cells turning on to meet the capacity demands of peak hours in the work scenario.



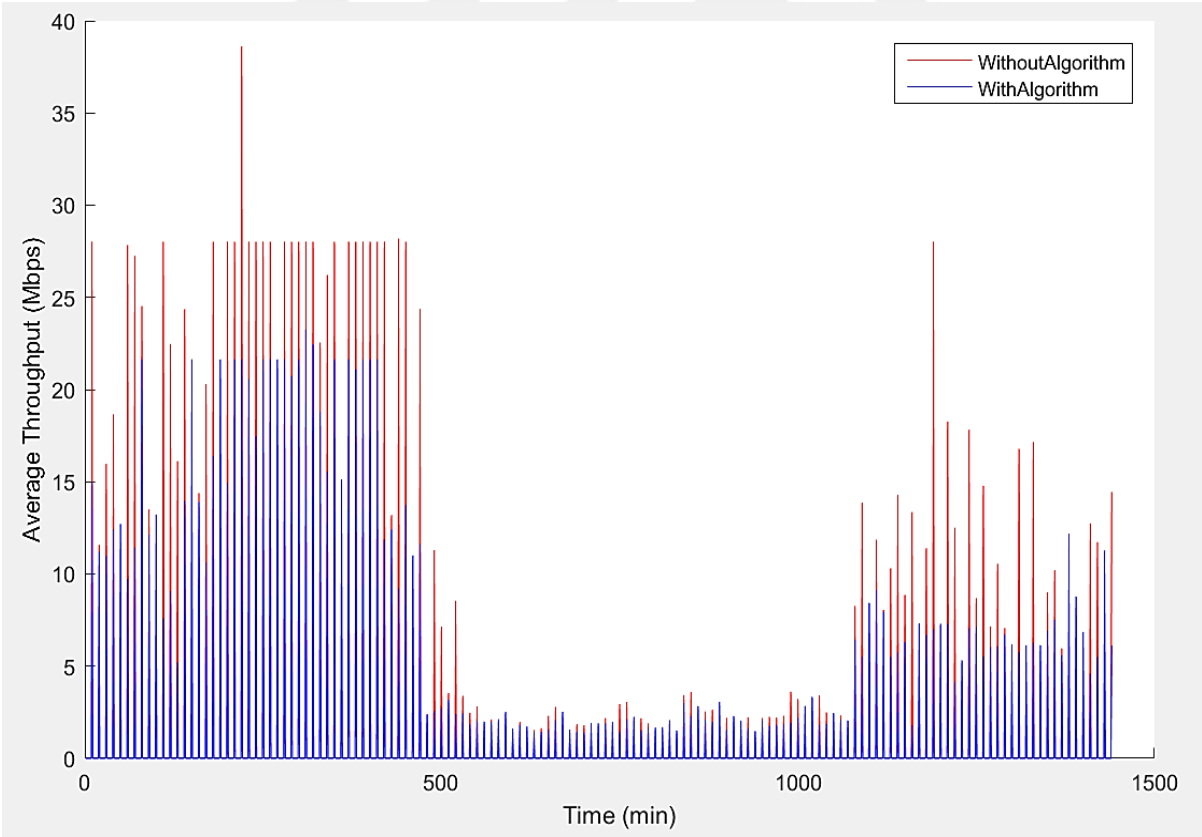
**Figure 4.2:** Power Consumption and Management with Algorithm vs. without Algorithm.

Figure 4.2 shows the details about management and power consumption in a macro cell before and after using the K-Means algorithm. The simulation duration is one day and each iteration is one minute. In general, the power consumption with the algorithm is less than without algorithm. In details, every time when the traffic load in the network increase, which leads to the increment of management and power consumption with the algorithm will increase first and then drop until reach a relatively stable state. This shows the effect of switching. The reward will have delay on action selection. Despite the good performance during the peak hours, the performance of the off-peak hours is not that remarkable. This is because the large proportion of the power consumption comes from macro cell base station, which makes the power saving from Femtocells is relatively subtle to be seen.

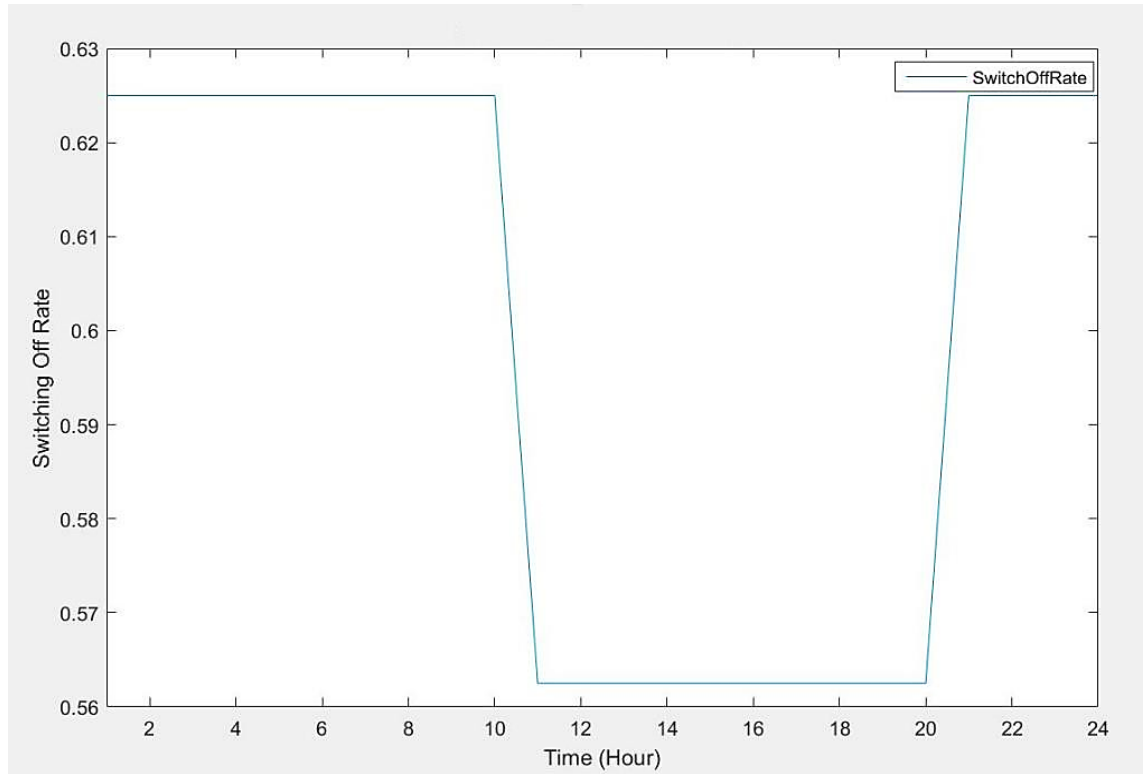
Comparing the data in Figure, when the frequency increases the total number of cells also increases, with a relative increase of 52% in mm-wave, 27% in bandwidth and 59% In base stations. Once again, the higher relative increase in the suburban environment can be explained by

it having a larger area than the urban one, but also if one considers that bandwidth municipalities are already quasi-all capacity-limited at 1 GHz, and that in the suburban ones there may be more coverage-limited cells, the logical conclusion would be that the increase in the number of cells will be higher in bandwidth, which is represented in the figure.

As stated before, any conclusion from the total or absolute number of cells cannot be directly taken, unless one acknowledges the environment composition per 5G management regions. The municipalities with higher percentages of urban environment are unlikely to yield much higher number of cells when the frequency increases due to the predominance of capacity-limited cells. On the other hand, municipalities with high levels of suburban or rural environments are more likely to have their number of cells increase by a higher percentage, simply due to them having a larger probability of coverage-limited cells at 1 GHz which turn into capacity-limited ones at 100 GHz.



**Figure 4.3:** Average Throughput in Macro Cell with Algorithm vs. without Algorithm (1 Day).



**Figure 4.4:** Classification and pose estimation results of Multiple Cars Scene dataset.

Figure 4.4 shows the comparison of average throughput in the macro cell between using the algorithm and not using the algorithm. Combining the result in figure 4.4, it is not hard to find that the average throughputs are similar during the peak hours since all small cells are switched on. While during those hours when the traffic loads are relatively low, the average throughputs are lower when the algorithm is used, i.e. some small cells are switching off to save energy. It is because by using the algorithm, some UEs have to be connected to the macro base station and add more traffic loads to BS. The throughput experienced by each user will decrease if many users share the resource. This helps illustrate the tradeoff between the higher throughput and lower power consumption. If better services are offered, more power will be consumed. However, it is not necessary to offer the highest throughput, the value within a sustainable range will be fine to save energy and offer service users needed. Figure 8 shows the details about the switching Off rate of small cells in the network. To show the result clearly, the simulation is run based on an hour for each iteration. The plot shows the trend that during those hours when traffic load is low, many

small cells are switched off to save energy. While in those traffic hours, small cells are switched on to meet the capacity requirements in the cell.

As the active device density increases more resources are required to serve the traffic profile load of the cell device population, which leads to capacity limited cells. In this case, the cell radius can severely be reduced from its original value and increase the number of required cells, which can be noticed in Figure 4.3, when comparing the reference scenario with the double and triple configuration values. On the other hand, the impact of increasing the active device density is heavier as more path losses are included, such as with obstructions, which is the reason the urban scenario requires much more cells than the other scenarios

## 5. DISCUSSION

### 5.1 DISCUSSION

Results of this research work including results in the throughput simulation, algorithm performance and network performance have been listed and analyzed above. From these plots and results, it could be concluded that off-policy K-Means Algorithm shows better performance in network power saving than on-policy different algorithm. Different choices of learning rate and reduction factor of the K-Means algorithm can show slightly different effect on power saving performance. By using the K-Means algorithm, small cells with less users can be switched off during the off-peak hours while switched on during the peak hours. By achieving this, the network power consumption can be reduced especially during the peak hours. However, delay is shown in the controlling process and power consumption during the off-peak hours cannot be reduced remarkably because the macro cell case station consumes large proportion of the total power consumption. By switching off some small cells, the throughput gets lower than that without the algorithm. It shows the tradeoff between the higher throughput and lower power consumption. Less small cells remaining working in the network means more users share the total spectrum resources, which lead to the decline of the average throughput. This kind of tradeoff can be balanced when the decrement of throughput is within an acceptable range.

**Table 5.1:** The comparison of different techniques with proposed technique.

ARTICLE	TECHNIQUE	ACCURACY
[48]	Standard Automated Model	90.00%
[49]	Convolutional Neural Network	96.40 %
Proposed	K-Means	97.82%

In general terms, as the available bandwidth in the cell increases the number of possible users that can be served also increases. This can be seen in Figure 4.2, for both frequency bands, with the

decreasing cell density values as the bandwidth increases. Since each cell has a higher capacity it will require less iterations, e.g., cell radius reduction cycles, to find the optimal radius necessary to fulfil both the throughput at the edge requirement and the global capacity requirements.

For the traffic profile considered in this thesis one finds, for the management of 5G band, that increasing the bandwidth serves of no usefulness from a certain threshold value, that is to say from 100 GHz on the difference in cell density is not very significant. This may be an indication that for this traffic profile an operator would not need more than 100 GHz in order to find a compromise between cost in terms of number of cells and of serving their customers. As it would be expected, the number of required cells for the same bandwidth is much higher at the higher frequency (100 GHz) than in the lower one (1 GHz).

This can be explained by average cell radius at the lower frequency being higher, while serving the same traffic profile as in the higher frequency, due to the lower path loss attenuation, both in outdoor and indoor environments. This metric is an indicator as to why the spectrum at the lower frequency bands is more expensive, since they require fewer cells installed in the same target geographical area.

Some basic features from the traffic load calculation are retrieved from this work, however the inclusion of numerologies due to the novelty network elements of 5G add a completely new layer in the capacity related algorithms in the model. The model performs an evaluation for both DL and UL, with respective different link budget parameters and different traffic profile configurations, then for each simulation or 5G management regions, it picks the worst case, i.e., the channel with lowest cell radius, or with highest number of cells. Furthermore, Chapter 3 includes the system model implementation where a description on the most relevant and important routines in the model are done, finishing with the model assessment, where a battery of tests was performed to verify the coverage and capacity models independently as the model was being developed.

The coverage assessment has started with the verification of the path loss and propagation distance results between the manual computation, in Excel, and the results provided by the simulator. Then, the cell radius did change as the frequency band increased for both propagation models and from different input parameters, such as the required throughput at cell edge, the BS and the MT heights.

Besides, the cell radius did decrease with the increase of the management and also decreased more when applying the high-loss indoor pathloss than the low-loss indoor path loss model, as it would be expected. The final output is the number of cells did increase while the frequency band increased.

The capacity assessment has started with the verification of the uniqueness process of randomly allocating users in each 5G management region and the number of BSs required by each user given its throughput requirement and available throughput configurations in terms of numerologies and performance curves, through means of scientific calculator, Excel and model results comparison. The number of users per cell increased generically when the user density increased, and the number of allocated BSs and bandwidth increased as the overall service throughput values increased. Furthermore, the cell radius is seen to decrease as the user density increased, which represents the cell radius reduction routine, and the throughput at the cell edge doubles when the reserved bandwidth doubles, as it would be expected. At last, the cell radius is never higher than the distance given by using only the lowest numerology configuration, which yields the highest distance, and the cell radius is never lower than the distance given by only using the highest numerology configuration, which yields the lowest distance, which is an expected result.

## **6. CONCLUSION**

### **6.1 CONCLUSION**

This research work develops an algorithm to switch on/off small cells to help save network energy and management of energy in 5<sup>th</sup> generation network and meanwhile meet the capacity requirement. A distributed implementation of switching on/off algorithm in a real environment scenario network with one macro cell and several small cells has been made. After the algorithm being introduced, small cells can offload the macro cell dynamically to help save the network energy. The algorithm is based on the machine learning based K-Means Algorithm. The method to get the best policy, on-policy K-Means Algorithm and off-policy K-Means Algorithm, have been taken into consideration. The final results show that the K-Means Algorithm shows better performance in saving power. More details about the parameters of K-Means Algorithm have been compared to get a better performance. To evaluate the performance of the algorithm, a simplified network model has been built. The data of traffic load comes from the simulation by using MATLAB Modeler, whose results are more realistic in the real environment scenario with an accuracy of 97.82%. The main evaluation is run in MATLAB and the final results show that the algorithm can save power consumption especially during the peak hours when traffic load is large. The solution can still be improved in the future. Although the traffic data are based on the realistic simulation results. Model built in MATLAB is simplified and may different from the result of much complex network in real case. The implementation is relatively complicated and need to change the model files in MATLAB simulation. At current stage, due to the limit in time and capability, the algorithm is evaluated in a simplified model rather than a complex network in real case for 5<sup>th</sup> generation networks.

### **6.2 FUTURE RECOMMENDATION**

The main contribution that we want to develop in future is one can take is that no solid contribution can be made by only considering the number of cells per 5G management regions in both frequency bands in 5G network. Hence, one should take other factors into consideration, such as the

environment composition per 5G management regions, the average number of devices per user or the set of mean and standard deviation values for the cell radius for all municipalities.

We want implement the cell limitation by coverage or capacity is an important concept that makes some results clearer for managing the 5<sup>th</sup> generation network. For instance, management with strongly composed of 5G network environments do not suffer a much relative increase in the number of cells, since they are already mostly capacity limited at the lower frequency band, while municipalities strongly composed of suburban or rural environments are much more prone to suffering larger relative increase values in the number of cells.

We will provide a user and device densities are also another metric that can strongly influence the number of cells within a specific propagation environment, e.g., the 5G management regions have similar environment composition, but where the former has an 83% increase in the number of cells, while increasing the frequency the latter only has 37%, and this is because 5G network has almost the double device density compared to 4G network. On the other hand, the municipalities with highest device density values, such as cellular networks are less likely to increase severely the number of cells when increasing frequency, the increase is merely around 20%. We would also try to add deep learning for the automated management of the 5G LTE network in future.

## REFERENCES

- [1] M. Wollschlaeger et al. "The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0," IEEE Industrial Electronics Mag., vol. 11, no. 1, pp. 17-27, 2017.
- [2] T. Maksymyuk et al., "Deployment strategies and standardization perspectives for 5G mobile networks," IEEE Int. Conf. on the Modern Problems of Radio Engineering, Telecommunications and Computer Science (TCSET'2016), Lviv-Slavske, Ukraine, pp. 953-956, Feb. 2016.
- [3] I. Hwang, B. Song, S. Soliman, "A holistic view on hyper-dense heterogeneous and small cell networks," IEEE Communications Magazine, vol. 51, no.6, pp. 20-27, 2013.
- [4] N. Bhushan et al., "Network densification: the dominant theme for wireless evolution into 5G," IEEE Communications Magazine, vol. 52, no. 2, pp. 82-89, 2014.
- [5] W. Liu, S. Han, and C. Yang, "Massive MIMO or Small Cell Network: Who is More Energy Efficient?" in Proc. WCNCN 13, Shanghai, China, Apr. 2013, pp. 24–29
- [6] V. Yatskiv et al., "The use of modified correction code based on residue number system in WSN," IEEE 7th International Conference on Intelligent Data Acquisition and Advanced Computing Systems, pp. 513-516, 2013.
- [7] V. Inzillo et al, "A low energy consumption smart antenna adaptive array system for mobile ad hoc networks," International Journal of Computing, vol. 16, no. 3, pp. 124-132, 2017.
- [8] V. Kochan et al., "Energy-efficient method for controlling the transmitters power of wireless sensor network," IEEE Int. Conf. on Electrical and Computer Engineering, pp. 1117-1120, 2017.
- [9] Katuwal, R.; Suganthan, P.; Zhang, L. An ensemble of decision trees with random vector functional link networks for multi-class classification. Appl. Soft Comput. 2018, 70, 1146–1153.

- [10] ITU News, Forging Paths to 5G, Feb. 2017.  
([https://www.itu.int/en/itu-news/Documents/2017/2017-02/2017\\_ITUNews02-en.pdf](https://www.itu.int/en/itu-news/Documents/2017/2017-02/2017_ITUNews02-en.pdf)).
- [11] Available Online: <https://electricalfundablog.com/5g-phone-cellular-network-technology/>
- [12] S. Obadan, Z. Wang, “A hybrid optimization approach for complex nonlinear objective functions,” *International Journal of Computing*, vol. 17, no. 2, pp. 102-112, 2018.
- [13] R. Razavi et al., “A fuzzy reinforcement learning approach for self-optimization of coverage in LTE networks,” *Bell Labs Technical Journal*, vol. 15, pp. 153–175, 2010.
- [14] I. Goodfellow et al., “Generative adversarial nets,” In *Advances in neural information processing systems*, pp. 2672-2680, 2014.
- [15] T. Maksymyuk et al., “An IoT based Monitoring Framework for Software Defined 5G Mobile Networks”, *Proceedings of the 11th ACM Int. Conf. on Ubiquitous Information Management and Communication (IMCOM'2017)*, article #5-4, Jan. 5-7, 2017.
- [16] Deep Learning Based Massive MIMO Beamforming for 5G Mobile Network - Scientific Figure on ResearchGate. Available from: [https://www.researchgate.net/figure/Heterogeneous-architecture-of-5G-with-combination-of-Massive-MIMO-and-small-cells\\_fig1\\_328836812](https://www.researchgate.net/figure/Heterogeneous-architecture-of-5G-with-combination-of-Massive-MIMO-and-small-cells_fig1_328836812)  
[accessed 4 Jul, 2020]
- [17] Kong, Y.; Zang, H.; Ma, X. Improving TCP Congestion Control with Machine Intelligence. In *Proceedings of the 2018 Workshop on Network Meets AI & ML, Budapest, Hungary, 24 August 2018*; pp. 60–66.
- [18] Nunes, B.A.; Veenstra, K.; Ballenthin, W.; Lukin, S.; Obraczka, K. A machine learning approach to end-to-end estimation and its application to TCP. In *Proceedings of the 20th International Conference on Computer Communications and Networks (ICCCN), Maui, HI, USA, 31 July–4 August 2011*; pp. 1–6.

- [19] Taherkhani, N.; Pierre, S. Centralized and localized data congestion control strategy for vehicular ad hoc networks using a machine learning clustering algorithm. *IEEE Trans. Intell. Transp. Syst.* 2016, 17, 3275–3285.
- [20] Fadlullah, Z.; Tang, F.; Mao, B.; Kato, N.; Akashi, O.; Inoue, T.; Mizutani, K. State-of-the-art deep learning: Evolving machine intelligence toward tomorrow's intelligent network traffic control systems. *IEEE Commun. Surv. Tutor.* 2017, 19, 2432–2455.
- [21] González-Landero, F.; García-Magariño, I.; Lacuesta, R.; Lloret, J. PriorityNet App: A mobile application for establishing priorities in the context of 5G ultra-dense networks. *IEEE Access* 2018, 6.
- [22] Lloret, J.; Parra, L.; Taha, M.; Tomas, J. An architecture and protocol for smart continuous eHealth monitoring using 5G. *Comput. Netw.* 2017, 129, 340–351.
- [23] Taha, M.; Parra, L.; Garcia, L.; Lloret, J. An Intelligent handover process algorithm in 5G networks: The use case of mobile cameras for environmental surveillance. In *Proceedings of the 2017 IEEE International Conference on Communications Workshops (ICC Workshops)*, Paris, France, 21–25 May 2017; pp. 840–844.
- [24] Khan, I.; Zafar, M.H.; Jan, M.T.; Lloret, J.; Basher, M.; Singh, D. Spectral and Energy Efficient Low-Overhead Uplink and Downlink Channel Estimation for 5G Massive MIMO Systems. *Entropy* 2018, 20, 92.
- [25] Sangeetha, G.; Vijayalakshmi, M.; Ganapathy, S.; Kannan, A. A Heuristic Path Search for Congestion Control in WSN. *Ind. Int. Innov. Sci. Eng. Technol.* 2018, 11, 485–495. 26. Elappila, M.; Chinara, S.; Parhi, D.R. Survivable path routing in WSN for IoT applications. *Pervasive Mob. Comput.* 2018, 43, 49–63.
- [26] Singh, K.; Singh, K.; Aziz, A. Congestion control in wireless sensor networks by hybrid multi-objective optimization algorithm. *Comput. Netw.* 2018, 138, 90–107.
- [27] Pal Varga, 5G support for Industrial IoT Applications— Challenges, Solutions, and Research gaps, *Sensors* 2020, 20(3), 828; <https://doi.org/10.3390/s20030828>.

- [28] Godoy, P.D.; Cayssials, R.L.; Garino, C.G.G. Communication channel occupation and congestion in wireless sensor networks. *Comput. Electr. Eng.* 2018, 72, 846–858.
- [29] Najm, I.A.; Ismail, M.; Lloret, J.; Ghafoor, K.Z.; Zaidan, B.; Rahem, A.A.R.T. Improvement of SCTP congestion control in the LTE-A network. *J. Netw. Comput. Appl.* 2015, 58, 119–129.
- [30] Najm, I.A.; Ismail, M.; Abed, G.A. High-performance mobile technology LTE-A using the stream control transmission protocol: A systematic review and hands-on analysis. *J. Appl. Sci.* 2014, 14, 2194–2218
- [31] Available Online: [https://en.wikipedia.org/wiki/5G\\_network\\_slicing](https://en.wikipedia.org/wiki/5G_network_slicing).
- [32] Liang, D.; Zhang, Z.; Peng, M. Access Point Reselection and Adaptive Cluster Splitting-Based Indoor Localization in Wireless Local Area Networks. *IEEE Internet Things. J.* 2015, 2, 573–585.
- [33] Liu, Y.; Wu, H. Prediction of Road Traffic Congestion Based on Random Forest. In *Proceedings of the 2017 10th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 9–10 December 2017*; pp. 361–364.
- [34] Park, H.; Haghani, A.; Samuel, S.; Knodler, M.A. Real-time prediction and avoidance of secondary crashes under unexpected traffic congestion. *Accid. Anal. Prev.* 2018, 112, 39–49.
- [35] Shu, J.; Liu, S.; Liu, L.; Zhan, L.; Hu, G. Research on link quality estimation mechanism for wireless sensor networks based on support vector machine. *Chin. J. Electron.* 2017, 26, 377–384.
- [36] Riekstin, A.C.; Januário, G.C.; Rodrigues, B.B.; Nascimento, V.T.; Carvalho, T.C.; Meirosu, C. Orchestration of energy efficiency capabilities in networks. *J. Netw. Comput. Appl.* 2016, 59, 74–87.
- [37] Adi, E.; Baig, Z.; Hingston, P. Stealthy Denial of Service (DoS) attack modelling and detection for HTTP/2 services. *J. Netw. Comput. Appl.* 2017, 91, 1–13.

- [38] Stimpfling, T.; Bélanger, N.; Cherkaoui, O.; Béliveau, A.; Béliveau, L.; Savaria, Y. Extensions to decision-tree based packet classification algorithms to address new classification paradigms. *Comput. Netw.* 2017, 122, 83–95.
- [39] Singh, D.; Nigam, S.; Agrawal, V.; Kumar, M. Vehicular traffic noise prediction using soft computing approach. *J. Environ. Manag.* 2016, 183, 59–66.
- [40] Xia, Y.; Chen, W.; Liu, X.; Zhang, L.; Li, X.; Xiang, Y. Adaptive multimedia data forwarding for privacy preservation in vehicular ad-hoc networks. *IEEE Trans. Intell. Transp. Syst.* 2017, 18, 2629–2641.
- [41] Tariq, F.; Baig, S. Machine Learning Based Botnet Detection in Software Defined Networks. *Int. J. Secur. Appl.* 2017, 11, 1–11.
- [42] Available Online: <https://www.grandmetric.com/knowledge-base/research/spectrum-toolbox-survey-evolution-towards-5g-2/>.
- [43] Chen, Y.-y.; Lv, Y.; Li, Z.; Wang, F.-Y. Long short-term memory model for traffic congestion prediction with online open data. In *Proceedings of the 2016 IEEE 19<sup>th</sup> International Conference Intelligent Transportation Systems (ITSC)*, Rio de Janeiro, Brazil, 1–4 November 2016; pp. 132–137.
- [45] Abar, T.; Letaifa, A.B.; El Asmi, S. Machine learning based QoE prediction in SDN networks. In *Proceedings of the 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, Valencia, Spain, 26–30 June 2017; pp. 1395–1400.
- [46] Pham, T.N.D.; Yeo, C.K. Adaptive trust and privacy management framework for vehicular networks. *Veh. Commun.* 2018, 13, 1–12.
- [47] 5G – Wireless Communications for 2020 - Scientific Figure on Research-Gate. Available from: [https://www.researchgate.net/figure/Overview-of-5G-frequency-spectrum-including-traditional-spectrum-6-GHz-cm-wave-bands\\_fig3\\_304532304](https://www.researchgate.net/figure/Overview-of-5G-frequency-spectrum-including-traditional-spectrum-6-GHz-cm-wave-bands_fig3_304532304) [accessed 16 Jul, 2020].

[48] Polese M, Giordani M, Mezzavilla M, Rangan S & Zorzi M, “Improved handover through dual connectivity in 5G mmWave mobile networks”, IEEE Journal on Selected Areas in Communications, Vol.35, No.9, (2017), pp.2069-2084.

[49] Lam, Jordan & Abbas, Robert. (2020). Machine Learning based Anomaly Detection for 5G Networks. 10.13140/RG.2.2.17317.86247.

